Advancing Process Science Toward Unstructured Data and the Individual Level

Dissertation

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Für meine Vorbilder Franz und Irmi

Ich möchte mich herzlich bei allen Wegbegleitern aus dem Freundes- und Familienkreis, insbesondere bei Gerti, Wolfi, Christian und Beate, für die vielfältige Unterstützung in den vergangenen Jahren bedanken.

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Abstract

The business process management (BPM) discipline is concerned with the continuous improvement of business processes to drive organizational success while adapting to changing market demands and regulatory requirements. In the last two decades, the availability of digital trace data (i.e., event data) extracted from information systems has led to the rise of various data-driven techniques in BPM. Process mining in particular has received increasing attention in academia and industry due to its ability to discover, monitor, and improve operational processes. The scope of process mining research is continuously expanding, and the potential to turn its results into economic success is reflected by the growing number of software vendors and adopters in industry. Despite these positive developments, process mining initiatives still encounter challenges in delivering the anticipated benefits for certain application scenarios. Process science has been introduced as an interdisciplinary research field that aims to comprehensively understand and influence complex process dynamics from different perspectives and levels. Therefore, this thesis adopts the holistic scope of process science and draws on its key principles to address two challenges that limit the applicability of data-driven process analysis and management.

The first challenge focuses on *integrating unstructured data into process mining* and relates to the importance of reliable and high-quality event data to comprehensively reflect reality for data-driven BPM techniques. At present, it is not possible to analyze processes from end to end if these processes are only partially digitized or do not leave digital traces in information systems. Unstructured data, such as video or text data, can contain process-related information that, enabled by recent advances in data science and machine learning, has the potential to fill in missing gaps in process analysis. This thesis makes two contributions toward the integration of unstructured data into the data-driven foundation of process science and process mining. Research Article #1 develops a reference architecture that consists of several computer vision components to enable the systematic use of video data for process mining. Research Article #2 provides a comprehensive overview on how different types of unstructured data are used in process mining and proposes a research agenda to guide future research in this area.

The second challenge concentrates on *expanding data-driven process discovery, explanation, and intervention* for complex process phenomena, as called for by process science. Since research that exceeds the scope of a single organization is scarce, Research Article #3 analyzes the cross-organizational turnaround process at Munich Airport. Research Articles #4 and #5 deviate from the traditional organizational perspective on processes and instead focus on the perspective of a single patient in a medical treatment process. The two articles design artifacts that use biomedical sensor data to predict bladder volume and thus enable prescriptive treatment for patients who have lost bladder sensation.

Overall, this thesis contributes to the interdisciplinary field of process science and expands process discovery, explanation, and intervention through a methodological portfolio that includes design science research (DSR), single case study research, and a systematic literature review. Specifically, the three proposed DSR artifacts extend the data-driven core of process science and process mining through unstructured data, and provide innovative solutions for intervening in healthcare processes at the individual patient level.

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Acronyms

ACDM	Airport Collaborative Decision Making
AI	Artificial intelligence
BPM	Business process management
CNN	Convolutional neural network
DL	Deep learning
DNN	Deep neural network
DSR	Design science research
EM	Ensemble model
LSTM	Long short-term memory network
ML	Machine learning
NBD	Neurogenic bladder dysfunction
NIRS	Near-infrared spectroscopy
NLUTD	Neurogenic lower urinary tract dysfunction
PCA	Principal component analysis
PM^2	Process mining project methodology
RF	Random forest
SVM	Support vector machine
UML	Unified modeling language
ViProMiRA	Video Process Mining Reference Architecture

I Introduction[1]

1 Motivation

The business process management (BPM) discipline comprises methods and tools that improve the effectiveness and efficiency of work within and across organizations through the continuous identification, discovery, analysis, (re-)design, implementation, and monitoring of business processes (Dumas et al. 2018; Grisold et al. 2022; Röglinger et al. 2022). Over the last two decades, the widespread adoption of process-aware information systems (e.g., ERP or BPM systems) has increased the availability of process-related digital trace data (i.e., event data) and paved the way for the integration of various data-driven techniques and technological innovations into BPM (Dumas et al. 2023; Mendling et al. 2020; Oberdorf et al. 2023).

Process mining, as the most prominent example of these data-driven BPM techniques, strives to discover, monitor, and improve operational processes by systematically using time-stamped event data (van der Aalst 2012; van der Aalst 2022). Starting with the technical and algorithmic foundations in the late 1990s (van der Aalst 2022), process mining research today covers a broad thematic spectrum that ranges from organizational perspectives on adopting and effectively using the technology (Mamudu et al. 2022; Martin et al. 2021; Milani et al. 2022) to predicting process executions (Di Francescomarino and Ghidini 2022; Kratsch et al. 2021) and recommending appropriate next best actions (Bozorgi et al. 2023; Leoni et al. 2020). Due to its capability to enable real-time decision-making for individual executions, process mining is today considered a business process intelligence technology (Badakhshan et al. 2022).

Reports on industrial use cases indicate a growing interest in process mining from the practitioner community (Grisold et al. 2021), suggesting significant value for operational process support and improvement (Badakhshan et al. 2022; Mamudu et al. 2023; Reinkemeyer et al. 2022). For example, Reinkemeyer (2020) reported savings of $20 million in the customer support process at Uber, while Celonis (2023) stated that Deutsche Telekom saved $66 million in the procure-to-pay process through process mining. In 2019, Gartner estimated process mining licensing and maintenance revenue at $320 million (Kerremans et al. 2020). Recent analyst reports expect the process mining market to grow at a compound annual growth rate of nearly 50% from over $1.6 billion in 2023 to $12.1 billion in 2028 (Fortune

[1] *The following sections are partly comprised of content from the research articles included in this thesis. To improve the readability of the text, I have omitted the standard labeling of these citations.*

Business Insights 2023; MarketsandMarkets 2023). This economic potential is also reflected in the development of the process mining software landscape and the acquisition of established vendors through large tech companies such as Microsoft and SAP (Graham 2022; SAP 2021). Currently, Gartner is monitoring 36 process mining vendors (Gartner, Inc. 2023), including the market leader Celonis, which was founded in 2011 and has reached a valuation of almost $13 billion in just over a decade (Celonis 2022).

BPM and process mining are inherently focused on business processes and process mining research still tends to concentrate on technical aspects (Mamudu et al. 2023). To broaden the spectrum of process-oriented research and to provide a platform for different disciplines, vom Brocke et al. (2021) introduced the field of process science. Process science provides a process-oriented, interdisciplinary, scientific lens for understanding and influencing processes (vom Brocke et al. 2021). It combines multiple perspectives (e.g., environmental, technological, and human) and studies a wide range of processes (e.g., biological, productive, and political) viewed as a coherent series of changes occurring at different levels (e.g., organizational and individual) (vom Brocke et al. 2021). Consequently, process science is well-suited to address the challenges posed by a hyper-connected world in constant change (Beverungen et al. 2021), in which the boundaries between business, private life, and other areas of society are blurring due to global phenomena such as digitalization, the Internet of Things, and process automation (Kerpedzhiev et al. 2017). The integration of BPM and process mining into the wider application context of process science also offers significant potential for the development of holistic process solutions.

Figure 1 depicts the three main activities of process science (i.e., *discovery*, *explanation*, and *intervention*), which - analogous to process mining - systematically leverage time-stamped event data (vom Brocke et al. 2021). Therefore, Figure 1 also includes the supporting *data extraction & processing* activity required to obtain high-quality event data from structured sources, such as process-aware information systems, and unstructured sources, such as text documents and sensors (van der Aalst 2022). Since the original data is often stored in a process-agnostic format, the data extraction & processing activity typically represents the greatest effort in process mining projects (Wynn et al. 2022). The *discovery activity* aims to capture and characterize a process of interest (vom Brocke et al. 2021). Process mining contributes to this activity with different process discovery techniques that use event data to produce a process model without needing a-priori information (van der Aalst et al. 2012; van der Aalst 2022). The *explanation activity* seeks to identify cause-effect relations that enable sense-making to comprehensively understand a process (vom Brocke et al. 2021). BPM and process mining feature a plethora of techniques that can be applied throughout the explanation activity (Fahland 2022; Schmiedel et al. 2020). For example, the detection of deviating process behavior (i.e., workarounds) (van der Aalst 2016; Weinzierl et al. 2022) can point to potential root causes of process-related problems and thus advance understanding of specific process contexts (Bartelheimer et al. 2023). A thorough process understanding is also a prerequisite for predicting future process outcomes (vom Brocke et al. 2021), which is enabled by forward-looking process mining techniques (Di Francescomarino and Ghidini 2022; Kratsch et al. 2021; van der Aalst 2022). The *intervention activity* draws on process insights to derive actionable measures that help direct the process toward a desired goal (vom Brocke et al. 2021). As the intervention activity is centered on actually implementing and realizing process changes, it has the potential to provide substantial utility and value for real-world problems (Badakhshan et al. 2022; Gross et al. 2021). BPM methods can assist in the intervention activity, either to incrementally improve existing business processes (i.e., exploitative BPM) or to pro-actively leverage emerging opportunities to deliver new value propositions (i.e., explorative BPM) (Grisold et al. 2022; Malinova et al. 2022). During and after an intervention, conformance-based process mining techniques can monitor whether completed and running process instances comply with the envisioned changes (Badakhshan et al. 2022).

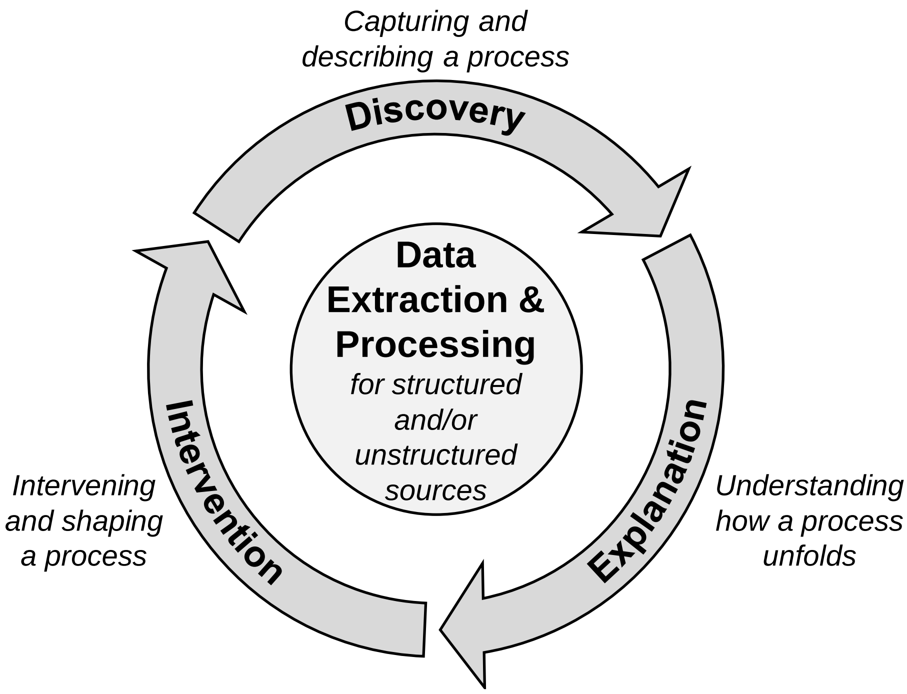

Figure 1: Illustration of relevant activities in process science based on vom Brocke et al. (2021)

The domain-spanning and holistic scope of process science makes it a well-suited lens to identify the new and contextualize the multiple existing challenges for BPM and process mining

(Beerepoot et al. 2023; Beverungen et al. 2021; Martin et al. 2021; van der Aalst 2020). While acknowledging the importance of advancing research in various organizational, algorithmic, and technological areas, this thesis focuses on the following two main challenges.

As shown in Figure 1, the extraction and processing of event data from both structured and unstructured sources is essential for process science. To date, 80% to 90% of available data is unstructured (Gandomi and Haider 2015; Harbert 2021), and the share of unstructured data is expected to increase (Balducci and Marinova 2018). Nevertheless, current process mining research mainly focuses on structured data sources. Hence, there are multiple techniques to extract event data from structured sources (Diba et al. 2020) and transform them into standard formats such as XES (Verbeek et al. 2011) or OCEL (Ghahfarokhi et al. 2021). Several process mining studies also provide methods to assess and improve the quality of extracted event data (Andrews et al. 2020; Fischer et al. 2022; Martin et al. 2022). Initial process mining research on unstructured data, such as text (e.g., Kecht et al. (2023)), sensor (e.g., Leotta et al. (2020)), and image and video data (e.g., Knoch et al. (2018)) has demonstrated its benefit for specific application scenarios. However, further research to generically exploit the different types of unstructured data in process mining and to enable the consideration of context-related insights for BPM (Beverungen et al. 2021) is still needed. Generic solutions for unstructured data could also help represent real-world processes more comprehensively (Grisold et al. 2021) and reduce blind spots (i.e., parts of processes that cannot be captured in event data yet (Kratsch et al. 2022)) in process analysis. Therefore, it is unsurprising that in a recent Delphi study, all academic experts voted that exploring unstructured and non-process-related data should be a high priority for BPM (Kerpedzhiev et al. 2021). As a necessary foundation to foster systematic progress in integrating unstructured data into process mining, research would also benefit from studies that structure the current state-of-the-art.

The adoption of process mining in industry and academia has expanded from primarily administrative and financial use cases to heterogeneous types of processes in various domains such as healthcare, education, manufacturing, and logistics (Emamjome et al. 2019; Garcia et al. 2019; Mamudu et al. 2022; van der Aalst 2020). The ongoing advancement of process mining software (Mamudu et al. 2022), including the integration of data connectors for common use cases (Reinkemeyer 2022), already promises to reduce the cost of mainstream process analysis and to increase the economic benefits required to initialize process mining projects (Grisold et al. 2021). Despite these positive developments, there are still process mining initiatives that do not achieve the expected outcomes for real-world problems (Emamjome et al. 2019). In line with process science, a thorough exploration of such process contexts would foster a deeper understanding (Emamjome et al. 2019), which is a prerequisite for improving resilience (Munoz-Gama et al. 2022) and ultimately implementing successful process interventions. In their systematic literature review on the use of process mining in organizations, Thiede et al. (2018) found that the analysis of processes that exceed a single organization's scope is scarce and, therefore, represents a promising area for future research. In addition, process science could improve process outcomes by analyzing processes at different levels (vom Brocke et al. 2021). In particular, the healthcare domain, where process mining initiatives are concentrated mostly on the organizational level of healthcare providers (Munoz-Gama et al. 2022), affords an application context in which process-oriented research with a stronger emphasis on the individual patient could lead to better process outcomes.

2 Research Objectives

Taking a process science view, this thesis addresses the identified challenges in two areas. First, although unstructured data offer significant potential to reduce blind spots in process analysis and account for relevant contextual factors, process mining research is currently focused on structured data sources. In addition, academic work on unstructured data in process mining has mostly proposed specialized artifacts for dedicated application scenarios. Thus, there is a need for solutions that provide generic extraction and processing capabilities to integrate different types of unstructured data into process science and process mining. To address the first challenge, this thesis proposes a reference architecture that integrates several data processing components from the field of computer vision and provides a generic approach to extracting event data from unstructured video data. As a second contribution, the thesis presents a systematic literature review which examines how unstructured data are used in process mining and compiles the most promising avenues for future research into a research agenda. Overall, this thesis' first research objective helps advance process science and process mining by contributing to their data-driven foundation.

Second, the discovery, explanation, and intervention of real-world processes can fall short of expectations, despite the growing maturity of BPM and process mining. Therefore, the second research objective of this thesis is to demonstrate how event data from different sources can enhance process analysis along the three main activities of process science. At the organizational process level, the thesis presents a case study of the turnaround process at Munich Airport that illustrates how process mining and data science techniques can be combined to enable the discovery and explanation of cross-organizational processes. At the individual process level, the thesis provides two artifacts that demonstrate how biomedical sensor data can be used to design wearable sensor solutions that show promise to improve prescriptive process intervention and patient well-being in the healthcare domain.

The overall goal of this thesis is to contribute to the multidisciplinary field of process science by incorporating unstructured event data and by expanding data-driven process discovery, explanation, and intervention at both organizational and, especially, individual levels. To this end, the thesis designs and evaluates multiple artifacts following the design science research (DSR) paradigm (Gregor and Hevner 2013) and draws on established data science techniques, such as machine learning (ML) and deep learning (DL). The research presented targets academics and practitioners alike. While the vendors of process mining software will need to establish solutions for managing unstructured data to remain competitive, their users can benefit from insights into data-driven process discovery, explanation, and intervention.

3 Structure of the Thesis and Embedding of the Research Articles

This cumulative doctoral thesis comprises five research articles in the field of process science. As shown in Figure 2, Research Articles #1 and #2, which address the research objective of integrating unstructured data into process mining, contribute to the data extraction & processing activity of process science. Research Articles #3, #4, and #5 expand the three main activities of process science. While Research Article #3 focuses on cross-organizational process discovery and explanation, Research Articles #4 and #5 concentrate on process intervention at the individual person level.

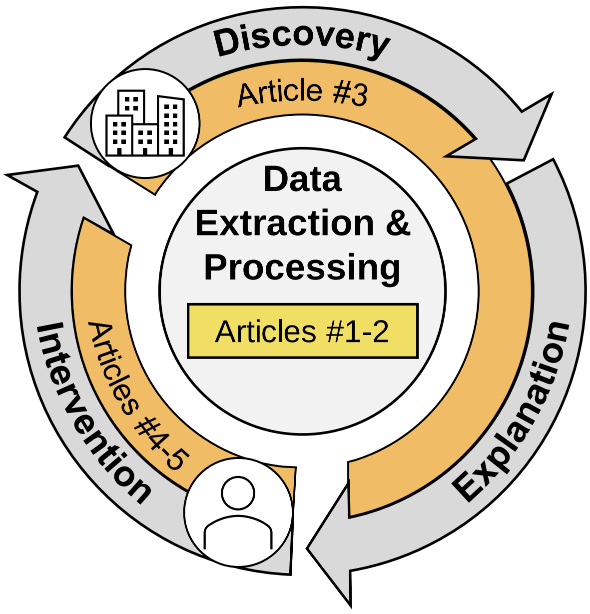

Figure 2: Positioning of the individual research articles in process science

Table 1 presents the structure of the thesis and the thematic embedding of the five research articles. Section II (including Research Articles #1 and #2) deals with integrating unstructured data into process mining and thus process science. Research Article #1 proposes a generic reference architecture that bridges the gap between process mining and computer vision. The reference architecture consists of several computer vision and process mining components that enable the extraction of structured process information from unstructured video data. The evaluation of the DSR artifact included a prototypical implementation that is publicly available and was tested on a real-world video dataset. Research Article #2 presents a systematic literature review, analyzing 24 primary studies selected from 1,379 research items at the intersection of unstructured data and process mining. To systematically guide future process mining research, the article proposes a research agenda that includes seven opportunities to address the identified research gaps.

Table 1: Structure of the thesis and embedding of the five research articles

I	**Introduction**
II	**Integrating Unstructured Data into Process Mining**
#1	**Shedding Light on Blind Spots – Developing a Reference Architecture to Leverage Video Data for Process Mining** *Kratsch W, König F, Röglinger M*
#2	**Unstructured Data in Process Mining: A Systematic Literature Review** *König F, Egger A, Kratsch W, Röglinger M, Wördehoff N*
III	**Expanding Data-Driven Process Discovery, Explanation, and Intervention**
#3	**Process Mining for Resilient Airport Operations: A Case Study of Munich Airport's Turnaround Process** *Rott J, König F, Häfke H, Schmidt M, Böhm M, Kratsch W, Krcmar H*
#4	**Near-Infrared Spectroscopy for Bladder Monitoring: A Machine Learning Approach** *Fechner P, König F, Kratsch W, Lockl J, Röglinger M*
#5	**How Artificial Intelligence Challenges Tailorable Technology Design – Insights from a Design Study on Individualized Bladder Monitoring** *Fechner P, König F, Lockl J, Röglinger M*
IV	**Conclusion**
V	**References**
VI	**Appendix**

Section III (including Research Articles #3, #4, and #5) expands data-driven process discovery, explanation, and intervention at both organizational and individual levels. To this end, Research Article #3 performs an in-depth analysis of the cross-organizational turnaround process at Munich Airport. The article employs the process mining project methodology (PM^2) by van Eck et al. (2015) with a focus on process discovery and explanation. Research Articles #4 and #5 adhere to the DSR paradigm and develop smart wearable healthcare artifacts. The artifacts combine biomedical sensor data and ML to improve bladder monitoring (i.e., measuring the urinary bladder volume) for patients who have lost bladder sensation. Since the artifacts aim to protect against over-distension of the bladder and its negative consequences, they can support prescriptive process intervention at the individual patient level. Research Article #4 introduces a wearable sensor device, which builds on the near-infrared spectroscopy (NIRS) technology. The article integrates state-of-the-art ML and DL models to evaluate the artifact on a real-world dataset and to assess whether bladder monitoring with NIRS data is possible. Research Article #5 builds on the findings of Research Article #4, developing an artifact for bladder monitoring that incorporates the core principles of individualized medicine. The artifact draws on deep transfer learning, which improves predictive performance for bladder monitoring and thus can enhance prescriptive patient treatment.

Section IV provides a summary and concludes the thesis with limitations and avenues for future research. Section V lists the references. The appendix in Section VI indexes the research articles (VI.1), reports on my contribution to each research article (VI.2), and includes the research articles themselves (VI.3 to VI.7).

II Integrating Unstructured Data into Process Mining

As argued for in Section I, process mining research primarily concentrates on structured business data, gathered from relational databases of process-aware information systems. Given the lack of solutions that can systematically integrate different types of unstructured data, it is not possible to analyze processes from end-to-end if these processes, for example, involve manual activities that are not recorded in information systems. Unstructured data may also contain information that enables a comprehensive understanding of process contexts (Beverungen et al. 2021), facilitating process explanation and intervention. In alignment with the goal of process science to leverage data from various sources, this thesis makes a twofold contribution to further advance the integration of unstructured data into process mining. Section II.1 (Research Article #1) introduces a generic reference architecture that allows to systematically exploit video data for process mining. Section II.2 (Research Article #2) structures research at the intersection of unstructured data and process mining and provides a research agenda to help guide future research in this area.

1 Leveraging Video Data for Process Mining

There are first process mining approaches that address the problem of blind spots in process analysis by applying natural language processing to text documents (Kecht et al. 2021; van der Aa et al. 2018). While text documents can contain valuable information, they often refer to activities performed within information systems (e.g., mail systems). Other approaches equip actors (Raso et al. 2018) or things (van Eck et al. 2016) with sensors to generate event logs. Such sensor-based approaches, however, cannot be scaled for use in wider contexts as measured values are dependent on the deployment location. Furthermore, full equipment with sensors appears to be an unrealistic scenario in the case of broad system boundaries or when external actors are included. While compliance with privacy regulations must be ensured and privacy aspects must be carefully considered (Elkoumy et al. 2021), video data from commonly used cameras has the potential to make processes with blind spots more observable. Early research at the intersection of computer vision and process mining has been applied with promising results (Knoch et al. 2018). However, there is no tried and trusted set of guidelines on how to holistically integrate computer vision capabilities into process mining. Thus, Research Article #1 poses the following research question: *How can video data be systematically exploited to support process mining?*

To address the research question and bridge the gap between process mining and computer vision, Research Article #1 proposes the generic Video Process Mining Reference Architecture (ViProMiRA). To this end, the article adopts the DSR paradigm (Gregor and Hevner 2013) and follows the DSR reference process proposed by Peffers et al. (2007). The article also integrates the method presented by Galster and Avgeriou (2011) into the DSR reference process, as this method supports the construction of reference architectures.

As a necessary basis for designing the ViProMiRA, the article reviews pertinent research to determine computer vision capabilities that can extract process-related information from video data (Guo et al. 2016; Moeslund et al. 2006; Voulodimos et al. 2018). With the exception of background subtraction and re-identification, Figure 3 exemplifies seven out of the nine identified computer vision capabilities, which are briefly described in the following.

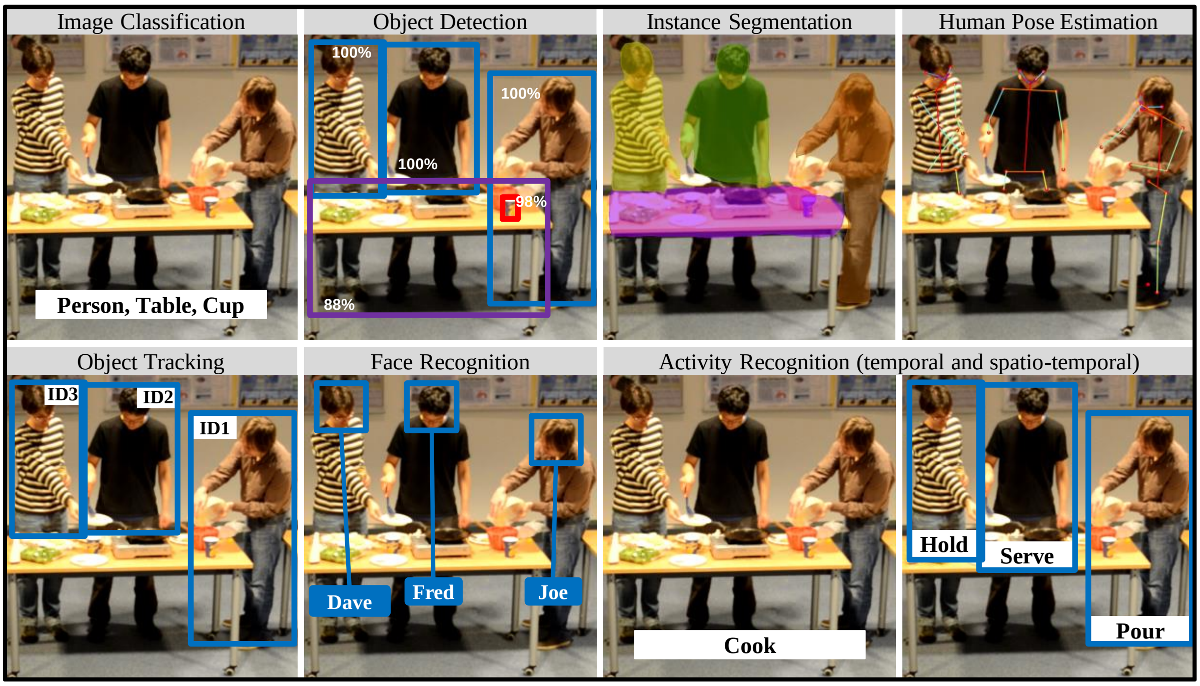

Figure 3: Illustration of computer vision capabilities with an image of the dataset from Lee et al. (2015)

Background Subtraction enables the detection of non-static information (e.g., moving objects) from video data recorded with a static perspective (Piccardi 2004). *Image Classification* predicts probabilities for the occurrence of certain object classes (e.g., people) in images (Guo et al. 2016). *Object Detection* finds instances of object classes and further localizes their positions (i.e., bounding boxes) (Guo et al. 2016; Voulodimos et al. 2018). *Semantic Segmentation* labels all pixels with their enclosing object class, while *Instance Segmentation* additionally distinguishes between instances of the same classes (Garcia-Garcia et al. 2018).

Human Pose Estimation addresses the problem of localizing human body parts or anatomical key points (e.g., elbow, wrist) in images (Poppe 2007; Sun et al. 2019). *Object Tracking* predicts the trajectory of a target object along a sequence of frames and assigns a stable track identifier (Wu et al. 2013; Yilmaz et al. 2006). *Re-identification* is a sub-capability that makes it possible to identify a person of interest across multiple cameras (Bedagkar-Gala and Shah 2014). *Face Recognition* (re)identifies individuals by their faces (Huang et al. 2008; Masi et al. 2018). *Activity Recognition* takes the output of other computer vision capabilities (e.g., object detection or human pose estimation) to identify the activities of at least one person in a sequence of image frames (i.e., video) (Aggarwal and Ryoo 2011; Chaquet et al. 2013). In temporal activity recognition, which bears a resemblance to image classification, an entire video sequence is assigned to one or several activity classes. Spatio-temporal activity recognition extracts several concurrent activities (e.g., the movements of two tennis players) in the same video sequence (Zhang et al. 2019).

Figure 4 presents the ViProMiRA as a unified modeling language (UML) diagram. The ViProMiRA integrates the computer vision capabilities illustrated in Figure 3 and provides guidance in the form of colored instantiation variants on how to systematically exploit their potential for process mining. The reference architecture consists of the three subsystem layers *Data Preprocessor*, *Information Extractor*, and *Event Processor*. To make sure the ViProMiRA can also be adapted to specific process mining use cases and BPM applications, it further comprises a range of optional components, as indicated by the dotted frames.

The *Data Preprocessor* subsystem serves as an interface to the raw video file or stream. It converts continuous video streams into single frames and ensures constant frame rates and image resolutions. The *Information Extractor* subsystem receives the preprocessed frame sequences and combines different computer vision capabilities to extract meaningful information in a hierarchical manner. It offers three instantiation variants. The blue instantiation variant can extract simple yet potentially important information by classifying single frames (e.g., differentiating between simple categories such as “normal” or “abnormal”). There are two instantiation variants for activity recognition. The Temporal Activity Recognizer is part of the orange variant and designed to target process scenarios without concurrency (i.e., activities that are sequentially performed by a single actor). The green instantiation variant is designed for scenarios with multiple resources that concurrently execute individual activities. It can locate actors and classify their respective activities. The *Event Processor* subsystem takes the low-level information from the Information Extractor (e.g., bounding boxes describing actors or objects), aggregates it to the level of detail required for the targeted process mining use cases (e.g., high-level business events), and provides interfaces to several information systems and related applications (e.g., event log or single event notifications).

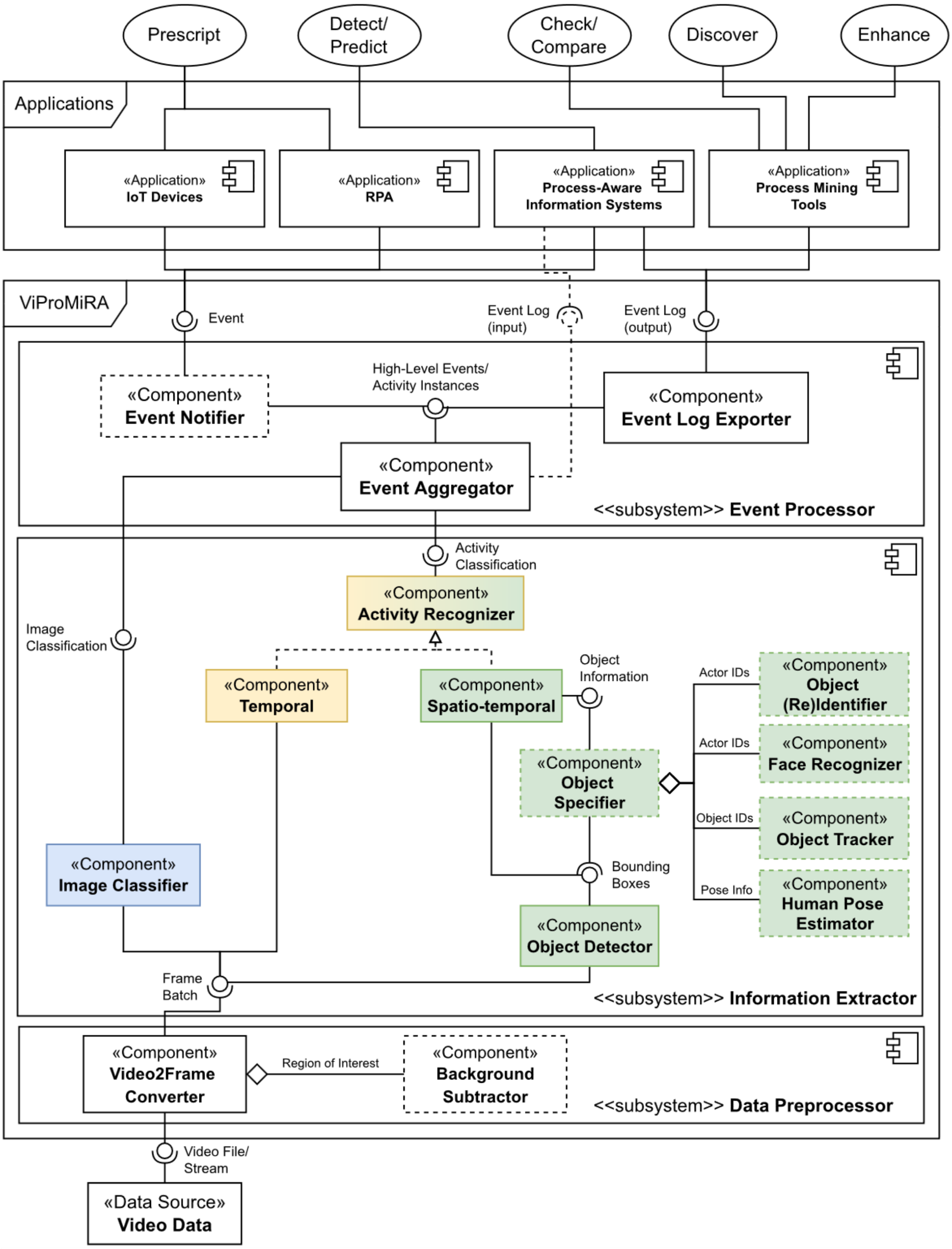

Figure 4: The ViProMiRA as a UML diagram
Dotted frames indicate optional components, colors indicate instantiation variants

In line with the DSR paradigm (Gregor and Hevner 2013), the research process involved multiple evaluation activities (i.e., EVAL1-EVAL4) (Sonnenberg and vom Brocke 2012), which ensured the selection of a relevant research problem (EVAL1) and allowed the continuous assessment of the ViProMiRA against established DSR criteria (March and Smith 1995; Sonnenberg and vom Brocke 2012). The ViProMiRA's design specification was evaluated through logical reasoning and an assessment by fellow researchers (EVAL2). The most extensive instantiation variant of the ViProMiRA was also implemented as a Python software prototype[2] to demonstrate the internal consistency and applicability of the ViProMiRA (EVAL3). The final evaluation activity (EVAL4) validated the usefulness and applicability of the ViProMiRA by applying the software prototype to a publicly available real-world video dataset (Center for Open Science 2017; Lee et al. 2015). The detailed process mining analysis revealed that the prototype detected a high degree of relevant events from the video data.

Research Article #1 contributes to the knowledge on integrating unstructured data into process mining. To the best of my knowledge, the ViProMiRA is the first approach to systematically exploit video data for process mining. Its prototypical implementation is also the first technical artifact that enables the unobtrusive extraction of concurrently running cases performed by multiple actors. Since the computer vision and process mining capabilities integrated into the ViProMiRA are presented independently of their technical implementation, the ViProMiRA can also adapt to technological advances. By providing a reference architecture that spans both the computer vision and the process mining domains, this thesis lays a theoretical foundation for video-based process discovery, explanation, and intervention in process science.

2 A Research Agenda for Unstructured Data in Process Mining

As demonstrated in Section II.1, unstructured data can, for example, enable a more comprehensive analysis of processes that are only partially captured in process-aware information systems. However, despite the successful use of different types of unstructured data in process mining (e.g., Leotta et al. (2020); Lepsien et al. (2023); Teinemaa et al. (2016)), the lack of a holistic overview impedes systematic progress in this research area. Therefore, to determine the extent to which unstructured data are currently accounted for in process mining, Research Article #2 addresses the following three research questions:

[2] *The repository is publicly available under https://github.com/FabiTheGabi/VideoProcessMining*

- RQ1: *Which types of unstructured data are used in process mining?*
- RQ2: *How are unstructured data leveraged for different process mining use cases?*
- RQ3: *What are the open challenges and areas for improvement?*

To answer the three research questions, Research Article #2 performs a systematic literature review with a focus on innovative, (semi-)automated solutions for integrating unstructured data into process mining. Based on the analysis of 24 studies selected from a total of 1,379 research items, the article proposes a research agenda comprising seven opportunities to advance future process mining and process science research.

The literature review was conducted according to the guidelines of Kitchenham and Charters (2007). First, to identify as many potentially relevant research items as possible, a database-driven search approach was used (Hiebl 2023), which resulted in 1,379 research items across seven prevalent databases in the fields of information systems and computer science. Second, to filter for studies within the scope of the research objective, two co-authors independently screened the initial results against a set of nine selection criteria. In a third step, the same two co-authors analyzed the final selection of 24 studies via deductive coding (Bandara et al. 2015). Essential aspects for answering the research question were captured via a coding scheme derived from the relevant literature. Figure 5 provides a publication timeline for the identified primary studies (i.e., only scientific, peer-reviewed studies without duplicates). Additionally, the distribution of the final sample of 24 research items is presented.

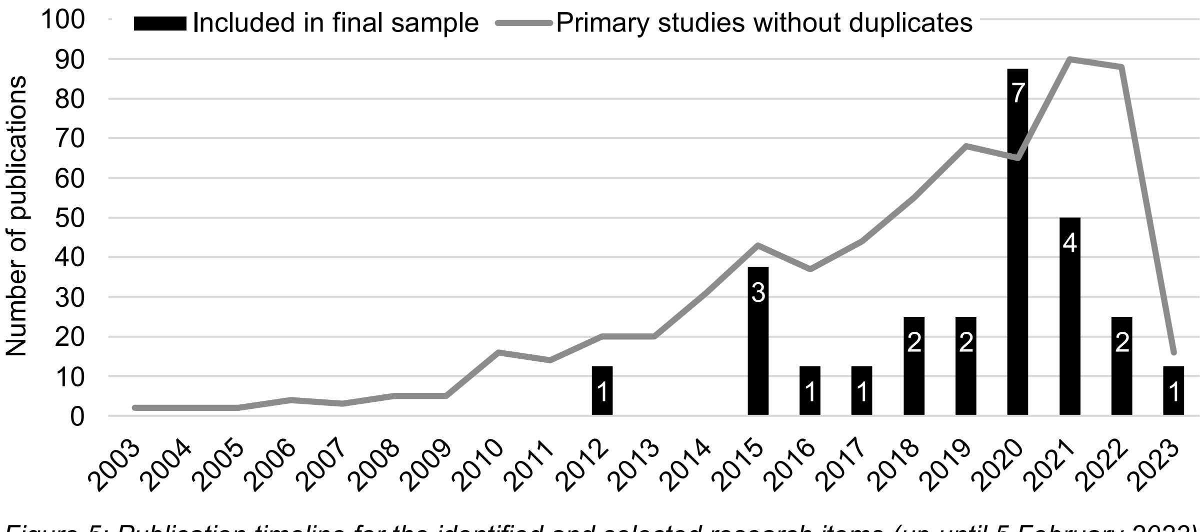

Figure 5: Publication timeline for the identified and selected research items (up until 5 February 2023)

As shown in Figure 5, research at the intersection of unstructured data and process mining increased slowly but steadily until 2013. However, from 2013 to 2022, annual research output more than quadrupled, indicating even faster growth than process mining research in general (van der Aalst 2020). This can possibly be attributed to the increasing adoption and maturity of process mining research (e.g., process mining manifesto (van der Aalst et al. 2012)) and the improved processing capabilities for unstructured data enabled by advances in data science.

Figure 6 summarizes selected aspects of the analysis results for RQ1 and RQ2. Regarding RQ1, 18 out of the 24 studies included in the final sample (75%) dealt with unstructured text data. Sensor data was the next most common type of data, with three occurrences of simple sensors (e.g., passive infrared sensors), and three occurrences of complex sensors (e.g., ultrasonic sensors). While two studies targeted video data, only one study used image data. The literature search did not reveal any research on audio data, suggesting untapped potential. Except for two studies that combined different types of unstructured data, all studies focused solely on one type of unstructured data.

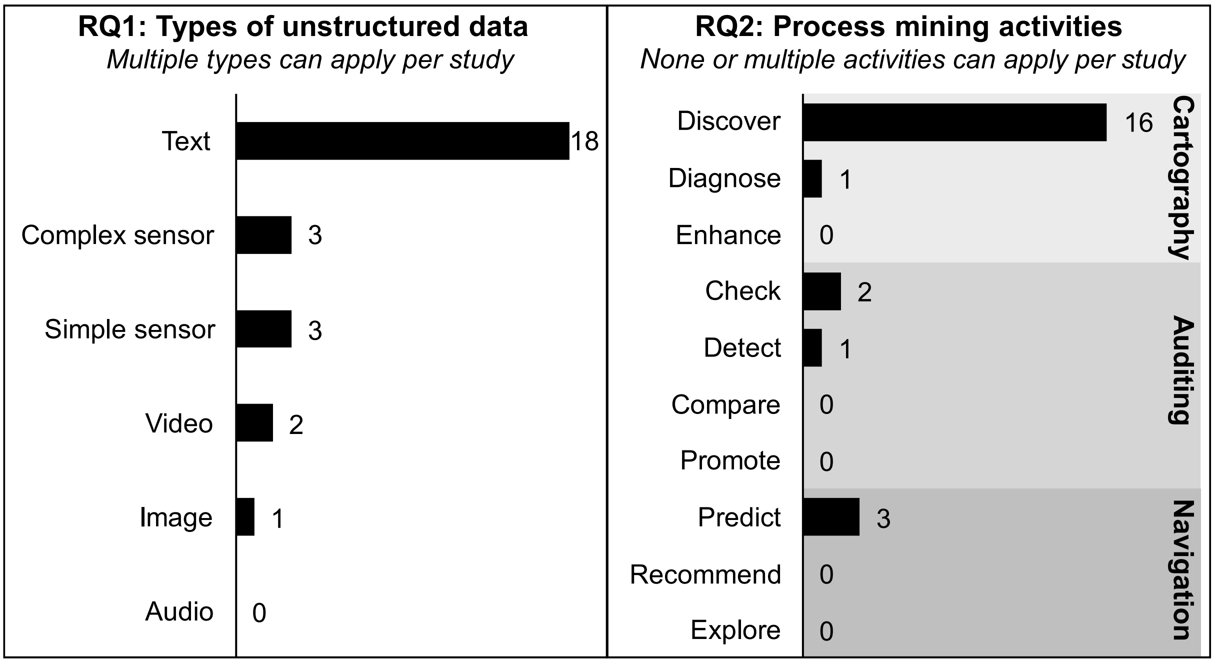

Figure 6: Overview of analysis results for RQ1 and RQ2 in the final sample of 24 studies

The analysis of RQ2 was based on the refined process mining framework proposed by van der Aalst (2016), which considers ten process mining activities grouped into three categories: *cartography*, *auditing*, and *navigation*. As shown in Figure 6, the majority of process mining activities were associated with the cartography category, specifically process discovery (67%). Several studies did not focus on any specific process mining activity. Instead, they aimed to identify process activities in unstructured data and extract appropriate event data for subsequent analysis. With three studies (13%) each, there was an equal amount of research in the auditing and navigation categories. While the two activities in the auditing category (i.e., *check* and *detect*) centered on traditional conformance checking, the three studies in the navigation category provided forward-looking operational support for process mining (i.e., *predict*). Based on the results for RQ1 and RQ2, Research Article #2 addresses RQ3 by proposing a research agenda that includes seven opportunities for future research:

- *Opportunity 1: Extending the scope beyond event log extraction for process discovery*
- *Opportunity 2: Extending the scope beyond text data*
- *Opportunity 3: Combining structured and different types of unstructured data*
- *Opportunity 4: Consolidating existing research to build integrative artifacts*
- *Opportunity 5: Providing process-oriented and open-access benchmark datasets*
- *Opportunity 6: Accounting for the human in the loop*
- *Opportunity 7: Considering privacy aspects*

Opportunity 1 and 2 advocate for a broader scope of research that exceeds the narrow focus on process discovery and textual data. Opportunity 3 and 4 reflect the need to provide generic and use case-independent solutions that enable the extraction, harmonization, and use of event data from diverse sources to capture a more complete picture of actual process behavior. While Opportunity 5 calls for more transparency and comparability of research results, Opportunity 6 emphasizes the importance of designing and evaluating socio-technical solutions to support process mining activities that require human judgment (e.g., *enhance*, *promote*, and *explore*). Opportunity 7 stresses the need to ensure privacy in process mining.

To summarize, Research Article #2 provides an overview of current research at the intersection of unstructured data and process mining. The literature review presented in the article takes a dual perspective on the data source (i.e., RQ1) and the application scenario in process mining (i.e., RQ2). Therefore, it contributes to the knowledge on the use of unstructured data in process mining. Furthermore, the proposed research agenda comprises seven opportunities to bridge the gap between existing research silos and systematically advance future research.

In essence, the two contributions presented in Section II strengthen the data-driven foundation of process science and process mining. First, Research Article #1 provides a generic artifact that allows the extraction of potentially relevant process-related information from unstructured video data, which benefits the goal of end-to-end process analysis. Second, taking a more comprehensive approach based on the results of a systematic literature review, Research Article #2 proposes a research agenda to advance the integration of unstructured data into process mining. Given their complementary nature, both contributions form a solid basis for future research on unstructured data in process science and process mining.

III Expanding Data-Driven Process Discovery, Explanation, and Intervention

Despite the increasing adoption of process mining in various domains (Garcia et al. 2019; Mamudu et al. 2022; van der Aalst 2020), data-driven process analysis and management face challenges in realizing expected outcomes for process contexts that are characterized by considerable complexity and variability (Emamjome et al. 2019; Martin et al. 2020; Syed et al. 2020). While these characteristics typically apply to processes that cross the boundaries of a single organization (Thiede et al. 2018), they also extend to intra-organizational processes that exhibit a high degree of heterogeneity, such as treatment processes in the healthcare domain (Goetz and Schork 2018). This thesis contributes to the existing knowledge on data-driven process discovery, explanation, and intervention by investigating challenging process contexts at the organizational and individual levels (vom Brocke et al. 2021). At the organizational level, Section III.1 (Research Article #3) exemplifies how process discovery and explanation can provide insights for the cross-organizational turnaround process at Munich Airport. At the individual level, Section III.2 (Research Articles #4 and #5) proposes two artifacts that build on biomedical sensor data to enable prescriptive process interventions for the treatment of patients who have lost bladder sensation.

1 Cross-Organizational Process Discovery and Explanation

The aviation industry has encountered numerous challenges in recent years. In 2018 and 2019, the issue of punctuality became a major concern at hub airports due to capacity restrictions and the strain on infrastructure caused by high utilization (EUROCONTROL 2020). From March 2020 to March 2022, COVID-19 led to a rapid decrease in the number of passengers (EUROCONTROL 2022a). Accordingly, airports, airlines, and ground-handling operators downsized personnel. This, in turn, resulted in a shortage of security and ground-handling staff when the number of travelers increased significantly since April 2022 (EUROCONTROL 2022a). Flights were rarely on time (EUROCONTROL 2022b), which frustrated passengers and overworked staff (Duffy 2022; von der Au 2022). Hence, the aviation industry is constantly seeking to optimize its processes in order to improve the passenger travel experience, reduce operating costs, and increase resilience (Gelhausen et al. 2013; Okwir et al. 2017). While process mining has led to business process improvement and cost savings for organizations in other sectors (e.g., Uber and Deutsche Telekom (Celonis 2023;

Reinkemeyer 2020)), its adoption in the aviation industry is limited, both in practice and research (Böhm et al. 2022; Garcia et al. 2019; Gunnarsson et al. 2019). Against this background, Research Article #3 explores the potential of process mining for the cross-organizational turnaround process. The article builds on event data generated within the Airport Collaborative Decision Making (ACDM) framework and investigates the following research question: *What insights can process mining, building upon ACDM timestamps, provide for the turnaround process at airports?*

The article uses a case study-based approach as described by Yin (2018) to answer the research question from an airport's perspective. The case study examines two embedded units of analysis (i.e., the turnarounds at Munich Airport in September 2019 and September 2021) and structures the process mining-related activities according to the process mining project methodology PM^2 proposed by van Eck et al. (2015).

The turnaround begins when the plane arrives at the gate after landing and ends when the aircraft is ready to take off and the chokes are removed. The characteristics of the turnaround depend on the aircraft type, the number of passengers, and the airline business model. Multiple stakeholders, including airports, airlines, and ground-handling corporations, collaborate in this cross-organizational process (Schmidt 2017). The ACDM framework aims to standardize the information exchange between the stakeholders and allows the tracking and sharing of different events of an aircraft turnaround (e.g., arrival and taxi-in) (EUROCONTROL 2017).

To ensure a holistic examination of the turnaround process along three key analysis questions, the project team responsible for the analysis consisted of two process experts, two process analysts, and three IT systems experts. To address the first analysis question, *What does the actual process look like?*, the project team discovered a fact-based process model that illustrated the control flow of the turnaround process. The fact-based process model revealed missing event data for specific process activities (e.g., the start and end times of boarding). It further highlighted the activity sequences with the most potential for improvement based on dwell time. Since the process experts confirmed that the discovered process model almost completely reflected the normative process defined in the documentation, no further unexpected anomalies could be identified. The second analysis question, *What are the discrepancies and commonalities between the observed and modeled process behaviors?*, focused on detecting deviant process behavior through conformance checking. While most of the deviations occurred on an individual basis, the project team identified two instances of more frequent, inconsistent process behavior (e.g., the aircraft's start-up request was followed by the begin of the aircraft's boarding for 676 turnarounds). The project team concluded that the timestamps of specific activities were not always reliable because of manual reporting by ground staff. The third analysis question, *How is the process performance concerning off-block delay and target off-block time quality?*, investigated the process performance for relevant key performance indicators using data science techniques on the event data. The project team found that, on average, delayed aircraft arrivals resulted in an even greater number of delayed departures, indicating the inability to handle a high volume of process instances. Another key insight was that particular operating airlines and ground-handling corporations had a considerable impact on delayed ground-handling. Specifically, the business experts estimated that belated communication of the target off-block time resulted in 25 days of idle work for the two embedded units of analysis.

In addition to analyzing the turnaround process, Research Article #3 conceptualizes the impact of process mining on airport resilience based on the results of the case study (Di Vaio et al. 2021; 2023). As shown in the conceptual framework in Figure 7, process mining has a positive effect on three resilience capabilities (i.e., flexibility, adaptability, and agility), which in turn have a positive influence on the performance of the airport and its relevant stakeholders (Erol et al. 2010; Janić 2022; Novak et al. 2021).

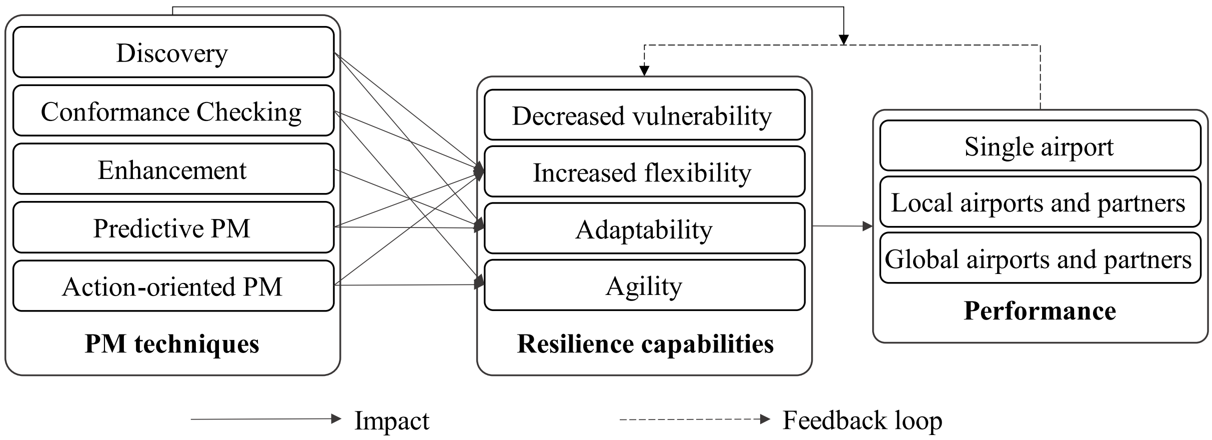

Figure 7: Conceptual framework of process mining impact on airport resilience

To conclude, Research Article #3 contributes to data-driven process analysis by showcasing how process mining and data science techniques can help to analyze and optimize operational airport processes. Specifically, the article presents several insights for the cross-organization turnaround process from an airport's perspective and reports on lessons learned for the application of process mining. The focus of the article is on process discovery and explanation, as the details of how to implement the proposed changes for process intervention have not yet been finalized at the time of writing. Since the event data for the turnaround process are based on the widely adopted ACDM framework, the analysis presented is easily transferrable and applicable to other airports. The insights gained can also serve as a point of reference for process mining and process science initiatives on other cross-organizational processes.

2 Process Intervention at the Individual Level

Despite the availability of many case studies in academia, the day-to-day application of process mining in healthcare is progressing slowly (Martin et al. 2020). This can be explained in part by the complexity, high variability, and multidisciplinarity of clinical processes compared to more standardized support processes (e.g., purchase-to-pay process) (Martin et al. 2020; Munoz-Gama et al. 2022). The heterogeneity of disease processes has led to the emergence of the concept of individualized medicine, which aims to tailor medical interventions to the unique and nuanced characteristics and contextual factors of each patient (Goetz and Schork 2018). Wearable technology (e.g., wristwatches, smart clothing, and miniaturized wearable sensors) plays a crucial role in the advancement of individualized medicine (Ho et al. 2020), as it allows the collection of person-specific biomedical digital trace data (Chan et al. 2012; Patel et al. 2012). This section, including Research Articles #4 and #5, demonstrates how process science can contribute to individualized medicine and ultimately improve treatment outcomes. It introduces two novel DSR artifacts for people who have lost bladder sensation. The artifacts collect biomedical sensor data and apply ML and DL to estimate bladder volume, enabling adaptive medical interventions at the individual patient level.

Worldwide, over 200 million people live with the diverse socio- and psychological implications of urinary incontinence (i.e., the involuntary loss of urine (Abrams et al. 2003)) (Milsom 2000; Norton and Brubaker 2006). From a health perspective, neurogenic bladder dysfunction (NBD) (Dorsher and McIntosh 2012; Verpoorten and Buyse 2008) and neurogenic lower urinary tract dysfunction (NLUTD) (Ginsberg et al. 2021; Tudor et al. 2016) are among the most serious causes of urinary incontinence. Patients living with NBD and NLUTD can lose bladder sensation and the ability to void voluntarily (Dorsher and McIntosh 2012; Samson and Cardenas 2007; Tudor et al. 2016). Therefore, to prevent over-distension of the bladder (i.e., exceeding the normal bladder capacity of 400-600 *ml* (Dorsher and McIntosh 2012; Norton and Brubaker 2006) by more than 20% (i.e., 80-120 *ml*) (Madersbacher et al. 2012)), current standard treatment requires patients to perform self-catheterization every three to four hours (Dorsher and McIntosh 2012; Shaw et al. 2008; Verpoorten and Buyse 2008). As urine production may vary due to multiple factors such as fluid or drug intake (Fechner et al. 2020;

Heesakkers et al. 2003; Verpoorten and Buyse 2008), this time-driven treatment is unsatisfactory in several respects. High bladder volumes may accumulate in less than three hours. Thus, standard treatment cannot reliably protect against over-distension of the bladder and its negative consequences (e.g., spontaneous voiding or damage to health from concomitant kidney disease (Dik et al. 2006)). Given that catheterization is time-intensive and increases the likelihood of urinary tract infections (Berger et al. 2022; Wyndaele et al. 2012), unnecessary catheterizations by timer despite low bladder volume are another disadvantage for patients. Hence, accurate information on bladder volume is essential to shift the focus from scheduled voiding toward a volume-responsive treatment process that allows for prescriptive interventions to empty the bladder only when needed. Although there are currently no solutions that can reliably measure bladder volume in everyday life, preliminary research has proposed several non-invasive techniques that use biomedical sensor data to predict bladder volume. The three predominant techniques are ultrasonic scanning (Kamei et al. 2019), electrical impedance analysis (Leonhardt et al. 2011; Shin et al. 2017), and NIRS (Fong et al. 2018; Molavi et al. 2014). However, despite promising results in laboratory settings, previous studies report reliability and validity issues (Kamei et al. 2019; Molavi et al. 2014) that restrict applicability in real-world scenarios.

The shortcomings of the standard treatment and the inability of current approaches to measure bladder volume in everyday life make the management of NBD and NLUTD a predestined application scenario for process science. Hence, given the need for a solution that can integrate novel biomedical sensor data to monitor the biological process of urine production in order to improve the treatment process for patients and support self-administered care, Research Article #4 focuses on the following research question: *How can a non-invasive, sensor-based solution allow patients with NBD to monitor their bladder volume autonomously and continuously?*

The article follows the DSR reference process proposed by Peffers et al. (2007) to design and evaluate a model for bladder monitoring as the central artifact. The artifact provides an end-to-end approach that includes the comparison of multiple ML and DL models for bladder monitoring. Patients are notified via a smartphone app when a predefined bladder volume is reached, which enables prescriptive process intervention.

The model for bladder monitoring is based on the NIRS technique. Although NIRS has received little attention from the scientific community, it can be regarded as a promising approach to continuously monitor the bladder as it does not pose any health risks (Gervain et al. 2011; Grandi and D'Ovidio 2020). NIRS requires the attachment of a sensor to the abdomen and estimates bladder volume using the difference in signal intensity of infrared radiation. Urine consists of approximately 95% water with an absorption peak for near-infrared light at 975 *nm* (Molavi et al. 2014). During filling, the bladder protrudes beyond the upper edge of the pubis and is no longer shielded by bone material when reaching its capacity (Woodburne 1968). As the bladder moves into the detectable range of the NIRS sensor, the water in the urine absorbs near-infrared light, which can be used to estimate bladder volume.

Figure 8 displays the model for bladder monitoring, which integrates three major components: *Data Collection and Interaction*, *Data Pre-Processing*, and *Bladder Volume Prediction*.

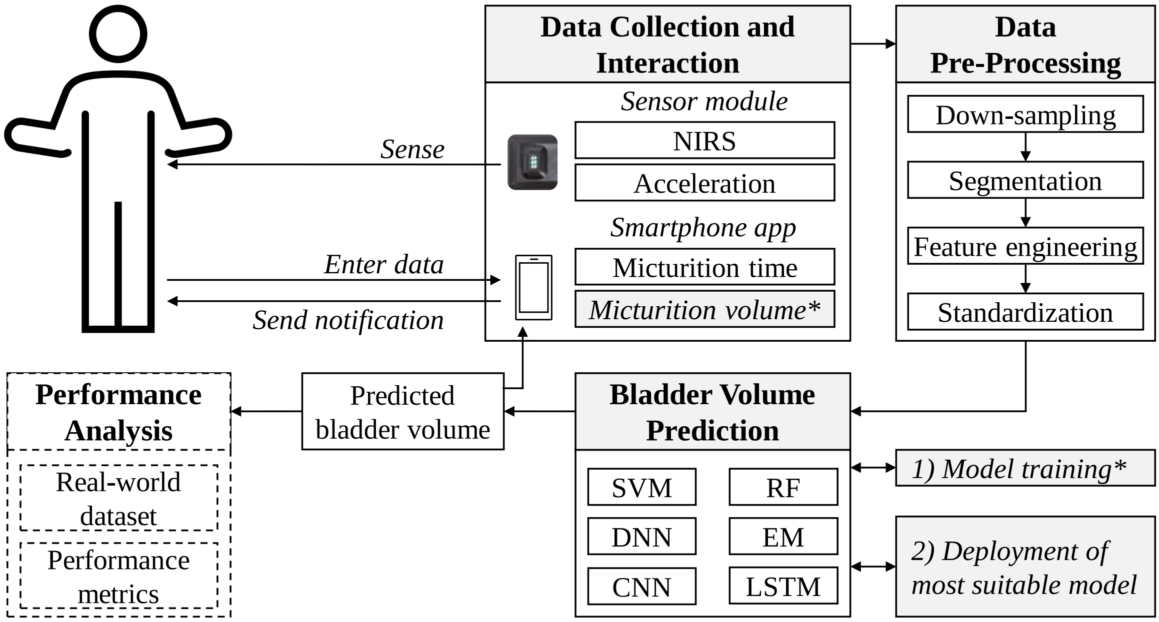

Figure 8: Model for bladder monitoring

The *Data Collection and Interaction* component comprises the sensing and interaction capabilities (Püschel et al. 2020) and, thus, bundles the functionality perceived by patients. It consists of a smartphone app and a sensor module. The sensor module builds on Molavi et al. (2014) and is attached directly to the skin at a point two-fingers-width above the pubic bone. It captures NIRS data at different wavelengths and records acceleration data in the X, Y, and Z directions. During productive use, the smartphone app displays the current predicted bladder volume and automatically sends notifications before a critical volume is reached. To gather labeled data for model training, patients manually log their micturition times and volumes in the smartphone app after each micturition. As indicated by the asterisk in Figure 8, the micturition volume serves as the target feature for the training of the ML and DL models included in the Bladder Volume Prediction component.

In the *Data Pre-Processing* component, the raw sensor and app data are pre-processed, which includes down-sampling, segmentation to a constant window size of five minutes, feature engineering, and standardization (Wang et al. 2019; Zhu et al. 2020). Since contextual information can improve the robustness of ML models (Wang et al. 2019), the time elapsed in seconds since the previous micturition is computed as additional feature. The *Bladder Volume Prediction* component receives the pre-processed data and predicts the current bladder volume in *ml*. The chosen five-minute interval for input data is the shortest possible measurement time required to make a prediction and enables smooth integration of the artifact into patients' everyday lives. The Bladder Volume Prediction component features an initial training phase for six state-of-the-art ML and DL models. These are support vector machine (SVM) and random forest (RF) (Uddin et al. 2019) as well as simple feedforward deep neural network (DNN), convolutional neural network (CNN), long short-term memory network (LSTM), and a meta-learning ensemble model (EM) (Ismail Fawaz et al. 2019; Ravi et al. 2017; Sagi and Rokach 2018). After training, the model that performs best is deployed for productive use.

The design of the model for bladder monitoring and its three evaluation activities (Sonnenberg and vom Brocke 2012) were guided by seven design objectives derived from relevant literature (Peffers et al. 2007). The first evaluation activity examined how well the model for bladder monitoring conformed to the design objectives. It included semi-structured interviews with ten patients living with NBD (Myers and Newman 2007). The second evaluation activity demonstrated the real-world applicability of the artifact by developing two prototypes consisting of a sensor module, an Android smartphone app extending Fechner et al. (2020), and a Python implementation of the Data Pre-Processing and Bladder Volume Prediction components. In the third evaluation activity, the applicability and usefulness of the final prototype was assessed on a real-world micturition dataset from five male volunteer test subjects. The comparison of different input features showed that the most promising results were obtained with a combination of sensor data (i.e., near-infrared and acceleration data) and the time elapsed since the previous micturition. Considering various performance metrics, the LSTM model performed best and achieved a mean absolute error of 116.7 *ml*.

To summarize, Research Article #4 shows how process science can contribute to prescriptive process intervention at the individual patient level by leveraging digital trace data and serving as a process-oriented interface for various disciplines (i.e., medicine, engineering, and data science). The presented model for bladder monitoring is the first end-to-end solution in the field of non-invasive bladder monitoring that uses a wearable NIRS sensor and additional time data for continuous bladder monitoring in a real-world scenario. Although not all predictions for the evaluation dataset fell within the medically acceptable range, the mean absolute error achieved with a combination of time and sensor data as input features is below the medically critical level of 120 *ml*. The transfer of Research Article #4 into practice can improve the treatment process and the daily routine of patients, prevent over-distension of the urinary bladder, and allow for demand-driven catheterization.

As this thesis' second contribution on process intervention at the individual level, Research Article #5 takes a further step toward a volume-responsive treatment of NLUTD and NBD. Despite the availability of patient-specific real-time data, a one-size-fits-all paradigm still prevails in data analysis for smart wearables. Many potential solutions train ML models that minimize predictions errors for a broad test population and use these general models to infer the state of all users (Chen et al. 2020). Since existing research on bladder monitoring has been mostly evaluated in strict laboratory settings (e.g., Fong et al. (2018); Kristiansen et al. (2004); Reichmuth et al. (2020)), the reported performance is likely to decline under realistic conditions (Argent et al. 2021). Against this backdrop, Research Article #5 examines whether more focus on the individual patient can enhance bladder monitoring in real-world scenarios. It builds on the finding of Research Article #4 that NIRS data can be used as a basis for bladder monitoring and investigates the following research question: *How can smart wearable sensors monitor the bladder of individual patients in real-world scenarios?*

Research Article #5 employs the DSR reference process proposed by Peffers et al. (2007) to address the above research question. It designs and evaluates a model for individualized bladder monitoring, which is also instantiated as a prototype. The focus of the article is to holistically incorporate the core principles of individualized medicine into the artifact. This is achieved in part by extending the smartphone app presented in Research Article #4 to enable the input of user-specific context features (i.e., sex, age, body mass index, and skin tone) and preferences (i.e., the alarm threshold in *ml*, when to send a notification, and the type of notification). To adapt further to the specific anatomical characteristics of the individual patient, the model for individualized bladder monitoring draws on artificial intelligence (AI) through deep transfer learning in multiple stages of tailoring.

Transfer learning is a technique that can improve the speed and effectiveness in training ML models (Lu et al. 2015). It has been successfully applied to sensor data, for example, in monitoring the self-care abilities of elderly people (Zhu et al. 2020). The central assumption of transfer learning is that knowledge gained from learning a specific task (i.e., source task) can be generalized and repurposed, thereby augmenting a related learning task (i.e., target task) (Pan and Yang 2010). Since DL models automatically learn feature representations across multiple successive information processing layers in an end-to-end manner (Deng and Yu 2014), transfer learning for DL generally follows a feature-representation-transfer approach (i.e., deep transfer learning). Deep transfer learning is particularly useful to address generalization problems of DL models fitted on small datasets (Weiss et al. 2016; Yim et al. 2017). Such small datasets also prevail in the case of bladder monitoring, as human biology limits the number of micturitions per day and, therefore, the amount of training data for each individual patient.

The model for individualized bladder monitoring evaluates two generic strategies for deep transfer learning illustrated in Figure 9 as they have the potential to enhance the predictive performance for individual patients. Both strategies use a model already trained for the source task (i.e., base model) to train a model for the target task (Chollet 2018; Lu et al. 2015). While the first layers of the base model typically contain generic representations, the last layers hold increasingly problem-specific representations (Lu et al. 2015). To preserve the more generic representations during the transfer learning process, weight changes can be disabled for specific layers (i.e., freezing a layer) (Iman et al. 2023). It is further possible to remove existing layers or add new ones before transfer learning (Chollet 2018; Iman et al. 2023).

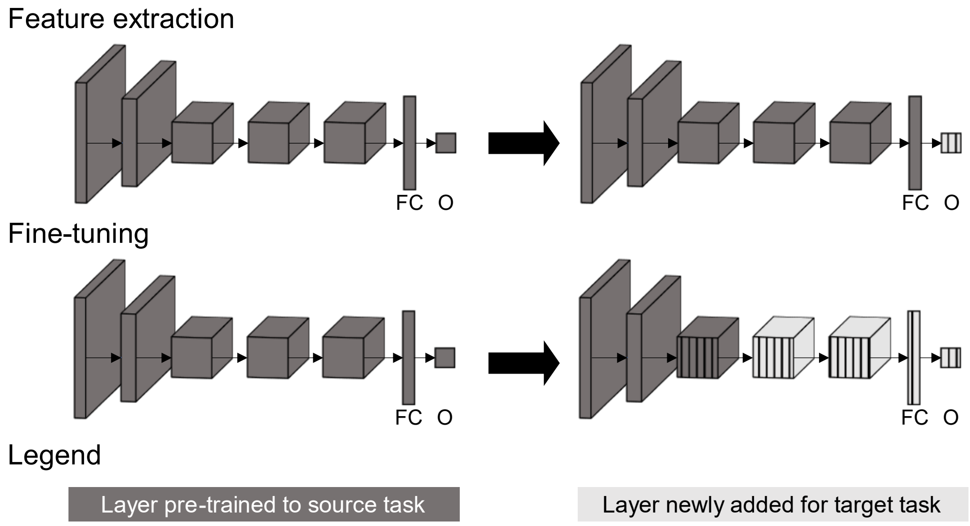

Figure 9: Exemplary illustration of the two strategies for deep transfer learning
Note: vertical patterns represent model layers that are not frozen
(FC = fully connected layer, O = output layer)

In the *feature extraction* strategy, a randomly initialized output layer (i.e., regressor) replaces the pre-trained output layer of the base model. The model is then trained for the target task using the feature representation capabilities of the otherwise frozen base model (Chollet 2018; Morales and Roggen 2016). The *fine-tuning* strategy focuses more on slightly adapting the original feature representation capabilities by unfreezing and re-training a predefined number of base model layers for the target task (Chollet 2018; Iman et al. 2023; Lu et al. 2015).

Figure 10 presents the model for individualized bladder monitoring. The model consists of three phases (i.e., *base model training*, *individualization*, and *bladder monitoring*) that prescribe the steps to individualize bladder monitoring for a single user through fine-tuning, as this technique has outperformed other ML techniques for a real-world dataset assessed in the DSR process.

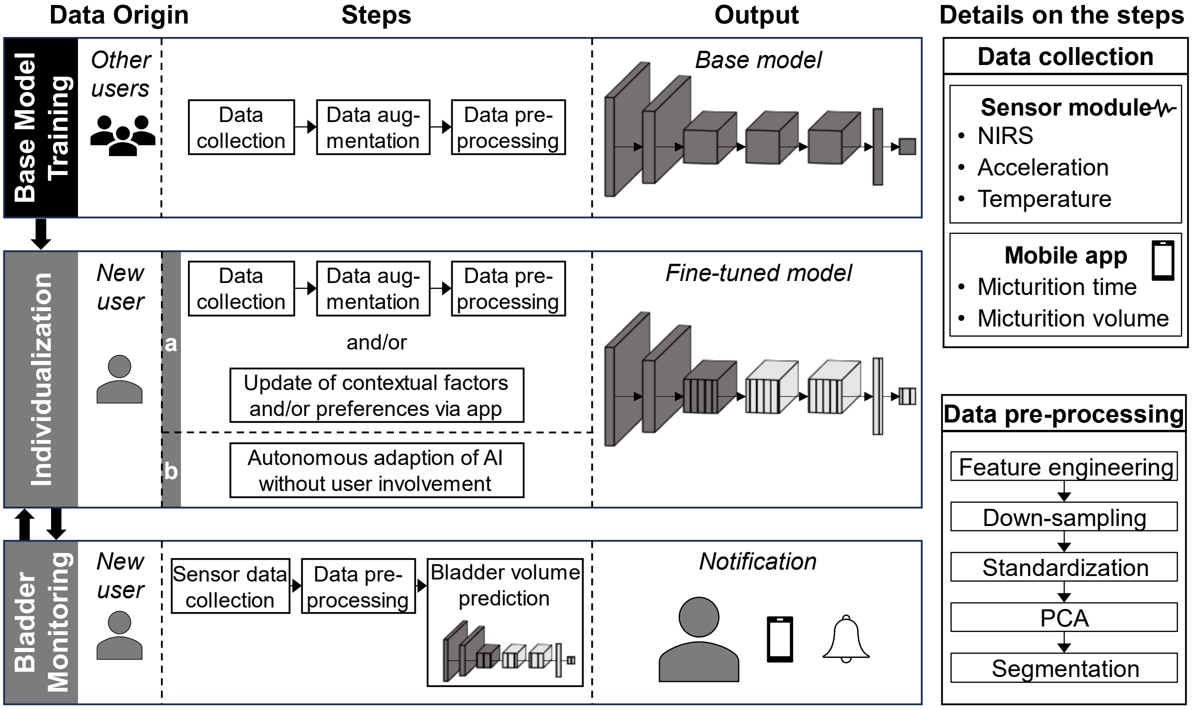

Figure 10: Model for individualized bladder monitoring

In the *base model training* phase, a DL model is trained on a generic multi-user dataset. The data collection step is performed via a non-invasive NIRS sensor module and a smartphone app, both building on Research Article #4 (Fechner et al. 2023). The sensor module captures key data points for bladder monitoring, including acceleration and NIRS data at varying wavelengths as outlined by Molavi et al. (2014). It also records temperature data for verifying sensor attachment during preprocessing. Users enter the micturition volume as the target feature for the DL model as well as the time of micturition as the basis for the temporal alignment of the sensor readings in the smartphone app. Each user also provides sex, age, body mass index, and skin tone as additional contextual input features via the smartphone app once, to account for any potential factors influencing the NIRS measurements (Matas et al. 2002; Saffarpour and Ghiasi 2018). To generate enough data for the training of the DL models, the data augmentation step samples artificial data points from the originally recorded micturition cycles (Forestier et al. 2017). The data pre-processing step applies feature engineering, down-sampling, and standardization. It also performs a principal component analysis (PCA) (Wang et al. 2019; Zhu et al. 2020) and segments the data into five-minute windows required for model training.

The *individualization* phase aims to optimize bladder monitoring for the individual user. The steps for data collection, data augmentation, and data pre-processing are analogous to the base model training phase. To ensure a constant high level of predictive performance, the individualization phase follows a two-stage approach that comprises intensified tailoring in the beginning and subsequent demand-driven re-tailoring and autonomous adaption interwoven into productive use. During the initial tailoring, the user provides contextual input features (see above) and user preferences (i.e., the alarm threshold in *ml*, when to send a notification, and the type of notification) via the smartphone app. The smartphone app also supports and interactively motivates the user to collect micturition cycles while wearing the sensor module. Once a minimum number of ten micturition cycles has been recorded, each additional micturition cycle triggers the fine-tuning process, increasing the level of individualization. The stage of intensified tailoring can be extended until the data points cease to enhance predictive performance, or the accuracy reaches an acceptable level according to the user's perspective. The subsequent individualization activities of the second stage occur between the actual episodes of use and account for changes of the user's anatomical characteristics and preferences over time. *Case a* as of Figure 10 results in interactive re-tailoring analogous to the intensified first stage, asking the user to enter micturition cycles via the smartphone app. It can be initiated by the user if further refinement of the predictive performance is desired (user-driven). It is also possible for the artifact to trigger re-tailoring (artifact-driven) when it detects that characteristics of the sensor measurements have changed or that user preferences, such as too-late notifications, leave room for improvement. *Case b* comprises autonomous adaptive capabilities of the artifact that do not rely on active feedback of the user. Since it is possible to use NIRS data to autonomously determine the time of bladder emptying, the artifact can generate corresponding estimates of micturition volume that can serve as surrogate truth labels for independent fine-tuning of algorithmic operations.

In the *bladder monitoring* phase, the new user wears the sensor and can retrieve information on bladder volume via the smartphone app. As soon as the bladder volume reaches the critical threshold, the app emits a notification, both as defined by the user.

Considering the socio-technical nature of the DSR project, Research Article #5 adopts the Human Risk & Effectiveness strategy proposed by Venable et al. (2016) as a blueprint for evaluation. The five evaluation episodes included multiple workshops with three ML and DL experts, interviews with 15 patients living with NLUTD, and several laboratory sensor experiments. In the fourth evaluation episode, multiple state-of-the-art ML and DL models (i.e., RF, XGBoost, DNN, CNN, and LSTM) and ML techniques (i.e., multi-task and single-task learning as well as feature extraction and fine-tuning) were benchmarked on a real-world dataset. The dataset was recorded by a heterogeneous cohort of 22 test subjects of varying age, sex, and medical conditions over a period of 12 months without any restrictions. The best performing combination was an LSTM model trained via fine-tuning, which achieved a mean absolute error of 104.96 *ml* using only sensor data. It outperformed other models, which had access to time and sensor features but were trained with a multi-task technique (i.e., the traditional one-size-fits-all paradigm), on most performance metrics. As final evaluation episode, the usefulness and real-world-fidelity of the instantiated artifact was tested in a case analysis with a participant living with spina bifida.

In summary, Research Article #5 extends the knowledge on process intervention at the individual level in three respects. First, the model for individualized bladder monitoring demonstrates how a smart wearable system can be designed to tailor technology and medicine to enhance prescriptive treatment interventions for the individual patient. Second, the evaluation on a real-world dataset has shown that deep transfer learning solely on sensor data can outperform a one-size-fits-all learning technique with access to sensor and time features as presented in Research Article #4. Collecting only sensor data reduces the patient's active involvement and, therefore, makes bladder monitoring more applicable in real-life scenarios. As a third contribution, the article extends the theory of tailorable technology design (Germonprez et al. 2007; 2011) by formalizing the aforementioned findings and, for the first time, focusing on the role and influence of AI components in the tailoring of intelligent and (partially) autonomous systems.

To conclude, Section III contributes to the examination of complex process contexts along the three main activities of process science. First, Research Article #3 illustrates how process mining can support the process discovery and explanation activities for the cross-organizational turnaround process. Second, Research Articles #4 and #5 propose two artifacts that leverage biomedical sensor data to enable prescriptive process intervention for the individual patient and have the long-term potential to fundamentally change current treatment. In combination, the two contributions can stimulate further interdisciplinary research in the field of process science.

IV Conclusion

1 Summary

Over the last decade, process mining has evolved into one of the most active research streams in BPM and has become increasingly established and successful in various industry sectors (Badakhshan et al. 2022; Mamudu et al. 2023; Reinkemeyer et al. 2022; van der Aalst 2020). As BPM and process mining are innately geared toward business processes, vom Brocke et al. (2021) have proposed the field of process science to encourage interdisciplinary research on a wider range of process-related phenomena. This doctoral thesis adopts the holistic view of process science to address two challenges that limit the uptake and usefulness of data-driven process analysis and management in real-world process contexts. First, since process analyses are constrained by the extent to which the event data provided reflect reality, the thesis investigates how unstructured data (e.g., text or video data) can be systematically integrated into process mining. Second, the thesis demonstrates how data-driven process discovery, explanation, and intervention can be achieved for complex application scenarios by examining process contexts at both the organizational and individual levels.

The consideration of unstructured data can reduce blind spots in the analysis of incompletely digitized processes (Grisold et al. 2021; Kratsch et al. 2022) and also add contextual insights as missing pieces for a holistic process view (Beverungen et al. 2021). Therefore, Section II comprises two contributions on *integrating unstructured data into process mining*. Research Article #1 constructs a reference architecture that enables the systematic use of video data for process mining. The proposed reference architecture was thoroughly evaluated, which included its instantiation as a publicly available software prototype. The application of the software prototype to a real-world video dataset demonstrated its ability to extract process-related event data from unstructured video data. While Research Article #1 concentrates on a single type of unstructured data, Research Article #2 conducts a systematic literature review to provide a more comprehensive overview. The article analyzes 24 primary studies that were selected from a total of 1,379 research items and outlines how the different types of unstructured data are used for different process mining use cases. Based on these findings, Research Article #2 compiles a research agenda that encompasses seven opportunities to guide future research at the intersection of unstructured data and process mining.

Section III consists of three research articles that address the challenge of *expanding data-driven process discovery, explanation, and intervention*. Research Article #3 exemplifies how event data obtained from the standardized ACDM framework can be used to analyze the cross-organizational turnaround process at Munich Airport. The article applies process discovery and conformance checking techniques and draws on data science to generate further insights for the turnaround process that build a solid basis for future process interventions. Considering the widespread adoption of the ACDM framework in Europe, the proposed approach can be easily transferred. While Research Article #3 takes an organizational business-oriented perspective, Research Articles #4 and #5 focus on the individual patient's perspective in medical treatment processes. Both articles design artifacts that enable prescriptive process interventions for patients who have lost bladder sensation. Specifically, Research Article #4 introduces the model for bladder monitoring as an end-to-end solution that, for the first time, uses biomedical NIRS sensor data to continuously measure bladder volume through ML and DL. The model for bladder monitoring comprises a smartphone app that alerts patients before a critical bladder volume is reached, empowering patients with more flexibility in their daily lives while preventing the negative health consequences of bladder over-distension. Research Article #5 presents an artifact that enhances the real-world-applicability and predictive performance of bladder monitoring, building on the results of Research Article #4. In line with the concept of individualized medicine, the artifact improves the consideration of individual patient characteristics and employs deep transfer learning to tailor its prediction component to the individual patient. The artifact was extensively evaluated with technical experts and patients from the target group. In sum, Research Articles #4 and #5 demonstrate the core principles of process science by utilizing novel digital trace data. The two articles put the biological process of bladder filling at the center of attention to provide interdisciplinary solutions that show potential to transform the current standard treatment process substantially.

2 Limitations and Future Research

The results of this thesis, as with any research endeavor, are subject to limitations that can be reduced and resolved in future research. While each of the five research articles included in this thesis discusses its specific limitations and offers avenues for future research (see Appendix VI.3 to VI.7), this section takes a bird's eye view and identifies the major themes to advance data-driven process science.

First, the methodological aspects of the five research articles provide grounds for future research. Research Articles #1, #4, and #5 adopt the DSR paradigm (Gregor and Hevner 2013) to create novel artifacts that solve relevant process science related problems. All three artifacts have been extensively evaluated, which demonstrated their applicability and usefulness. However, given the technical novelty of the artifacts, future research would benefit from assessing their use and acceptance over a longer period of time in naturalistic settings. To this end, future research should strive to further enhance the technical implementation of the artifacts and to increase the scalability and efficiency of the various integrated ML and DL components. This also represents a crucial step toward long-term solutions for industrial application. Research Article #2 conducted a systematic literature review on unstructured data in process mining. The article focuses on peer-reviewed academic work and is thus limited to the research items that were identified through a database-driven literature search. To gain a broader perspective, future research should consider complementary evidence that could involve technical specifications of commercial solutions, grey literature, and interviews with leading practitioners and researchers. To generalize the findings of Research Article #3, a multiple case study approach would be a promising avenue for future research.

Second, regarding the challenge of integrating unstructured data into process mining, this thesis presents the ViProMiRA as an artifact that enables the use of video data for process mining. Though the artifact successfully addresses a novel research gap, it also exhibits limitations that nicely illustrate some of the opportunities for future research identified in Research Article #2. Future research at the intersection of unstructured data and process mining should build integrative artifacts that provide generic data extraction and processing capabilities for other types of unstructured data (e.g., audio data). As the ViProMiRA employs a supervised learning approach, its extraction capabilities are restricted by the comprehensiveness of the training data provided. Therefore, designing solutions that can continuously expand their extraction and processing capabilities represents another opportunity for future research. Furthermore, the assessment of data quality (Andrews et al. 2020; Fischer et al. 2022; Martin et al. 2022) has to be extended to unstructured data sources. Otherwise, the probabilistic and uncertain nature of information extracted from unstructured sources (van der Aalst 2020) can lead to intransparent or incorrect decision-making. Consequently, it is also necessary to extend existing process mining techniques to be able to deal with uncertain event data (van der Aalst 2020). To fully realize the potential of unstructured data in context-aware end-to-end process analysis, future research should strive to establish a single point of truth for process-related event data. This necessitates approaches that can correlate data from diverse structured and unstructured sources. In this regard, it is of the utmost importance to carefully consider privacy and confidentiality aspects when handling sensitive and personal data (Elkoumy et al. 2021).

Third, this thesis' contributions to the challenge of expanding data-driven process discovery, explanation, and intervention also have limitations. While the analysis of the turnaround process at Munich Airport led to novel insights, it also revealed the necessity to involve multiple stakeholders when studying cross-organizational processes. Future research should employ the concepts of federated process mining (Rafiei and van der Aalst 2023) to share data between stakeholders and reduce blind spots in cross-organizational process analysis. It is also important to note that interventions in cross-organizational settings may have favorable outcomes for certain stakeholders while adversely affecting others. Thus, a further opportunity for future research lies in exploring value distribution mechanisms between different stakeholders to overcome resistance to end-to-end processes improvements. As demonstrated in Research Articles #4 and #5, process science aspires to study the complex dynamics of contemporary phenomena. Hence, to advance the interdisciplinary study of a broader range of processes, additional process science research that harmonizes individual and organizational perspectives is needed. Finally, to fully exploit the potential of process science, future research should develop additional methodological guidance that helps operationalize the interdisciplinary and process-oriented nature of process science in research and industry.

To sum up, the increasing volume of structured and unstructured digital trace data enables the analysis and management of complex process dynamics and phenomena at both organizational and individual levels. I hope that this thesis will assist researchers and practitioners in developing interdisciplinary solutions for successful process discovery, explanation, and intervention in a world in constant change.

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VI Appendix

1 Index of Research Articles

Research Article #1: Shedding Light on Blind Spots – Developing a Reference Architecture to Leverage Video Data for Process Mining
Kratsch W, König F, Röglinger M (2022). Shedding light on blind spots – Developing a reference architecture to leverage video data for process mining. In: *Decision Support Systems* 158:113794.

(VHB-JOURQUAL3: Category B, Impact Factor: 7.5, Senior Scholars' List of Premier Journals)

Research Article #2: Unstructured Data in Process Mining: A Systematic Literature Review
König F, Egger A, Kratsch W, Röglinger M, Wördehoff N. Unstructured Data in Process Mining: A Systematic Literature Review. Submitted to: *ACM Transactions on Management Information Systems*.

(VHB-JOURQUAL3: Category B, Impact Factor: n/a)

Research Article #3: Process Mining for Resilient Airport Operations: A Case Study of Munich Airport's Turnaround Process
Rott J, König F, Häfke H, Schmidt M, Böhm M, Kratsch W, Krcmar H (2023). Process Mining for resilient airport operations: A case study of Munich Airport's turnaround process. In: *Journal of Air Transport Management* 112:102451.

(VHB-JOURQUAL3: n/a, Impact Factor: 6)

Research Article #4: Near-Infrared Spectroscopy for Bladder Monitoring: A Machine Learning Approach
Fechner P, König F, Kratsch W, Lockl J, Röglinger M (2023). Near-Infrared Spectroscopy for Bladder Monitoring: A Machine Learning Approach. In: *ACM Transactions on Management Information Systems* 14.

(VHB-JOURQUAL3: Category B, Impact Factor: n/a)

Research Article #5: How Artificial Intelligence Challenges Tailorable Technology Design – Insights from a Design Study on Individualized Bladder Monitoring
Fechner P, König F, Lockl J, Röglinger M. How Artificial Intelligence Challenges Tailorable Technology Design – Insights from a Design Study on Individualized Bladder Monitoring. Submitted to: *Outlet hidden due to the double-blind review process of the journal*.

I also co-authored the following research article, which is not included in this doctoral thesis:

Gimpel H, Kerpedzhiev G, König F, Meindl O (2020). Teaching an Old Work System New Tricks: Towards an Integrated Method for Work System Transformation in Times of Digitalization. In: *Proceedings of 28th European Conference on Information Systems (ECIS)*, An Online AIS Conference.

(VHB-JOURQUAL3: Category B, Impact Factor: n/a)

2 Individual Contribution to the Research Articles

This cumulative doctoral thesis comprises five research articles. Each research article was developed with multiple co-authors. This section describes the respective research settings and my contribution to each research article.

Research Article #1 (Kratsch et al. 2022) was developed by a team of three authors. As the second author, I had a key role in all parts of the research project. I contributed to the evolution of the overall research goal and the research design. In addition, I drove the evaluation of the artifact as part of the DSR process. To this end, I also implemented the presented artifact as a software prototype. In the writing phase, I was responsible for drafting and reviewing several sections of the original manuscript. I also contributed significantly to the revision of the manuscript for re-submission.

Research Article #2 (König et al.) was developed by a team of five authors. As the first author, I had a key role in all parts of the research project. Specifically, I was involved in formulating and refining the overarching research goal and the research questions. I also had a key role in the design of the research methodology for the systematic literature review. I was primarily responsible for data curation (i.e., performing the literature search) and setting up the coding scheme. With a co-author, I was involved in the study selection and coded the studies included in the final sample. In addition, I led the analysis and presentation of the results. Finally, I was responsible for drafting most sections of the initial manuscript and for reviewing and editing the entire manuscript.

Research Article #3 (Rott et al. 2023) was developed by a team of seven authors. As the second author, I had a key role in most parts of the research project. I was involved in formulating the overarching research goal and the research question. I also contributed to the design of the research methodology, focusing on the integration of the process mining project methodology. Furthermore, I co-implemented the script to create the final event log and was primarily responsible for the data and process mining analysis. In the writing phase, I was responsible for drafting several sections of the initial manuscript. I was also involved in reviewing the original manuscript and contributed to the revision of the manuscript for re-submission.

Research Article #4 (Fechner et al. 2023) was developed by a team of five authors. As the second author, I had a key role in most parts of the research project. I contributed to formulating the overarching research goal and was involved in the research design. I also co-designed the artifact and was mainly responsible for its visualization. Moreover, I contributed significantly to the implementation of the data orchestration pipeline of the software prototype. In addition, I provided guidance on how to benchmark the different ML and DL models (e.g., choosing appropriate performance metrics). As for writing, I drafted several sections of the initial manuscript and had a key role in revising and editing the manuscript throughout all pre-publication stages.

Research Article #5 (Fechner et al.) was developed by a team of four authors. As the second author, I had a key role in most parts of the research project. I co-formulated and refined the overarching research goal. In addition, I was primarily responsible for the design of the research methodology. I also drove the design and visualization of the artifact. In addition, I regularly participated in research discussions and provided feedback to advance software development and data analysis. I was responsible for drafting several sections of the initial manuscript and for reviewing and editing most sections of the manuscript. Furthermore, I contributed substantially to the revision of the manuscript.

3 Research Article #1: Shedding Light on Blind Spots – Developing a Reference Architecture to Leverage Video Data for Process Mining

Authors: Kratsch W, König F, Röglinger M

Published in: Decision Support Systems, 158 (2022)
DOI: *10.1016/j.dss.2022.113794*

Abstract: Process mining is one of the most active research streams in business process management. In recent years, numerous methods have been proposed for analyzing structured process data. In many cases, however, only the digitized parts of processes are directly captured by process-aware information systems, whereas manual activities often leave blind spots in the process analysis. While video data can contain valuable process-related information that is not captured in information systems, a standardized approach to extracting event logs from unstructured video data remains lacking. To solve this problem and facilitate the systematic usage of video data in process mining, we have designed the ViProMiRA, a reference architecture that bridges the gap between computer vision and process mining. The various evaluation activities in our design science research process ensure that the proposed ViProMiRA allows flexible, use case-driven, and context-specific instantiations. Our results also show that a prototypical implementation of the ViProMiRA is capable of automatically extracting more than 70% of the process-relevant events from a real-world video dataset in a supervised learning scenario.

Keywords: Computer Vision, Process Mining, Reference Architecture, Unstructured Data

4 Research Article #2: Unstructured Data in Process Mining: A Systematic Literature Review

Authors: König F, Egger A, Kratsch W, Röglinger M, Wördehoff N

Submitted to: ACM Transactions on Management Information Systems

Extended Abstract of the Working Paper:

A large proportion of available data is in unstructured form such as text, image, and video data (Davis 2019; Gandomi and Haider 2015; Balducci and Marinova 2018). As data analysis methods continue to improve, it becomes easier to tap into and exploit unstructured data. Even in the process mining discipline, which is traditionally focused on structured data stored in process-aware information systems, solutions that integrate unstructured data receive increasing attention (e.g., Teinemaa et al. (2016); Leotta et al. (2020); Lepsien et al. (2023)). To date, however, there is no overview on how unstructured data is leveraged in process mining. Against this backdrop, the research article aims to uncover to what extend unstructured data are accounted for in process mining, structure the current state-of-the-art, and provide a research agenda. To ensure that the research article adequately addresses the key aspects of unstructured data and process mining, it poses three research questions.

- RQ1: *Which types of unstructured data are used in process mining?*
- RQ2: *How are unstructured data leveraged for different process mining use cases?*
- RQ3: *What are the open challenges and areas for improvement?*

To address the above research questions, the research article conducts a systematic literature review according to the steps recommended by Kitchenham and Charters (2007). Following the construction of a review protocol, a total of 1,379 research items were identified through a database-driven search in seven prevalent databases (Hiebl 2023). Subsequently, 24 relevant primary studies were selected based on multiple selection criteria. Next, quality assessment and deductive data extraction were performed (Bandara et al. 2015). Finally, the most important insights were synthesized.

The literature review revealed that annual research output at the intersection of process mining and unstructured data has increased significantly from 2013 to 2022. The final sample of 24 primary studies predominantly focused on text data, indicating that there is potential for investigating other types of unstructured data. In addition, a concentration on process discovery and event log extraction was observed, which could be explained by the lack of prior knowledge about process execution and the high variability of the underlying processes.

To guide future research at the intersection of unstructured data and process mining, the research article proposes a research agenda that includes seven opportunities to address the identified research gaps. The research article also proposes a generic conceptualization and definition for the umbrella term unstructured data by summarizing and consolidating existing definitions.

Keywords: Unstructured Data, Process Mining, Business Process Management, Systematic Literature Review

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5 Research Article #3: Process Mining for Resilient Airport Operations: A Case Study of Munich Airport's Turnaround Process

Authors: Rott J, König F, Häfke H, Schmidt M, Böhm M, Kratsch W, Krcmar H

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DOI: *10.1016/j.jairtraman.2023.102451*

Abstract: The aviation industry has faced significant challenges in recent years, including a punctuality crisis in 2018/19 and the ongoing impact of COVID-19 on operations since March 2020. Hence, the industry seeks innovative ways to optimize its operations and become more resilient. Process Mining (PM) has proven valuable in various settings and industries by analyzing event-log data extracted from existing information systems. As airports play a critical role within the aviation network, we expand on a case study-based methodology and employ PM techniques to analyze data generated within the airport collaborative decision-making (ACDM) framework for the turnaround process at Munich Airport. We show that applying PM enhances operational transparency, reveals performance differences between ground-handling corporations and airlines, and identifies data quality problems with the implemented ACDM framework. Additionally, we develop a conceptual framework demonstrating the positive influence of PM on airport resilience. Our study contributes to the aviation literature and resilience theory by showcasing the potential of PM for analyzing and optimizing operational airport processes. Since the ACDM framework is widely used in Europe, researchers and practitioners can apply our approach to improve turnaround processes at other European airports.

Keywords: Process Mining, Turnaround Process, Resilience Theory, Airport Collaborative Decision Making (ACDM), Munich Airport

6 Research Article #4: Near-Infrared Spectroscopy for Bladder Monitoring: A Machine Learning Approach

Authors: Fechner P, König F, Kratsch W, Lockl J, Röglinger M

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DOI: *10.1145/3563779*

Abstract: Patients living with neurogenic bladder dysfunction can lose the sensation of their bladder filling. To avoid over-distension of the urinary bladder and prevent long-term damage to the urinary tract, the gold standard treatment is clean intermittent catheterization at predefined time intervals. However, the emptying schedule does not consider actual bladder volume, meaning that catheterization is performed more often than necessary which can lead to complications such as urinary tract infections. Time-consuming catheterization also interferes with patients' daily routines and, in the case of an empty bladder, uses human and material resources unnecessarily. To enable individually tailored and volume-responsive bladder management, we design a model for the continuous monitoring of bladder volume. During our design science research process, we evaluate the model's applicability and usefulness through interviews with affected patients, prototyping, and application to a real-world in vivo dataset. The developed prototype predicts bladder volume based on relevant sensor data (i.e., near-infrared spectroscopy and acceleration) and the time elapsed since the previous micturition. Our comparison of several supervised state-of-the-art machine and deep learning models reveals that a long short-term memory network architecture achieves a mean absolute error of 116.7 ml that can improve bladder management for patients.

Keywords: Machine Learning, Deep Learning, Supervised Learning, Design Science Research, Urinary Bladder Management

7 Research Article #5: How Artificial Intelligence Challenges Tailorable Technology Design – Insights from a Design Study on Individualized Bladder Monitoring

Authors: Fechner P, König F, Lockl J, Röglinger M

Submitted to: *Outlet hidden due to the double-blind review process of the journal* (second round of revision)

Extended Abstract of the Working Paper:

Artificial intelligence (AI) has significantly advanced healthcare and created unprecedented opportunities to enhance patient-centeredness and empowerment (e.g., Chatterjee et al. (2018); Zhu et al. (2020)). This progress promotes individualized medicine, where treatment and care are tailored to each patient's unique needs and characteristics (Goetz and Schork 2018). The Theory of Tailorable Technology Design has considerable potential to contribute to individualized medicine as it focuses on information systems (IS) that users can modify and redesign in the context of use (Germonprez et al. 2007; 2011). While the theory accounts for both the designer and user perspectives in the lifecycle of an IS, it does not reflect the inductive learning and autonomy of AI (Baird and Maruping 2021; Berente et al. 2021) throughout the tailoring process. Therefore, this research article posits the conjecture that the knowledge on tailorable technology design does not effectively account for AI-enabled IS.

To investigate this conjecture, the research article conducts a design study in the form of an advanced design science research (DSR) project (Peffers et al. 2007). The DSR project involved an AI-enabled individual IS for bladder monitoring (i.e., the continuous monitoring of the urinary bladder volume), aimed to tailor to and improve the treatment process for patients who have lost bladder sensation (Ginsberg et al. 2021). From a designer's perspective, the artifact consisted of a smartphone app, a non-invasive sensor module using acceleration and near-infrared data (Molavi et al. 2014), and a prediction component that built on deep transfer learning to predict bladder volume (Weiss et al. 2016; Yim et al. 2017). From a user's perspective, the artifact included three phases that explicitly consider that

users modify and tailor the artifact through initial tailoring before productive use and subsequent demand-driven and autonomous re-tailoring interwoven with productive use.

To address the socio-technical nature of tailorable technology design, multiple stakeholders were included in the creation and evaluation of the artifact (Venable et al. 2016). Hence, the design study provided a situational context for collecting extensive qualitative and quantitative evidence similar to a single-case study (Eisenhardt 1989). It therefore served as a revelatory example to critically challenge the Theory of Tailorable Technology Design (Tsang 2014; Yin 2009). Based on the empirical evidence from the design study, the primary contribution of the research article lies in three propositions for the design of tailorable technology (Lee and Baskerville 2003), culminating in a Revised Theory of Tailorable Technology Design. As the outcome of the design study, the secondary contribution of the research article is concrete design knowledge for AI-enabled individualized bladder monitoring systems that empower patients with neurogenic lower urinary tract dysfunction.

Keywords: Theory of Tailorable Technology Design, Individualization, Smart Wearables, Neurogenic Lower Urinary Tract Dysfunction, Bladder Monitoring, Deep Transfer Learning

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