big data and cognitive computing

MDPI

Article

Descriptive Process Mining of Pulmonary Clinical Pathways Before and During COVID-19

Luca Murazzano [1,2,3,4,5,6], Paolo Landa [1,2,3,4,6,*], Jean-Baptiste Gartner [2,5,6,7] and André Côté [2,5,6,7]

1 Département D'opérations et Systèmes de Décision, Faculté des Sciences de L'administration, Université Laval, Québec, QC G1V 0A6, Canada; luca.murazzano.1@ulaval.ca
2 Axe Santé des Populations et Pratiques Optimales en Santé, Centre de Recherche du CHU de Québec, Québec, QC G1S 4L8, Canada; jean-baptiste.gartner@fsa.ulaval.ca (J.-B.G.); andre.cote@fsa.ulaval.ca (A.C.)
3 Centre Interuniversitaire de Recherche sur les Reseaux D'entreprise, la Logistique et le Transport (CIRRELT), Université Laval, Québec, QC G1V 0A6, Canada
4 Groupe de Recherche en Écologie Buccale (GREB), Université Laval, Québec, QC G1V 0A6, Canada
5 Centre de Recherche du CISSS de Chaudière-Appalaches, Lévis, QC G6V 3Z1, Canada
6 Centre de Recherche en Gestion des Services de Santé, Université Laval, Québec, QC G1V 0A6, Canada
7 Département de Management, Faculté des Sciences de L'administration, Université Laval, Québec, QC G1V 0A6, Canada
* Correspondence: paolo.landa@fsa.ulaval.ca

Abstract

Understanding how clinical pathways evolve over time is essential for characterizing care processes. It also helps identify potential shifts in diagnostic and organizational practices. This study provides a descriptive analysis of patient trajectories for four major respiratory conditions: lung cancer, interstitial fibrosis, chronic obstructive pulmonary disease (COPD), and pneumonia. Trajectories were compared between a pre-COVID-19 period (2018–2019) and a COVID-19 period (2020–2022) in a specialized hospital. Using process mining applied to administrative event logs, we examined three aspects of care: the structure and sequencing of activities, the timing of transitions between care encounters, and imaging timeliness. The analysis spanned inpatient, emergency department, and outpatient settings. Indicators of care duration and transition timing revealed heterogeneous temporal patterns. Several conditions showed shorter intervals in the COVID-19 period, whereas others varied little. Activity-level analyses complemented these findings. Process maps indicated stable structural components in many pathways, together with differences in timing and execution. In the emergency department, care shifted toward bedside radiography, whereas CT chest volumes remained relatively stable across periods and settings. Imaging timeliness stayed consistently high in the emergency department and relatively stable for most inpatient conditions. Outcome-related indicators, including 30-day readmission and prolonged care trajectories, showed only modest differences between periods. Overall, the study demonstrates the value of process mining for describing real-world clinical pathways and identifying temporal variations in care. These results provide a foundation for future work that integrates richer clinical information and analytical approaches capable of assessing causal relationships.

Keywords: process mining; clinical pathways; healthcare analytics; pulmonary diseases; patient flow; healthcare processes; descriptive analysis; COVID-19

Check for updates

Academic Editors: Carson K. Leung, Fei Hao and Xiaokang Zhou

Received: 27 May 2026
Revised: 11 July 2026
Accepted: 28 July 2026
Published: 10 August 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

1. Introduction

Chronic respiratory diseases, including chronic obstructive pulmonary disease (COPD), pneumonia, lung cancer, and pulmonary fibrosis, are among the leading causes of morbidity and mortality worldwide [1]. According to the World Health Organization, COPD was the third leading cause of death globally in 2019. It has since remained among the leading global causes of mortality, ranking fourth in 2021 and third again in 2023 [2,3]. Over the same period, lung cancer was the leading cause of cancer-related deaths worldwide, with the highest mortality rates among both men and women [3,4]. In Canada, COPD remains a major public health concern. Its prevalence has been close to 10% over the past decade [5], and its long-term decline in incidence was briefly interrupted during the COVID-19 pandemic [6]. Lung cancer is projected to be the most common cancer in both men and women in 2026 [7]. The prevalence of COPD and asthma alone continues to rise, which challenges healthcare systems in managing long-term care for these patients [8]. The increasing burden of pulmonary diseases strains healthcare systems worldwide due to the complexity of managing chronic conditions that require ongoing monitoring, specialized treatments, and frequent hospitalizations [9]. These diseases not only affect the physical health of individuals but also place a considerable economic and social burden on society, contributing to a lower quality of life for patients and increased healthcare costs [10].

In addition to existing pressures, the COVID-19 pandemic has introduced unprecedented challenges, exacerbating the strain on healthcare systems around the world [11]. Patients with chronic respiratory conditions, already vulnerable to complications, have faced increased risks during the pandemic, with COVID-19 severely disrupting care delivery, delaying routine treatments, and altering care protocols [12]. These disruptions have made it essential to reassess clinical pathways and ensure that healthcare systems can continue to meet the needs of pulmonary patients in a rapidly evolving healthcare landscape. In Québec, the first major wave of COVID-19 began in January 2020, followed by several subsequent surges that substantially affected hospital activity. According to data from the Institut national de santé publique du Québec (INSPQ) [13], hospitalizations in the administrative region where the study hospital is located (Capitale-Nationale) increased sharply from spring 2020 onward. Pronounced peaks occurred during the fall and winter 2020 and the spring 2021 waves. The region did not experience the extreme system overload reported in early epicenters such as Northern Italy or New York City. Even so, the healthcare system faced sustained pressure, service reorganization, and temporary reductions in non-urgent care [14].

The aging population of Quebec [15] and the rising prevalence of chronic pulmonary diseases [16] pose significant challenges for the public healthcare system, particularly in managing care for this vulnerable group. Almost three million people in Quebec, out of a total population of roughly nine million, live with lung disease. Pulmonary diseases are the second leading cause of death in the province [17]. This burden underscores the importance of efficient service delivery and well-designed clinical pathways for improving patient outcomes and resource utilization. In this context, the pandemic altered patient flow, treatment protocols, and resource allocation, which makes it important to re-assess these changes for chronic respiratory diseases [14].

Clinical pathways are structured, evidence-based care plans that guide patient management across the continuum of care, from prevention to palliative care [18]. Gartner et al. [18] describe them as systematic interventions designed to enhance care coordination for specific patient groups. Understanding and modeling these pathways is essential for ensuring consistency with clinical guidelines and optimizing patient outcomes [19,20]. Process mining is particularly useful in healthcare because it enables providers to analyze real-world patient journeys based on actual event data captured in electronic health records. By reconstructing

clinical pathways from this data, healthcare organizations can visualize deviations, inefficiencies, and bottlenecks that may not be apparent in traditional process evaluations [21,22]. These insights help refine care delivery, streamline resource utilization, and enhance patient throughput. Moreover, process mining ensures that medical procedures adhere to best practices by identifying variations that could lead to unnecessary delays or suboptimal treatments [23–25]. However, while its benefits are significant, large-scale implementation faces challenges due to the need for comprehensive, high-quality process data [26,27]. The COVID-19 pandemic drastically disrupted clinical pathways, forcing healthcare systems to rapidly adapt to shifting priorities [11,28]. Resources were reallocated, non-urgent procedures were delayed, and telemedicine replaced many in-person visits [29–31]. These changes introduced inefficiencies that affected timely diagnoses, treatment initiation, and overall patient care quality [32,33].

Process mining plays a vital role in addressing these disruptions. By analyzing patient pathways before, during, and after the pandemic, healthcare providers can quantify the impact of COVID-19 on routine care and identify strategies for mitigating its negative effects. For instance, by detecting bottlenecks in resource allocation and delays in critical procedures, organizations can optimize workflows to improve responsiveness in future crises. Additionally, process mining helps evaluate the effectiveness of new care models, such as telemedicine, by assessing patient transitions and treatment outcomes [34,35]. Puthur et al. [36] demonstrated the usefulness of process mining in studying pandemic-induced disruptions in Accident and Emergency and Maternity pathways at a UK hospital. Their findings highlight how process mining can provide actionable insights into care delivery changes, helping healthcare organizations refine strategies to enhance resilience and efficiency.

This study provides a descriptive analysis of clinical pathways for patients with four chronic pulmonary diseases: chronic obstructive pulmonary disease (COPD), lung cancer, pulmonary fibrosis, and chronic pneumonia. Using process mining techniques, we characterize and compare patient pathways observed in the pre-COVID-19 (2018–2019) and COVID-19 (2020–2022) periods. The analysis focuses on episode durations, transition times between clinical activities, the frequency of episodes, and variations in activity patterns. These results offer a data-driven overview of how clinical pathways evolved across the two periods and highlight observable differences in care processes. The paper is structured as follows: In Section 2, the methodology details the data collection and process mining techniques adopted. In Section 3, the results are presented with visual aids to highlight key findings. In Section 4, the discussion interprets these results and offers practical recommendations. Finally, in Section 5, the conclusion summarizes the study's contributions and suggests directions for future research.

2. Materials and Methods

This study builds on a previously published work on clinical pathway discovery using process mining [37], from which the data sources and extraction framework are derived. Here, we focus on a specific descriptive comparison of patient pathways across two time periods.

We adopt standard process mining terminology, distinguishing between *cases* and *activities*. An *episode* is defined as a significant interaction between a patient and the healthcare system related to their chronic disease. Episodes are categorized into three types: inpatient admissions, ED visits, and outpatient visits. Two complementary levels of analysis are considered: *Episode level (macro-level)* where patient pathways are modeled as sequences of episodes over time, and *Activity level (micro-level)* where individual episodes are decomposed into clinical activities (e.g., exams and procedures).

The objective is to characterize and compare clinical pathways observed in the pre-COVID-19 (2018–2019) and COVID-19 (2020–2022) periods. The analysis considers four main indicators: (i) episode counts, (ii) median duration of inpatient and ED episodes, (iii) direct transition times between episodes, and (iv) activity-level pathway patterns.

The two considered periods differ in length and may reflect underlying secular trends unrelated to the pandemic. Changes in case mix, hospital policies, disease severity, access restrictions, and patient avoidance of care may also influence observed differences. For this reason, the analysis is descriptive and does not aim to attribute causal effects to the pandemic.

2.1. Data Sources

The data were provided by the Institut universitaire de cardiologie et de pneumologie de Québec, Université Laval (IUCPQ-UL), a specialized hospital in cardiovascular and respiratory care serving a population of over 2.2 million. Our study utilized four primary databases, each containing distinct but complementary sets of information:

- *Inpatient Admissions Database* : Contains detailed records of patient admissions to hospital facilities;
- *Emergency Department (ED) Database*: Includes data on patient access to emergency;
- *Outpatient Visits Database*: Provides records of patient visits to outpatient clinics;
- *Medical Imaging Database*: Contains reports and findings from diagnostic imaging procedures.

The databases mentioned share a common identifier, the patient's ID, enabling the integration and cross-analysis of data from all four sources. The research team did not access the original operational databases directly. Instead, we received structured CSV extracts generated by the institution's data management unit. All variables were provided in predefined, dedicated columns and stored in standardized formats. A key challenge concerns the integration of medical imaging data, which are not directly linked to episodes. Following the approach described in the main article, imaging records are associated with episodes using patient identifiers and timestamp information. All data are derived from objective event logs of the hospital information system and do not include patient self-reported content.

The data used in this study include only patients with chronic pulmonary conditions who are formally identified and followed as chronic patients by the institution. In total, the cohort comprises 1179 COPD patients, 970 lung cancer patients, 285 pulmonary fibrosis patients, and 2280 chronic pneumonia patients. The data extraction was part of a broader institutional project [38] targeting these chronic disease cohorts, and therefore does not include the full population of patients presenting with acute respiratory conditions. Importantly, the dataset does not contain information on SARS-CoV-2 testing results or COVID-19 diagnostic codes, and COVID-19 is not included as a disease category in the analysis.

The provided dataset contains only limited sociodemographic and clinical severity information. Variables such as ICU admission, standardized severity scores, and comorbidity counts are not available or are inconsistently coded across the four databases. For this reason, subgroup analyses based on age categories, disease severity, or comorbidity burden could not be performed without introducing substantial bias or misclassification. The analysis is therefore restricted to stratification by disease type and time periods.

2.2. Ethical Process and Consent to Participate

The original study was approved by the research ethics committee of the Institut universitaire de cardiologie et de pneumologie de Québec, Université Laval (IUCPQ-UL) on 23 June 2022 (reference no. 2022-3826, 22200). The present work is a retrospective secondary

analysis conducted exclusively on fully anonymized data extracted from institutional clinical databases under the data use authorization granted by IUCPQ-UL. Because the research team had no access to identifiable information and, in accordance with institutional and national regulations, this secondary analysis did not require a full new ethics review, and written informed consent from patients was not required. The reuse of the anonymized data for the present analysis was authorized by the institution, and no waiver of consent was necessary.

2.3. Data Preparation

Raw collected data underwent multiple rounds of refinement and validation. Because this process involved several key activities, we held regular meetings with domain experts—both medical and management professionals—to define and refine the goals of information extraction. We first identified the IDs of patients affected by the four diseases under consideration and removed all data associated with other patients. Patient assignment to disease groups was not performed by the research team: the hospital formally identifies and follows these individuals as chronic patients within dedicated clinical programs, and it provided the corresponding patient lists.

Episodes were reconstructed using patient identifiers, episode identifiers, and admission and discharge timestamps. All activities associated with a given episode were regrouped and arranged in chronological order. For inpatient admissions and ED visits, only episodes with a clearly defined start and end were retained. Within each episode, we kept only activities whose timestamps fell between the recorded admission and discharge times. This ensured that the event log reflected exclusively the clinical actions performed during the documented episode window. Episodes that began before 1 January 2018, or ended after 31 December 2022, were excluded to ensure temporal coherence. Overlapping or recurrent episodes were resolved using predefined temporal rules based on clinical plausibility and the documented admission–discharge intervals.

Disease-related episodes were isolated through a rule-based filtering procedure developed with clinical experts. The database may contain episodes and activities that pertain to a patient but are not linked to their chronic disease. For each disease group, we retained only episodes containing activities, procedures, or diagnostic elements clinically associated with the chronic condition, and excluded unrelated episodes. Medical imaging records were linked to episodes using patient identifiers and timestamp-based assignment rules. When multiple candidate episodes overlapped, we resolved the ambiguity using temporal proximity and clinical plausibility criteria.

Missing, implausible, or duplicated timestamps were addressed through systematic plausibility checks and outlier detection using the interquartile range (IQR) method. Outlier removal was not intended to exclude clinically meaningful long episodes. For this reason, we performed a sensitivity check by repeating the analyses without outlier removal, and confirmed that the main descriptive patterns (pathway structure, transition frequencies, and diagnostic timeliness) remained unchanged. Given the descriptive aim of the study, the IQR rule served solely as a robustness-oriented preprocessing step rather than as a clinical filtering criterion. Implausible sequences were corrected when possible or removed when necessary. Finally, the dataset was divided into two subsets: one covering the pre-COVID-19 period and the other the COVID-19 era. The first subset included episodes that began before 31 December 2019, including those extending into early 2020, to account for uncertainty about the precise onset of the pandemic.

All algorithms used in this phase were coded in Python version 3.12. After data preparation, the cleaned dataset was used as input for the process mining tool, which analyzed the information to generate meaningful insights. This iterative approach ensured

that the extracted information was continually refined for accuracy and relevance, for both the pre-COVID-19 and the COVID-era datasets.

2.4. Data Analysis

A process mining tool was used to explore both macro and micro trajectories within patient clinical histories. This allowed us to examine patient interactions and treatments within individual episodes. This granular analysis helped pinpoint areas for refinement and efficiency improvement. The initial phase provided preliminary maps and tables that revealed early patterns and issues. We used Disco by Fluxicon® [39], operating under an academic license, to analyze and visualize clinical pathways. The tool was selected because it is specifically designed for high-variability and noisy processes, such as clinical pathways, and provides abstraction and filtering mechanisms that allow meaningful visualization of complex event logs. Given the descriptive aim of the study and the heterogeneous structure of the dataset, no formal comparison with other discovery algorithms was performed. To complement the qualitative comparison of pathway structures, we computed the Graph Edit Distance (GED) process models. GED was calculated as the minimum number of node and edge insertions or deletions required to transform one model into the other. In addition, we extracted the frequency of key clinical activities in both periods to provide a descriptive quantification of changes in activity patterns.

To complement pathway characterization, we computed two outcome-related indicators that could be reliably derived from the available data. First, the 30-day all-cause readmission rate was defined as any new episode for the same patient occurring within 30 days of discharge. Second, we calculated the proportion of episodes lasting more than 30 days, which serves as a proxy for prolonged or complex clinical trajectories. In-hospital mortality was not available in the dataset and is therefore not reported. Furthermore, to approximate concordance with international clinical guidelines, we derived two diagnostic timeliness indicators based on recommendations from guidelines for acute respiratory presentations [40–43]. For inpatient episodes, we assessed whether chest imaging occurred within 24 h of admission. For emergency department episodes, we evaluated whether initial imaging occurred within 6 hours of arrival, reflecting the "prompt" or "urgent" imaging recommended for acute respiratory conditions. These time limits were based on established operational definitions reported in the literature [44].

Episode duration distributions were compared between periods using Mann–Whitney U tests, a non-parametric method suitable for comparing two independent groups [45]. These tests were included only as supplementary summaries of distributional differences, as the primary aim of the study is descriptive rather than inferential. Given the exploratory nature of the analysis and the presence of multiple comparisons across diseases and episode types, p-values are interpreted cautiously and are not used as the main basis for conclusions. A Bonferroni-adjusted significance threshold ($\alpha = 0.00625$ for eight comparisons) is reported for transparency, although the study does not rely on hypothesis testing for its substantive findings.

3. Results

This section presents the findings of the analysis of clinical pathways for patients with pulmonary diseases; the results are structured to highlight the differences observed between the pre-COVID-19 and COVID-19 eras, with particular attention to patient flow, bottlenecks, and deviations in care processes.

3.1. Episode Counts and Temporal Trends

Figures 1–3 illustrate the annual number of episodes for each disease type and episode category, including inpatient admissions, ED admissions, and outpatient visits. The two colors distinguish pre-COVID-19 from COVID-era years, and the arrows represent the year-over-year percentage change. The graphs show a clear upward trend before the onset of the pandemic. Specifically, between 2018 and 2019, the number of episodes increased across all categories. From 2020 onward, the dataset revealed a general decline in episode numbers, with a few exceptions. On average, inpatient admissions dropped by 27.4% annually, ED admissions by 23.8%, and outpatient visits by 15%. Notably, between 2020 and 2021, ED admissions showed an increase for cancer patients (8.6%) and fibrosis patients (6.7%). Similarly, outpatient visits rose for COPD patients (1.5%), lung cancer patients (7.1%), and fibrosis patients (10.9%). Overall, the differences between the two periods were evident. The decrease between 2019 and 2020 was particularly marked, averaging 20.7% across all diseases and episode types, and the declining trend continued from 2020 onward.

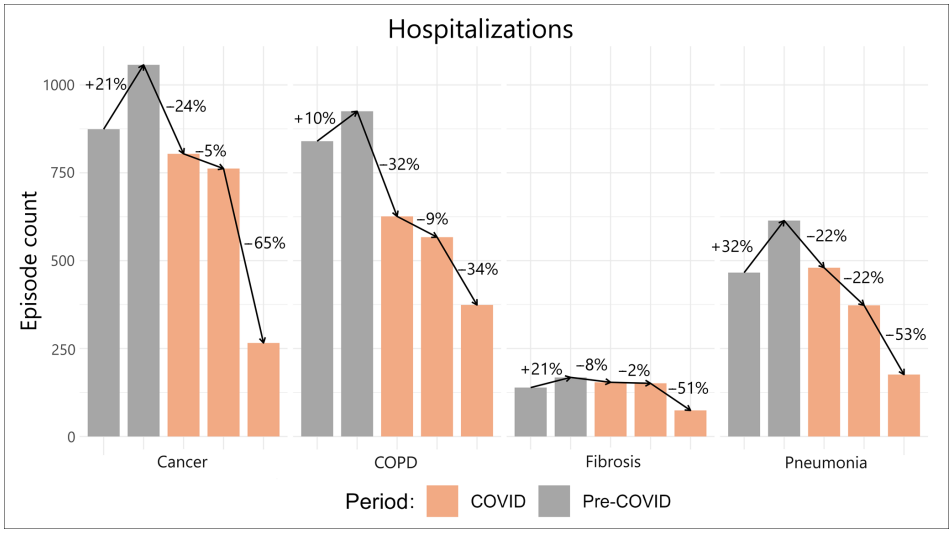


Figure 1. Count of inpatients episodes per year and percentage changes year to year, with a sharp decrease beginning in 2020.

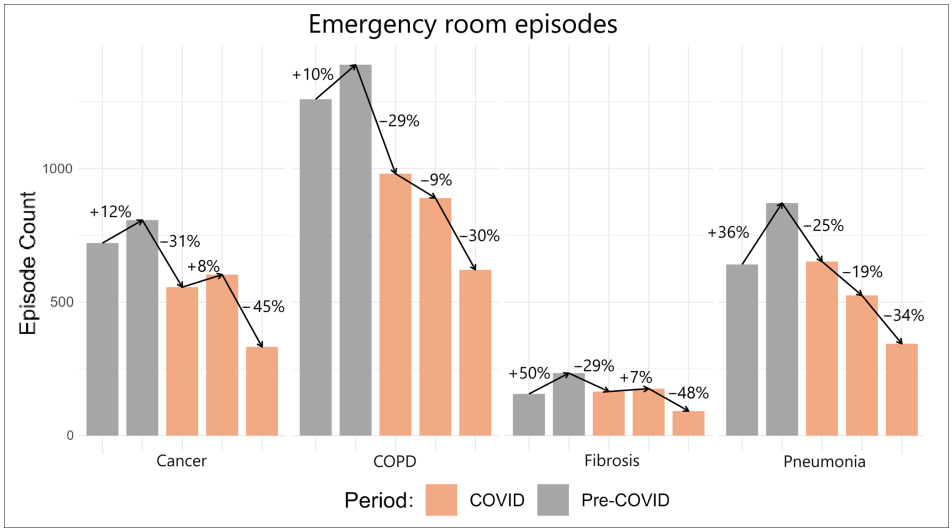


Figure 2. Count of ED episodes per year and percentage changes year to year, to notice a general decrease beginning in 2020.

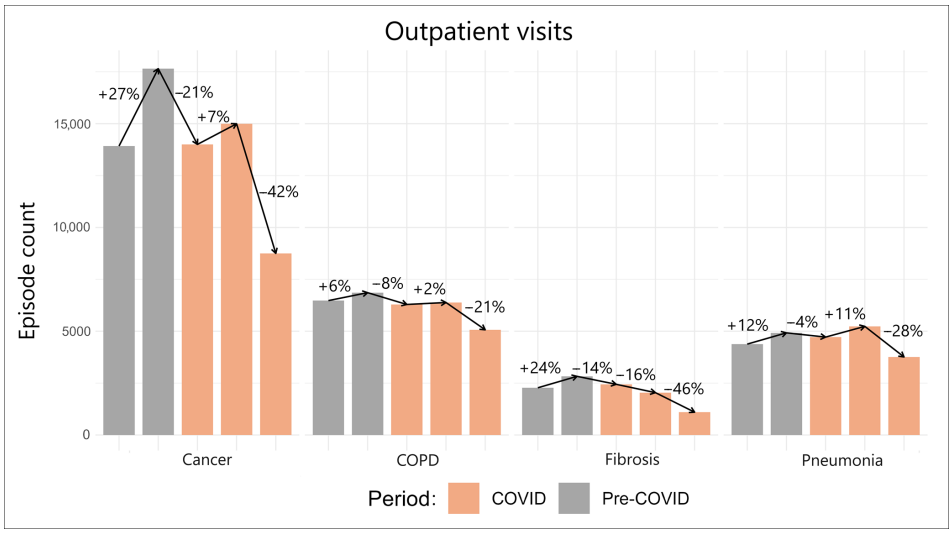


Figure 3. Count of outpatient visit episodes per year and percentage changes year to year, with a moderate decrease beginning in 2020.

3.2. Inpatients and Emergency Department Durations

The median duration of inpatient and emergency department episodes was analyzed for the four pulmonary diseases across the two periods. The overall distributions are reported in Figures 4 and 5.

For inpatient episodes, fibrosis-related hospitalizations show median durations of 6.93 days in the pre-COVID-19 period and 6.56 days in the COVID-19 period. Lung cancer hospitalizations show medians of 4.76 and 4.35 days, respectively. COPD hospitalizations present similar values across periods (6.86 vs. 6.90 days), while pneumonia episodes show medians of 5.87 and 5.92 days. Variability in hospitalization duration is illustrated by the boxplots: fibrosis and lung cancer episodes display more compact distributions in the COVID-19 period, whereas COPD and pneumonia episodes retain broader distributions.

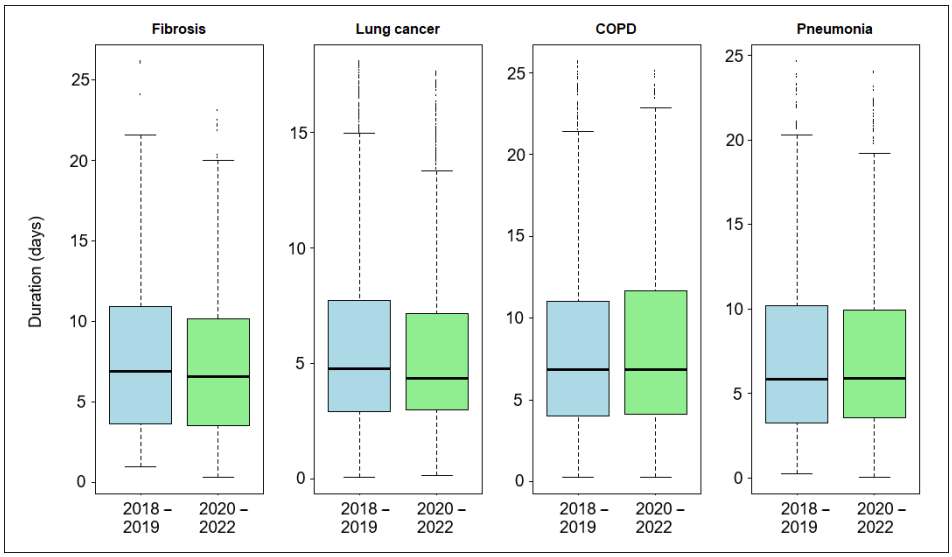


Figure 4. Distribution of duration in days of hospitalization episodes, divided into pre-COVID-19 and COVID-19 years. To note the decrease in the median duration, especially for Fibrosis and Lung cancer.

For ED episodes, fibrosis-related episodes show median durations of 9.92 h in the pre-COVID-19 period and 9.82 h in the COVID-19 period. Lung cancer episodes show medians of 9.62 and 9.38 h, respectively. COPD episodes show medians of 12.66 and 11.37 h, while pneumonia episodes show medians of 11.47 and 10.22 h. Variability in ED duration

follows a similar pattern, with more compact distributions for fibrosis and lung cancer, and broader distributions for COPD and pneumonia across periods.

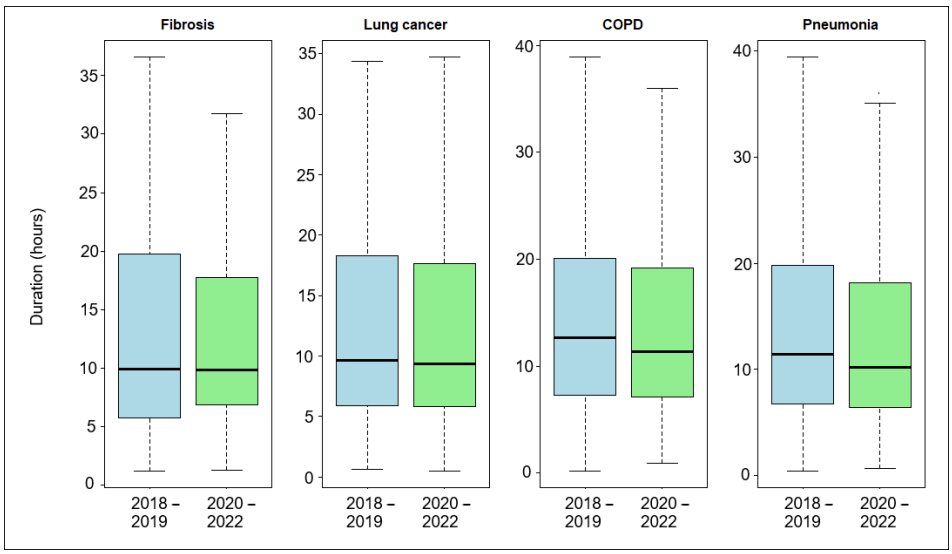


Figure 5. Distribution of duration in hours of ED episodes, divided into pre-COVID-19 and COVID-19 years. To note the decrease in the median duration for every disease.

3.3. Direct Transition Times and Process Maps

Direct transition times between healthcare episodes were analyzed at a macroscopic level, together with activity-level process maps. A direct transition refers to a transition between two episode types without intermediate episodes. Table 1 reports the average duration (in days) and frequency of selected transitions for each disease and period.

Table 1. Comparison of some direct transitions between episode types (Outpatient Visit (OV), Emergency Department (ED), Hospitalization (H)) for patients with cancer, fibrosis, COPD, and pneumonia during the pre-COVID-19 (2018–2019) and COVID-19 (2020–2022) periods. The table displays the average duration (in days) between transitions, the frequency of these transitions as a percentage of all episodes for each disease, and the change in duration (Delta) between the two periods.

	Ep. 1	Ep. 2	Pre-COVID Avg Duration (d)	Pre-COVID Freq.	COVID Avg Duration (d)	COVID Freq.	Delta Duration (d)
Cancer	OV	ED	13	36.0%	11.1	23.4%	−1.9
	OV	H	6.1	11.5%	8.5	8.3%	2.4
	H	OV	14.7	13.2%	13.1	12.1%	−1.6
	ED	OV	6.8	32.6%	6	25.1%	−0.8
	OV	OV	12.9	84.7%	8.1	83.7%	−4.8
Fibrosis	OV	ED	22.5	70.7%	33.6	50.9%	11.1
	OV	H	12.1	9.8%	3.3	5.3%	−8.8
	H	OV	17.4	9.8%	24.8	5.3%	7.4
	ED	OV	5.6	64.6%	4.1	59.6%	−1.5
	OV	OV	17	81.7%	23	80.7%	6
COPD	OV	ED	19.1	50.0%	15.2	46.2%	−3.9
	OV	H	13.9	41.6%	7.3	28.1%	−6.6
	H	OV	10.8	29.4%	13.9	32.7%	3.1
	ED	OV	6.2	61.9%	4.5	60.2%	−1.7
	OV	OV	7	55.9%	6.9	55.0%	−0.1
Pneumonia	OV	ED	38.9	36.2%	34.7	28.4%	−4.2
	OV	H	83.1	3.0%	6.3	1.9%	−76.8
	H	OV	41	2.6%	39.9	3.5%	−1.1
	ED	OV	11.5	47.5%	5	50.6%	−6.5
	OV	OV	9.1	36.2%	16.2	44.7%	7.1

Differences between periods are observed across several transitions. For example, the transition from outpatient visits to ED episodes for cancer patients shows values of 13 days in the pre-COVID-19 period and 11.1 days in the COVID-19 period. For COPD, the same transition shows 19.1 and 15.2 days, respectively. Transition frequencies also differ between periods. For instance, fibrosis patients show outpatient visit to ED transitions in 70.7% of cases in the pre-COVID-19 period and 50.9% in the COVID-19 period, while COPD patients show outpatient visit to hospitalization transitions in 41.6% and 28.1% of cases, respectively. Some transitions present higher durations in the COVID-19 period; for example, fibrosis patients show values of 22.5 and 33.6 days for outpatient visit to ED transitions.

At the activity level, process maps were generated for ED and hospitalization episodes for each disease in both periods. These maps represent the most frequent sequences of activities within episodes. Edge thickness reflects the proportion of cases following a given transition, and percentages are reported for both transitions and activities. Time annotations indicate median durations between or within activities. The GED analysis (Table 2) showed heterogeneous levels of structural change across diseases and settings. Hospitalization pathways for cancer and fibrosis exhibited minimal or no differences between periods, whereas emergency pathways displayed substantial structural modifications, reflected in higher GED values. COPD-related pathways showed moderate changes, with stable activity sets but several reconfigured transitions.

Table 2. Graph Edit Distance (GED) between pre-COVID-19 and COVID-19 process models.

Disease	Episode Type	GED Nodes	GED Arcs	GED Total
Cancer	Inpatient	0	0	0
Cancer	ED	7	15	22
Fibrosis	Inpatient	0	4	4
Fibrosis	ED	5	16	21
COPD	Inpatient	1	11	12
COPD	ED	1	11	12
Pneumonia	Inpatient	1	11	12
Pneumonia	ED	5	14	19

A selected example illustrates observed differences between periods. For COPD ED pathways (Figure 6), "*Chest X-ray 2 views or less*" is the initial activity in 71% of episodes in the pre-COVID-19 period, while "*Bedside chest X-ray*" is the initial activity in 63.6% of episodes in the COVID-19 period, with "*Chest X-ray 2 views or less*" accounting for 22.8%.

Across both ED and inpatient settings, the frequency of imaging activities showed clear shifts between the pre-COVID-19 and COVID-19 periods. As reported in Tables 3 and 4, chest X-ray examinations generally decreased across most diseases, while bedside chest X-ray increased, particularly in ED access. CT chest volumes remained comparatively stable, with only modest changes across diseases and care settings.

Beyond overall differences between periods, subgroup analyses based on episode duration revealed consistent patterns across diseases. Episodes lasting more than 30 days showed pathway structures that were broadly similar to those observed in the general population, with the same core set of activities and transitions represented in the process maps. However, these prolonged episodes exhibited a higher concentration of patients following the most common transitions. This effect was particularly evident in inpatient episodes for all diseases, where prolonged stays amplified the prominence of the main diagnostic and therapeutic sequences. In the ED setting, prolonged episodes were rare and observed almost exclusively in fibrosis, where a similar consolidation of pathway patterns was noted.

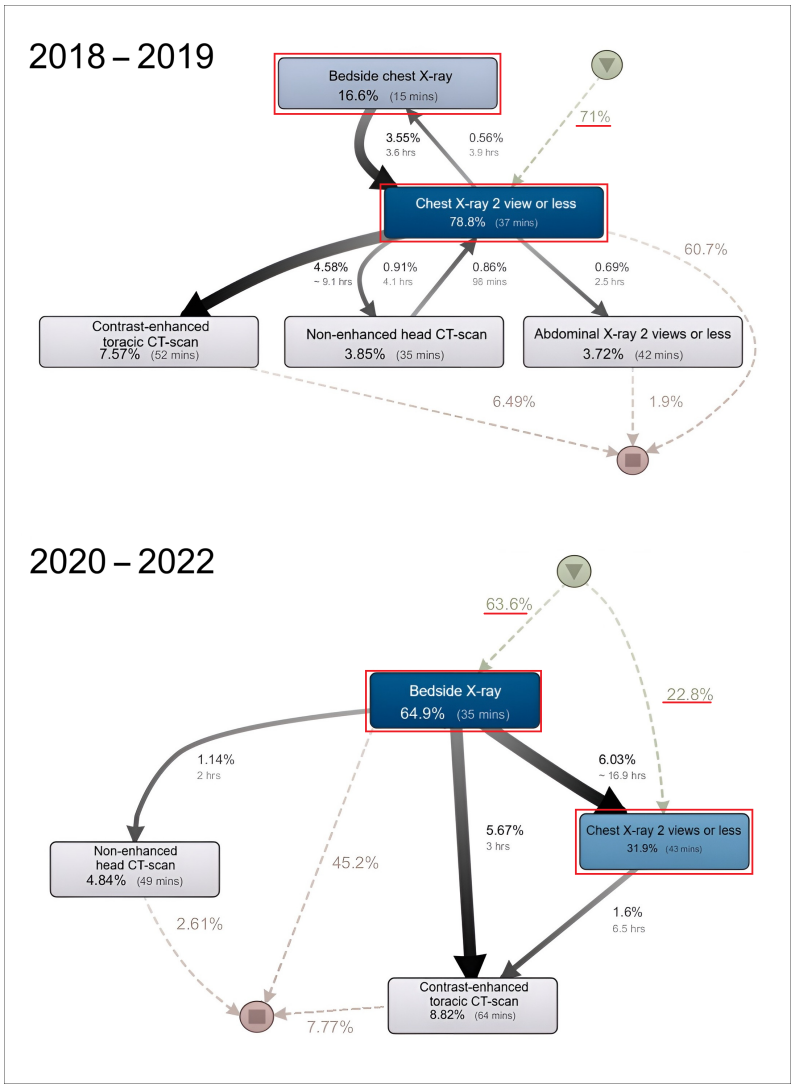


Figure 6. ED average trajectory for a patient with COPD, pre-COVID-19 era and COVID-19 era. To note the position of the two early-stage activities "Chest X-ray 2 views or less" and "Bedside chest X-ray", and the different percentage of patient performing the initial steps, all of them in red boxes or underlined in red. The map includes all activities and variants observed in the event log (100% activity and path coverage). Frequencies are calculated over all episodes in the corresponding cohort.

Table 3. Imaging activity frequencies for ED episodes in pre-COVID-19 vs. COVID-19 periods, stratified by disease. 'Avg. annual total' indicates the mean value of the yearly totals across the period.

Activity	Disease	Pre-COVID-19 Avg. Annual Total	COVID Avg. Annual Total	Delta	Delta (%)
Chest X-ray	Cancer	546	188	−358	−65.6
	Fibrosis	63	38	−25	−39.7
	COPD	0	0	0	0.0
	Pneumonia	1148	311	−837	−72.9
Bedside chest X-ray	Cancer	126	553	427	338.9
	Fibrosis	19	110	91	478.9
	COPD	430	1436	1006	234.0
	Pneumonia	207	750	543	262.3
CT chest	Cancer	217	236	19	8.8
	Fibrosis	41	43	2	4.9
	COPD	236	238	2	0.8
	Pneumonia	141	154	13	9.2

Table 4. Imaging activity frequencies for inpatient episodes in pre-COVID-19 vs. COVID-19 periods, stratified by disease. 'Avg. annual total' indicates the mean value of the yearly totals across the period.

Activity	Disease	Pre-COVID Avg. Annual Total	COVID Avg. Annual Total	Delta	Delta (%)
Chest X-ray	Cancer	5287	3906	−1381	−26.1
	Fibrosis	155	72	−83	−53.5
	COPD	0	0	0	0.0
	Pneumonia	452	297	−155	−34.3
Bedside chest X-ray	Cancer	2287	2250	−37	−1.6
	Fibrosis	159	91	−68	−42.8
	COPD	1375	869	−506	−36.8
	Pneumonia	435	515	80	18.4
CT chest	Cancer	204	161	−43	−21.1
	Fibrosis	34	35	1	2.9
	COPD	212	157	−55	−25.9
	Pneumonia	44	59	15	34.1

3.4. Diagnostic Timeliness, Episode Duration, and Readmissions

Table 5 reports diagnostic timeliness, episode duration, and 30-day readmission indicators for inpatient episodes across diseases and periods. Compliance with the 24-h imaging indicator remained relatively stable for cancer and MPOC, while remaining low for fibrosis and pneumonia. Median time to imaging was generally short for cancer and MPOC (20–34 h), but substantially longer for fibrosis and pneumonia (35–38 h), reflecting the presence of prolonged or complex inpatient trajectories. The proportion of episodes lasting more than 30 days was highest for fibrosis and pneumonia, and lower for MPOC (6%) and cancer (3%). The 30-day readmission rate showed modest differences between periods, decreasing for cancer (12.3% to 10.5%) and MPOC (15.1% to 14.2%), remaining stable for fibrosis (2.1% in both periods), and decreasing for pneumonia (1.3% to 0.0%).

Table 5. Summary of inpatient episode characteristics, including first imaging timeliness, first imaging compliance, prolonged length of stay (>30 days), and 30-day readmission rates. Period 1 refers to (2018–2019), while Period 2 refers to (2020–2022).

Disease	Period	Episode Count	Imaging Compliance (%)	Median First Imaging Time (h)	LOS >30 Days (%)	Readmission <30 Days (%)
Lung cancer	1	1640	60.98	19.93	2.99	12.3
	2	1547	61.54	20.02	2.71	10.5
Fibrosis	1	48	12.50	37.50	83.75	2.1
	2	48	10.42	36.23	81.67	2.1
COPD	1	1120	36.16	31.30	5.98	15.1
	2	966	32.61	34.05	5.59	14.2
Pneumonia	1	153	12.42	37.67	87.58	1.3
	2	153	21.57	35.20	84.97	0.0

Table 6 summarizes diagnostic timeliness and outcome indicators for ED episodes. Compliance with the 6-hour imaging indicator increased during the COVID-19 period for all diseases. Median time to imaging remained consistently rapid across diseases (1.8–2.7 h). As expected, the proportion of episodes lasting more than 30 days was negligible for most ED presentations, except for fibrosis, where it increased from 22.54% to 32.08%. The 30-day readmission rate was highest for cancer and COPD, moderate for pneumonia, and lowest for fibrosis. Differences between periods were modest and consistent with overall trends.

Table 6. Summary of ED episode characteristics, including first imaging timeliness, first imaging compliance, prolonged length of stay (>30 days), and 30-day readmission rates. Period 1 refers to (2018–2019), while Period 2 refers to (2020–2022).

Disease	Period	Episode Count	Imaging Compliance (%)	Median First Imaging Time (h)	LOS >30 Days (%)	Readmission <30 Days (%)
Lung cancer	1	1351	45.30	2.73	0.00	23.6
	2	1284	59.35	2.03	0.00	19.6
Fibrosis	1	142	51.41	2.13	22.54	5.6
	2	159	74.84	1.85	32.08	4.4
COPD	1	2315	86.83	2.12	0.00	23.5
	2	2188	88.35	1.80	0.00	21.7
Pneumonia	1	1376	72.97	2.22	0.00	19.9
	2	1381	77.84	1.90	0.00	19.5

3.5. Statistical Significance on Episodes Duration

Table 7 reports p-values from Mann–Whitney U tests comparing episode durations between pre-pandemic and pandemic periods. For hospitalization episodes no comparisons reached statistical significance. For ED episodes, comparisons for COPD ($p = 0.0199$) and Pneumonia ($p = 0.0104$) were statistically significant at $\alpha = 0.05$. After applying a Bonferroni correction for eight comparisons (adjusted $\alpha = 0.00625$), none of the Mann–Whitney U tests remain statistically significant. This confirms that differences in episode duration between periods are small and consistent with the descriptive patterns observed in the pathway analyses.

Table 7. Mann–Whitney U tests comparing episode duration between periods for each disease and episode type. A Bonferroni correction was applied for eight comparisons ($\alpha = 0.00625$). None of the contrasts remain statistically significant after correction, consistent with the descriptive nature of the study.

Disease	Episode Type	*p*-Value	Bonferroni-Adjusted α	Significant After Correction
Cancer	Inpatient	0.3270	0.00625	No
Cancer	ED	0.0412	0.00625	No
Fibrosis	Inpatient	0.6125	0.00625	No
Fibrosis	ED	0.0881	0.00625	No
COPD	Inpatient	0.0723	0.00625	No
COPD	ED	0.0199	0.00625	No
Pneumonia	Inpatient	0.1542	0.00625	No
Pneumonia	ED	0.0104	0.00625	No

4. Discussion

Across the four diseases considered, differences are observed in both episode durations and transition times. In particular, inpatient and ED episodes show shorter median durations for several conditions, while other diseases present limited or no variation. Similarly, transition times between episodes tend to be shorter in several cases, although increases are also observed for specific disease–transition combinations. These results highlight that differences are not uniform across diseases or care settings.

At the activity level, process maps provide additional detail on how care processes differ across periods. For example, for COPD patients in the ED, the most frequent starting activity differs markedly between periods, with a higher share of bedside imaging in the COVID-19 period. This change suggests a reconfiguration in how early diagnostic steps are performed within ED episodes. Such a shift may reflect pandemic-related adaptations, such as reduced patient movement to limit infection risk and changes to emergency triage policies. Overall, the GED analysis shows heterogeneous effects of the pandemic on pathway

structures. Emergency trajectories for several conditions experienced substantial reconfiguration, whereas inpatient pathways—such as lung cancer hospitalization—remained structurally stable, with differences emerging mainly in timing rather than in activity sequences. For example, shorter intervals between repeated imaging activities were observed, consistent with the reduction in episode duration at the aggregate level. In parallel with these structural patterns, the frequency analysis of imaging activities provides additional context on how care processes shifted across periods. In both ED and inpatient settings, conventional chest X-ray decreased while bedside radiography increased, indicating a reorganization of early diagnostic steps consistent with the changes observed in the process maps. CT chest volumes remained comparatively stable, aligning with the overall structural stability captured by the GED analysis for several inpatient pathways. These quantitative differences in activity use complement the pathway-level findings and reinforce the notion that pandemic-related adaptations affected not only the sequencing of activities but also the operational modalities through which they were delivered. Taken together, these observations suggest that clinical pathways may combine structural stability with variability in timing and execution. Differences across diseases further indicate that pathway behavior is condition-specific and may vary depending on clinical characteristics and care processes.

The variability observed in activity durations and transition times also highlights the heterogeneity of clinical workflows. In particular, the time between request and completion of exams or procedures shows mixed patterns, with both shorter and longer durations observed across different activities and diseases. This heterogeneity suggests that aggregate indicators, such as median duration, may mask more complex underlying dynamics at the activity level. For inpatient episodes, compliance with the 24-h imaging indicator remained relatively stable for lung cancer and COPD, while remaining low for fibrosis and pneumonia. These differences likely reflect underlying clinical heterogeneity: patients with chronic fibrotic disease or severe pneumonia often follow prolonged and complex inpatient trajectories, as also indicated by the high proportion of episodes exceeding 30 days in these groups. The stability of compliance rates across periods suggests that, despite operational pressures during the pandemic, hospitals maintained broadly comparable diagnostic timelines for most inpatient respiratory conditions. In the emergency department, imaging timeliness improved across all diseases during the COVID-19 period. This finding aligns with reports of reorganized ED workflows and increased reliance on rapid imaging for respiratory presentations during the pandemic. The consistently short median time to imaging (2 h) across both periods further supports the notion that ED diagnostic processes remained resilient, even under increased demand.

Outcome-related indicators provide additional context. The 30-day readmission rate showed only modest differences between periods, with slight reductions for cancer and COPD and stable values for fibrosis and pneumonia. These patterns suggest that continuity of care and post-discharge stability were not markedly affected by the pandemic, at least within the scope of what can be inferred from administrative event logs. Similarly, the proportion of episodes lasting more than 30 days remained largely unchanged across periods, indicating that the pandemic did not substantially alter the distribution of prolonged or complex inpatient trajectories.

This study is descriptive in nature and does not aim to test formal hypotheses or infer causal differences between periods. Statistical tests are therefore used only as supplementary summaries of distributional contrasts, while the main conclusions rely on the structural and temporal characterization of clinical pathways. Because multiple comparisons were performed across diseases and episode types, we report adjusted significance levels for completeness; however, these corrections do not materially change the interpretation of the

results. Differences in episode duration and activity use remain small in magnitude and consistent with the descriptive patterns observed in the pathway and transition analyses.

This study has several important limitations. First, the analysis is purely descriptive and does not aim to establish causal relationships. Therefore, it is not possible to infer any direct impact of COVID-19 on clinical pathways, patient outcomes, or healthcare system performance. The dataset does not include information on air pollution or other environmental exposures, which are known to influence the incidence and severity of pulmonary diseases. The absence of such variables limits the ability to account for potential environmental confounding. Future research should integrate air quality indicators and other environmental data to provide a more comprehensive understanding of pathway variations and their determinants. The study includes limited clinical or performance indicators, which limits the ability to assess whether the observed differences are associated with changes in care quality or patient outcomes. Furthermore, the analysis is based on data from a single institution, which may limit the generalizability of the findings.

Differences observed between the two periods should be interpreted with caution. Although the COVID-19 pandemic represents a major contextual disruption, the observed variations in episode counts, durations, and transitions may also reflect non-pandemic factors. These include secular trends in service utilization, evolving hospital policies, changes in clinical prioritization, shifts in patient case mix or disease severity, and temporary access restrictions or patient avoidance of care. As such, the findings describe temporal changes in clinical pathways but do not isolate the specific contribution of the pandemic.

These limitations position this work as a preliminary, data-driven characterization of clinical pathways. Future research could extend the analysis by incorporating post-COVID-19 data to assess longer-term trends, integrating clinical and performance indicators to evaluate care quality, and applying analytical approaches aimed at assessing potential causal relationships.

Despite these limitations, the study illustrates the value of process mining as a tool for analyzing real-world healthcare data. By combining episode-level and activity-level perspectives, it enables a detailed representation of patient pathways across different care settings. Such descriptive analyses can support further investigations and provide a foundation for more advanced analytical approaches in healthcare analytics.

5. Conclusions

This study presents a descriptive analysis of clinical pathways for pulmonary patients at a specialized hospital, comparing patterns observed across two periods using process mining techniques.

The results highlight differences in the number, duration, and sequencing of episodes across inpatient, ED, and outpatient settings. In particular, shorter episode durations are observed for several conditions, alongside variations in transition times between episodes and changes in activity-level pathways. These differences, however, are not uniform across diseases or care processes, and considerable variability is observed across indicators. At a more detailed level, process maps show that clinical pathways combine stable structural components, such as consistent sequences of activities, with variations in timing and execution. Differences in the frequency of specific activities and in time intervals between them further illustrate the heterogeneity of care processes across diseases and settings.

Overall, this study highlights the potential of process mining for analyzing real-world healthcare data and describing patient pathways across multiple levels of care. Such descriptive analyses provide a foundation for more advanced investigations in healthcare analytics and can support the development of data-driven approaches to better understand healthcare processes.

Author Contributions: Conceptualization, L.M. and P.L.; methodology, L.M.; software, L.M.; validation, P.L., J.-B.G. and A.C.; formal analysis, L.M.; resources, A.C.; data curation, L.M.; writing—original draft preparation, L.M.; writing—review and editing, P.L.; visualization, L.M.; supervision, P.L.; project administration, A.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to privacy restrictions.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Institute for Health Metrics and Evaluation. Chronic Respiratory Diseases. Available online: https://www.healthdata.org/research-analysis/diseases-injuries-risks/factsheets/2021-chronic-respiratory-diseases-level-2 (accessed on 25 May 2026).
2. World Health Organization. Chronic Obstructive Pulmonary Disease (COPD). Available online: https://www.who.int/news-room/fact-sheets/detail/chronic-obstructive-pulmonary-disease-(copd) (accessed on 2 June 2026).
3. Institute for Health Metrics and Evaluation (IHME). Global Burden of Disease 2023: Findings from the GBD 2023 Study. 2025. Available online: https://www.healthdata.org/research-analysis/library/global-burden-disease-2023-findings-gbd-2023-study (accessed on 25 June 2026).
4. World Health Organization. Lung Cancer. Available online: https://www.who.int/news-room/fact-sheets/detail/lung-cancer (accessed on 2 June 2026).
5. Government of Canada. Canadian Chronic Disease Surveillance System. Available online: https://health-infobase.canada.ca/ccdss/data-tool/ (accessed on 31 May 2026).
6. Public Health Agency of Canada. Canadian Chronic Disease Surveillance System (CCDSS) Data Tool. 2026. Available online: https://health-infobase.canada.ca/ccdss/data-tool/index?G=00&V=7 (accessed on 25 June 2026).
7. Brenner, D.R.; Gillis, J.; Demers, A.A.; Ellison, L.F.; Ng, C.; Zhang, S.X.; Finley, C.; Fitzgerald, N.; Saint-Jacques, N.; Shack, L.; et al. Projected estimates of cancer in Canada in 2026. *CMAJ* **2026**, *198*, E526–E534. [CrossRef] [PubMed]
8. Amegadzie, J.E.; Lee, T.Y.; Sadatsafavi, M.; Lynd, L.D.; Sin, D.D.; Johnson, K.M. Trends in hospital admissions for chronic obstructive pulmonary disease over 16 years in Canada. *CMAJ* **2023**, *195*, E1172–E1179. [CrossRef] [PubMed]
9. Vatrella, A.; Maglio, A.A.; Di Palo, M.P.; Garofano, M.; Falco, A.; Ragusa, C.M.; Andretta, V.; Pessolano, C.; Marino, A.; Calabrese, M.; et al. Unburdening healthcare systems through telenursing in chronic respiratory disease management: A systematic review. *Front. Digit. Health* **2026**, *8*, 1746693. [CrossRef] [PubMed]
10. Vadlamudi, N.K.; Gomes, K.; Chow, E.; Bourdeau, M.; Embree, J.; Halperin, S.A.; Jadavji, T.; Kazmi, K.; Langley, J.M.; Le Saux, N.; et al. Healthcare costs and resource utilization for acute respiratory syncytial virus pediatric hospitalizations in Canada: A population-based study. *Lancet Reg. Health Am.* **2025**, *51*, 101257. [CrossRef] [PubMed]
11. Moynihan, R.; Sanders, S.; Michaleff, Z.A.; Scott, A.M.; Clark, J.; To, E.J.; Jones, M.; Kitchener, E.; Fox, M.; Johansson, M.; et al. Impact of COVID-19 pandemic on utilisation of healthcare services: A systematic review. *BMJ Open* **2021**, *11*, e045343. [CrossRef] [PubMed]
12. Sabetkish, N.; Rahmani, A. The overall impact of COVID-19 on healthcare during the pandemic: A multidisciplinary point of view. *Health Sci. Rep.* **2021**, *4*, e386. [CrossRef] [PubMed]
13. Institut National de Santé Publique du Québec. Données COVID-19 au Québec. 2026. Available online: https://www.inspq.qc.ca/covid-19/donnees (accessed on 25 June 2026).
14. Canadian Institute for Health Information. Overview: COVID-19's Impact on Health Care Systems. 2026. Available online: https://www.cihi.ca/en/covid-19-resources/impact-of-covid-19-on-canadas-health-care-systems/the-big-picture (accessed on 25 June 2026).
15. Institut de la statistique du Québec. Population—Effectifs et Proportions Selon les Groupes D'âge. 2026. Available online: https://statistique.quebec.ca/vitrine/vieillissement/themes/population/effectifs-proportions-groupes-age (accessed on 25 June 2026).
16. Adeloye, D.; Song, P.; Zhu, Y.; Campbell, H.; Sheikh, A.; Rudan, I.; NIHR RESPIRE Global Respiratory Health Unit. Global, regional, and national prevalence of, and risk factors for, chronic obstructive pulmonary disease (COPD) in 2019: A systematic review and modelling analysis. *Lancet Respir. Med.* **2022**, *10*, 447–458. [CrossRef] [PubMed]

17. Association Pulmonaire du Quebec. Available online: https://poumonquebec.ca/sante-pulmonaire/maladies-pulmonaires/ (accessed on 3 May 2026).
18. Gartner, J.; Abasse, K.; Bergeron, F.; Landa, P.; Lemaire, C.; Côté, A. Definition and conceptualization of the patient-centered care pathway, a proposed integrative framework for consensus: a Concept analysis and systematic review. *BMC Health Serv. Res.* **2022**, *22*, 558. [CrossRef] [PubMed]
19. Lawal, A.K.; Rotter, T.; Kinsman, L.; Machotta, A.; Ronellenfitsch, U.; Scott, S.D.; Goodridge, D.; Plishka, C.; Groot, G. What is a clinical pathway? Refinement of an operational definition to identify clinical pathway studies for a Cochrane systematic review. *BMC Med.* **2016**, *14*, 35. [CrossRef] [PubMed]
20. Aspland, E.; Gartner, D.; Harper, P. Clinical pathway modelling: A literature review. *Health Syst.* **2019**, *10*, 1–23. [CrossRef] [PubMed]
21. Mans, R.S.; Van der Aalst, W.; Vanwersch, R.J.B. *Process Mining in Healthcare: Evaluating and Exploiting Operational Healthcare Processes*, 2015th ed.; SpringerBriefs in Business Process Management, Springer: Berlin/Heidelberg, Germany, 2015. [CrossRef]
22. Allen, D.; Gillen, E.; Rixson, L. The effectiveness of integrated care pathways for adults and children in health care settings: A systematic review. *JBI Evid. Synth.* **2009**, *7*, 80–129. [CrossRef] [PubMed]
23. Guzzo, A.; Rullo, A.; Vocaturo, E. Process mining applications in the healthcare domain: A comprehensive review. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2022**, *12*, e1442. [CrossRef]
24. Martin, N.; De Weerdt, J.; Fernández-Llatas, C.; Gal, A.; Gatta, R.; Ibáñez, G.; Johnson, O.; Mannhardt, F.; Marco-Ruiz, L.; Mertens, S.; et al. Recommendations for enhancing the usability and understandability of process mining in healthcare. *Artif. Intell. Med.* **2020**, *109*, 101962. [CrossRef] [PubMed]
25. Arias, M.; Rojas, E.; Aguirre, S.; Cornejo, F.; Munoz-Gama, J.; Sepúlveda, M.; Capurro, D. Mapping the patient's journey in healthcare through process mining. *Int. J. Environ. Res. Public Health* **2020**, *17*, 6586. [CrossRef] [PubMed]
26. Munoz-Gama, J.; Martin, N.; Fernandez-Llatas, C.; Johnson, O.A.; Sepúlveda, M.; Helm, E.; Galvez-Yanjari, V.; Rojas, E.; Martinez-Millana, A.; Aloini, D.; et al. Process mining for healthcare: Characteristics and challenges. *J. Biomed. Inform.* **2022**, *127*, 103994. [CrossRef] [PubMed]
27. Martin, N.; Wittig, N.; Munoz-Gama, J., Using Process Mining in Healthcare. In *Process Mining Handbook*; van der Aalst, W.M.P.; Carmona, J., Eds.; Springer International Publishing: Cham, Switzerland, 2022; pp. 416–444. [CrossRef]
28. Woolliscroft, J.O. Innovation in response to the COVID-19 pandemic crisis. *Acad. Med.* **2020**, *95*, 1140–1142. [CrossRef] [PubMed]
29. Rodríguez-Leor, O.; Cid-Álvarez, B.; Ojeda, S.; Martín-Moreiras, J.; Ramón Rumoroso, J.; López-Palop, R.; Serrador, A.; Cequier, Á.; Romaguera, R.; Cruz, I.; et al. Impact of the COVID-19 pandemic on interventional cardiology activity in Spain. *REC Interv. Cardiol.* **2020**, *2*, 82–89. [CrossRef]
30. Markus, H.S.; Brainin, M. COVID-19 and stroke-A global World Stroke Organization perspective. *Int. J. Stroke* **2020**, *15*, 361–364. [CrossRef] [PubMed]
31. Ganjali, R.; Jajroudi, M.; Kheirdoust, A.; Darroudi, A.; Alnattah, A. Telemedicine solutions for clinical care delivery during COVID-19 pandemic: A scoping review. *Front. Public Health* **2022**, *10*, 937207. [CrossRef] [PubMed]
32. Muhrer, J.C. Risk of misdiagnosis and delayed diagnosis with COVID-19: A Syndemic Approach. *Nurse Pract.* **2021**, *46*, 44–49. [CrossRef] [PubMed]
33. Matos, L.L.; Forster, C.H.Q.; Marta, G.N.; Castro Junior, G.; Ridge, J.A.; Hirata, D.; Miranda-Filho, A.; Hosny, A.; Sanabria, A.; Gregoire, V.; et al. The hidden curve behind COVID-19 outbreak: the impact of delay in treatment initiation in cancer patients and how to mitigate the additional risk of dying-the head and neck cancer model. *Cancer Causes Control* **2021**, *32*, 459–471. [CrossRef] [PubMed]
34. Brambilla, A.; Sun, T.Z.; Elshazly, W.; Ghazy, A.; Barach, P.; Lindahl, G.; Capolongo, S. Flexibility during the COVID-19 pandemic response: Healthcare facility assessment tools for resilient evaluation. *Int. J. Environ. Res. Public Health* **2021**, *18*, 11478. [CrossRef] [PubMed]
35. Heffron, R.J.; Körner, M.F.; Schöpf, M.; Wagner, J.; Weibelzahl, M. The role of flexibility in the light of the COVID-19 pandemic and beyond: Contributing to a sustainable and resilient energy future in Europe. *Renew. Sustain. Energy Rev.* **2021**, *140*, 110743. [CrossRef] [PubMed]
36. Puthur, C.; Aljebreen, A.; McInerney, C.; Mebrahtu, T.; Lawton, T.; Johnson, O. Measuring the impact of COVID-19 on hospital care pathways. In *Lecture Notes in Business Information Processing*; Springer Nature Switzerland: Cham, Switzerland, 2023; pp. 391–403. [CrossRef]
37. Murazzano, L.; Landa, P.; Gartner, J.B.; Raki, M.H.; Côté, A. Clinical pathways discovery for long-term and chronic patients: A process mining approach. *Comput. Biol. Med.* **2026**, *204*, 111539. [CrossRef] [PubMed]
38. Gartner, J.B.; Côté, A. Optimization of care pathways through technological, clinical, organizational and social innovations: A qualitative study. *Health Serv. Insights* **2023**, *16*, 11786329231211096. [CrossRef] [PubMed]
39. Disco by Fluxicon. Available online: https://fluxicon.com/disco/ (accessed on 25 May 2026).

40. National Institute for Health and Care Excellence (NICE). Idiopathic Pulmonary Fibrosis in Adults: Diagnosis and Management (NICE Clinical Guideline CG163). 2013. Available online: https://www.nice.org.uk/guidance/cg163 (accessed on 26 June 2026).
41. National Institute for Health and Care Excellence (NICE). Chronic Obstructive Pulmonary Disease in Over 16s: Diagnosis and Management (NICE Guideline NG115). 2018. Available online: https://www.nice.org.uk/guidance/ng115 (accessed on 26 June 2026).
42. National Institute for Health and Care Excellence (NICE). Lung Cancer: Diagnosis and Management (NICE Guideline NG122). 2019. Available online: https://www.nice.org.uk/guidance/ng122 (accessed on 26 June 2026).
43. National Institute for Health and Care Excellence (NICE). Pneumonia in Adults: Diagnosis and Management (NICE Guideline NG250). 2023. Available online: https://www.nice.org.uk/guidance/ng250 (accessed on 26 June 2026).
44. Tanabe, N.; Nakagawa, H.; Sakao, S.; Ohno, Y.; Shimizu, K.; Nakamura, H.; Hanaoka, M.; Nakano, Y.; Hirai, T. Lung imaging in COPD and asthma. *Respir. Investig.* **2024**, *62*, 995–1005. [CrossRef] [PubMed]
45. Hettmansperger, T.P.; McKean, J.W. *Robust Nonparametric Statistical Methods*; Kendall's Library of Statistics; Edward Arnold: London, UK; John Wiley & Sons, Inc.: New York, NY, USA, 1998; Volume 5, p. 467.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.