Open Access Library Journal
2023, Volume 10, e10838
ISSN Online: 2333-9721
ISSN Print: 2333-9705

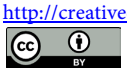
A Disco Approach to Process Discovery of Ear, Nose, and Throat (ENT) Clinical Processes

Linda Uchenna Oghenekaro[1], Victor Enamegwolo Mragbozo[1], Ediriverere Nosa Oghenekaro[2]

[1]Department of Computer Science, University of Port Harcourt, Rivers, Nigeria
[2]ENT Department, University of Port Harcourt Teaching Hospital, Rivers State, Nigeria
Email: linda.oghenekaro@uniport.edu.ng

How to cite this paper: Oghenekaro, L.U., Mragbozo, V.E. and Oghenekaro, E.N. (2023) A Disco Approach to Process Discovery of Ear, Nose, and Throat (ENT) Clinical Processes. *Open Access Library Journal*, **10**: e10838.
https://doi.org/10.4236/oalib.1110838

Received: September 29, 2023
Accepted: December 2, 2023
Published: December 5, 2023



Abstract

Improved clinical processes remains a main challenge for healthcare institutions, as there are numerous inefficient processes that consume high process cost and contributes very little to business profit. The study adopted the Disco process mining framework to mine the clinical processes within the Ear, Nose, and Throat (ENT) Department, so as to give hospital management a true picture of the actual processes that occurred in their environment, rather than the ideal picture that they assume to have occurred. Data was manually extracted from patients' hospital files, and captured as event logs in the hard drive of the computer system. The data went through the preprocessing stage and was cleaned of every attribute that was not Case ID, time stamp, or activity. The actual running process was generated as a petrinet, which revealed that there were bottlenecks and deviations present within the event logs. This study aims to introduce process mining techniques to researchers and hospital managers, so as to make their processes more efficient.

Subject Areas

Computer Science

Keywords

Process Mining, Healthcare, Event Logs, Bottlenecks, Process Discovery, Deviations

1. Introduction

Healthcare organizations have a common purpose of delivering medical services and upholding good health and well-being of human beings, although they can vary in structure, size, and scope of service [1]. Unfortunately, healthcare con-

tinues to be confronted with countless challenges, one of which is the adaptation to improved clinical processes based on emerging technology. Healthcare institutions struggle to manage and improve their clinical processes, in a bid to provide better quality care to patients. The increased need to improve healthcare processes and the generation of more process data in this sector has led to a growing interest in applying process mining to healthcare. The Ear, Nose and Throat (ENT) Department of tertiary healthcare institutions within our country Nigeria, is a referral department, which receives patients that are referred from other hospitals or from the general out-patient department (GOPD). The clinical processes within the ENT department refer to the clinical practices and procedures in ENT clinics carried out within the unit on a daily basis, and such processes include the patient's initial presentation, consultation, diagnosis and examination, use of diagnostic tools, referral for further investigation, formulation of a treatment plan or book for surgery, and close of patient case. Most healthcare institutions have a clear idea of how processes should run but have little or no technical know-how of how they actually run. Hence, the ability to discover running processes automatically in a healthcare system will help to reduce process costs and increase business profit [2]. Process discovery is one of the main categories of process mining algorithms, and it is defined as the act of creating process models that reflect the behavior of a process, as captured in an event log (which are the raw data obtained from process-aware information systems—PAIS). The process mining algorithms focus on discovering the order of activities in the process, such as the control flow, trajectories, activity paths, and care pathways. The input for process discovery is a set of events, and the output is a process model. The process discovery model can be used to uncover deviations and bottlenecks within the processes. Each event in the event log is related to a case ID, or an activity, and has a timestamp, with potentially many other attributes. The events in a case are ordered based on their timestamps to form a sequence, referred to as a trace.

Process mining as a technology involves using data, in the form of event logs, from systems like hospital information systems to gain insights into how processes are being executed, and to identify areas for improvement. However, real-life data often has many problems, such as missing events and incorrect timestamps, making process mining difficult. Hence, more research is being done to address these data quality issues before applying process mining techniques. The number of processes whose event logs are being recorded is highly increasing. Process mining is a promising approach that can turn these logs into valuable insights about processes. According to [3], process mining refers not only to techniques used in discovering process model but also to techniques that enhance existing process model and techniques that ensures conformance of present models. In this domain, an enormous amount of data is being generated by clinical processes, but clinical process models that reflect reality are seldom available. On the one hand, healthcare expenditure is consistently rising (independently of

outcomes and countries), and on average, it amounts to 10% of the gross domestic product (GDP) of countries across the world [4]. On the other hand, the demand for high-quality care at low cost is increasing, especially in our aging society. Consequently, healthcare service providers are highly motivated to use their data to improve the quality and performance of their care processes and lower their costs. Process mining is an approach that promises to support the analysis and understanding of running processes. This study focused on applying the disco framework to discover the processes running in the ENT clinic of a tertiary healthcare institution. This focus strengthens the overall purpose of the research, which serves to introduce managers of health institutions and researchers to how machine learning techniques can be used to mine not only data but also the processes that these data undergo.

2. Literature Review

Information Technology (IT) in general has played a significant role in improving healthcare by enhancing the efficiency and effectiveness of the healthcare delivery system. One of the major contributions of IT in healthcare is the development and implementation of Electronic Health Records (EHRs) and Electronic Medical Records (EMRs). These systems provide healthcare professionals with easy access to patient information, reducing the risk of errors associated with paper-based records. Studies have shown that the use of EHRs and EMRs can result in improved patient outcomes, as well as cost savings for healthcare organizations. Another important contribution of IT to healthcare is the use of telemedicine. Telemedicine allows healthcare professionals to deliver care remotely, which is particularly useful in rural or underserved areas where access to healthcare may be limited. A review of telemedicine studies found that telemedicine was effective in improving access to healthcare and patient outcomes, while also reducing costs. IT has also been used to develop Clinical Decision Support Systems (CDSS) which use data and algorithms to provide healthcare professionals with real-time information and recommendations to aid in the diagnosis and treatment of patients. Studies have shown that the use of CDSS can result in improved patient outcomes, as well as cost savings.

Studies in the literature show the potential and importance of process mining in the healthcare domain and highlight the need for further research. [5] focused on the use of process mining in the healthcare field. A case study was conducted using data from a complex care process at the AMC hospital. The study focused on gaining insights into the care flow by examining the control flow, organizational, and performance perspectives. Initial results were presented for these three perspectives. The results showed that it is possible to mine complex hospital processes and gain valuable insights. Additionally, existing techniques were used to create understandable models for large groups of patients, which were confirmed by staff at the AMC hospital. [6] investigated process mining in healthcare. They found that process mining can be used to identify areas for im-

provement in patient care pathways, such as reducing unnecessary waiting times and improving the coordination of care between different healthcare providers. [7] applied process mining techniques to improve the efficiency and quality of care in a tertiary care hospital. Another study, "From Event Logs to Clinical Process Models: An Application of Process Mining in Healthcare [6], presents a novel approach to process discovery and improvement in healthcare by combining event data with process models. [5] provided an overview of the applications of process mining in healthcare, including process discovery, conformance checking, and improvement [5]." Process mining in clinical workflows: "A systematic review" which focuses on the use of process mining in clinical workflows and identifies the challenges and opportunities in this field. [8] reviewed the existing literature on the use of process mining to improve the quality of healthcare and highlighted the benefits and limitations of this approach. [9] provided a bibliographic survey about process mining algorithms, tools, challenges, and case studies in healthcare processes. As this review was not done systematically, the number of papers in the survey needed to be mentioned. The publications cited in this paper and referring to at least one algorithm, tool, technique, or case study show that the survey covers 30 unique papers. The paper presents an overview of the characteristics of different approaches, including types of processes, types of data, process mining tools, frequently posed questions, methods and algorithms, used methodologies, and implementation strategies. Moreover, the survey characterized some case studies according to their geographical location and leading medical field. [9] extended their previous paper [10], as they conducted another bibliographic survey about the application of process mining in healthcare, covering 74 papers that report case studies in this context. [9] aim to provide a useful overview of the works undertaken in the field of process mining in healthcare and help researchers select process mining algorithms, tools, techniques, methodologies, and approaches for their studies. To this end, they tried to identify and characterize the case studies, providing an overview of the state of the art of process mining in healthcare. In addition, trends and challenges regarding the future of process mining in healthcare are discussed.

3. Material and Methods

In the Disco framework, the "start import" process refers to the act of importing data into the framework so that it can be processed and analyzed. This involves several steps, including:

1) Loading the data: The first step was loading the data into the Disco framework. This was done by reading data from local files.

2) Preprocessing the data: Once the data is loaded, it needs to undergo some preprocessing steps, such as cleaning, transforming, or filtering, to ensure that it is in the correct format for further analysis.

3) Creating a Disco job: A Disco job that defined the processing logic was created to enable the data to be processed in the Disco framework. This typically

involved writing a MapReduce program that performed the desired data processing operations.

4) Starting the import: Once the data has been preprocessed and a Disco job has been created, the job is submitted to the Disco cluster. The cluster then executed the MapReduce operations on the data.

The operational support systems at the ENT department included; patient files, staff schedules (Doctors and Nurses), and care pathways. Table 1 shows the data collected from the ENT department, which comprises three attributes; Case ID, Activity and Time stamp.

Table 1. Data collected from the ENT clinic.

Case ID	Activity	Date	Case ID	Activity	Date
1023	Registration	2/2/2023	1025	Diagnostic	3/3/2022
1023	Consultation	2/2/2023	1025	Medical History	3/3/2022
1023	Diagnostic	2/2/2023	1044	Registration	6/6/2022
1023	Surgery	2/3/2023	1044	Consultation	6/6/2022
1023	Treatment plan	2/3/2023	1044	Medical History	6/6/2022
1034	Registration	6/7/2022	1044	Diagnostic	6/8/2022
1034	Consultation	6/7/2022	1044	Treatment plan	6/6/2022
1034	Surgery	6/8/2022	1044	Treatment Admn	6/6/2022
1034	Treatment Admn	6/8/2022	1044	Billing	6/6/2022
1034	Billing	6/9/2022	1044	Discharge	6/6/2022
1024	Registration	2/1/2022	1031	Registration	8/4/2022
1024	Medical History	2/1/2022	1031	Diagnostic	8/4/2022
1024	Surgery	2/3/2022	1031	Surgery	8/4/2022
1024	Treatment plan	2/3/2022	1031	Treatment plan	8/4/2022
1032	Registration	8/4/2022	1031	Follow up	8/13/2022
1032	Consultation	8/4/2022	1031	Discharge	8/13/2022
1032	Diagnostic	8/4/2022	1026	Registration	2/9/2022
1032	Treatment Admn	8/4/2022	1026	Consultation	2/9/2022
1032	Billing	8/4/2022	1026	Diagnostic	2/9/2022
1032	Prescription Filing	8/27/2022	1026	Surgery	2/10/2022
1025	Registration	3/3/2022	1026	Treatment Admn	2/9/2022
1025	Consultation	3/3/2022	1026	Follow up	2/12/2022
1025	Treatment plan	3/4/2022	2208	Registration	6/26/2022
1025	Surgery	3/5/2022	2208	Surgery	6/26/2022
1025	Diagnostic	3/3/2022	2208	Treatment plan	7/28/2022

The graphical representation of the process flow within the ENT department is represented with a flowchart as seen in Figure 1. The diagram captured and modeled the interactions between actors and the system for the process discovery of ENT Consultation. The actors involved are the Patient, Doctor, Nurse and administrative staff. Some activities involved in the process flow include:

1) Book Consultation: This use case represents the patient's action of booking an appointment with an ENT specialist.

2) Consultation Request: The system receives the consultation request from the patient and sends a notification to the doctor.

3) Accept/Reject Request: The doctor can either accept or reject the consultation request.

4) Patient Information: The patient provides their personal and medical information to the system.

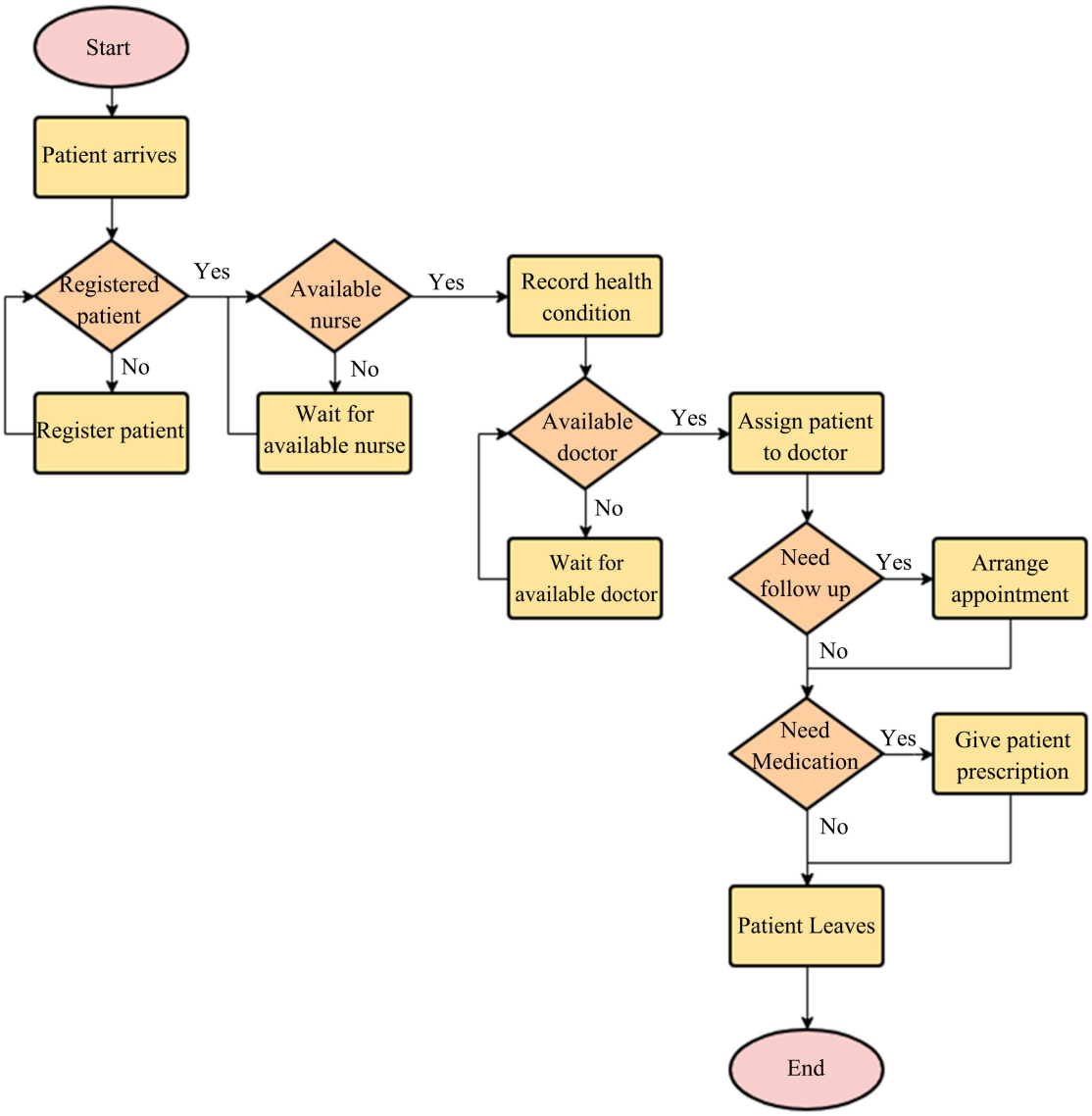


Figure 1. Process flow of the ENT clinical process.

5) Schedule Appointment: The doctor schedules an appointment with the patient.

6) Confirm Appointment: The patient confirms the appointment with the doctor.

7) Consultation: The doctor conducts the ENT consultation with the patient.

8) Record Consultation: The doctor records the consultation details in the system for future reference.

9) Review Consultation: The patient can review the details of the consultation after it has taken place.

The clinical process as summarized in **Figure 1** has five decision points, and nine process boxes, depicting the flow of the activities of the ideal processes running during the ENT clinics, however, **Figure 2** will demonstrate the actual manner in which the processes mined from the event-log data occurred. The graphical model used to represent the actual flow is known as a petrinet, which has an acronym PN, and it is a common tool for mathematical and graphical modelling of states in parallel, distributed and asynchronous control systems [6]. They are directed bipartite graphs having two types of nodes, representing transitions and places.

The Disco process miner presents a detailed demonstration of the ENT clinical processes. The disco environment as shown in **Figure 2** has three main tabs; the Map tab that carries the petrinet, as seen in **Figure 2**, and has additional features of zooming in on activities and pathways. It also has the option of viewing the frequency of travelling a given pathway, or viewing the performance. The statistics tab, as shown in **Figure 3**, is the second tab that carries the variation of each trace, and the final tab, as seen in **Figure 4**, is the case tab that gives additional information on every case with the event log.

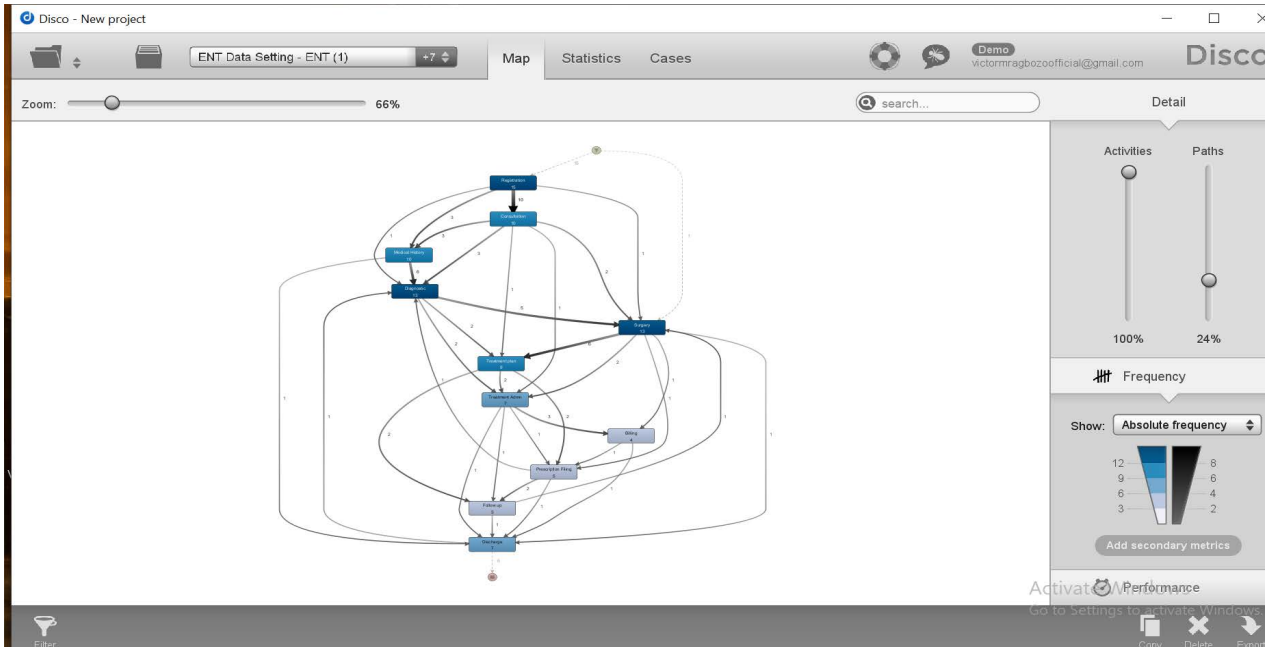


Figure 2. Generated petrinet from disco process miner.

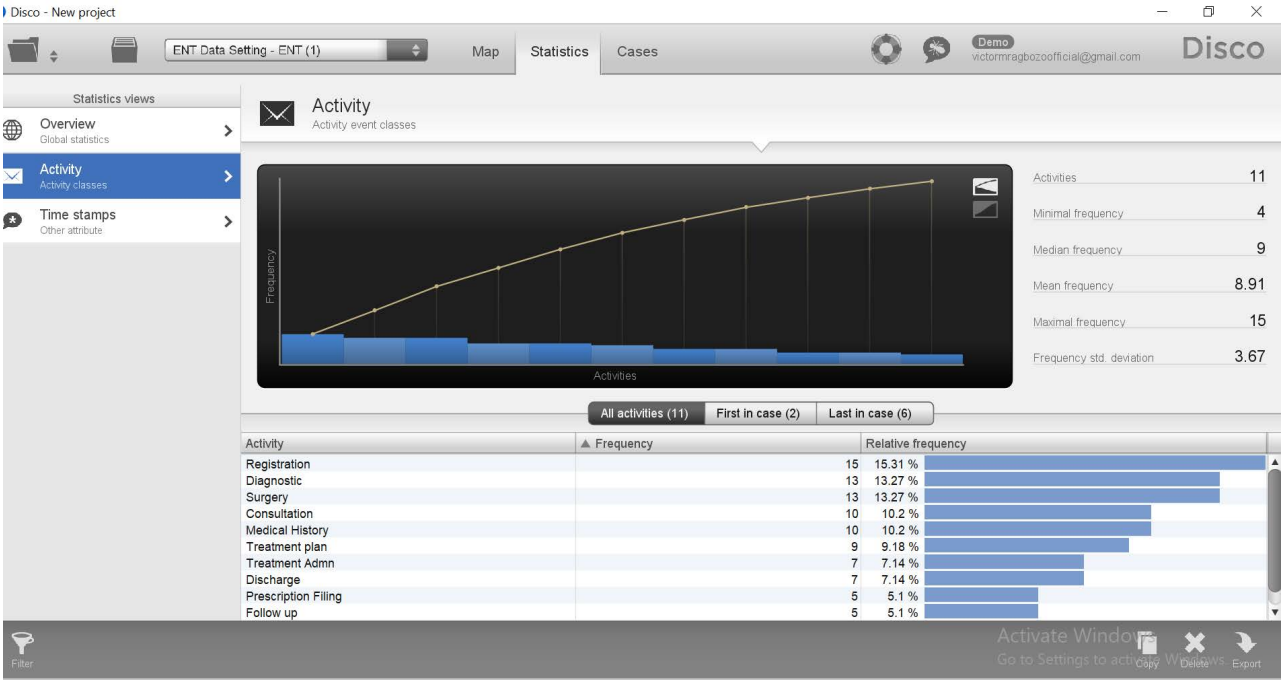


Figure 3. Statistics view of disco process miner.

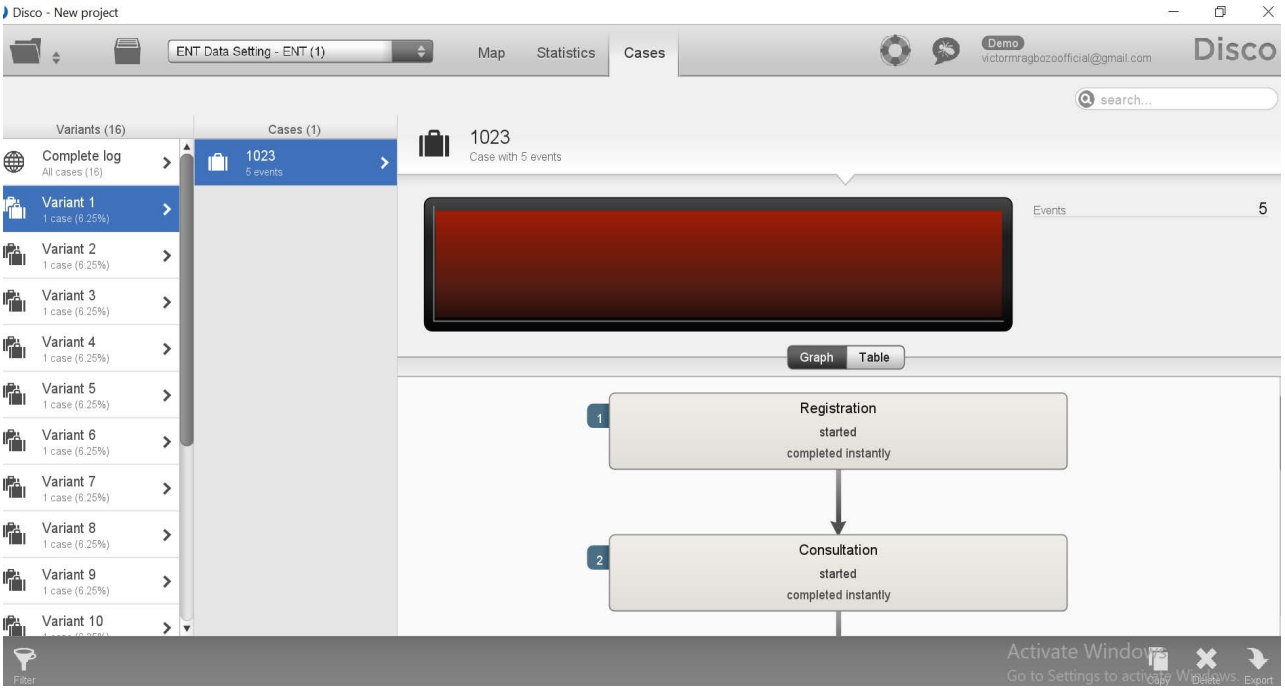


Figure 4. Case view of disco process miner.

4. Result Discussion

The generated petrinet revealed that 15 patients presented to the ENT clinic within the given period, and all patients were registered. 3 of the 15 patients were old patients as the ENT department had their medical history, while 10 of the 15 were presenting for the first time at the clinic. However, it was revealed

that 2 patients were unaccounted for. There was a bottleneck experienced at both the diagnostic and booking for surgery activities, as the statistics tab recorded a high percentage of 23% for both activities. Some processes were also noted from the petrinet to have deviated from the ideal pathway; processes such as precision filing and treatment administration.

The findings from the Disco framework assisted the ENT department in identifying bottlenecks, and deviations. Elimination of these inefficient processes leads to improved efficiency in patient management, resulting in more streamlined workflows and reducing delays in diagnosis and booking for surgery activities.

The Disco framework also allows for data collection and analysis, which can lead to valuable insights and research opportunities in the field of ENT. By systematically documenting and analyzing patient data using the Disco framework, ENT clinics can generate evidence-based practices and contribute to developing the best clinical practices. However, it is important to acknowledge the challenges and limitations in implementing the Disco framework in an ENT clinic. One potential limitation is the need for adequate training and familiarity with the framework among healthcare providers. Additionally, integrating the Disco framework into existing electronic health record systems or workflows may require technical and logistical considerations, such as data input, storage, and security.

5. Conclusion

By analyzing data from electronic medical records, process mining can help identify patterns in patient-doctor communication. For example, process mining can be used to identify patients who have a high number of missed appointments or who have trouble understanding their treatment plan. This information can be used to improve communication and engagement with these patients, leading to better health outcomes. Process mining can also help in reducing the financial burden on patients, by identifying inefficiencies and bottlenecks in the healthcare system. With the rising costs of healthcare, many patients are struggling to afford their care. Process mining can be used to identify areas where costs can be reduced or where care can be delivered more efficiently. By identifying these areas and taking action to address them, process mining can help make healthcare more affordable and accessible for patients. Additionally, process mining can help in analyzing the data of patient's visits and follow-up appointments. It can provide insight into how frequently patients are visiting the clinic and how many follow-up appointments are missed which can help in identifying the patients who need more follow-ups and better care and can help in improving their overall health outcomes. Process mining can be used to improve the patient-doctor relationship in a number of ways, by working together to leverage process mining; patients and healthcare providers can take proactive steps to improve the healthcare system and achieve better health outcomes for patients.

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Kassner, E. and Shortell, S.M. (2018) Structure and Organization of Health Care in Jonas and Kovner's Health Care Delivery in the United States. 12th Edition, Springer Publishing Company, New York.

[2] Oghenekaro, L.U., Ugwu, C. and Onyejegbu, L.N. (2020) A Hierarchical Temporal Memory Based Framework for Mining Event Logs. *International Journal for Computer Science and Information Security*, **18**, 145-151.

[3] van der Aalst, W.M.P. (2011) Process Mining: Discovery, Conformance, and Enhancement of Business Processes. Springer Science & Business Media, Berlin. https://doi.org/10.1007/978-3-642-19345-3

[4] World Health Organization (2023) Global Health Expenditure Database. https://apps.who.int/nha/database

[5] van der Aalst, M.C., Song, M., Bk, M. and Munoz-Gama, J. (2019) Process Mining in Clinical Workflows: A Systematic Review. *International Journal of Medical Informatics*, **121**, 85-97.

[6] van der Aalst, W.M.P., Adriansyah, A., De Medeiros, A.K.A., Arcieri, F., Baier, T., Blickle, T. and Chomicki, J. (2016) Process Mining in Healthcare: A Literature Review. *Journal of Biomedical Informatics*, **61**, 224-236. https://doi.org/10.1016/j.jbi.2016.04.007

[7] Munoz-Gama, J., Martin, N., Fernandez-Llatas, C. and Johnson, O.A. (2022) Process Mining for Healthcare: Characteristics and Challenges. *Journal of Biomedical Informatics*, **127**, Article 103994. https://doi.org/10.1016/j.jbi.2022.103994

[8] Carmona, J., Aleman, M.L., Fernandez, A. and Sanchez, D. (2019) Using Process Mining to Improve Quality in Healthcare: A Systematic Literature Review. Journal of Healthcare Quality Research, **34**(6), 385-398.

[9] Rojas, E., Munoz-Gama, J., Sepúlveda, M., Capurro, D. and Fernandez-Llatas, C. (2016) Process Mining in Healthcare: A Literature Review. *Journal of Biomedical Informatics*, **61**, 224-236. https://doi.org/10.1016/j.jbi.2016.04.007

[10] Ajit Kumar, R. (2016) Impact of Big Data Analytics on Healthcare and Society. *Journal of Biometrics & Biostatistics*, **7**. https://doi.org/10.4172/2155-6180.1000300