Using Process Mining to Connect Process Orientation and Data-driven Decision Making in Healthcare: a Qualitative Assessment and Integration of New Data Sources

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Abstract

Healthcare organizations face increasing pressure to deliver care that is not only efficient and cost-effective, but also patient-centered and responsive. In this context, process orientation (PO) and data-driven decision making (DDDM) are widely promoted as complementary paradigms to improve healthcare delivery. However, their integration in daily practice remains fragmented. While PO fosters end-to-end thinking across organizational silos, DDDM relies on the growing availability of healthcare data to support operational and clinical decisions. The central aim of this doctoral research is to strengthen the connection between PO and DDDM by enriching process insights with experiential and engagement-related dimensions of care. Process mining bridges both approaches by analyzing real-world care pathways. Yet, most applications only focus on execution data, which limits the scope of how the patient experienced the process. This doctoral research explores how non-traditional data sources, specifically remote health monitoring and patient-reported experience data can be integrated into process mining analyses. In doing so, the research identifies key methodological, technical, and organizational challenges that arise when extending process mining beyond its conventional data foundations. The research is structured around three interrelated studies: (1) a qualitative study of Flemish hospital departments to assess the current state, opportunities and challenges of integrating PO and DDDM; (2) a process mining study using remote monitoring data in a cardiology context; and (3) a process mining study at a hospital that combines event logs with patient experience data in a breast cancer care pathway. Together, these studies aim to advance both the conceptual understanding of process mining as a means to integrate PO and DDDM, and its methodological application in data-rich, patient-centered healthcare environments.

Keywords

Process Mining, Process Orientation, Data-driven Decision Making, Healthcare, Remote Monitoring, Patient Experience

1. Introduction

Healthcare organizations are under growing pressure to provide care that is not only efficient and cost-effective, but also tailored to the needs and expectations of patients. To address this, process orientation (PO) and data-driven decision making (DDDM) are increasingly promoted as complementary approaches to enhance healthcare delivery. Yet, their integration into daily practice remains limited and fragmented [1, 2].

In healthcare, PO is all about creating patient-centered care pathways that go beyond the usual boundaries between departments. By organizing healthcare activities into clear and efficient processes, hospitals can boost both the quality and efficiency of the care they provide. Research has shown how powerful this approach can be, especially when it comes to improving teamwork across different functional or clinical areas and making sure healthcare services are actually meeting patient needs [3, 4]. At the same time, the growing availability of healthcare data and the rise of advanced analytics are fundamentally transforming healthcare practice. With access to detailed data from sources such as electronic health records and real-time monitoring systems, healthcare providers are increasingly able to make timely and evidence-based decisions. By systematically analyzing operational and clinical

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data, organizations can optimize decision-making processes, enhance workflow efficiency, and build a more adaptable and sustainable healthcare system [5, 6]. Process mining serves as a crucial bridge between PO and DDDM in healthcare. By extracting insights from event logs, process mining enables organizations to analyze and improve workflows based on process execution data [7]. This approach offers a unique way to uncover inefficiencies, visualize patient pathways, and align workflows with clinical guidelines [8, 9, 10, 11].

As healthcare and the societal context in which it is positioned is always evolving, it is crucial to keep improving processes and data strategies to match changes in clinical practices and patient needs [1, 12]. Two notable developments in this regard are the rise of remote health monitoring and the growing emphasis on patient experience as a quality indicator [13, 14, 15]. These evolutions bring new types of data into the healthcare setting, including patient-generated data from wearable devices and survey-based insights into patients' perceptions of care. While these sources capture valuable behavioral and experiential aspects of care [16, 17, 18], they are still rarely leveraged in process mining research and applications. As a result, their potential to enrich process analysis and optimization remains largely unexplored.

This doctoral research explores how non-traditional data sources, specifically remote health monitoring and patient experience data can be integrated into process mining. It also investigates the methodological and technical challenges that arise when adding these non-traditional data types to process mining projects. To better understand how PO and DDDM are currently applied in practice, the research includes three interrelated studies: (1) a qualitative study of Flemish hospital departments to assess the current state, opportunities and challenges of integrating PO and DDDM; (2) a process mining study using remote monitoring data; and (3) a process mining study at a hospital that combines event logs with patient experience data. The relationship between these projects is presented in Figure 1. Together, these studies aim to deliver both conceptual and practical contributions to the inclusion of new data sources in process mining projects for the healthcare domain.

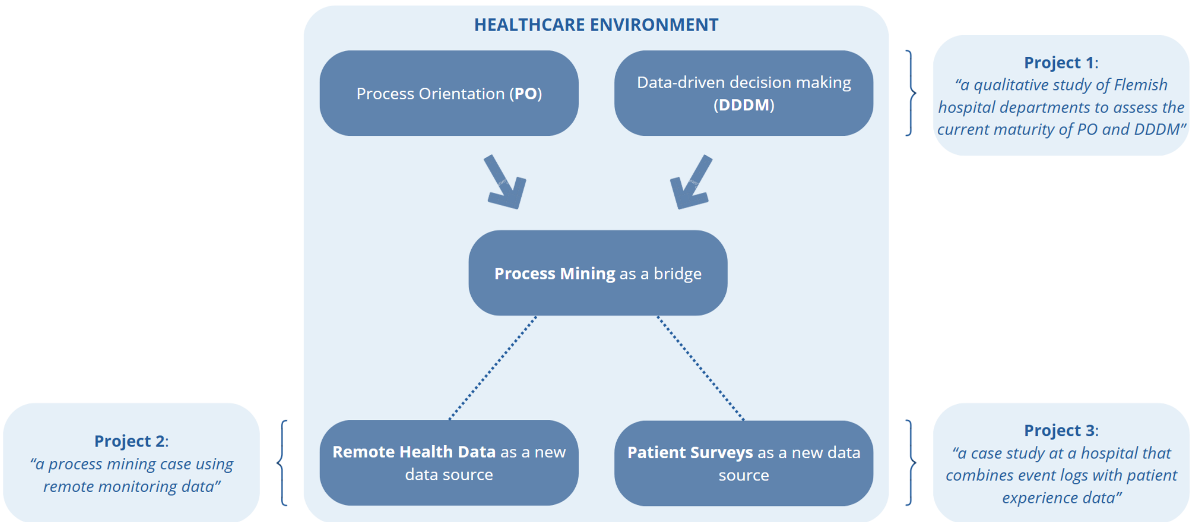

Figure 1: Overview of the research context and relationship between the three studies

2. Related Work

Process mining has gained significant traction in healthcare research as a technique for enabling data-driven process analysis. Numerous studies and review papers have illustrated a variety of use cases, including patient flow mapping, treatment variation analysis, and bottleneck identification in care delivery [19, 11, 20, 12]. Other studies have demonstrated the feasibility and value of applying process mining in healthcare contexts. De Roock et al. [20] reviewed 263 papers and confirmed the growing maturity of the field, with a broad range of applications across clinical and administrative domains. Mans et al. [8] conducted one of the earliest case studies by analyzing gynecological oncology care pathways in a Dutch hospital using real event log data. Their work showed how process mining techniques can uncover deviations and variations in clinical pathways. More recently, Agostinelli et al. [9] used process mining to support governance in hospital settings. Their case study demonstrated how clinical processes can be reconstructed and monitored to assess compliance and identify inefficiencies, thereby providing actionable feedback to management.

These studies confirm that process mining can generate added value in healthcare by reconstructing real-world processes to identify areas of improvement using the event data captured and derived from the HIS [8, 9]. However, HIS data often focus on administrative and clinical transactions, and therefore provide only a partial view of the actual experience and patient engagement [21]. Recent developments in healthcare have introduced new types of data, particularly patient-generated health data from remote monitoring devices and patient experience data [17, 16], but their integration into process mining is still absent.

Anhang et al.[22] highlight the value of patient experience data for improving healthcare processes and outcomes. Patient surveys are increasingly used to gather structured feedback on different aspects of care. Gualandi et al.[15] showed that collecting patient-reported data at multiple moments in the patient journey offers a more detailed view on patient experience than traditional satisfaction surveys, which are typically administered at a single point in time. Elliott et al. [14] report consistent improvements across nearly all dimensions of patient experience following the implementation of systematic hospital surveys.

In parallel with the growing attention for patient experience data, remote health monitoring technologies are becoming increasingly important for ensuring continuity of care beyond the hospital setting [23]. This is particularly evident in the management of atrial fibrillation (AF), where smartphone-based tools such as FibriCheck have shown promising results. The TeleCheck-AF project, presented by Gawałko et al.[13], demonstrated that remote rhythm monitoring via app-based photoplethysmography (PPG) is technically feasible across multiple healthcare settings, achieving high patient compliance and positive evaluations from professionals. Beerten et al.[24] confirmed FibriCheck's usability and patient engagement in Belgian general practices, and Knaepen et al. [25] showed that remote data from the app can effectively support teleconsultations.

Despite their growing importance, patient experience data and remote monitoring data have not yet been empirically integrated into process mining analyses within healthcare. Most existing process mining studies continue to rely on transactional and clinical data from HIS, with little attention given to the experiential and patient engagement aspects of care [11, 20]. At the same time, the literature on patient experience surveys largely focuses on survey design, implementation, and their role in satisfaction or quality improvement initiatives [15, 14], rather than on integrating this data into process analytics. Similarly, research on remote monitoring technologies such as FibriCheck primarily addresses clinical effectiveness, user compliance, and technical feasibility [13, 25, 24], with limited consideration of their potential for process-level analysis.

This doctoral research aims to fill that research gap. It investigates how non-traditional data sources, specifically remote health monitoring and patient experience surveys, can be meaningfully included in process mining projects. These types of data introduce specific methodological challenges, such as aligning asynchronous or loosely structured data streams with clinical event logs, dealing with data quality issues like wearable accuracy, patient persistence, and poor connectivity, as well as handling subjective and context-dependent input [26, 27, 17]. Particularly in the case of patient feedback, additional challenges include mapping survey responses to concrete process activities and filtering out noise [28]. Addressing these challenges is essential to unlock the full potential of these data sources for process-oriented decision-making in healthcare.

This need is further motivated by Muñoz-Gama et al. [12], who highlight the importance of analyzing healthcare processes from the patient's perspective. They advocate for including patient experiences and data beyond hospital walls to better understand the care journey through the "patient's eyes". Our focus on remote monitoring and patient-reported experience data responds directly to this call, offering complementary views that extend traditional, institution-centered process mining. In line with this, Erdogan and Tarhan [29] emphasize that healthcare data stem from heterogeneous sources, and that addressing data integration challenges is essential for the effective application of process mining in healthcare.

3. Research objectives and methods

This doctoral research aims to explore how novel data sources can be integrated into process mining. While process mining has become a mature method for analyzing event data, its potential to incorporate non-traditional data types such as remote patient monitoring and patient-reported experience measures remains underexplored. The relationship between these different concepts can be found in Figure 1.

The central research question is: "How can the integration of process orientation and data-driven decision-making in healthcare be better understood and supported through qualitative insights and process mining techniques using new data sources?". To address this question, the research is organized into three interrelated projects. Currently, the first project is nearing completion, while projects two and three are being co-developed with partner hospitals. Study protocols are under construction in close collaboration with clinical and data stakeholders.

3.1. Project 1: a qualitative study of Flemish hospital departments to assess the current state, opportunities and challenges of integrating PO and DDDM

The objective of project 1 is to assess the current state, opportunities and challenges of integrating PO and DDDM within Flemish hospital departments. Despite the widespread availability of healthcare data and the growing interest in process orientation, little is known about how these paradigms are implemented and perceived at the departmental level. This project seeks to fill that gap.

A qualitative study based on semi-structured interviews with head nurses and medical department leads will be conducted across multiple hospitals in Flanders. The interviews explore three central themes: (1) current practices and challenges related to data use in clinical and operational decision-making, (2) how processes are currently defined, coordinated, and monitored, and (3) perceived opportunities and barriers for increasing PO and DDDM maturity.

Interviews are guided by a structured protocol covering both data and process dimensions, and transcripts are analyzed thematically using an inductive coding approach [30]. The analysis aims to identify common patterns, differences across hospital types or departments, and actionable insights to inform subsequent case studies. To date, all interviews took place and are now being analyzed. This study forms the contextual basis for project 2 and project 3.

3.2. Project 2: a process mining study using remote monitoring data

Project 2 explores the integration of remote health monitoring data into process mining analyses. The case study takes place in a cardiology department where patients are monitored for AF recurrence after an ablation procedure using a smartphone-based application. The goal is to analyze how patient behavior and responsiveness of hospital staff unfold in this hybrid care setting.

The study leverages two main data sources: (1) the smartphone-based application, which captures daily heart measurements, symptoms and alerts, and (2) the hospital's electronic health record, which contains timestamps for clinical actions such as follow-up consultations or medication adjustments. Process mining techniques are applied to model patient monitoring trajectories, examine response times to alarms, and analyze behavioral patterns over time, such as measurement adherence and frequency of symptom reporting.

We also investigate the methodological and technical challenges of combining patient-generated data with clinical event logs, such as aligning wearable accuracy, patient persistence, poor connectivity and lack of integration with electronic medical record systems [26, 27, 17]. The project will deliver both descriptive insights into monitoring workflows and a set of structured integration steps for applying process mining to remote health data. The results are co-interpreted with clinical stakeholders to ensure practical relevance and feasibility.

3.3. Project 3: a process mining study at a hospital that combines event logs with patient experience data

Project 3 focuses on combining traditional process mining with patient-reported experience data in a breast cancer care pathway. While patient satisfaction is a key indicator of care quality, it is rarely analyzed in conjunction with process execution data. This project aims to bridge that gap by integrating satisfaction scores into process analysis.

In this case study, we collaborate with a hospital that collects patient satisfaction data at several touchpoints along the breast cancer care trajectory. These touchpoints include consultations, treatments, and discharge moments. Using process mining techniques, we reconstruct the patient journey from event logs and enrich this with satisfaction data to perform a layered analysis. The analysis investigates how such process differences relate to variation in patient satisfaction at different touchpoints. The goal is to provide a methodology for adding patient feedback data to process execution data, facing challenges such as aligning feedback moments with specific process events, filtering out irrelevant or noisy responses, and preserving the contextual richness [28]. Since surveys are often anonymous, we are discussing a prospective setup with the hospital to enable linkage. This approach may introduce social desirability bias, where patients respond less honestly when not anonymous [31]. However, the project's main goal is to explore how subjective feedback can be ethically and technically integrated into process mining analysis. The outcome will be a proof-of-concept approach for linking process data with patient experience scores, including design principles for future application.

4. Conclusion

The added value of this research lies in expanding the process mining toolbox to include non-traditional data types, specifically patient-generated data from remote monitoring and patient experience data. These data streams are increasingly available in modern care settings, yet remain underutilized in data-driven process analysis [16, 17, 18].

The first study provides a foundational understanding of the current maturity in PO and DDDM across Flemish hospitals, identifying the current state, opportunities and barriers. This qualitative insight guides the case studies that follow. The second project uses remote health monitoring data to evaluate how patients behave in digital follow-up trajectories. The third project enriches traditional process models with patient satisfaction data, allowing for layered analyses that connect process variants to patient-reported outcomes.

Together, these projects contribute to the theoretical development of process mining methods by demonstrating how new data types can be structurally embedded in process mining frameworks. They also provide actionable insights to healthcare practitioners seeking to design more responsive and patient-centered care pathways.

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Declaration on Generative AI

During the preparation of this work, the author used ChatGPT-4o in order to: paraphrase and reword. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the publication's content.

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