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Data-Driven Business Process Improvement

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Abstract

This research presents an analytical method to improve organizational workflow efficiency by utilizing data from the organization's information system, which was recorded as event logs from a hospital's outpatient department. Through the application of Process Mining techniques using the Disco tool and Fuzzy Miner algorithm, we created a process model for efficiency analysis. The research results demonstrated the effectiveness of the proposed method in analyzing outpatient service processes involving 12,836 patients, which revealed 4,293 distinct process variants. This diversity reflects the complexity of medical service delivery. Through frequency and time analysis, our research demonstrates how organizations can optimize resource allocation, establish SLAs, and develop effective staff training plans. The study confirms that Process Mining techniques provide accurate and effective means for improving work processes through the analysis of existing organizational data.

Keywords: Process Mining, Event Log, Efficiency Improvement, Fuzzy Miner

1. Introduction

In the current digital era, organizations in Thailand, especially hospitals, are facing challenges in improving service quality and increasing operational efficiency amidst the growing complexity of healthcare processes and rising patient expectations. However, this increased complexity may lead to various issues such as delays in service delivery. Therefore, analyzing and improving hospital work processes is crucial for elevating medical services and enhancing competitiveness.

Process Mining is a technique gaining attention for analyzing and improving work processes using real organizational data (1). This technique utilizes event logs stored in an organization's information system to create a diagram of current work processes (as-is process). Process Mining offers several advantages, such as rapid and accurate analysis of large volumes of data, the discovery of hidden patterns and relationships within processes, and real-time monitoring of process efficiency. Additionally, it helps address limitations of traditional process improvement methods, such as stakeholder interviews or work observations, which often suffer from subjectivity and partial views.

The application of Process Mining in hospitals for data-driven business process improvement is particularly important in the era of Big Data and digital transformation. Hospitals can use Process Mining to analyze and improve patient service processes, especially in outpatient departments where process complexity and diversity are high (2). However, implementing Process Mining in hospitals still faces challenges such as the complexity of medical data, the diversity of treatment processes, and patient privacy constraints.

Analysis through Process Mining enables organizations to identify opportunities for efficiency improvements, reduce waiting times, enhance treatment quality, and elevate patient satisfaction. Furthermore, it aids in creating opportunities for appropriate allocation of medical resources, determining Service Level Agreements (SLAs), and developing effective staff training plans. These are crucial factors in increasing competitiveness and raising medical service standards in the current era.

2. Theory and Related Research

2.1 Business Process Improvement (BPI)

Business Process Improvement is a practice aimed at enhancing the efficiency of existing work processes. Its goal is to increase the speed, accuracy, and reliability of processes. BPI is a systematic method that helps organizations significantly improve key business processes (3). Therefore, BPI is not a one-time operation but a continuous process that must be consistently implemented to maintain competitive advantage.

BPI comprises several crucial steps, including identifying problems or opportunities in current processes, developing and implementing solutions, and monitoring outcomes. The main objective of BPI is to deliver value through quality enhancement, service improvement, cost reduction, and increased efficiency of existing business activities or processes. BPI is an essential tool for continuous analysis and improvement of business processes (4).

The importance of BPI has grown as all organizations rely on business processes to drive operations, whether it's processing payments or resolving IT issues. Inefficient or incorrect processes can result in significant financial losses. Organizations lose up to $1 trillion annually (5) due to inefficient processes. Therefore, BPI is a crucial strategy for reducing losses and increasing overall organizational efficiency.

The benefits of BPI are diverse, including time savings, improved outcomes, increased customer satisfaction, enhanced transparency, and waste reduction. BPI can lead to significant improvements in cost, quality, service, and speed (3). Time savings result from reducing unnecessary steps and increasing process efficiency, while improved outcomes stem from enhanced employee performance and greater focus on process goals.

2.2 Business Process Management (BPM)

Business Process Management (BPM) is a systematic approach that focuses on discovering, modeling, analyzing, measuring, improving, and optimizing business processes to achieve results that align with an organization's strategic goals (6). BPM encompasses the modeling, automation, execution, control, measurement, and optimization of business activities. Its objective is to support organizational goals through the involvement of employees, customers, and business partners both within and outside the organization.

The BPM approach aims to manage business processes efficiently by optimizing various steps, including managing internal organizational rules, improving tool utilization, and creating efficient workflows. Process automation is a crucial component of BPM, which supports daily transactions and human work, resulting in reduced operational costs and increased overall team efficiency.

Effective implementation of BPM enables organizations to improve efficiency, productivity, and agility, as well as continuously enhance the quality of products and services (3). Moreover, it helps organizations respond quickly to changing customer and market demands, and efficiently adapt to new technologies and business models. This results in increased competitiveness and long-term success for the organization.

2.3 Process Mining

Process Mining has gained significant attention in both industry and academia, supported by the IEEE Task Force on Process Mining since 2009 (8).

Process Mining is a data science technique used to analyze event logs from an organization's information systems to discover, examine, and improve business processes (7). This technique primarily aims to create process models that reflect actual operations, help identify bottlenecks, inefficiencies, and deviations from standards, as well as propose opportunities for efficiency improvements and automation.

Process Mining comprises three main objectives: Process Discovery, Conformance Checking, and Enhancement (1), as shown in Figure 1. Process Discovery focuses on creating process models from event log data, while Conformance Checking compares actual processes with reference models to identify deviations and potential issues.

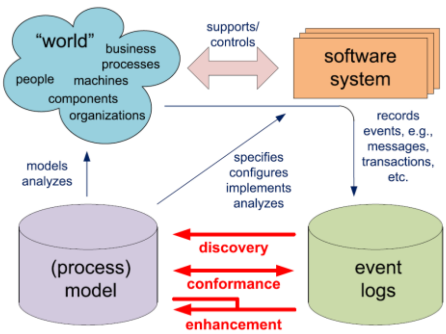


Figure 1 The Overview of Process Mining (1)

Enhancement in the context of Process Mining is an ongoing process that uses advanced data analysis techniques, such as data mining and machine learning, to improve business processes (8). This method enables organizations to identify improvement opportunities, which may include process modifications, task automation, and optimal resource allocation.

Process Mining can be applied to various business processes, such as manufacturing, supply chain management, customer service, and human resource management (7). This technique provides organizations with deep insights into the relationships between different activities in business processes, leading to more effective decision-making in process improvement.

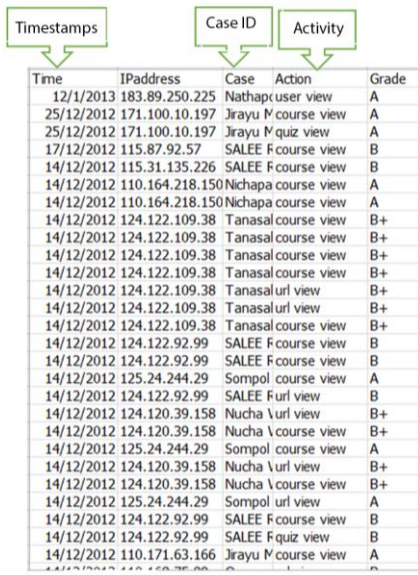
Process Mining has gained significant attention in both industry and academia, supported by the IEEE Task Force on Process Mining since 2009 (8). The integration of Process Mining with other data analysis techniques, such as statistical analysis and machine learning, further enhances the capability to analyze and improve business processes more effectively.

Process Mining integrates advanced techniques such as machine learning and advanced analytics to uncover hidden process patterns, measure performance, and identify improvement opportunities.

2.4 Event Logs

Event Logs are crucial data for analyzing business processes, especially in Process Mining (1). They consist of information automatically recorded from an organization's information systems, such as ERP systems and production systems.

The data necessary for Process Mining includes Case ID, Activity, Timestamp, Resource, and additional information, as shown in Figure 2.



Time	IPaddress	Case	Action	Grade
12/1/2013	183.89.250.225	Nathapo	user view	A
25/12/2012	171.100.10.197	Jirayu M	course view	A
25/12/2012	171.100.10.197	Jirayu M	quiz view	A
17/12/2012	115.87.92.57	SALEE F	course view	B
14/12/2012	115.31.135.226	SALEE F	course view	B
14/12/2012	110.164.218.150	Nichapa	course view	A
14/12/2012	110.164.218.150	Nichapa	course view	A
14/12/2012	124.122.109.38	Tanasal	course view	B+
14/12/2012	124.122.109.38	Tanasal	course view	B+
14/12/2012	124.122.109.38	Tanasal	course view	B+
14/12/2012	124.122.109.38	Tanasal	course view	B+
14/12/2012	124.122.109.38	Tanasal	url view	B+
14/12/2012	124.122.109.38	Tanasal	url view	B+
14/12/2012	124.122.109.38	Tanasal	course view	B+
14/12/2012	124.122.92.99	SALEE F	course view	B
14/12/2012	124.122.92.99	SALEE F	course view	B
14/12/2012	125.24.244.29	Sompol	course view	A
14/12/2012	124.122.92.99	SALEE F	url view	B
14/12/2012	124.120.39.158	Nucha \	url view	B+
14/12/2012	124.120.39.158	Nucha \	course view	B+
14/12/2012	125.24.244.29	Sompol	course view	A
14/12/2012	124.120.39.158	Nucha \	url view	B+
14/12/2012	124.120.39.158	Nucha \	course view	B+
14/12/2012	125.24.244.29	Sompol	url view	A
14/12/2012	124.122.92.99	SALEE F	course view	B
14/12/2012	124.122.92.99	SALEE F	quiz view	B
14/12/2012	110.171.63.166	Jirayu M	course view	A

Figure 2 Event logs

3. Research Methodology

In researching data-driven business process optimization, the data preparation step is crucial in making the data ready for further analysis. All real data comes from the information system of a particular hospital, in the form of event logs, which include data from various sections such as patient service data, disease diagnosis data, payment data, and revenue data. In this research, we utilized the full-scale version of Disco software through a formal partnership with Fluxicon, the software developer. This partnership provides access to the complete suite of advanced process mining capabilities, including unrestricted analysis of large datasets, comprehensive visualization tools, and detailed performance metrics. The partnership ensures that our analysis can handle the full scope of healthcare process data without any technical limitations. The selection of the Fuzzy Miner algorithm within Disco is particularly appropriate for our healthcare process analysis as it excels at handling unstructured event logs with high variability.

Fuzzy miner algorithms are especially suitable for complex processes with many variations, healthcare and service-oriented processes where paths are not strictly defined, data with noise and exceptional cases, and large datasets where abstraction is necessary for meaningful visualization. These characteristics align perfectly with the nature of outpatient department processes, where patient care pathways can vary significantly based on individual circumstances.

This data collection comprises a total of 154,485 entries from the outpatient department, from 01.08.2023 to 01.09.2023, involving 12,836 patients. The research methodology is as follows:

1) Identification of Data Types for Process Mining

2) Data import into Disco software

3) Statistical values from Disco software

3.1 Identification of Data Types for Process Mining

The preparation of data for Process Mining begins with classifying and transforming the data into an appropriate format. This involves identifying the type of each column according to Process Mining principles, which include:

Case ID (unique identifier for each case)

Activity (name of the activity in the process)

Timestamp (time when the activity occurred)

Resource (resource used in carrying out the activity)

This correct classification of data types is a crucial foundation for efficient process analysis and model creation. It enables accurate tracking and analysis of the sequence of activities, durations, and resource utilization in the process, as shown in Table 1.

Table 1 Column Types for Process Mining

Column Name	Meaning	Column Type
HN	Patient Identification Number	Case ID
VN	Service Visit Number	Other
department	Department where the patient received service	Other
staff	Name of responsible staff	Resource
pdx	Disease diagnosis code	Other
ovstist	Service visit status	Other
visit_type	Type of service visit	Other
pttype	Type of treatment rights	Other
spclty	Specialty department	Other
income	Total income from service visit	Other
drug_income	Income from medications	Other
lab_income	Income from lab diagnostics	Other
xray_income	Income from X-rays	Other
nurse_income	Income from nursing services	Other
er_emergency_level	Emergency level in ER	Other
time	Time when activity occurred	Timestamp
activity	Activity that occurred	Activity

Table 2 presents details of medical activities in the Outpatient Department (OPD), including activity names, meanings, and process descriptions. It covers processes from patient data recording to printing invoices. This information is crucial for efficient management of medical services and can be used in Process Mining analysis to create models that reflect actual operations. It helps provide an overview of the process and leads to systematic and effective management improvements.

Table 2 Meanings of Activity Names in the Process

Activity Name	Process Meaning	Process Description
mrl_save	Record Medical Record Log	Record treatment history for OPD patients
mrl_print	Print Medical Record Log	Print medical data for OPD patients
start_screen	Start time of patient screening	Begin screening and preliminary data check
finish_screen	End time of patient screening	Complete screening and refer patient
lab_order	Laboratory test order	Order additional laboratory tests
lab_receive	Receive laboratory test samples	Receive samples for laboratory analysis
lab_report	Report laboratory test results	Send lab results to the doctor
start_doctor	Start of doctor's examination	Begin treatment by the doctor
end_doctor	End of doctor's examination	Complete examination and diagnosis by the doctor
start_rx	Start of prescription	Begin the prescription process by the doctor
print_rx	Print prescription or treatment documents	Print prescription or treatment plan
admit	Admit patient for hospital treatment	Admit patient for inpatient care
print_bill	Print invoice	Print treatment cost bill
xray_request	Request X-ray examination	Order additional X-ray examination
xray_examined	X-ray examination	Perform X-ray examination as ordered

3.2 Importing Data into Disco Software

In the data import step for Process Mining, this data table consists of multiple columns representing various characteristics of data related to the hospital's work processes. This data is prepared for further analysis of the hospital's work processes through Disco software, as shown in Figure 3.

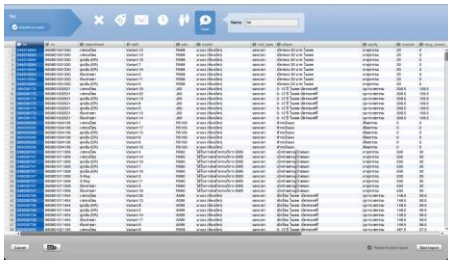


Figure 3 Data preparation for Process Mining analysis

Figure 4 shows a Spaghetti Model, which is the result of data import and Process Mining in Disco software. This image illustrates the complex and intricate workflow of the hospital's processes. It displays numerous connections between various activities, allowing visualization of the links and movements between different activities in the process.

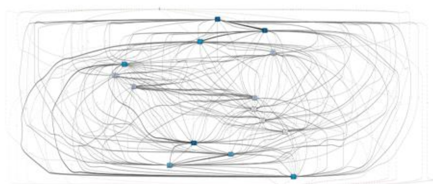


Figure 4 Spaghetti Model

3.3 Statistical Values from Disco Software

After importing the data into Disco software, the statistical results are displayed as shown in Figure 5. This data represents the hospital's operations from August 1, 2023, to September 1, 2023. There are a total of 154,485 events from 12,836 treatment cases, covering 15 main activities. Additionally, the graph showing the distribution of events over time aids in analyzing trends and resource allocation.

Meanwhile, there are 4,203 data patterns, as shown in Figure 6. This reveals the diversity in treatment patterns, ranging from a few minutes to several days. This information can be used for in-depth analysis to improve service efficiency, reduce congestion, and identify processes that may cause delays in the healthcare system.

Figure 5 In-depth statistical data on hospital operations

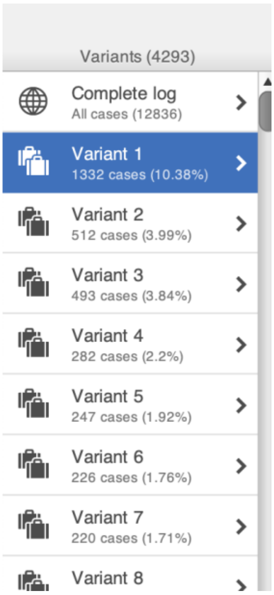


Figure 6 Different patterns of service

4. Summary of Research

This research employs the Fuzzy Miner algorithm from Disco software to analyze the efficiency of business processes, focusing on the frequency and duration of various activities. This method enables the creation of an overview of the process and efficiently identifies bottlenecks. The analysis results reveal significant differences in the frequency and duration of activities, particularly in the connections between the start and end points of the process. Identifying these issues leads to process improvements and increased service efficiency.

The use of technology in monitoring and tracking results helps elevate overall service quality. This research demonstrates the benefits of Process Mining techniques in analyzing and improving outpatient service systems. The analysis is divided into three main parts:

1) Analysis using Fuzzy Miner from a Frequency Perspective

2) Analysis using Fuzzy Miner from a Time Perspective

3) Analysis after Data Classification

4.1 Analysis using Fuzzy Miner from a Frequency Perspective

The application of the Fuzzy Miner technique using Disco software from a frequency perspective reveals in-depth insights into the frequency of events occurring at each stage of patient service. It also demonstrates the interconnectedness and complexity of various processes that take place.

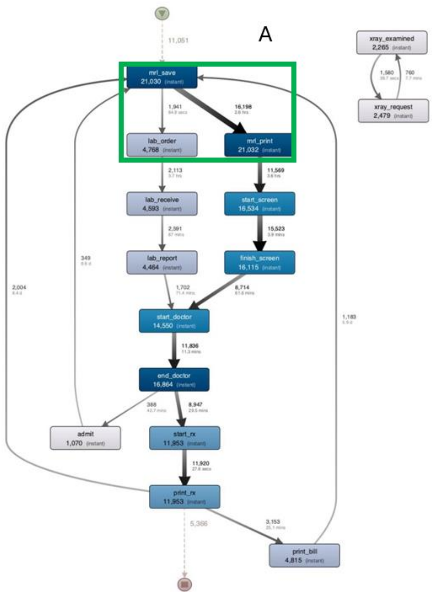


Figure 7 Happy path with HN as Case ID

The analysis of the outpatient (OPD) service process using Hospital Number (HN) as the Case ID shows the continuity of treatment and the relationships between various activities. In Figure 7, Frame A illustrates the critical starting point of the process, beginning with medical data recording (mri_save) 21,030 times, branching into two main paths: laboratory test orders (lab_order) 1,941 times (10.7%) and medical data printing (mrl_print) 19,198 times (89.3%). This bifurcation reflects the management of patients according to their diverse medical needs, which is a crucial starting point in determining the treatment path for each patient.

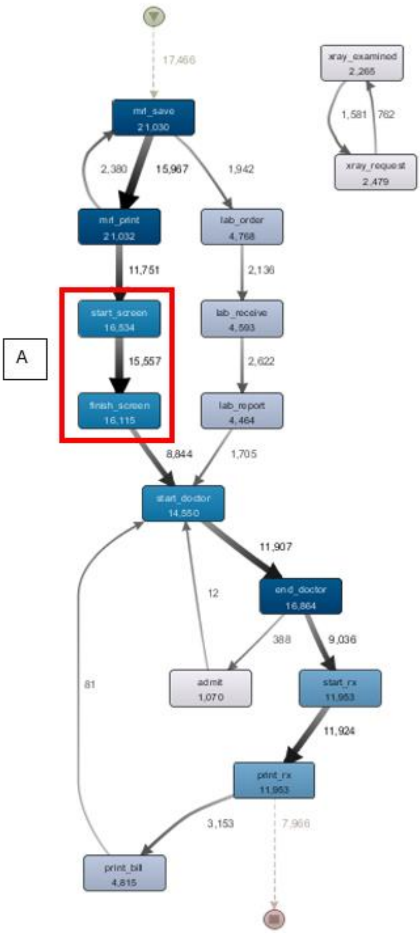


Figure 8 Happy path with VN as Case ID

In contrast, the analysis using Visit Number (VN) as the Case ID in Figure 8 presents a different process image, focusing on the service provided during each patient visit. Frame A in this figure shows important activities that mark the beginning and end of service delivery, including start_screen (16,534 times) and finish_screen (16,115 times), with 15,557 transfers between these activities. Although the numbers do not fully align, they reflect the complexity of the service process and may indicate opportunities for improving system efficiency. An in-depth analysis of the discrepancies between the number of start and end activities could lead to the discovery of ways to further enhance service quality.

4.2 Analysis using Fuzzy Miner from a Time Perspective

The application of the Fuzzy Miner technique using Disco software from a time perspective reveals in-depth insights into the time taken for events occurring at each stage of patient service. It also clearly shows bottlenecks or densities in service delivery.

Figure 9 illustrates the relationships and sequence of various activities, from patient data recording (mrl_save) to bill printing (print_bill). Each box represents an activity, and the connecting lines show the sequence of activities along with the average time between them. The thickness of the lines indicates the time taken; thicker lines represent longer durations than thinner ones.

Frames A and B in Figure 9 show the points with the longest durations in the process, with three points taking 8.6 days, 6.4 days, and 5.9 days respectively. These durations reflect the time intervals between patient follow-ups after previous treatments or examinations. These periods could represent waiting times for additional diagnostic results, treatment follow-ups, or intervals set by physicians for subsequent appointments.

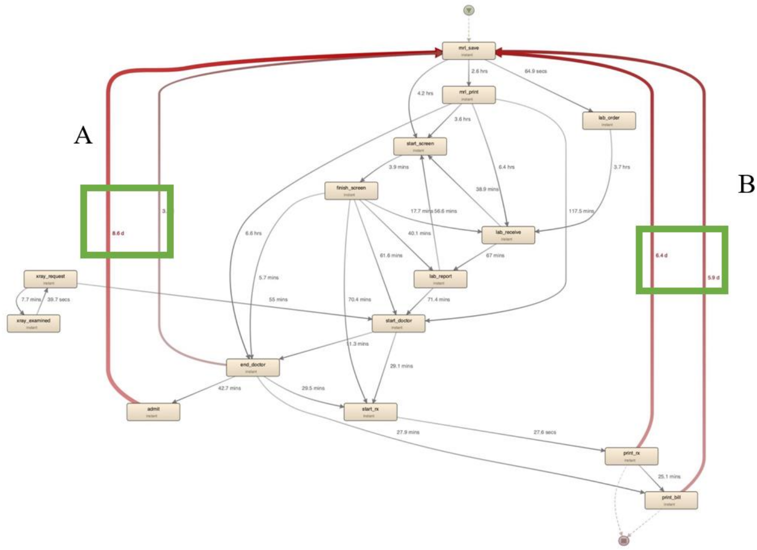


Figure 9 Workflow of the outpatient data management system (HN)

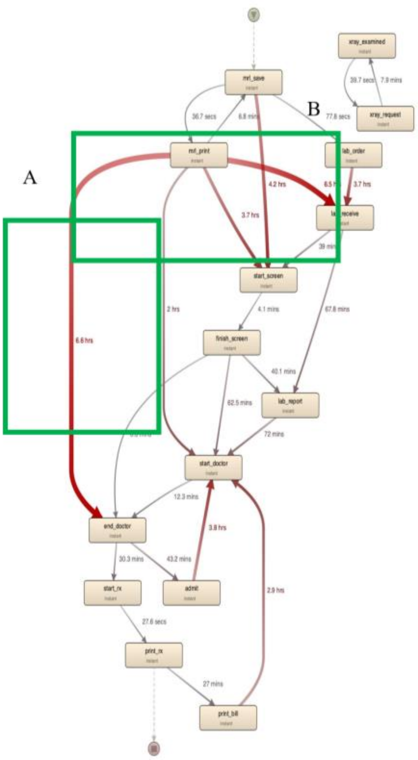


Figure 10 Workflow of the outpatient data management system using VN as Case ID

Figure 10 depicts the workflow of the outpatient data management system (VN). This diagram shows the relationships and sequence of various activities, from data recording (mrl_save) to bill printing (print_bill). Each box represents an activity, and the connecting lines show the sequence of activities along with the average time between them. This diagram provides an overview of the time spent in the outpatient service process and the duration of each step, which is useful for analyzing and improving service efficiency.

Frame A in Figure 10 shows the process of receiving laboratory samples (lab_receive), which has input paths from multiple activities. The longest durations are 6.5 hours from mrl_print and 4.2 hours from lab_order. The hospital can analyze these values to determine whether the time taken for transfers between each task is appropriate, using actual data to support decision-making.

Frame B in Figure 10 shows the process from mri_print to end_doctor, which has a total duration of approximately 6.6 hours. In the normal path, the waiting process for the doctor takes 2 hours. This process demonstrates the time patients must wait from document printing to the end of the doctor's examination, with doctors spending an average of 12.3 minutes examining each patient.

4.3 Analysis after Data Classification

In analyzing the outpatient treatment process, classifying data according to service access patterns is a crucial step in understanding the complexity of the system. Using process mining techniques in conjunction with frequency and duration analysis at each stage can reveal patient flow patterns, relationships between activities, and unforeseen repetitive points in the process. As shown in the Disco software, service access is classified into six categories: "Scheduled Appointment," "Walk-in (Registration Office)," "Transfer from Other Healthcare Facilities," "Home Visit," "Referred by EMS," and "Transfer from Emergency Room," as shown in Figure 11. This type of analysis not only helps understand the proportion and frequency of each type of service access but also facilitates the overall improvement of the healthcare service system by identifying bottlenecks and opportunities for efficiency enhancement throughout the patient care process.

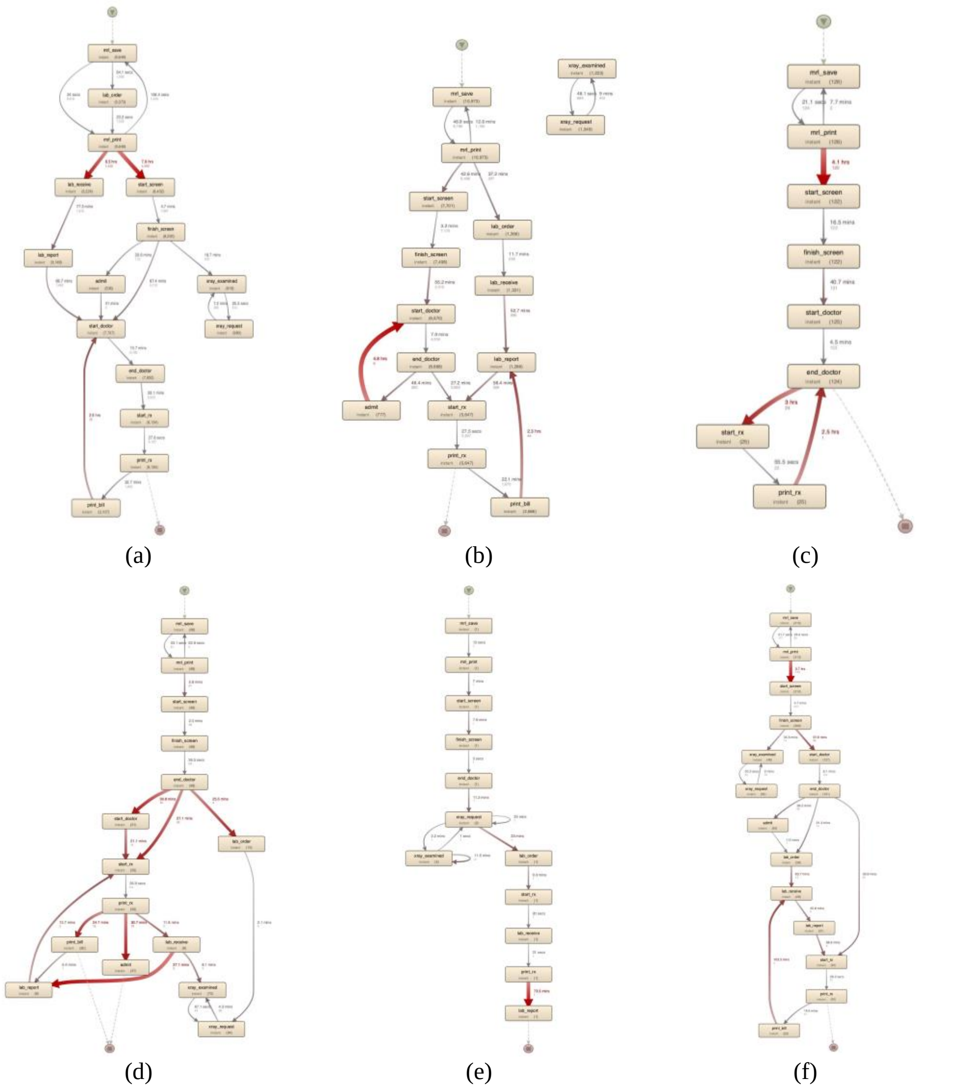


Figure 11 Service Access Process Patterns (a) Scheduled Appointment (b) Walk-in (c) Home Visit (d) Referred by EMS (e) Transfer from ER and (f) Transfer from Other Facilities

The analysis results show that the "Scheduled Appointment" group has the highest frequency of service access (50.31%), followed by "Walk-in" patients (47.7%). The analysis of process flow diagrams reveals significant bottlenecks in each group. For instance, in the "Scheduled Appointment" group, delays were found between "mrl_print" and "start_screen," and "lab_receive," while in the "Walk-in" group, delays were observed between "admit" and "start_doctor," and between "print_bill" and "lab_report."

For patient groups with specific characteristics, such as "Home Visit," "Referred by EMS," and "Transfer from ER," the frequency of service access was lower than other groups, but the complexity and urgency of management were higher. This was especially true for the "Referred by EMS" and "Transfer from ER" groups, which required special management and had longer durations in some steps compared to other groups.

The comprehensive analysis of 4,293 process variants has provided valuable insights that serve multiple concrete purposes for service improvement. First, it enables the identification of the most common patient pathways and their associated timeframes, helping the hospital standardize processes for common scenarios while maintaining necessary flexibility for unique cases. Understanding these patterns has proven crucial for predicting resource needs and managing patient flow more effectively.

Furthermore, the analysis supports optimal resource allocation through detailed frequency patterns that highlight peak usage times and resource demands. This empirical data enables evidence-based decisions for staff scheduling and facility management, moving away from assumption-based planning to data-driven resource utilization. The patterns revealed through this analysis have been particularly valuable in identifying periods of high demand and potential resource constraints.

Additionally, this detailed process analysis provides a solid foundation for establishing data-driven Service Level Agreements (SLAs) that reflect real operational conditions. Rather than relying on theoretical estimates, the hospital can now set performance metrics and service standards based on actual process data. These SLAs can be tailored to different patient groups and service areas, acknowledging the unique characteristics and requirements of each service access pattern identified in the study.

This comprehensive understanding of process variants, combined with the classification of service access patterns, provides hospital administrators with concrete data for implementing targeted improvements across different patient groups and service areas. It represents a significant step forward in evidence-based healthcare management and service optimization.

5. Suggestions for Future Work

Research to improve business process efficiency using data-driven approaches has introduced methods for analyzing workflows using Process Mining techniques through tools like Disco, which employs the Fuzzy Miner algorithm. This method uses event logs from organizational information systems to create models or workflow diagrams that reflect real conditions. The resulting models show both the frequency and efficiency (time) of each activity, helping managers to allocate resources appropriately, establish service level agreements that align with reality, and plan staff development efficiently.

Applying this technique to the outpatient service process demonstrates its effectiveness in analyzing highly complex processes. It was found that there are 4,293 different service patterns, reflecting the diversity of treatment processes in hospitals, which presents a challenge for efficiency improvement. However, analysis using Process Mining techniques can accurately handle this complexity using real data available in the organization, enabling the identification of areas for improvement and proposing concrete ways to increase efficiency.

Based on our research findings utilizing Process Mining in hospital outpatient processes, several key suggestions emerge for improving research process efficiency. The primary focus should be on enhancing data integration and quality through automated data collection systems, standardized data formats across departments, and real-time validation mechanisms. Additionally, process optimization can be achieved through continuous monitoring using advanced tools like Disco, reducing transfer times between departments, and developing standardized pathways for common patient scenarios while maintaining necessary flexibility for unique cases.

Furthermore, resource allocation strategies should be refined based on analyzed patterns rather than assumptions, with particular attention to peak usage times and specific patient group needs. This can be supported by developing integrated information systems that efficiently link departmental data, implementing automated notification systems for process delays, and creating real-time monitoring dashboards. The improvement of research methodology through expanded data collection, incorporation of patient feedback, and integration of advanced analytics techniques such as machine learning will also contribute to overall process efficiency. These enhancements will collectively lead to more effective healthcare service delivery and improved patient outcomes.

For future development, research should focus on enhancing automated data collection systems and improving interdepartmental data connectivity efficiency through the establishment of standardized data formats and the development of real-time monitoring systems. The integration of Artificial Intelligence (AI) technology, especially Generative AI, with Process Mining techniques, will enhance the efficiency of analyzing both input data and results. AI's ability to process large and complex datasets will reduce analysis time, increase accuracy in identifying hidden patterns, and present more appropriate process improvement approaches. Furthermore, the use of AI in trend prediction and scenario simulation will help organizations anticipate the impact of process changes in advance, enabling more effective strategic decision-making and providing a more comprehensive approach to healthcare service optimization.

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Declaration of Conflicting Interests
The authors declared that they have no conflicts of interest in the research, authorship, and this article's publication.

Reference

1. van der Aalst W. Data Science in Action. Process Mining: Data Science in Action. Berlin, Heidelberg: Springer Berlin Heidelberg; 2016. p. 3-23.
2. Mans RS, Van der Aalst WM, Vanwersch RJ. Process mining in healthcare: evaluating and exploiting operational healthcare processes. Heidelberg: Springer International Publishing; 2015 Mar 12.
3. Harrington HJ. Business Process Improvement: The Breakthrough Strategy for Total Quality, Productivity, and Competitiveness. New York: McGraw-Hill Education; 1991.
4. Fondas N. Process Innovation: Reengineering Work Through Information Technology. Acad Manag Perspect. 1993; 7(2):100-3.
5. Gartner. Gartner Says Organizations Are Failing to Manage Their Business Processes Effectively. Gartner Research Report; 2018.
6. Hammer M, Champy J. Reengineering the corporation: Manifesto for business revolution, a: Zondervan; 2009.
7. Măruşter L, van Beest NRTP. Redesigning business processes: a methodology based on simulation and process mining techniques. Knowl Inf Syst. 2009;21(3): 267-97.
8. de Leoni M, van der Aalst WMP, Dees M. A general process mining framework for correlating, predicting and clustering dynamic behavior based on event logs. Inf Syst. 2016;56:235-57.

