Decision-support Simulation of Patient Treatment Process

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Abstract. The transition from being a medical student, with limited responsibilities and a high level of supervision, to becoming a medical intern or newly qualified doctor, with medical responsibility for individual patients and less supervision, is difficult and stressful. Occasionally medical trainees experience high levels of uncertainties in diagnosing patients' issues and making decisions about proper treatment for them which may be life-threatening for patients. Therefore preparing medical interns and junior doctors with the skills necessary to deal with real medical experiences is crucial. For efficient acquisition of medical knowledge and skill without compromising patient safety, a simulation-based approach can be considered as an appropriate option. The main contribution of this research lies in developing a decision-support simulation tool for the patient treatment process to assist medical interns and junior doctors to transform their theoretical knowledge into practice. To do so, we propose the combined process mining and data mining techniques to analyze and discover patient treatment process models to support the construction of simulation models.

Keywords: decision-support simulation · Process mining · patient treatment process · Knowledge intensive process.

1 Research context

The transition from being a medical student, with limited responsibilities and a high level of supervision, to becoming a medical intern or newly qualified doctor, with medical responsibility for individual patients and less supervision, is difficult and stressful. Especially, being able to identify the patient's issues, make decisions, and prepare a plan for the patient is a challenge. Medical interns and junior doctors experience high levels of anxiety, less confidence in diagnostic skills and decision-making. Because finding the right diagnosis and initiating a treatment plan in real cases is different from the student's perspective, where decisions seemed more clear-cut. Sometimes these uncertainties in choosing the right diagnostic tests, prescriptions, and procedures, and the treatment follow-up put patients lives at risk [1, 2].

Clinical Guidelines (CGs) offer the best practice in medical activities and play an important role in improving medical quality as well as reducing risks.

However, evidence in CG is essentially a form of static knowledge. It captures the generalities of patients classes and also always assumes necessary resources are available [3]. But patient treatment process is dynamic and influenced by a variety of patient-related factors (e.g. patient socioeconomic status, emergency conditions, patient history, etc.) and features of hospitals (e.g. medical supplies, equipment, and infrastructures, etc.). Therefore, due to diversity, variability, and uncertainty of factors in patient treatment process, CG can not cover the whole process [4, 5]. For efficient acquisition of medical knowledge and skill without compromising patient safety, a predictive simulation approach can be considered as an appropriate option [6]. The simulation model is close to the clinical experience, representing real-life characters involved in the clinical process. It helps and supports the decision making procedure, reduces costs, increases process transparency, and as a final objective provides a good quality of training for medical trainees and new doctors based on real-world processes without any harm to patients.[7, 6]

A detailed simulation of the patient treatment process requires modeling and analysis of this process from multiple points of view such as medical knowledge and decision-making points. Recently, business process management (BPM) has become to be considered a key valuable asset in the healthcare domain. It is increasingly adopted by healthcare organizations because it helps improving healthcare processes by taking into account the increasing complexity in patient treatment and the continuous reduction of available resources. Various modeling languages have been developed to cover different types of processes [8]. However As pointed out by some authors [9, 10], most of the existing BPM methods are suitable for procedures that can be relatively easily represented in the form of well-defined stable tasks and activities. But many healthcare processes exhibit characteristics that pose significant challenges to common process management techniques. One important such class is Knowledge-Intensive Processes (KIPs) that are usually unrepeatable, collaboration-oriented, and mostly unpredictable. Their execution is heavily dependant on various interconnected tasks that are performed by knowledge workers. We can see numerous examples of KIP in the patient treatment procedures [11–13].

In recent years, the need to deal with KIPs has emerged as a leading research topic in the BPM domain, due to the prominent role of knowledge workers in modern organizations [12]. BPM researchers have recently recognized the need to extend existing approaches to support KIPs and meet their challenging requirements, like integrating knowledge and decision dimensions with the original process, which actual BPM frameworks are not able to handle adequately [14]. Process mining is a Business Intelligence (BI) tool that can address some of these issues by amalgamating the knowledge of information technology and management science. Applying process mining in healthcare contributes to extracting the knowledge of processes and decision points [15]. Unlike many mainstream BI and data mining tools which are data-centric, process mining is process-centric and aims to bridge the gap between data mining and BPM. The combination of both process models and data allows new forms of knowledge-centric process analytics, which leads to the understanding of the process diversity and complexity, as well as the real behavior of resources and the patients. [16]. In this study, we try to establish and promote understanding of the decision support simulation, KIPs, and nature of the process characteristics to generate forward-looking and explainable patient treatment process training solutions.

2 Research Goal

The main contribution of this research lies in developing a decision-support simulation tool for the patient treatment process to assist medical interns and junior doctors to transform their theoretical knowledge into practice. This prototype can be complementary to clinical guidelines. To that purpose, we propose the combined process mining and data mining techniques to analyze and discover patient treatment process models to support the construction of simulation models.

3 Challenges

From the technical perspective, applying process mining to healthcare data is challenging due to data quality, veracity, and complexity [17]. Based on existing works and literature reviews, the following limitations can be listed :

- In reality, care providers support multiple, simultaneous, diverse pathways for patients with highly variable personal needs, and many of the interactions, events, and decisions are not stored in information systems.
- Data sources are heterogeneous and hard to use jointly (patient file, vital signs, medical history)
- Health-care processes (clinical pathways) are inherently variable and unstructured, therefore performing the process mining on all the available events inevitably creates incomprehensible spaghetti-like models.

4 Objectives and Research questions

Through this study, we aim to achieve three main objectives which are comprehensively discussed in the following sections.

4.1 Objective 1: Determine an integrated decision-driven process modeling approach

KIPs such as patient treatment flow, require flexibility and scalability in modeling, as well as profound integration of data and decisions into the process [18]. The goal of this step is to propose a decision-driven approach to support flexible KIP healthcare processes. There is a wide range of process modeling languages available that claim to be able to model this type of process, both imperative ones (i.e. Business Process Model and Notation (BPMN), Petri nets) and declarative ones (Declare and Case Management Model and Notation (CMMN)) [19]. Yet, it is demonstrated that current approaches do not incorporate all the details needed. More specifically, they are unable to model decision logic, which is important when attempting to fully capture these processes [20, 21, 14]. The recent introduction of the Decision Model and Notation standard (DMN) provides an opportunity for shifting in favor of a separation of concerns between the decision logic and process model. Decision modeling, and especially DMN, provide an apt paradigm for representing knowledge-intensive and complex decisions that are based on multiple inputs and stages [22, 23, 19, 24].

Purpose: In the first step we focus on the identification and documentation of the KIPs. For this task, we examine both imperative and declarative modeling approaches (BPMN, CMMN, and DECLARE) for representing knowledge-intensive processes. Then to consider the decision logic, the combination of these languages with DMN as another approach will be investigated. Finally, there will be a comparison between them based on Knowledge-intensive process ontology (KIPO) considering the knowledge within their actions, decisions, and specific working rules [25]. KIPO is based on the Unified Foundational Ontology (UFO) and is composed of five sub-Ontology that cover different perspectives within a KIP: Collaborative Ontology (CO), Business Process Ontology (BPO), Business Rules Ontology (BRO), Decision Ontology (DO), and Knowledge-Intensive Process Core Ontology (KIPCO). The following research questions will be answered for this objective:

RQ1.1: A comparative study of the existing declarative and imperative process modeling approaches to identify best possible solutions for modeling KIP process

RQ1.2: Select a combination of modeling methods to achieve a comprehensive decision-aware process model.

Methodology and steps:

for this objective, a qualitative method is used to model and analyze a real KIP by various modeling approaches.

- Obtain a clear overview of relevant process modeling approaches from literature and discuss which certain modeling methods are suitable.
- Define clear modeling rules and guidelines for linking process modeling techniques with DMN to clarifying how the different modeling methods should be used together as consistent models that cooperate but not obstruct each other.
- Investigate how the data layer needs to be organized to reach consistency in the integration of processes, cases, and decisions.
- Evaluate the correlation between process modeling language elements and KIPO ontology concepts.
- Apply the integrated decision-driven process modeling approach on the knowledge-intensive patient treatment process.

4.2 Objective 2: Determine Optimal process mining techniques for process analysis

Process mining is a relatively young research discipline that sits between computational intelligence and data mining on the one hand, and process modeling and analysis on the other hand. The idea of process mining is to discover, monitor, and improve real processes (not assumed processes) by extracting knowledge from event logs. Process mining includes process discovery (i.e., extracting process models from an event log), conformance checking (i.e., monitoring deviations by comparing model and log), social network/organizational mining, automated construction of simulation models, model extension, model repair, case prediction, and history-based recommendations. The ability to use process mining techniques for discovering process models and analyzing their performance provides valuable opportunities for taking advantage of information stored in event logs. Using these methods not only ensures such procedures can be firmly understood but also generate benefits associated with process efficiency [26]. The most commonly used algorithms in healthcare for unstructured processes are Heuristics Miner and, Fuzzy Miner. Heuristics Miner is a discovery algorithm that can generate process models and is very robust in dealing with noise in event logs. Fuzzy Miner is a configurable discovery algorithm that can generate multiple models at different levels of detail, helping to deal with unstructured processes by tuning its parameter [27, 28]. Our strategy for this objective is to evaluate existing process mining techniques and algorithms to discover novel ways to deal with KIPs that are flexible, unstructured, complex.

Purpose: For this purpose we suggest four steps: In the first stage event logs and data need to be extracted from information systems and domain experts such as medical practitioners. This requires an understanding of "What can be used for analysis? In the second stage, the model is constructed by process discovery techniques and linked to the event log. The discovered process model may already provide answers to some of the questions and triggers redesign or adjustment actions. Through the third stage, the relation between an existing process model is compared with an event log of the same process. This can be used to check if reality, as recorded in the log, conforms to the discovered model and vice versa. Ultimately in the fourth stage, The knowledge will be extracted from historical event data and combined with information about running cases to be used for decision making and predicts patient treatment path during simulation.

RQ2.1: select a discovery algorithm for obtaining holistic decision and process models from recorded data.

RQ2.2: determine a framework to check the conformance of event logs or the resulting process with the existing real process at hospitals.

Methodology and steps:

- Identify and evaluate existing case studies where process mining has been applied to healthcare processes.
- Generate a characterization of this project case, including a description of the most important aspects of main peculiarities of a process such as types

of activities, different actors with particular roles, expertise level, knowledge, etc.

- Select and combine appropriate process mining algorithms and techniques for process discovery and process analysis.

4.3 Objective 3:Develop Decision support simulation of patient treatment process

Healthcare process mining presents opportunities for understanding some of the reality of real patients journeys through care pathways. However, one important fact about process mining is that it is backward-looking and cannot be used to answer what if questions. To fill this gap, simulation can help communicate process mining discoveries and explore what if scenarios. Simulation offers a vigorous way to test out variables and potential solutions or changes to a system without increasing patient risk, wasting precious recourse on untested pilots. This tool brings new knowledge and allows the evaluation of various scenarios through processes [29]. Simulation models are typically created by simulation experts based on insights from traditional information sources such as process documentation, interviews, and observations. Issues with these information sources may contribute to the discrepancy between the constructed simulation model and reality because the perception of the actual process is influenced by the experience of the human studying it. Moreover, this approach is not easily reproducible as the model is built on a case-by-case basis [30]. To avoid these biases this study uses a combination of traditional resources and event logs in simulation construction. Event loges contain highly relevant information on the actual behavior of the care process. To extract this information we need process mining techniques. So Process mining can be used to make better simulation models and to enable the simulation to run with actual behaviors. On the other hand, simulation can be used to make process mining more forward-looking and explore different process changes. Given the above, it is very natural to combine process mining and simulation. [29, 31, 32].

Purpose: In this research we use an advanced approach by using a combination of process mining and simulation. process mining techniques are used to discover a comprehensive simulation model [33]. Meanwhile, a specific form of decision support approach simulation will be performed based on the current state of the process [29]. The idea is to enable the incorporation of new data into an existing simulation model continuously, and thus to allow the model to dynamically steer the upgrading process. This simulation is like a quick look in the near future. So it is possible to see what happens if the current situation is modified (e.g. change in the patient conditions or medical resources). It is also possible to see the effect of certain decisions in the near future without the need for any additional modeling effort. [32, 29].

RQ1: Completeness of the simulation in terms of coverage of the behavior of the patient treatment process.

RQ2: evaluation the quality of simulation as a decision support tool in practice.

Methodology and research plan:
This stage will be applied based on the design science research paradigm by focusing on the design, development, and evaluation of the simulation tool.

- Decide on the purpose of the simulation and what key performance indicators (KPI) we want to monitor.
- Create a simulation model based on discovered model.
- Evaluate the conformance between the simulated process model and the process model to compare observed behavior and modeled behavior.
- Simulation performance diagnostics by evaluating specific KPIs proposed in the first step.
- Select the best alternative based on performance checking results, to continue or redesign the simulation.

5 Work Plan

The work plan, presented in the three steps, includes the main objectives and research questions(RQ) to accomplish, along with the publication's expectations.

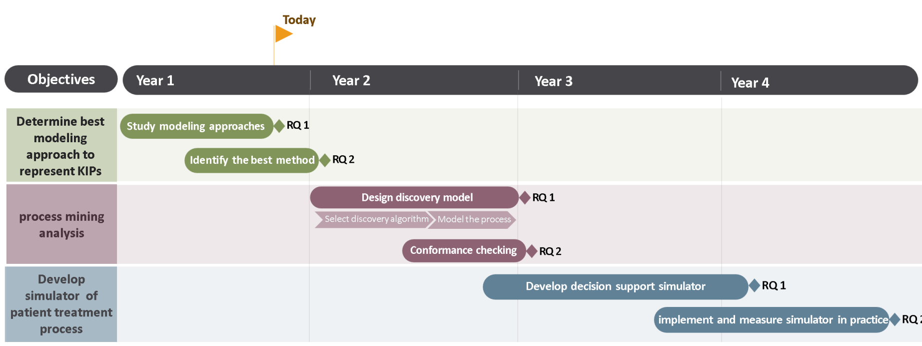

Fig. 1. Work plan of the project

Publications Goals
The scientific publication will cover the main areas related to the doctoral research proposal:

- comparing declarative and imperative modeling languages
- process mining analysis for discovering model
- development of decision support simulation

The initial publications will target doctoral consortium, and more specific workshops and conferences, which are focused on specific research subjects. this can provide valuable comments and contributions to the undergoing work. Later, when the scientific work will be more mature, top-level conferences will become the main objective for publication. At last, in the final stages of the work, journal publications will be attempt when final and robust results are expected to be achieved.

6 Conclusion

In conclusion, clinical patient treatment simulation can bridge the gap between theoretical-medical knowledge and practice by creating a realistic and safe learning environment for medical students with no or minimal practical experiences (e.g. interns and residents). The optimal integration of simulation into medical interns, residents, and newly arrived doctors require additional outcome studies to determine the effect of simulation-based training on the performance of health professionals and improving patient outcomes which is the ultimate goal of the medical profession.

Acknowledgement

This work has been funded by Research Foundation Flanders (FWO) under the supervision of Prof. Dr. Frederik Gailly, assistant professor at the faculty of business and economics, Ghent University.

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