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Monitoring patient pathways at a secondary healthcare services through process mining via Fuzzy Miner

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Abstract

Background This study explored workflow pathways followed by patients seeking secondary healthcare services at a local hospital in a rural part of Turkey using process mining to improve hospital resource management.

Methods The study used process mining to discover process flows as patient pathways implied by hospital records for in-patient, out-patient, biochemical laboratory, and radiology services. Utilizing its flexibility, visualizations and robustness, authors implemented fuzzy-miner algorithm. First, we processed the relevant data from patient records. Then, this data was transformed into event and activity logs. Subsequently, all data components were collected into a data warehouse, and the process mining algorithm was applied. The process mining specified resource usage levels and workload, service waiting times, associated bottlenecks in hospital services, and related statistics/measures.

Results The results from the proposed process mining analysis offer insights and decision support to improve hospital resource management. For example, the resulting statistics indicate the high waiting times (e.g., median of waiting times around 2 h within the selected time period) in the General Surgery and Cardiology services, whose resources were highly utilized (2,699 and 6,162 times). Overloads at laboratories and radiological imaging seem to be contributing to these long waiting times, and capacities for the associated services may need to be improved. Waiting times and resource workloads are higher on specific dates related to local commercial and social activities.

Conclusions Process mining successfully identified the real work flows, bottlenecks, and long waiting times at services within the considered local hospital and provided insights to the hospital management for improving their practices. Moreover, the analyses revealed unique challenges in providing care at a local hospital located far from the city center, emphasizing the potential of process mining to improve healthcare delivery tailored to the specific hospital environment.

Clinical trial number Not applicable.

Keywords Local hospitals, Rural healthcare delivery, Workflow analysis, Process mining, Polyclinic and laboratory operations, Medical resource management

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Introduction

Local hospitals provide critical secondary healthcare services, especially to remote communities, including outpatient examinations, inpatient follow-ups, initial and/or follow-up treatments as well as laboratory and imaging services [1]. Patients undergo numerous examinations and interventions receiving services from different hospital units of local hospitals following various process flows that is also defined as patient pathways. Healthcare institutions try to deliver a quality service regarding examinations, treatments, and further phases. Continuous process flows with minimized waiting times is also the crucial part of these services. This issue arises more often at local healthcare services, thus administrators of these institutions aim to deliver health services effectively often with limited clinical resources [1–3]. Thus, they need to carefully analyze resulting process flows or patient pathways, and efficiently manage their resources accordingly. In such hospitals, working dynamics result in fluctuations in workload that can occur not only between clinics and units but also across different days of the week. Healthcare services operate within these critical dynamics, requiring the optimization of both human resources, such as doctors and other healthcare staff, and physical resources.

The balance is essential to ensure that resources are neither underutilized nor overburdened, thereby preventing both idle resources and the delivery of substandard care to patients. Achieving this balance necessitates that managers conduct detailed analyses of processes and closely monitor electronic health records end-to-end, much like a detective. This comprehensive examination enables a deeper understanding of resource usages and patient pathway dynamics. This can be accomplished through business process management, a discipline that involves identifying process cycles and conducting continuous, rigorous analysis and optimization of process performance metrics [4]. Process mining is commonly used in various sectors, including manufacturing, healthcare, and finance, to increase efficiency, reduce costs, and improve customer satisfaction [5, 6]. Recent developments in health literature address process mining to discover process flows and analyze the related statistics about these processes [7–11]. Prominent performance metrics for monitoring healthcare processes include waiting and service completion times, which can be derived from patient records. These metrics help hospitals identify bottlenecks in their operations, whose elimination is especially important for remote clinics serving communities far from the city center under strict personnel and medical resource limits [12]. Such clinics often do not have the manpower to analyze the operations in each hospital unit separately through customized approaches. Instead, they can greatly benefit from generic and easy-to-use methods to analyze various hospital operations collectively [13, 14].

In this regard, this study proposes a process mining framework for patient flow analysis through all hospital operations collectively. We then demonstrate potential insights from this methodology by applying it to a local hospital providing secondary healthcare to the communities far from the center in West Turkey. Applying process mining to a collection of services from multiple hospital units is associated with additional challenges in the data collection (e.g., the need for data processing and preparation, combining data from different units, etc.) and analysis stages. Ensuring high-quality data is a critical prerequisite for effective process mining, as the accuracy and reliability of the insights derived are inherently dependent on the underlying data. Two primary challenges arise during data collection: the heterogeneity of data sources, requiring extensive integration and harmonization efforts, and issues related to data quality, such as inconsistencies, manual entry errors, and missing or inaccurate timestamps. Additionally, ensuring data privacy and compliance with regulatory standards is a critical consideration throughout the data preparation and analysis process. Addressing these challenges during data pre-processing is essential to ensure the accuracy, validity, and ethical integrity of process mining analyses [15, 16].

Sharing our experiences with these challenges is another contribution to the literature. The growing demand for medical services is pushing healthcare institutions to optimize processes and reduce costs. Process mining enhances hospital efficiency but requires event logs, which existing tools like XESame and Nitro make complex for non-experts. To solve this, Orellana García et al. [17] proposed a user-friendly software component that extracts XES-formatted logs directly from Hospital Information Systems (HIS), enabling healthcare professionals to apply process mining for better decision-making. Ramires & Sampaio [18] examined the integration of process mining with lean six sigma for process improvement. By analyzing data from core information systems, researchers identified inefficiencies in order processing and unnecessary purchases. The findings demonstrate how combining these methodologies within the DMAIC framework enhances process visibility and accelerates optimization. Partington et al. [19] employed process mining to analyze variations in clinical practice and care delivery across hospitals. Preliminary findings from South Australia's improvement initiatives examine 10,000 patient journeys from two hospital systems, focusing on chest pain management in four public hospitals. Kurniati et al. [20] analyzed MIMIC-III, a freely accessible critical care dataset, for process mining in healthcare. Using Weiskopf and Weng's electronic health record data

quality framework, it assesses data reliability and the impact of a 2008 electronic health record system change on process models. A cancer treatment case study illustrates strategies to address data quality challenges. As evidenced by these examples, process mining is becoming increasingly valuable in healthcare, leveraging the advanced capabilities of adopted information systems to generate critical insights for quality improvement. A key observation in published research is the varying scopes of study frameworks, with most focusing on specific clinics or diagnostic groups. In contrast, our study differs by analyzing a local hospital while encompassing all clinics and services, tracking patients' entire hospital journeys. This broader perspective enhances our contribution to the field.

Background

Process mining

Process mining is a data-driven method for identifying, analyzing, and improving business processes by utilizing the digital footprints left by different corporate systems [7, 8]. Process mining algorithms can detect bottlenecks, unearth hidden patterns and inefficiencies, and rebuild the real flow of a process by extracting and examining event logs. The capacity of process mining to focus on all facets of a process, including step timing and flow fluctuations, is one of its main benefits [9].

A conceptual basis for comprehending the makeup of processes inside an organization is offered by the theory of the long tail of business processes, which has been covered in the literature. This hypothesis states that the "long tail" is made up of numerous low-volume processes, while the majority of activity is attributed to a small number of high-volume processes. Studies on process mining have shown how crucial it is to examine this long tail since it may provide insightful information and optimization options [21].

Process mining techniques are categorized into four main use cases: automated process discovery, conformance checking, performance mining, and variant analysis. Automated process discovery generates a process model from event logs, reflecting observed behaviors. It is used in process discovery or performance monitoring efforts. Conformance checking compares event logs with a process model (or business rules) to identify discrepancies or violations, revealing errors or exceptions in process execution. Performance Mining enhances process models by adding elements like bottleneck indicators to identify inefficiencies and answer performance-related questions. Variant analysis compares two event logs (e.g., successful vs. unsuccessful cases) to diagnose why processes sometimes fail to achieve desired outcomes [8]. All techniques rely on structured event logs, requiring prior resolution of challenges in collecting and preparing these event logs. An event log is a structured dataset that records the sequence of paths followed, state transitions, activities performed, and the resources involved during the execution of a process, all annotated with timestamps. This structure can be extended with additional dimensions if necessary [8, 22]. For example, in a healthcare process, when a patient arrives at a facility and initiates a registration procedure with a receptionist, this action—captured with a timestamp—constitutes a single event log entry. The completion of the registration or the patient's check-in to the doctor's office is also recorded as an event. In this context, the occurrence of a subsequent event implies the completion of the previous one.

The application of techniques and algorithms used in process mining relies on the development of specialized software or the provision of code libraries that allow other researchers to execute these algorithms. In this sense, these algorithms are often recognized in conjunction with the software environments they are integrated into [23]. For instance, ProM has been a prominent open-source platform since the inception of process mining concepts, offering a comprehensive analysis environment with numerous algorithms. In addition to ProM [24] libraries for process mining can also be found in coding environments such as R [25] and Python [26], though their algorithmic diversity is relatively limited. Each algorithm and software environment come with its own set of advantages and disadvantages. While these challenges can often be overcome by researchers in academic settings within short to medium timeframes, practical applications and non-expert practitioners require more user-friendly environments. These environments are typically developed by researchers contributing to the field of process mining. Among the most widely used tools are software platforms such as Celonis [26–28], Apromore [26, 29], and Disco [26, 30]. For example, ProM or ProM-based extensions include algorithms such as the Alpha Miner, Heuristic Miner, Inductive Miner, and Fuzzy Miner [31, 32].

Process mining tools have evolved from scarce resources in the early 2000s to a mix of open-source (e.g., ProM, Apromore) and commercial (e.g., Disco, Celonis) solutions. However, commercial tools offer limited algorithmic customization, and most rely on graphical interfaces, restricting large-scale experimentation. While initiatives like RapidProM integrate process mining into data science workflows, they lack flexibility. PM4Py has been developed as a process mining library that integrates with modern data science frameworks [26]. ProM offers a large variety and high-performance solutions but has a complex interface. A practical approach may be chosen with a user-friendly tool like Disco or MyInvenio before transferring to ProM especially if the analysis team or executives are not familiar to the theoretical

background of process mining. Celonis, an AI-powered web-based tool, is rapidly evolving with versions like Celonis PI for advanced process mining [27]. Managing large process model collections is challenging, especially for long-term consultation, updates, and reuse. As introduced in [28], APROMORE, an open-source SaaS repository, addresses this by offering advanced model-based analysis, filtering, and merging beyond traditional data management. It serves practitioners, technology vendors, and researchers, enhancing process model usability and integration. Apromore extensions enhance variant analysis which aids in consolidation, cost reduction, performance issue detection, and compliance auditing [29]. As process behavior dynamics evolve and automation capabilities advance, the demand for process mining and diverse analysis models continues to grow. Consequently, various software and analytical environments are being developed and enhanced [33]. In summary, process mining serves as a bridge between process science and data science, enabling data-driven process analysis and optimization. Recent developments also introduced Object-Centric Process Mining which extends traditional process mining by allowing events to reference multiple objects, enabling more realistic modeling. Adopted by tools like Celonis Process Sphere, OCPM enhances process discovery and supports forward-looking mining through simulation [34].

Process mining in healthcare

Process mining offers significant potential for the healthcare sector by enabling the analysis and enhancement of various processes such as patient care, resource allocation, and administrative functions. By examining patient care processes, it can uncover bottlenecks and inefficiencies that may delay or compromise care delivery while highlighting opportunities to optimize process flows or adopt innovative technologies for better outcomes [11]. Additionally, process mining helps identify redundant or unnecessary activities within healthcare operations, enabling organizations to cut costs and improve overall efficiency [35]. It also provides comprehensive process visibility, aiding healthcare organizations in adhering to best practices and regulatory standards while pinpointing deviations from established protocols. Furthermore, process mining enhances transparency by offering clear visual representations of process flows and identifying gaps in knowledge or communication within the organization [36]. By analyzing resource usage patterns, it highlights areas of underuse or overuse and provide findings to suggest strategies for improving resource allocation. Overall, process mining equips healthcare organizations with the tools to enhance patient care, streamline costs, and boost efficiency by providing deeper insights into their processes and revealing areas for improvement [37].

A comprehensive literature review on the terms *process mining*, *health*, *clinic*, *patient*, and *care* reveals that the field has garnered significant attention over the past fifteen years, with a steadily increasing number of publications [11, 38–40]. Owing to its mathematical foundation and the necessity for data and software integration, process mining in healthcare is inherently interdisciplinary. This research area intersects domains such as medical informatics, healthcare policy, healthcare science, computer science, and operations research. Studies in this domain exhibit considerable diversity in problem areas, data structures, technologies, and methodologies employed [10, 41].

Event logs constitute the primary data source for process mining studies. However, these logs are not readily available within information systems. Healthcare organizations often operate systems derived from multiple databases, making it necessary to integrate disparate records to generate event logs suitable for process mining. Consequently, terms like *hospital information systems*, *electronic health records*, *event abstraction*, and *event logs* frequently appear in study keywords. Researchers often encounter significant challenges during data collection, integration, and preparation for analysis. To address these issues and guide future research, scholars share their methodologies and experiences in their publications [42–46]. Terms such as *data quality*, *data privacy*, *data analytics*, and *data analysis* underscore these challenges and reflect the nuances of working with healthcare data [15, 16]. This section is elaborated in detail also in our study because, during the event log generation process, determining which features from hospital information system records should be selected as event logs and structuring them as a data warehouse significantly impacts the benefits that can be derived from process mining. In this study, a specialized extract, transform, and load (ETL) process was implemented for this purpose, and the corresponding event log file was created.

Early studies on process mining in healthcare predominantly aimed at objectives like business process management, process analysis, and workflow extraction. Keywords such as *business process modeling*, *process analysis*, *workflow*, and *patient flow* were prominent during this period. Over time, the focus shifted toward managerial applications such as *value-based healthcare* and *healthcare management* [47, 48]. More recently, advanced analyses such as *conformance checking* and *real-time systems* have emerged as key areas of interest [49, 50]. Open-source software like PROM has gained prominence in application environments. Methodological advancements have evolved from foundational approaches using alpha algorithms and Petri nets [51, 52] to techniques like inductive visual mining [53] and interactive process discovery [54, 55]. Recent developments

integrate these foundational methods with machine learning and artificial intelligence to enhance analytical capabilities [44, 56–58].

Application areas of process mining in healthcare include emergency departments [59, 60], primary care [55], outpatient clinics [61], oncology [62], surgery [35, 63], and breast cancer treatment units [63–65]. During the COVID-19 pandemic, studies underscored the critical role of process mining in managing dynamic healthcare demands. Over time, the terminology used in these studies has evolved from general expressions like *workflow* to more specific phrases such as *patient flow*, *care pathways*, *clinical pathways*, *clinical flows*, and *patient journey*.

Similar to the research papers reviewed above, this study employs process mining to discover the process flows as the patients' pathways undergo at a state hospital serving a regional population, identifying potential areas for improvement. Difference of our research arises in the scope of these pathways; therefore, it is significantly comprehensive since it involves all flows at all units. The automated process discovery and analyses then reveal the findings regarding the patient pathways in the hospital, detailing breakdowns in terms of process flows, resource usages, and time-related statistics.

Turkish healthcare system

The Turkish healthcare system underwent a comprehensive update process in 2003, with the primary objectives of improving citizens' access to healthcare services [66], enhancing service quality, and ensuring financial sustainability [67, 68]. The reforms not only enhance coverage and improve equity but also incorporate market and managerial reforms driven by state initiatives. The core pillars of the healthcare system include public hospitals, private sector facilities, and university hospitals [68, 69]. The main elements of the transformation program were the implementation of universal health insurance, the introduction of a family medicine system, and the modernization of healthcare infrastructure [70, 71].

The Turkish healthcare system delivers primary care services through family medicine, emphasizing early diagnosis and addressing basic health needs. Secondary and tertiary care are provided by public and private hospitals, offering more specialized treatments. Projects such as city hospitals aim to modernize technological infrastructure to ensure the delivery of high-quality healthcare services. Social security systems have been unified, a performance-based payment system has been introduced, and patient rights have been strengthened. These reforms have collectively fostered a general perception of improvement within the healthcare system [69, 71, 72]. Challenges such as universal health coverage, high workloads for healthcare personnel and the shortage of physicians in rural areas remain ongoing issues. Thus, the efficient use of existing resources, effective service planning, and maintaining a certain level of patient and caregiver satisfaction through the provision of quality care are of critical importance [73]. Recognizing this reality, the researchers in this study particularly focus on patient pathway analysis in a local hospital.

Methodology

Problem statement and research questions

The existing literature and the requests made by the considered hospital's management implied the need for a framework to analyze the service pathways patients follow in a secondary healthcare facility serving a remote region.

Building on the previously outlined issues and motivations, we proposed a data-driven decision support system to identify and help address bottlenecks and resource management challenges in polyclinic, laboratory, and other clinical services. Following the problem identification, the design and development phase aimed at discovering patient pathways involved structuring a data preprocessing and analysis framework. For the demonstration phase, the methodology was applied to a real-world case study, revealing both the applicability of the framework in a healthcare setting and the insights gained through this practical implementation (Fig. 1). A data-driven decision support system brought to light the experiences encountered while discovering overall flow patterns in an actual healthcare environment.

First, the patient records from individual units were stored as raw data, which was then preprocessed and transformed into event logs specifying tags for case IDs, activities, tasks, and resources as well as timestamps. After that, process mining is applied to the resulting event log data using a fuzzy-miner algorithm, which identifies the patient flow pathways, specifies resource usages and bottlenecks, and provides relevant performance measures/statistics. The analysis is completed by analyzing and interpreting these outcomes to address the following questions:

Q1 How can the holistic patient pathways be revealed at a local hospital at different detail levels, and accordingly how can process mining identify inefficiencies and bottlenecks in patient pathways?

Q2 What are the most frequently repeated variants (process flow groups) activities (process flows)?

Q3 What are the resource usage statistics, and how do they reflect the corresponding workload levels, and also what are the congestion and waiting time differences

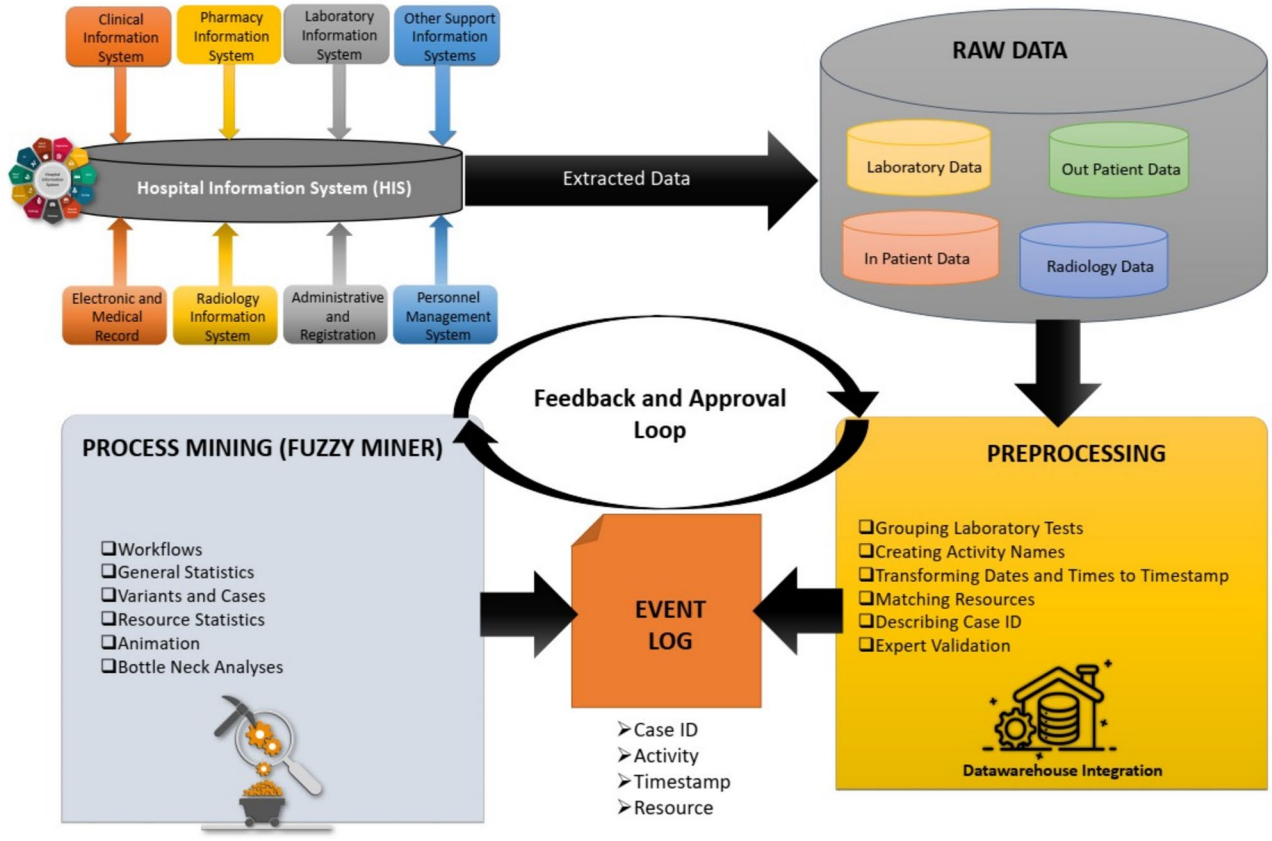


Fig. 1 The process flow for the proposed methodology

between polyclinic (out-patient units), in-patient service, radiology, and laboratory units?

Q4 How frequently and why did patients revisit particular units?

While reporting findings, the overall process flow (all patient pathways) will be revealed by using even log file in the process mining process. Patient pathways can be observed through an animation to discover patient traffic flows and jams. For the central tendency of time based performance measures, median is used which gives the value in the middle of the ordered data. Median is more accurate to make comparisons since the variation of the durations is high and there is no symmetry in the distribution.

Medical data

Data sources and collection

After obtaining ethical clearance and approval from the Dokuz Eylul University Institutional Review Board, and Bergama Hospital, Izmir Provincial Directorate of Heath in 2022, we collected clinical records and registries in the hospital information system for all patients who received care from the Bergama State Hospital between January 1, 2021, and February 28, 2021. This timeframe was chosen for illustrative purposes to showcase sample inferences. After excluding those with incomplete or inconsistent entries, the collected data was composed of records from 51,298 patients.

For these patients, we obtained admission entries (entry time, anonymized patient protocol number, demographics, location, patient history), outpatient records (clinic and referral entries, clinician information, re-examination status, examination records, diagnosis records, lab requests, etc.), inpatient records (entry date, ward information, service records, lab requests, clinician information, discharge time, referral records), laboratory records (lab entries, lab ID, completion time), and radiological examination records (patient entries, lab ID, requesting unit, completion status, completion time) (Fig. 1). These records were obtained from different clinical units and the hospital's central information system through various software platforms.

Data privacy and ethics

The data were extracted by the system administrators following the personal data usage rights and proper anonymization process for ensuring compliance with ethical standards. The use of personal data, particularly health data, is governed by stringent regulations and

a rigorous approval process. Approval obtained from healthcare institutions alone is not sufficient. Researchers are required to secure ethical committee approval from their own institutions, and, with these two permissions, they must submit the full details of the study to the local representatives of the Ministry of Health for further approval. Access to data is strictly prohibited without obtaining this final authorization.

It is important to emphasize that no patient-specific identifiable records were used in this research. Instead, anonymized and modified protocol numbers were generated to ensure data de-identification. These values were used to analyze features such as the timing of visits to hospital units, usage levels of healthcare resources, and referrals to other departments. This approach ensures compliance with privacy regulations while enabling meaningful analysis of healthcare data. The focus of this study is not on the patients themselves but rather on the workflows within the hospital.

Event-log construction

The process mining algorithms require the input data in the event-log format. For our case, this format includes the attributes listed in Table 1, *which* were generated through preprocessing steps applied to the raw data from the hospital records. Patient records from the databases of different hospital units were merged using the anonymized patient protocol number, which serves as the attribute of "Case ID" in the event log. Each patient record from each hospital unit specifies particular timestamps (i.e., date and time) and activity records (activity description, start/end time) which constitute the other attributes of the event log. From each record source, a unified event-log file was obtained by merging the anonymized patient identifier, activity description, timestamp, and name of the record source. The record source often refers to hospital units, and thus, resources used in these units for providing the services associated with each activity. This integration resulted in a singular event-log file where all components were consolidated.

Table 1 Event-log attributes extracted from electronic patient records from the hospital information systems

Event-log attributes	Descriptions
CASE ID	An anonymized patient identification number.
TIMESTAMP	Entry dates and times for various activities existed in the columns of databases at different hospital units. These columns have been consolidated into a single stream of data flow.
ACTIVITY (outpatient clinic records)	Examination-arrival, examination-start, and examination-end activities have been created and processed along with the relevant time dimension.
ACTIVITY (laboratory records)	Sample collection, laboratory processing, and lab result activities have been created and matched with respective dates.
ACTIVITY (radiology records)	Radiology examination requests and radiology examination activities have been created and matched with the relevant dates.
ACTIVITY (inpatient records)	The admission activity is associated with the admission date, while the discharge reason is linked as a separate activity with the discharge date.
RESOURCE	The resource attribute specifies hospital resources utilized for each activity. It includes the associated service name where the examination is conducted for outpatient clinic records; the laboratory analysis name in laboratory records; the radiology unit number where the procedure is performed for radiological examination records; and the service name in inpatient records.

The event-log data repository created through these preprocessing steps has 373,008 event transactions with 7,777 different variants (i.e., patient pathways) for 51,298 distinct patients. Preliminary studies conducted on event logs were evaluated in collaboration with hospital administrations and IT specialists from the considered secondary care hospital. A validation loop was iterated until an expert-opinion-based face validity was achieved. Additionally, processes that should be prioritized and can be improved for the hospital have been identified through expert opinions. Among the more than one hundred patient pathways were examined, and the most noteworthy findings are shared in the results section. All these processes can be swiftly modified in the presence of different types of records to extend the analyses to other services or healthcare institutions.

Process mining framework: Fuzzy Miner

Process mining is a set of data-driven techniques used to analyze and improve real-life processes with a primary goal of visualizing and mapping out processes from institutional event log data. Process mining applications aim to explore and analyze processes, evaluate system performance over time, identify bottlenecks and inefficiencies, and even predict future process states [7, 8]. The starting point and core of the process mining methodology are rooted in event log data, enabling the discovery of actual flows—patient journeys or paths—that patients experience in practice, rather than those merely designed on paper. Furthermore, process mining visualizes these flows using standardized graphical representations, incorporating elements such as flow intensities and repetitions. This provides managers with accurate and insightful process maps for decision-making.

In this study, fuzzy miner algorithm is used to discover process flows or pathways within Disco software [74], thus additional statistical and visual advantages of Disco were utilized to obtain more insights. Fuzzy Miner is a technique used to derive process models from event logs. Unlike traditional process mining algorithms, Fuzzy

Miner focuses on the strength of relationships between activities rather than their exact sequential order within the process. In this study, particular advantages were taken into account to select a tool tailored to the needs of health professionals, who may lack process mining expertise but require its outcomes for their research. The selected approach emphasizes usability and accessibility, ensuring that even those without prior experience in process mining can leverage its benefits effectively. The user interface for the application of the approach is available as Disco software [74]. This approach is, in fact, also used independently in various research areas [37, 75].

More specifically, the selected approach is a customized fuzzy-miner algorithm to generate data visualization and statistical reports on workflow, resource usages, and event start/completion times. Fuzzy Miner employs fuzzy logic to evaluate activity relationships, allowing for the accommodation of uncertainty and gradations instead of relying on rigid binary evaluations. This approach expresses relationships in terms of levels such as "high," "medium," or "low," providing greater flexibility in analyzing activity connections. The algorithm follows a structured process beginning with data preprocessing, where event logs are converted into a format suitable for analysis. Next, a relationship matrix is constructed by calculating significance and correlation values for each activity pair. Based on this matrix, activities are grouped through fuzzy clustering, which identifies different stages or subprocesses within the overall process. Finally, a process model is created using these activity groups and their interrelations, illustrating the sequences of activities and the probabilities of transitions between them. This process results in a comprehensive model that captures both the strength and likelihood of transitions, offering a detailed and nuanced representation of activity flows [76].

If A and B are event related activities, then the significance and the correlation between A and B can be calculated through the following equations:

$$S_{(A,B)} = f_{(A \wedge B)} / f_A$$

$$C_{(A,B)} = f_{(A \wedge B)} / f_{(A \prec B)}$$

where

$f_{(A \wedge B)}$: The number of occurrences where both A and B happen together

f_A: The number of occurrences of A.

$f_{(A \prec B)}$: The number of occurrences where A happens before B.

$S_{(A,B)}$: Significance between A and B.

$C_{(A,B)}$: Correlation between A and B.

The fuzzy-miner approach utilizes significance and correlation measurements to simplify complex and unstructured process flows by clustering/grouping similar flows based on these two metrics. Significant measures specify the priority. Significance is defined in various ways within the automated process discovery framework (e.g., frequency, routing count, or binary significance). Based on these primary metrics aggregations, abstractions can be made based on the occurrences, thresholds are applied to determine the points of edge filtering. We used the frequency significance in our analyses, i.e., the more frequent event or the more frequently used resource is considered to be more important. Unlike its traditional definition, in process mining, correlation measures binary and/or distance-based correlations (e.g. proximity, endpoint, originator, data value correlations), unveiling relationships between events through overlapping data attributes and similarities in event names [74, 76].

The adaptability, ease of use, and effectiveness of the fuzzy miner algorithm in managing large datasets are its defining features. It is appropriate for settings where operations are not carried out optimally or unexpected occurrences arise since it is made to handle the complexity of real-world processes and can tolerate noisy or partial data. It is a strong tool for process mining since it can produce relevant process models in these kinds of circumstances. Fuzzy miner algorithm has evolved, and modifications have been reported [77].

The Fuzzy Miner method serves as the basis for Disco software, which improves it with an easy-to-use interface and more analytical features. The platform enables users to effectively complete the following tasks. Process analysts and business users may clearly view and understand even complex processes because to the algorithm's excellent user-friendly design. Finding possible areas for improvement is made easier by this visualization feature. Furthermore, it saves a great deal of time and money by processing large datasets quickly and efficiently, making it a good fit for intricate procedures in big businesses.

Healthcare processes are very complex and challenging; thus, process mining applications in this industry require serious stakeholder involvement to achieve a profound understanding of the underlying system and improvement opportunities [8, 78]. For this purpose, we closely collaborated with the hospital management at every stage of the research, including model development and validation. Throughout these steps, revisions have been made to the data and model based on the feedback and emerging requirements from the hospital administration and staff. Consequently, managers have been able to visualize and understand the workload, and flow of processes from the output of the process mining algorithm and verify that the proposed approach reasonably represents hospital operations. We analyzed holistic process flows with

different detail levels, bottlenecks on the flows. Furthermore, we went into details about process flow clusters, i.e. variants, and examined prominent ones to see most frequent patient pathways. Even, individual pathways could be observed to reveal if any recursive or linked pathways among the clinical units.

The outputs of the process mining application included process flows showing patient pathways, process time and frequency measures, most/least repeated patient pathways, hospital resource usages, and other case-based performance measures. The animated flow maps showing patient pathways through hospital operations helped visualize system bottlenecks. Then, the remaining outputs were explored in detail to develop insights related to the highly utilized or bottleneck units, and prominent diagnoses and subsequent resource planning options were collaboratively reviewed and discussed with the hospital management.

Results

Process discovery and pathways

Based on the log data derived from the clinical records, the process mining algorithm examined the process flows or here patient pathways within the hospital, the visited hospital units, and the time spent between activities in these units. This part provides answers for the first research question, and moreover the visuals are the primary outputs of process mining. This examination generated an initial process discovery for the considered hospital as shown in Fig. 2 (for larger figure size, Supplement 1 is provided). This high-level process flow presents all patient pathways, the associated hospital activities, and their timing. This high-level illustration visualized the complex network of hospital processes and helped us verify that all critical processes have been captured by process mining approach.

By changing the activity and pathway detail levels of the process flow which specifies the percentage of activities made visible based on activity frequencies, we obtained alternative versions of the patient flow map. For instance, when all activity and pathway details were removed, the process flow illustrated the most commonly observed patient flow which involves visits and revisits in outpatient clinics (Fig. 3).

According to the overall statistics, the average time between a patient's arrival at the clinic and the start of his/her examination was 77.8 min (median = 8 min). On average, the examinations took 13.9 min (median = 32 s) and patients who completed their examinations revisited the hospital after an average of 60.7 h (median = 26.1 h) commonly due to follow-up examinations and less commonly due to a new complaint.

It is possible to interactively explore the flow between Fig. 2, which presents the most detailed overview, and Fig. 3, which displays the least detailed flow, by adjusting only the level of detail. The analyses conducted at this stage provide answers to the first research question. Exploring patient flows by changing the detail level in the analytics provided insights into patient circulation within the hospital and revealed service durations that exceeded the expected values. For example, Fig. 4a, shows the process flow when 10% of activity details with 30% pathway details are allowed. The figure shows patient flows between very common activities such as examination-arrival, -start, and -end, laboratory-processing, laboratory-results, radiological-examination-request, and radiological-examination-results as well as the flow of patients who could not admitted due to various reasons and leave the hospital without examination. Process flow maps highlighted the number of patients following each pathway arc (Fig. 4b) and bottleneck points (Fig. 4c -for animated, version, please see supplement 2), highlighting the services with significant waiting times. In visuals (a) and (b) grouped under Fig. 4, the thickened arrows indicate areas of increased flow intensity, while in (c), the bubbles representing blocked queues in a heated-up

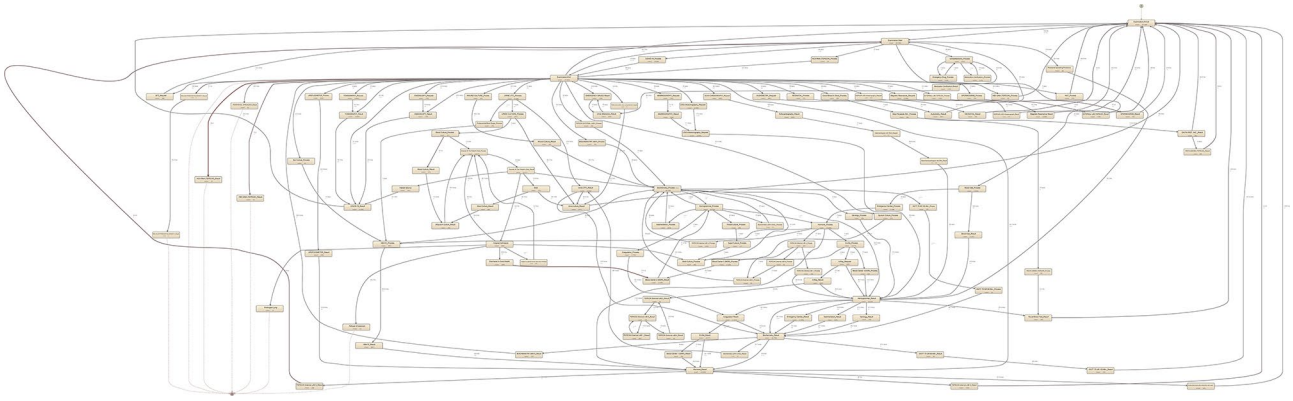


Fig. 2 The high-level process from the process mining algorithm illustrating all patient pathways, associated activities, and time spent between activities (The arcs represent patient flow directions with the average duration between activities.) (for larger figure size, supplement 1 is provided)

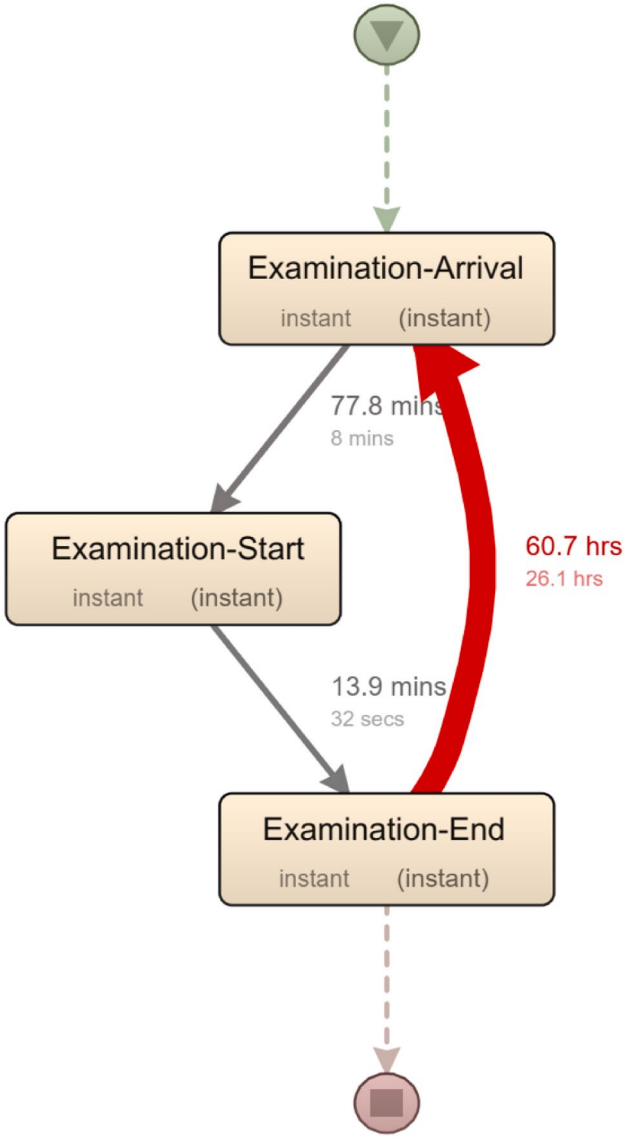


Fig. 3 The process flow developed by the process mining algorithm when all activity and patient pathway details are removed. The arcs represent patient flow directions with the average duration between activities. The thick red arrow highlights the patient revisiting the hospital after a long duration

system highlight congestion points—together, these elements point to density concentrations within the system, and thus the need for service capacity improvements. At the given detail level, certain examination activities exhibit high density, with the resulting intense flow creating traffic within the system. Notably, activities related to imaging units and diagnostic laboratories demonstrate critical congestion points. Transitions between tests in these areas—particularly the interval between a test or imaging request and the receipt of its result—form bottlenecks, as illustrated in Fig. 4(c). The activities performed by the tomography, hemogram, and biochemistry laboratories—and the intensities observed in the transitions between them—constitute a significant finding, clearly reflected in the flow at this level of detail. The overlap of the dataset with the COVID-19 period is another phenomenon reflected in the activity flows, with the increased density observed in testing and diagnosis processes also clearly represented in the maps. As the level of detail in the process increases, the sub-flows between the start and end points of the examination become more visible, allowing for the investigation of various state transitions. As the level of detail increases, the core activities remain unchanged-pattern clearly observable in Fig. 1. However, with greater granularity, returns between activities, low-frequency laboratory tests, and different types of system exits become visible. This enhanced visibility allows for answering critical questions such as how many patients returned to the hospital, after how long, when they were discharged, and whether they were admitted. Moreover, the noticeable gaps between mean and median values suggest that these transition times are distributed over a wide range with considerable variability.

We presented the insights developed through the process mining to the hospital management using the animation feature of the application platform. This feature simulated the flow and waiting times in the hospital based on the log data, providing real-time visualization of the duration and impact of instantaneous bottlenecks on the flow. Animating the realization of the bottlenecks, the accumulation of patient flows around them, and how the bottleneck shifts towards other activities in time due to the temporal changes in new patient arrivals supported the developed insights and improved the credibility of our interpretations and the proposed analysis approach (See the supplemental materials).

Cases, variants, and resources

In process mining, cases represent patients, and variants are created by grouping cases based on the similarities in the paths they follow. Several inferences can be obtained in terms of the second research question; however, some examples were presented from thousands of alternatives according to selection of hospital administrators. Our dataset contains 129 distinct activities, 7,777 variants (i.e., routes patients followed between activities and hospital units), and a total of 373,008 events reflecting the variability in provided healthcare services and diagnostics requests of clinicians. The process mining algorithm labels these pathways with relevant summary statistics such as pathway frequency, number of involved events/activities, and average (and also median) process durations to depict hospital processes for specific patient groups following similar pathways. Overall dashboard to navigate these variants and the related pathway groups is given in the Supplement 3. Overall dashboard

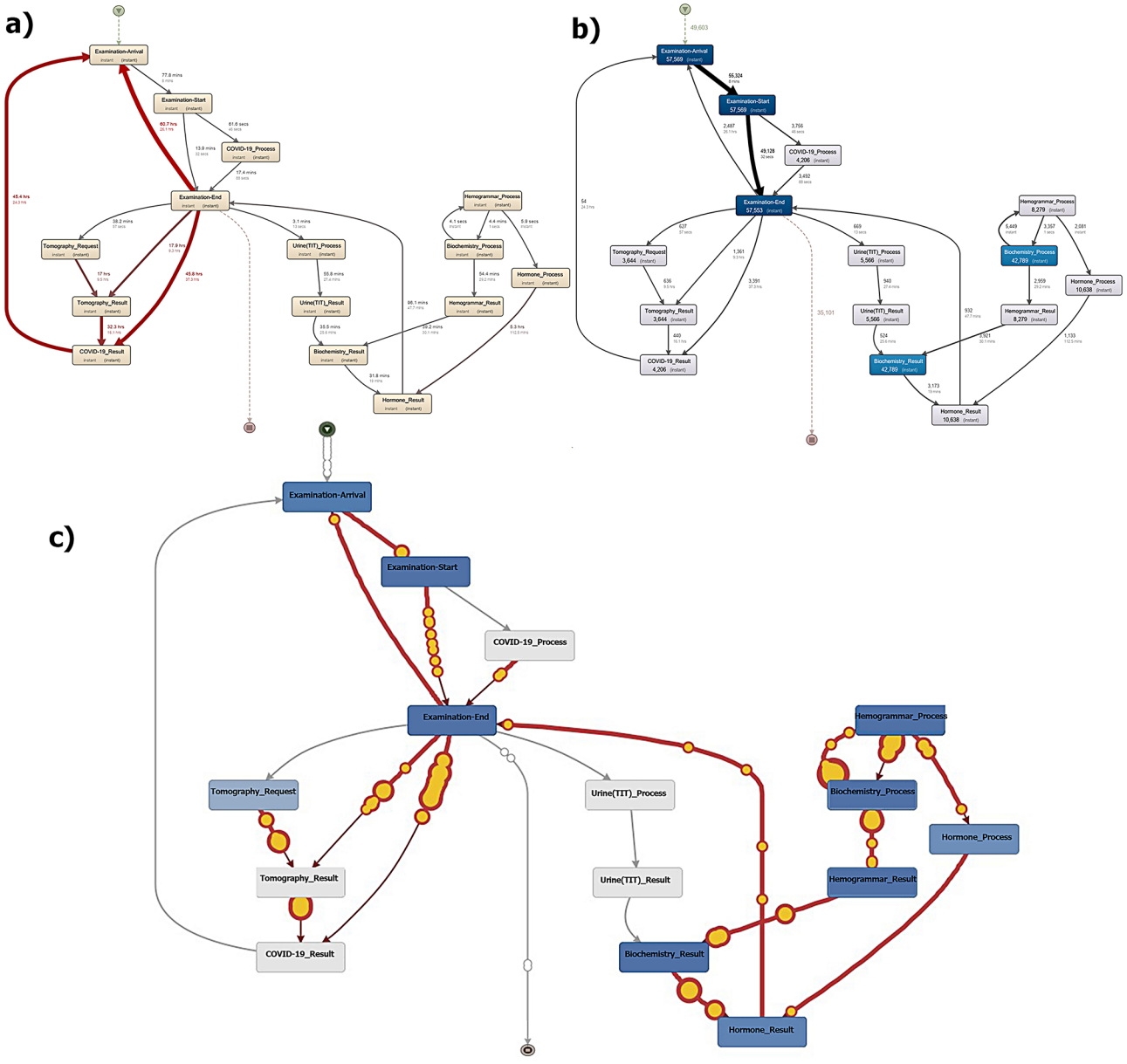


Fig. 4 The process flow developed by the process mining algorithm when 10% of activities and patient pathways are displayed

summarizes activity frequencies, variant and overall statistics highlighting 129 distinct activities with median of 78.7 min, and mean of 19.6 h. This preliminary overview indicates the cases requiring daily examinations and outpatient treatments while having an average pathway duration of around 20 h implies frequently prolonged examinations or stays in the hospital after admissions.

Naturally, in highly detailed and complex flows, making direct comparisons between units becomes quite challenging. To address this, one can delve into variants—where flows are clustered based on their similarities, and the units in which these flows occur can be analyzed. Such analyses offer valuable insights in response to the second research question.

Process mining further facilitates the variant analysis by specifying which patient groups compose each pathway, what sequence of activities and hospital units were visited, and specific times spent in and waiting for each activity. We can also provide these details specifically for a particular patient illustrating his/her individual journey through the healthcare processes. Therefore, such as Fig. 5 presenting Variant #4, which was followed by 602 patients underwent five different activities including an urology examination and a radiology test. Among these patients, the flow for the patient with identifier number "9149434" unfolded as follows: first, an entry for the arrival at the examination was recorded, approximately 21 min later the examination commenced, followed by

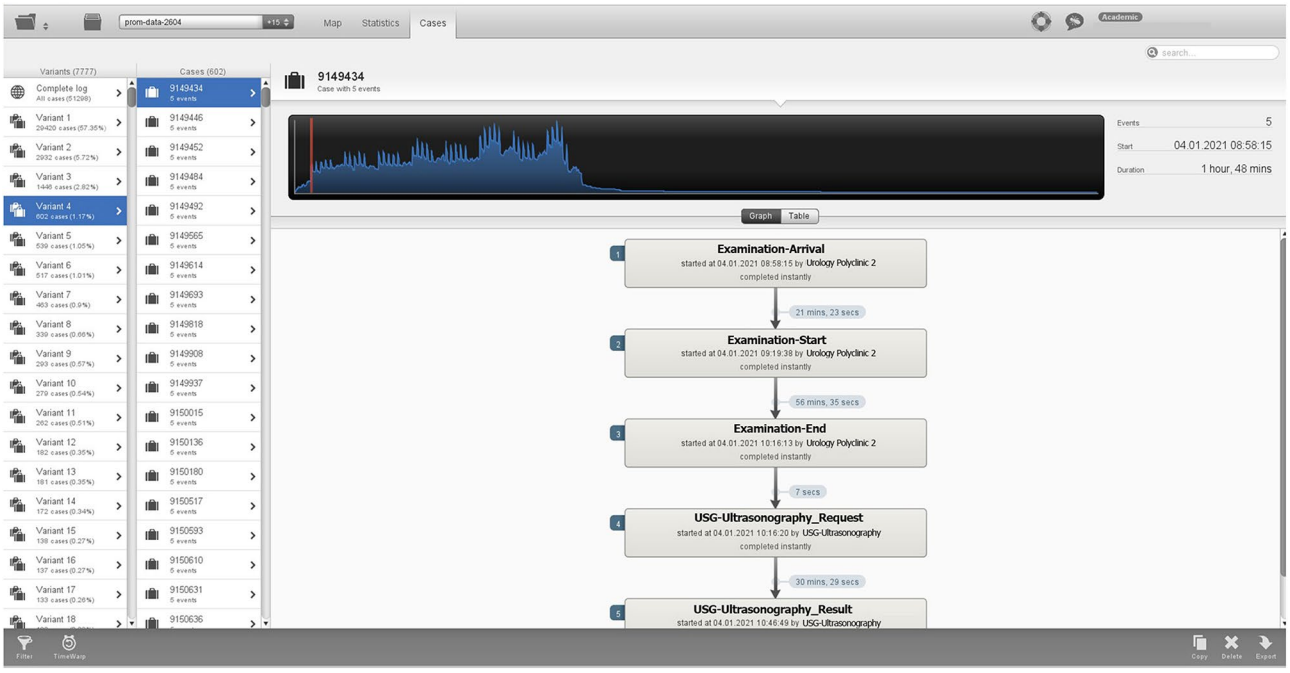


Fig. 5 Overview of patient-specific pathway statistics sample: including urology examination and radiology test

a 56-minute examination, and subsequently, a radiological test (USG) was performed, concluding within 30 min. Other patients within the same variant (i.e., a process mining terminology referring to pathway) followed the same flow with different durations. Delving into the details of each variant allows for the identification of patterns, trends, and outliers within specific patient cohorts. This enhances the overall comprehension of the process and also aids in tailoring healthcare strategies to address the specific needs of diverse patient populations.

Another key result provided by our process mining analysis was the activity statistics reflecting how frequently each activity was performed. These findings support answers for the second research question. Activity frequencies for health services inform about their accessibility levels, and thus, the adequacy of clinical resources. Therefore, these statistics, portraying the dynamics of the patient flows within the hospital are important for capacity improvement investments to reduce patient waiting times or referrals. 129 different hospital activities were performed in the dataset. The frequencies varied between 1 and 57,569 with an average of 2,891.53 times and a median of 109 times. These statistics imply a left-skewed distribution of activity frequencies (See Supplement 3).

The most frequently performed activities within the workflows were the initiation and completion of patient examinations, as well as patient arrivals. These were followed by activities related to laboratory tests. Some of these tests were requested for diagnostic purposes, while others were routine preventive screenings. The number of Elisa tests was found to be quite intriguing by the administrators for a local hospital.

Statistics related to resource usages for the healthcare services provided to patients are crucial for effective resource management and timely capacity improvement interventions. Statistics provided along with process discovery presents these vital statistics offering insights into peak demand periods, potential bottlenecks, and underutilized resources to better address the ever-changing demands of patient care. These findings were evaluated for the third research question. 160 different resources recorded in the dataset in decreasing intensity of use (See Supplement 3). In the first two months of the selected year, the biochemistry laboratory was the most intensively utilized unit with a use frequency of 85,578 times. This is reasonable given that the lab receives referrals from most other units as a shared hospital service/resource.

Emergency department A and B (7863 + 23679), the COVID-19 clinic (11732), radiology-tomography (7288), neurology (6321), cardiology (6162), internal medicine (5655 + 4251), and MR (4132 units were among the units with high workloads. The waiting times between activities vary across variants, that is, they differ depending on the activities themselves and the units in which they occur. In the first case of Variant #4, in Fig. 5, the flow begins in the urology unit. It can be observed that there is a 21-minute interval between the patient's arrival at the hospital and the start of the examination. An ultrasound (USG) is requested, and the results are obtained in approximately 30 min. The duration between the start

and end of the examination is 56 min. On the left side of the figure, the list of variants is displayed, and it is even possible to drill down to the case level within the selected variant.

The high workload at the emergency department is reasonable as it is the most well-equipped emergency facility serving a large remote area. The data period provided by the hospital for this research overlaps with the timeframe of COVID-19 cases. Consequently, the workload in units dedicated to COVID-19 diagnosis and treatment during that period can be attributed to this overlap. Moreover, relatively high workloads were observed in other units as well. Bottlenecks and queue clusters were identified in the process flows within these units. It was stated by the administrators that this situation aligned with negative patient feedback. Notably, even without such feedback, process mining analyses can highlight these units and the associated process flow bottlenecks, offering a proactive approach to identifying and addressing issues before negative feedback arises. This underscores the potential of process mining to enhance operational efficiency and patient satisfaction in healthcare environments. Whether these patterns were due to a seasonal series of cases or a general trend should be elucidated through process mining analyses conducted at different time intervals.

The macro-level findings obtained through process mining applications can be further explored by delving into the data and getting more information on specific activities and services associated with high usage levels or workloads. Such explorations can inform the hospital management and decision-makers about the urgency and importance of addressing the identified issues. We analyzed more than hundreds of activities and thousands of variants. The results present overall findings but we could only exemplify few visuals related to these analyses. For instance, among the outpatient clinics, process mining findings and the administrators' views identified the cardiology, neurosurgery, urology, obstetrics, gynecology, orthopedics, dermatology, psychiatry and neurology clinics (See Supplement 3 for details) as the units with heavy traffic. When we examine the findings specific to the cardiology outpatient clinic, upon deeper inspection of the data, it was revealed that this unit stands out for vital diagnoses such as chest pain, palpitations, hypertension, abnormal heartbeats, heart failure, anxiety disorders, atrial fibrillation, tachycardia, venous insufficiencies, mitral disorders, myocardial infarction, and more. Given the necessary time required for each diagnosis, and the vitality of these diagnoses for the well-being of patients, increasing the capacity of cardiology services and reducing the heavy patient traffic around it would be beneficial. Similarly, the situations of shared laboratories and radiology units are another area worthy of scrutiny. For example, we observed a significant concentration in biochemistry tests, which emphasized that although a level of normalcy was attained at the beginning of 2021, the patient at risk of COVID-19 infection continued to heavily influence hospital processes.

The fourth research question explores whether patients are compelled to return to the hospital within short periods, aside from routine check-ups. These flows can be observed across all levels of activity flows (Figs. 3, 4 and 5) as well as within the variants. Particularly through analyzing patient flows and the clusters of their variants, analyses offer a robust approach to addressing this question. It is crucial for healthcare administrators to meticulously examine these variants, regardless of their frequency.

For instance, if a patient discharged home from the emergency department is forced to return shortly after, it may indicate overlooked issues during initial care, though non-service-related factors might also contribute. Nevertheless, such occurrences diminish the agility of critical and high-demand units like the emergency department, ultimately prolonging wait times for other patients. In the hospital, this pattern was observed in the variant #3, where patients initially treated and discharged from the emergency department returned within a few hours, suggesting potential gaps in the initial care process. According to the flow followed by the first case in Variant #3, the patient who presented it to the emergency department was treated without delay within 14 min. The same patient returned to the emergency department 10 h later. Was this a follow-up examination? Did the patient return with the same complaint? Or did a new condition arise? These are all critical questions that can be explored by administrators through the flow, making it a valuable source for identifying and evaluating key findings.

Although variant#3 includes only 2.82% of all patients, it was investigated due to its potential to involve critical cases. This situation indicates that it should be evaluated by specialists not only based on the intensity of the variants but also in terms of their scope of impact.

Discussion

We applied process mining on a short-term but comprehensive dataset for a local secondary care hospital to (i) create a proof of concept highlighting the potential of process mining as a decision support tool for such a healthcare setting, and (ii) identify some of the inherent patient flow issues and associated capacity management challenges in a local hospital serving a remote community. Our analyses provided a detailed examination of the workload and patient flow across different units. By examining the patterns in derived performance metrics over various units, the hospital management gained a holistic understanding of the dynamics within the organization and developed valuable insights to improve

their practice and future planning. The outcomes of the process mining analysis provided snapshots of the state of the hospital operations for any given time with a preferred level of detail (for all comers or a particular patient). This is valuable information for facilitating continuous monitoring, analysis, and improvement of patient journeys through hospital departments, which is vital for sustainable healthcare and addressing the ever-changing needs of the patients [41, 79]. Our process mining analysis also provided detailed quantitative evidence to the hospital administrators for making prompt and informed decisions regarding resource allocation, staffing, and process optimization, and for promoting their needs and capacity expansion plans to the governing bodies.

Our study distinguishes itself by focusing on a local hospital while incorporating all clinics and services, enabling the tracking of patients' complete hospital journeys. This comprehensive approach provides a broader perspective and strengthens our contribution to the field. We have identified interesting interactions between all hospital services and unique challenges within this specific healthcare setting. For example, existing process mining applications on tertiary hospital operations emphasized the need for effective service processes to reduce waiting times for outpatient treatment processes [80]. In line with these earlier findings, our study also reveals that examination activities in outpatient clinics of the considered hospital may have long waiting times with significant variations, e.g., the average time between a patient's application to the outpatient clinic and the beginning of the examination was 77.8 min, with a median time of 8 min. Unlike the existing studies, our analyses also captured the effects of the load created by the outpatient examinations on biochemical laboratory services as our work considers all of the hospital operations collectively. Besides providing such specific insights, process mining applications are associated with other advantages and challenges.

Process mining facilitates the direct utilization of clinical data for the analysis of hospital systems. Unlike conventional approaches including such as comprehensive statistical/mathematical or simulation model analyses, which would require significant time, effort, and expertise, process mining directly uses the clinical data to facilitate evidence-based capacity management decisions [10, 43, 46, 81]. However, this advantage comes at the expense of requiring an accurate collection of high-quality institutional data and preprocessing it into the event-log format. Errors or deficiencies in the collection of data from different sources, the data itself, or/and the preprocessing stage negatively impact the quality of the analysis, its results, and derived insights [42, 44–46, 79]. Therefore, it becomes crucial to (i) conduct a data cleaning step before the pre-processing, (ii) identify sources of missing or erroneous data entries, and (iii) take necessary steps to improve the quality of the data collected in the hospital. Other challenges in implementing process mining in healthcare may include the high diversity of healthcare services, temporal variabilities, challenges in combining data from different databases with different coding systems, and administrative variations in documenting care [82, 83].

In our case, we tested numerous patient cases to ensure the quality of the flow data was sufficient for a process mining application. We encountered challenges in data harmonization due to overlooked, incomplete, or inaccurately filled fields in the patient records. These issues were discussed with the hospital management and a data cleaning plan was developed collectively. We first compared the entries of the same patients in different hospital databases so that missing data from one database could be corrected using the entries from another one. Once this step is completed, the remaining missing information is filled by using the time intervals between the last known service completion before the missing data point, and the beginning of the next service. To address these challenges in the long run, we recommended hospital management organize training sessions to enhance awareness around these database issues and refine data collection processes and integration strategies. We also recommended this intervention be followed by proactive measures including regular audits and continuous training initiatives for the sustainability of the desired data quality. The proposed actions would also positively contribute to the long-term performance of the hospital in general.

In addition, process mining analyses provide an in-depth understanding of interactions and dynamics among hospital units as well as associated activities and resources through the identification of commonly followed patient pathways. We identified such pathways and learned about to what extent sub-processes in different units impact the main processes in terms of waiting times for shared resource usages, and issues related to patient services. For instance, emergency clinics, neurology, cardiology, internal medicine, physical therapy, neurosurgery, urology, obstetrics and gynecology, otorhinolaryngology, orthopedics, dermatology, psychiatry, and pediatrics are among the most intensively demanded clinics. Moreover, when the entire journeys of patients within the hospital were mapped (including repeated visits, occasional hospital stays, and transfers), we observed that the median length of hospital stay could extend up to 80 days in some variants. However, in the cases with immediate interventions or direct transfers, this duration decreased to mere minutes. If there was no transfer to another institution, the most significant causes of delays were laboratory analyses and radiological imaging

because these services are shared by various hospital units with limited lab capacities for biochemical analyses and radiological imaging. These resources were, thus, highly utilized. For example, biochemical analyses were carried out more than 85,000 times. The median (mean) frequency of using radiology imaging among possible modalities was 297 (7,481.86) times, e.g., tomography was utilized 7,288 times. All these findings highlighted the need for improvement of lab and imaging capacities. Issues related to lab capacities and the need to increase the laboratory workforce or open new labs to meet increasing demand have been reported in the literature [84, 85]. Such decisions should be grounded in quantitative evidence and careful cost-benefit evaluation for effective resource management, which can be facilitated by process mining analyses [41].

The clinic considered in our study is a rural local secondary care hospital distanced from urban centers due to its geographic location. Unlike research/teaching hospitals or urban tertiary care hospitals these local hospitals encounter additional resources and personnel constraints. They may even need to address shortages through temporary assignments or referrals, which in return may lead to disruptions in critical services or care delays threatening the well-being of the patients [14, 86]. We identified such potential issues in the local hospitals considered. Particularly, our process mining analysis highlighted the high waiting times (e.g., median waiting times around 2 h) in the General Surgery and Cardiology services, whose resources were highly utilized (2,699 and 6,162 times). Laboratories and radiological imaging units, which serve as shared resources for outpatient clinics, contribute significantly to patient wait times. Although these units may not individually rank among the top causes of delays, their collective workload is substantial when considered together. Additionally, variations in the number of clinicians also play a crucial role as a primary factor affecting the efficiency of this service. According to patient records within the hospital information system, the clinicians in these specific units saw approximately 1300 patients/month on average which is higher than the ideal number. These results have indicated the need for additional medical professionals and staff. Upon bringing this evidence to the hospital management, they realized that the hospital was providing services with personnel numbers below the unit-specific minimum physician requirements set by the Ministry of Health [87]. This inadequacy was concerning given that the remoteness of the hospital limits alternative care options for patients and creates challenges in maintaining a consistent workforce and addressing fluctuations in patient demand. Therefore, future planning should involve collaborative efforts with relevant authorities to develop sustainable solutions that mitigate the impact of personnel shortages and enhance the resilience of healthcare delivery in rural areas.

The findings also revealed units with low workload levels, highlighting that departments such as intensive care tend to have relatively lower usage rates compared to others. As shown above, the process mining identified potential bottleneck services based on summary statistics like waiting times and resource usages. The verification of bottleneck statuses of these services, which patient groups (i.e., pathway clusters) suffer most from these bottlenecks, and when (i.e., what time of the day) further resources are needed, were determined by analyzing the patient pathways involving these services with higher detail level and using the animation feature of application platform. For example, the Emergency Polyclinics emerged as the most heavily utilized unit. A careful analysis of pathways associated with the emergency units implied that its patients often sought secondary care directly from the emergency services rather than scheduled outpatient clinic appointments or through referrals from their primary care providers. The Administrators inferred that there could be several reasons for this behavior including travel time requirements from remote communities which limits access to outpatient clinics during regular work times, the effect of the COVID-19 pandemic, and faster and cheaper service in emergency departments covered by the Universal Health Insurance in Turkey. The behavior of Turkish patients from rural areas predominantly seeking direct care from emergency services has been also reported in the literature [88]. The results showed longer waiting times and higher service workload during particular days (Mondays), on which residents mainly gather in the town center (where the hospital is) to engage in scheduled commercial and social activities (e.g., agricultural markets and livestock auctions). This finding was reached by navigating the variants and the cases under these variants. This situation was also confirmed by the hospital administrators. These days, many residents both engage in their social/commercial activities and follow up with their routine healthcare service needs. Therefore, hospital management can reduce waiting times by scheduling more personnel on the bottleneck units such as emergency care, cardiology, and radiology units as well as the biochemical laboratory, especially on specific days or hours of the day, and create additional value for patients.

Our work has particular limitations. Our analyses were conducted mainly for the Turkish healthcare system, which could be quite different from other healthcare systems due to its centralized structure [89]. Also, our results could still resonate well for the healthcare facilities within other centralized healthcare systems such as those in Canada and the United Kingdom. While there may be differences between systems in terms of

institutional types, regulations, or social security support, all ultimately require high-quality service delivery for their clients and efficient, effective process structures and management for their internal components within the service industry. Therefore, although findings may focus on a specific hospital, the dimensions emphasized in challenges, problems encountered, and areas for improvement are common and the results are generalizable.

One of the challenges faced in the study was the difficulty in transforming the data stored in the information system into an event log. Despite the advancements in the information system, when data entry relies on individuals, issues such as missing data, timing errors, and incorrect entries can arise. We ensured the quality of flow data by testing multiple patient cases. A collaborative data cleaning plan was implemented, comparing entries across hospital databases and estimating missing values using service intervals. While this posed a significant challenge for the research, it also raised awareness among hospital administration about these issues. Consequently, they have planned actions to prevent such problems in the future to improve long-term data quality such as staff training, regular audits, and continuous improvement initiatives, which could also enhance overall hospital performance.

Conclusions and future work

We adopted a process mining methodology and explored the workloads and patient flow concentrations across different units for a secondary care hospital in a rural region. Our analysis provides a detail study demonstrating the applicability of the proposed methodology to draw insights from real experiences on how hospital services can be improved. Although, the hospital administrators had existing information systems for tracking detailed standard performance statistics and report screens provided by the Ministry of Health, they benefited greatly from the results derived by our process mining analysis such as detailed process maps and statistics related to process flows. The administrators were provided simple but holistic view of ongoing issues in their hospital. From these results, general recommendations for improving information systems have been derived through joint meetings with the hospital management, and then, evidence-based capacity improvement plans have been developed. Additional issues regarding inherent data management issues and data quality have been raised and training plans for personnel have been established. Updates have been made to the forms, and additional data entry options have been generated to eliminate confusion for the data management operations and future process mining studies. In addition to all this, the study encompasses the entire journey of a patient within a hospital. This approach can also be applied to customer or product journeys in different industries. The key point here is the ability to create a seamless flow using data gathered from various systems, as demonstrated in this study. This highlights the potential value of the research not only for the healthcare industries but for all industries.

Future work could focus on specific clinics and their services to produce customized solution approaches to their capacity planning challenges. In addition, this study uses short-term, but future research could extend this analysis by incorporating medium and long-term data to explore trends and patterns over an extended period. At this stage, we considered the identification of bottleneck services, and indirect specification of service capacities or resources needing improvement, without explicitly analyzing the effects of such improvements. In future studies, process mining could be jointly used with validated simulation models to specify exact intervention recommendations as well as the associated performance improvements and cost-benefit analyses. Furthermore, the studies may focus on comparative analyses across different hospitals and integrate process mining with patient outcomes for a more comprehensive evaluation. Real-time monitoring systems, models for optimizing resource use, and patient-centered analyses could also be explored.

Supplementary Information

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Supplementary Material 1

Supplementary Material 2

Supplementary Material 3

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Author contributions

Güzin Özdağoğlu: Conceptualization, methodology, software, validation, formal analysis, data curation, writing - original draft, writing - review & editing, visualization. Muhammet Damar (corresponding author): Conceptualization, Methodology, software, data curation, writing - original draft, writing - review & editing, visualization. Fatih Safa Erenay: Conceptualization, methodology, investigation, writing - review & editing, supervision. Hale Damar: Conceptualization, Investigation, validation, writing - review & editing. Osman Himmetoğlu: Conceptualization, validation, investigation, writing - review & editing, supervision.Andrew D. Pinto: Conceptualization, validation, investigation, supervision.

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Data availability
The datasets generated and/or analyzed during the current study are not publicly available due privacy but are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
This study was approved by the Dokuz Eylul University Institutional Review Board, and Bergama Hospital, Izmir Provincial Directorate of Health. Because this research was a secondary analysis of EMR data and the risk of privacy leakage was low, the informed consent of individual participants was not required. All the experiment protocols involving human data were in accordance with the Izmir Provincial Directorate of Health Privacy Board and Internal Review Board guidelines. Our research was provided a waiver of informed consent from the Izmir Provincial Directorate of Health IRB granted under E-42056799-619.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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