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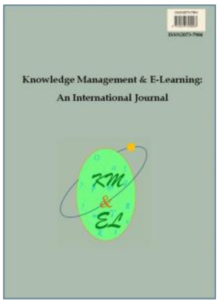

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Process mining leveraging the analysis of patient journey and outcomes: Stroke assistance during the Covid-19 pandemic

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Abstract: The patient journey had to be modified because of the Covid-19 pandemic, causing insecurity, especially in health conditions in a time-sensitive treatment. Identifying these changes and their consequences is essential to improving the healthcare process and guaranteeing patient safety. Process mining (PM) helps evaluate the patient journey discovering care delays, bottlenecks, and non-conformities. This paper aims to apply PM to discover and analyze the patient pathway during stroke care in two different contexts, before and after the Covid-19 outbreak, and to correlate these pathways to patient outcomes. It was a retrospective cross-sectional study including 509 analyzed event logs, employing the most relevant population-based stroke registry of Latin America. Two process models were uncovered to illustrate the patient journey before and during the pandemic. The main findings were the worsening of the patient's health status at their hospital admission, the reduction of hospitalization time, the increased delay for receiving reperfusion therapies after hospital admission, and the preference for the referral hospital instead of emergency services. PM assisted in identifying time-sensitive events and allowed the improvement of patient safety. This methodology can be replicated in other healthcare studies.

Keywords: Process mining; Patient journey; Progressive patient care; Stroke

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1. Introduction

The patient journey consists of spatio-temporal distribution of patient interactions with several care settings (Carayon et al., 2020); the trajectory in health care can be defined within this journey as "the assembling, scheduling, monitoring, and coordinating of all necessary steps to complete the work of patient care. The term trajectory refers not only to the pathophysiological process of a patient's disease state, but also to the total organization of work done throughout all nurse and patient interactions and the impact of patient care processes on those interactions and the organization" (Alexander, 2007).

In this context, when patients are transferred from one care setting to another, a high-risk care process, called transition of care, occurs (Clancy, 2006). It represents an interruption in the continuity of the patient journey and requires transferring all relevant information from one entity to the subsequent and transferring authority and responsibility (Cook et al., 2000; Beach et al., 2003; Wears et al., 2004). Miscommunications and inconsistencies threaten the quality and safety of care during this transition (Beach et al., 2003; Carayon & Wood, 2009; Schultz et al., 2007). Concerns for patient safety arise if important information is incorrectly or incompletely transferred and can negatively impact patient care, such as delays in treatment and adverse events (Wears et al., 2003; Carayon & Wood, 2009).

Therefore, the patient journey can be audited by mapping the healthcare process to identify problems and propose improvements in the quality and efficiency of clinical management. The patient´s journey map shows each interactive touchpoint that the patient experiences during the continuation of care, providing a visual presentation of the complete route a patient follows during all stages of a care trajectory. It allows the visualization and comprehension of the patient's experience once it separates the management or treatment of a specific condition into consecutive events or steps. The sequence between two steps in the patient journey is a patient pathway or care process (Kim et al., 2006; Trebble et al., 2010; Joseph et al., 2020; Borycki et al., 2020).

The background of Process Mining (PM) is a relatively young research discipline that can be a valuable strategy to uncover actual processes, like patient pathways, verify compliance of health practices, and obtain bottleneck insights by extracting knowledge from event logs. These event logs are obtained from data stored on databases, such as healthcare information systems, allowing the discovery of the healthcare process. An event log can be viewed as a set of traces, each containing activities executed for a particular process instance, and it may come from more than one single source of information (Rojas et al., 2016; van der Aalst, 2011).

Although healthcare processes are complex and subject to significant variations over time due to multiple factors (such as different conditions of patients and sequences in which activities can be performed), PM can promote additional benefits for improving the healthcare process. Identifying bottlenecks, performance analysis, reduction of waiting and servicing times, collaboration among peers, and prediction of patient's behaviour according to previous cases are some examples (Homayounfar, 2012; Rojas et al., 2016; Arias et al., 2020).

In the first half of 2020, Covid-19 reached pandemic proportions, affecting millions of people worldwide. Since the outbreak, many countries have adopted unprecedented social distancing measures such as closing borders and establishing nationwide lockdowns (Remuzzi & Remuzzi, 2020; Rosenbaum, 2020). This scenario inevitably disrupted the operation of healthcare services all over the world. Suspension of routine care activities, changes in medical protocols, and a sharp decrease in the number of emergency department visits by patients with non-related Covid-19 symptoms were reported in several countries (Baracchini et al., 2020).

Diversion of healthcare resources, insufficient medical supplies, and capable professionals threaten the quality of care of other health conditions. Therefore, the prevention and treatment of chronic diseases, like stroke, are at risk of being neglected (Bersano et al., 2020; Markus & Brainin, 2020). Consequently, it is necessary to evaluate the new patient journey considering patient safety, effectiveness, and performance.

Thus, the objective of this paper is to apply process mining to discover, compare, and analyze the patient pathway in two different contexts, before and after the Covid-19 outbreak, and to correlate these pathways to patient outcomes. Then, employing the most relevant population-based stroke registry of Latin America, the stroke patient journey was analyzed considering aspects related to the transition of care that can affect the patient outcome: transportation to the referral hospital (Mobile Emergency Medical Services named as "SAMU", private car or private ambulance), whether the patient went to a non-reference healthcare service (as non-reference public hospital or a public emergency care unit), before admission to the referral hospital, and the patient's location when symptoms started.

Since stroke treatment is time-sensitive, the pandemic may threaten the number of patients receiving treatment within the therapeutic window that represents the best moment for intervening in cerebral ischemia's pathological process and minimizing damage to the central nervous system (Fisher & Garcia, 1996). However, this window lasts only a few hours, so any change in the onset-to-door-time (interval of time between the onset of stroke symptoms and the admission to the referral hospital) can indirectly affect the patient outcome - measured by the Modified Rankin Scale (mRS), which classifies the degree of disability or dependence in patients who have suffered a stroke. The score varies from 0 to 6, whereas 0 indicates a patient with no symptoms and 6 indicates the worst possible outcome (death) (Baggio et al., 2014).

This analysis is relevant because the aspects analyzed in this study go beyond the intra-hospital pathway and contemplate the transitions of care affecting the patient safety and consequently their outcome. Furthermore, PM can assist in identifying time-sensitive care locations, working as a tool to improve patient outcomes and reduce possible disabilities, allowing stakeholders to intervene in the patient journey, and improving patient safety management. Additionally, this methodology can be replicated to analyze the patient journey of other healthcare conditions.

2. Methods

This paper presents a retrospective cross-sectional study, and its methodology was based on the "Process Mining Manifesto" (van der Aalst et al., 2012), which describes a method composed of five stages (0 to 4). Stage 0 includes planning and justification. Available data and domain are assimilated in this step. The justification consists of several changes to the stroke patient journey during the Covid-19 pandemic (Diegoli et al., 2020) and it is necessary to analyze and evaluate the now modified patient pathways for improving the healthcare system.

Data from a population-based stroke registry called Joinvasc (https://vbhcprize.com/joinvasc-stroke-program/) were used in this study. This database is included in a stroke care program established in Joinville, Brazil, to improve stroke prevention and patient outcome. It includes clinical and epidemiological data, patient-reported outcomes, radiological and genetic information for the complete care cycle (up to date five years after stroke). The data sources are patient electronic healthcare records, medical history taking, telephone assessment, and others.

In Stage 1, it must be defined which data will be used in the analysis. After this, data extraction from the information system is performed. Event logs were analyzed from electronic healthcare records of 509 stroke patients of a public hospital in the state of Santa Catarina from October 2, 2019, to August 31, 2020. The data sample was divided into two groups based on the same number of days (166 days). The time frame of the first group spans from October 2, 2019, to March 16, 2020, and 241 electronic healthcare records were included in this group. The second group consists of 268 electronic healthcare records, and its time frame was from March 17, 2020, to August 31, 2020. This initial date was chosen since it represents the start of Santa Catarina's social distancing measures.

The variables analyzed were timestamped based on the first symptoms, the location where the help was requested, the timestamp of the patient's request for help, transportation to the stroke referral hospital, the timestamp of admission to the referral hospital, mRS score at the referral hospital admission, whether reperfusion therapies (thrombolysis, thrombectomy) were done, the timestamp of reperfusion therapies and the patient mRS score at hospital discharge.

The mRS is used by the Joinvasc team to measure the degree of disability or dependence in the daily activities of people who have suffered a stroke. There is excellent reliability, feasibility, and inter-rater agreement from mRS, and it is measured through face-to-face and telephone assessments. The score varies from 0 to 6, whereas 0 indicates the patient who had the least possible sequelae and 6 indicates the worst outcome, in this case, death (Baggio et al., 2014). To simplify the presentation of results, the mRS score was grouped into different ranges: 0-1 (no disability and/or no significant disability), 2-3 (slight and/or moderate disability), 4-5 (moderate to severe and/or severe disability) and 6 (death). Table 1 presents the mRS classification and description.

The control-flow model was constructed and linked to event logs in Stage 2. At that moment, PM techniques are executed, and event logs may be filtered and tested employing a specialized model (Song & van der Aalst, 2008). In this study, after the data extraction from the information system, data were pre-processed, excluding missing, incomplete, and undefined values in an Excel spreadsheet. The sample was separated into two Excel files: before and after the Covid-19 outbreak for the analysis. Subsequently, the Disco toolkit from Fluxicon was used to discover the process model.

Table 1
Modified rankin scale (Baggio et al., 2014)

Score	mRS Classification	Description
0	No Disability	No symptoms at all.
1	No Significant Disability	Able to perform all usual duties and activities.
2	Slight Disability	Unable to perform all pre-stroke activities but able to look after own affairs without assistance.
3	Moderate Disability	Requires some external help but can walk without the assistance of another individual.
4	Moderate Severe Disability	Unable to attend to own bodily needs without assistance but not bedridden.
5	Severe Disability	Bedridden, incontinent, requires continuous care.
6	Dead	Dead.

A CSV or Excel file is input into the Disco software, enabling the configuration of which columns are assigned to 'caseID,' 'timestamps,' 'activity names,' and the definition of other attributes that should be included in the analysis after the file is imported. The Disco miner is based on the Fuzzy Miner combined with process metrics and modelling strategies (Günther & Rozinat, 2012). Therefore, it is possible to export temporal analysis to a CSV file using the software. We exported both files "before the Covid-19 outbreak" and "after the Covid-19 outbreak", which were integrated using Excel to facilitate some evaluations.

Other process perspectives were analyzed in Stage 3, such as timestamps and resources. In this phase, a specialist knowledgeable on the stroke patient journey helped us understand the processes discovered and relevant findings. The models discovered in Stage 3 could then be used in Stage 4 for making interventions, predictions, and recommendations. The results of Stages 2 and 3 are presented in the "Results" section of this paper.

3. Results

The PM techniques discovered two process models that illustrate the stroke patient journey before (Process Model 1) and during the Covid-19 pandemic (Process Model 2), highlighting the different touchpoints in the healthcare pathway in stroke care. They are presented in Fig. 1 and Fig. 2: the first figure shows the mean duration between different events of stroke care pathways before the Covid-19 pandemic, and the second figure presents the same information but during the Covid-19 pandemic.

In both figures, the inverted triangle indicates the start of the flowchart, the rectangles represent the events (which vary in color according to the amount of time spent: the "lighter" color indicates a shorter duration, and the "reddish" color indicates a longer duration), the arrows represent the pathway followed (which vary in width and color according to the time performance of each path), the numbers next to the arrows represent the mean time between events and the end of the flowchart is indicated by the square inside the red circle.

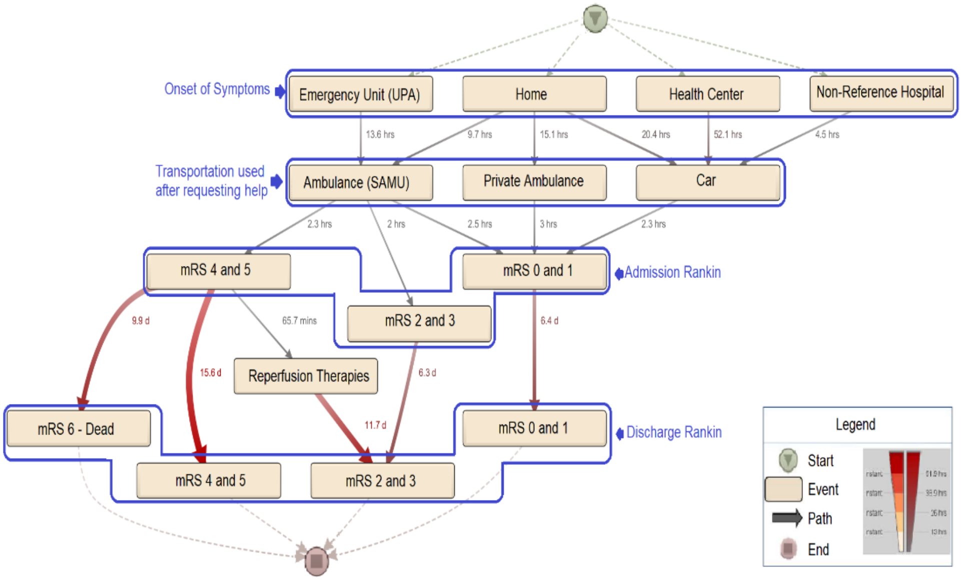

Fig. 1. Analysis of the mean duration between events of the stroke care before Covid-19 pandemic

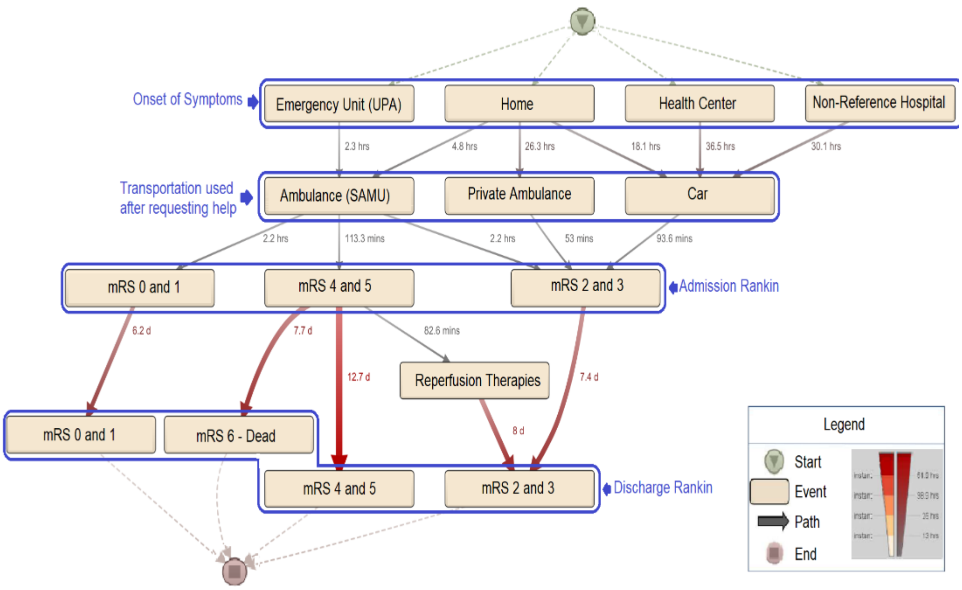

Fig. 2. Time analysis of patients' stroke assistance during Covid-19 pandemic (mean duration)

The time frame from the onset of symptoms until the request for help was analyzed considering the transportation mode. In both process models, SAMU is mainly called by the Emergency Unit (UPA) and by the patient at home. Although SAMU is a public and free of charge service, public and private health centers and non-reference hospitals rarely call this transportation mode. A private car is the most commonly used transportation. Furthermore, before the Covid-19 pandemic, the most prolonged mean duration from onset of symptoms until the request for help occurred when the patient was either at "Health Center" or "Home". During the pandemic, on the other hand, the most extended mean duration occurs when the patient departs from a "Health Center" or a "Non-Reference Hospital". Therefore, when the patient goes to a "Health Center" after the onset of symptoms, a longer delay to the correct treatment is verified.

During the pandemic, a decrease was noted in the mean transfer duration between UPA and the referral hospital when using SAMU. Good performance was observed when "private ambulance" is called, as displayed in Fig. 1 and Fig. 2. However, when a "private ambulance" is chosen, the time between the onset of symptoms and the request for this service is more prolonged; one hypothesis that could explain this finding is the high cost of this service. The mean hospitalization time of patients admitted and discharged on mRS between 4 and 5 decreased from 15.6 days to 12.7 days after the Covid-19 outbreak. It illustrates a reduction of hospitalization time when comparing the two process models.

The mean delay for receiving "Reperfusion Therapies" after hospital admission increased from 65.5 minutes (before the Covid-19 pandemic) to 82.2 minutes during the pandemic period. It can be explained due to changes in hospitals' internal workflow or other issues that need further investigation. After receiving "Reperfusion Therapies" treatment, a reduction was observed in the meantime of hospitalization (from 11.7 days to 8 days), emphasizing the decreased hospital stay.

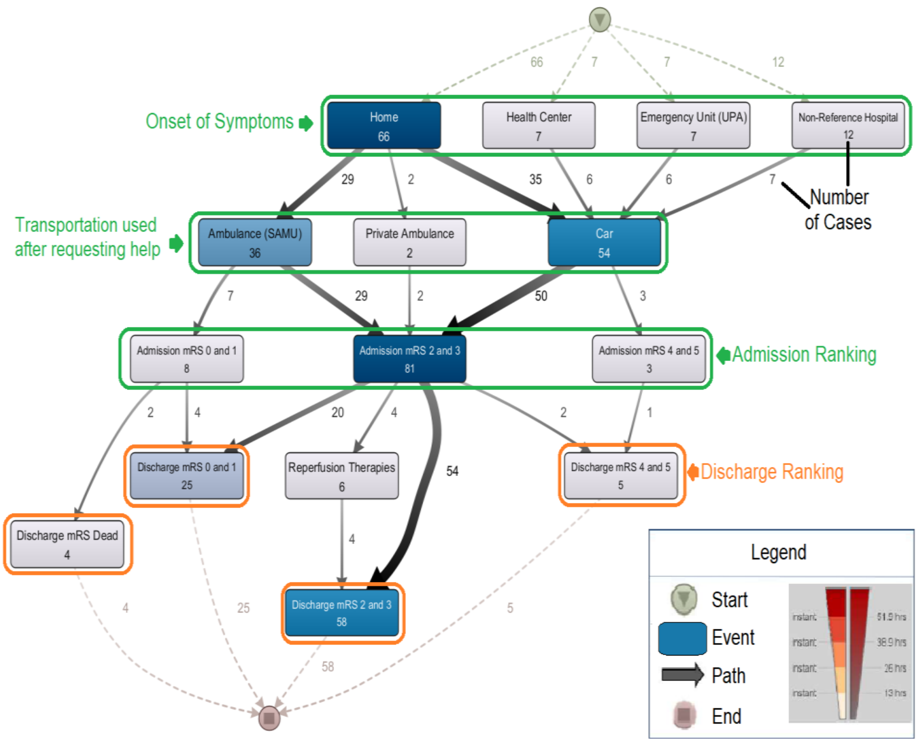

Fig. 3. New pathways of patients' stroke care during the Covid-19 pandemic

There was a total of 68 possible pathways discovered when considering the two process models: 42 pathways were identified before the Covid-19 pandemic, and, after the outbreak, 26 new pathways were identified, as presented in Fig. 3. In this figure, the inverted triangle indicates the starting point of the flowchart, the rectangles represent the events (which vary in color according to the number of patients and number of cases being treated for an event: the "lighter" color indicates a fewer number of cases, and the "bluish" color indicates a more significant number of patients being treated for an event), the arrows represent the pathway followed (changing in width and color according to the intensity of patients being treated through that pathway), the numbers inside the rectangles or near to the arrows represent the number of cases, that is, the number of patients that have gone through that pathway, respectively. Finally, the square inside the red circle indicates the end of the flowchart.

It is also noted in Fig. 3, most of the cases happened in the following pathways:

1st	Home	→ Car	→ Admission mRS 2 and 3	→ Discharge mRS 2 and 3
2nd	Home	→ SAMU	→ Admission mRS 2 and 3	→ Discharge mRS 2 and 3
3rd	Home	→ SAMU	→ Admission mRS 2 and 3	→ Discharge mRS 0 and 1

Twenty-seven of the most common pathways discovered before and during the Covid-19 pandemic are presented in Table 2. The main pathways identified in stroke care of patients before and during Covid-19 are presented in Table 3, and this table is linked to Table 2 by the 'Pathway Code' field. In Table 3, the pathway frequency is specified on the 'Ranking' field, and the 'Code' field identifies the pathway sequence (correlated with Table 2); The 'Case' field displays the number and percentage of patient cases following each pathway. The total mean process duration is also displayed.

According to Table 3, before the Covid-19 pandemic, the five most frequent pathways followed by patients were:

1st	UPA	→ SAMU	→ Admission mRS 0 and 1	→ Discharge mRS 0 and 1
2nd	Home	→ Car	→ Admission mRS 0 and 1	→ Discharge mRS 0 and 1
3rd	Home	→ SAMU	→ Admission mRS 0 and 1	→ Discharge mRS 0 and 1
4th	UPA	→ SAMU	→ Admission mRS 2 and 3	→ Discharge mRS 2 and 3
5th	UPA	→ SAMU	→ Admission mRS 2 and 3	→ Discharge mRS 0 and 1

During the pandemic period, those five most frequent pathways changed to:

1st	Home	→ SAMU	→ Admission mRS 2 and 3	→ Discharge mRS 2 and 3
2nd	Home	→ Car	→ Admission mRS 0 and 1	→ Discharge mRS 0 and 1
3rd	UPA	→ SAMU	→ Admission mRS 0 and 1	→ Discharge mRS 0 and 1
4th	Home	→ Car	→ Admission mRS 2 and 3	→ Discharge mRS 2 and 3
5th	Home	→ Car	→ Admission mRS 2 and 3	→ Discharge mRS 0 and 1

After the first stroke symptoms occurred in the Covid-19 pandemic, when considering the information mentioned previously, UPA was no longer the first choice as they started to call the SAMU ambulance or go straight to Referral Hospital by private car. Furthermore, a worse admission Rankin score was noted during the Covid-19 pandemic than before, going from 0-1 to 2-3 on the admission Rankin score.

A hypothesis to explain the reduction of admissions to emergency services during the Covid-19 pandemic may be related to the changes in the healthcare network flows due to the priority to attend patients with Covid-19 symptoms. The study was conducted in Joinville, where some UPA's became a reference service for Covid-19, consequently reducing the attendance of other medical conditions and transferring chronic diseases care to other healthcare services. In addition, the increase of the admission Rankin could be associated with the patient's fear of becoming infected by the SARS-CoV-2. Because of that, several campaigns have been promoted to encourage the early treatment of stroke worldwide, including Brazil, such as the #StrokeDoesntStayHome campaign by the World Stroke Organization, which was developed to improve the early diagnosis of these patients.

Table 2
List of the main pathways identified in stroke healthcare

Pathway Code	Onset of Symptoms Place	Mode of Transportation	Admission Rankin	Reperfusion Therapies	Discharge Rankin
1	Home	SAMU	2 and 3	---	2 and 3
2	Home	Car	0 and 1	---	0 and 1
3	UPA	SAMU	0 and 1	---	0 and 1
4	Home	Car	2 and 3	---	2 and 3
5	Home	Car	2 and 3	---	0 and 1
6	Home	SAMU	4 and 5	---	Dead
7	Home	SAMU	4 and 5	---	4 and 5
8	Home	SAMU	2 and 3	---	0 and 1
9	Home	SAMU	0 and 1	---	0 and 1
10	UPA	SAMU	2 and 3	---	2 and 3
11	Home	SAMU	4 and 5	Yes	2 and 3
12	UPA	SAMU	4 and 5	---	2 and 3
13	Non-Reference Hospital	Car	0 and 1	---	0 and 1
14	Home	Car	4 and 5	---	4 and 5
15	UPA	SAMU	4 and 5	---	4 and 5
16	Home	SAMU	2 and 3	Yes	2 and 3
17	Home	Car	4 and 5	---	Dead
18	Non-Reference Hospital	SAMU	0 and 1	---	0 and 1
19	UPA	SAMU	2 and 3	---	0 and 1
20	Health Center	SAMU	2 and 3	---	2 and 3
21	UPA	SAMU	4 and 5	---	Dead
22	UPA	Car	0 and 1	---	0 and 1
23	Home	SAMU	4 and 5	---	2 and 3
24	Health Center	Car	0 and 1	---	0 and 1
25	UPA	SAMU	2 and 3	Yes	0 and 1
26	Home	Private Ambulance	0 and 1	---	0 and 1
27	Home	Car	4 and 5	Yes	2 and 3

Table 3
It compares the main pathways for stroke healthcare before and during the Covid-19 pandemic

Before the Covid-19 Pandemic					During the Covid-19 Pandemic				
Pathway		Cases		Total Mean Process Duration	Pathway		Cases		Total Mean Process Duration
Ranking	Code	(n)	(%)		Ranking	Code	(n)	(%)	
1st	3	35	14,5	6 d, 18 hrs.	1st	1	23	9	7 d, 13 hrs.
2nd	2	27	11	7 d, 2 hrs.	2nd	2	21	8	7 d, 5 hrs.
3rd	9	18	7,5	8 d, 18 hrs.	3rd	3	20	7,5	4 d, 23 hrs.
4th	10	14	5,8	6 d, 21 hrs.	4th	4	17	6	9 d, 14 hrs.
5th	19	12	5	8 d, 6 hrs.	5th	5	15	5,6	7 d, 17 hrs.
6th	1	10	4	7 d, 1 hr.	6th	6	13	4,8	7 d, 19 hrs.
6th	7	10	4	18 d, 23 hrs.	7th	7	12	4,5	15 d, 6 hrs.
8th	21	9	3,7	9 d, 7 hrs.	8th	8	10	3,7	6 d, 13 hrs.
8th	22	9	3,7	5 d, 10 hrs.	8th	9	10	3,7	5 d, 22 hrs.
10th	6	7	3	14 d, 21 hrs.	10th	10	9	3,4	6 d, 15 hrs.
11th	23	6	2,5	8 d, 18 hrs.	11th	11	6	2	8 d, 3 hrs.
11th	24	6	2,5	11 d, 13 hrs.	11th	12	6	2	6 d, 19 hrs.
13th	13	5	2	4 d, 10 hrs.	11th	13	6	2	9 d, 21 hrs.
14th	12	4	1,6	8 d, 7 hrs.	14th	14	5	1,9	12 d, 9 hrs.
14th	15	4	1,6	13 d, 23 hrs.	15th	15	4	1,5	8 d, 13 hrs.
14th	25	4	1,6	9 d, 3 hrs.	15th	16	4	1,5	8 d, 13 hrs.
17th	11	3	1,2	11 d, 1 hr.	15th	17	4	1,5	6 d, 11 hrs.
17th	20	3	1,3	6 d, 19 hrs.	15th	18	4	1,5	6 d, 22 hrs.
17th	26	3	1,2	10 d, 2 hrs.	15th	19	4	1,5	7 d, 22 hrs.
20th	8	2	0,8	3 d, 15 hrs.	20th	20	3	1	7 d, 15 hrs.
20th	16	2	0,8	6 d, 14 hrs.	37th	21	1	0,4	1 d, 11 hrs.
20th	27	2	0,8	5 d, 21 hrs.	37th	22	1	0,4	2 d, 8 hrs.
27th	14	1	0,4	4 d, 7 hrs.	20th	23	3	1	4 d, 13 hrs.
27th	17	1	0,4	15 hrs.	20th	24	3	1	6 d, 12 hrs.
42th	4	0	0	NULL	37th	25	1	0,4	1 d, 13 hrs.
42th	5	0	0	NULL	37th	26	1	0,4	5 d, 16 hrs.
42th	18	0	0	NULL	37th	27	1	0,4	1 d, 16 hrs.

Table 3 also shows the decrease in total mean duration between the onset of symptoms and hospital discharge during the Covid-19 pandemic. Before this period, the five longest total mean durations were:

1st Home → SAMU → Admission mRS 4 and 5 → Discharge mRS 4 and 5
Total mean duration: 18 d, 23 hrs.

2nd Home → SAMU → Admission mRS 4 and 5 → Dead
Total mean duration: 14 d, 21 hrs.

3rd UPA → SAMU → Admission mRS 4 and 5 → Discharge mRS 4 and 5
Total mean duration: 13 d, 23 hrs.

4th Health Center → Car → Admission mRS 0 and 1 → Discharge mRS 0 and 1
Total mean duration: 11 d, 13 hrs.

5th Home → SAMU → Admission mRS 4 and 5 → Reperfusion therapies → Discharge mRS 2 and 3
Total mean duration: 11 d, 1 hr.

On the other hand, during the Covid-19 pandemic, the five longest total mean durations were:

1st Home → SAMU → Admission mRS 4 and 5 → Discharge mRS 4 and 5
Total mean duration: 15 d, 6 hrs.

2nd Home → Car → Admission mRS 4 and 5 → Discharge mRS 4 and 5
Total mean duration: 12 d, 9 hrs.

3rd Non-Reference Hospital → Car → Admission mRS 0 and 1 → Discharge mRS 0 and 1
Total mean duration: 9 d, 21 hrs.

4th Home → Car → Admission mRS 2 and 3 → Discharge mRS 2 and 3
Total mean duration: 9 d, 14 hrs.

5th UPA → SAMU → Admission mRS 4 and 5 → Discharge mRS 4 and 5
Total mean duration: 8 d, 13 hrs.

5th Home → SAMU → Admission mRS 2 and 3 → Reperfusion therapies → Discharge mRS 2 and 3
Total mean duration: 8 d, 13 hrs.

The reduction in hospitalization could have happened due to internal healthcare workflow changes and hospital bed reductions, which may have encouraged early hospital discharge. In this study, during the Covid-19 pandemic, we observed a decrease of 2 to 3 days in hospitalization than before the pandemic. In Table 3, the pathways coded 4, 5, and 18 present new patient pathways during the pandemic and their respective outcome.

4. Discussion

In this study, just like in the study of Fernandez-Llatas et al. (2019), that analyzed how PM can support health professionals in the analysis of stroke emergency processes, the use of PM made it possible to discover the stroke clinical processes and help support the optimization of the patient journey during healthcare assistance. According to Trebble et al. (2010), it is crucial to identify and analyze problems and give suggestions to improve the patient journey and its management through the discovery and mapping of the healthcare process.

We noted the inclusion of expert knowledge in event logs, increasing stored information, and facilitating new types of analysis as an emerging trend similar to the Rojas et al. (2016) study. In this study, expert knowledge using ontologies for the timely identification of cases requiring special attention and previous knowledge on the organization of the health system and its changes proved to be essential for the interpretation of discovered models. There are suggestions for new methodologies using reference models and considering healthcare experts' most frequently posed questions.

In the Rojas et al. (2016) study, just like in this paper, PM helped discover and understand the actual pathway of patients; verify the number of patient cases in each pathway, understand new pathways, analyze the time performance, interpret the results with the help of stroke specialists, and make suggestions for redesigning the process. Given the Covid-19 scenario, the use of PM can aid in identifying flows and processes more effectively so that decision-making can happen more quickly. Thus, in the healthcare field, the PM technique is a tool to assess patient pathways and help to discover the patient journey maps (Joseph et al., 2020; Arias et al., 2020).

Since the patient's outcome is extremely time-sensitive in the case of strokes, it is essential to measure the pathway and time between the first symptoms and the hospitalization during the pandemic to define strategies that reduce time delays in acute stroke patients. It was noted that the patient's mode of transport did not influence the onset-to-door time once in the majority of the time the patients were within the therapeutic window of 4.5 hrs.; however, seeking help in health centers and non-reference institutions increased the onset-to-door time. These results were similar to those found by a study that evaluated the time relationship between the medical service sought by the patient regarding stroke signs and symptoms (Nguyen et al., 2021).

According to the municipality's stroke protocol, all patients with suspected stroke or transient ischemic attack are transported by SAMU to the reference hospital and receive acute treatment, including, whenever possible, reperfusion therapies (thrombolysis, thrombectomy). Early care and rehabilitation occur within the hospital by a specialized multidisciplinary team. The municipality's stroke protocol document has changed during the pandemic period, and due to changes in the operation of healthcare services to provide support for covid-19 patients, these changes have occurred in stroke patient care. A previous study was performed by Diegoli et al. (2020) in the exact location of this study. It presented a reduction in admissions for transient, mild, and moderate strokes, a 16% bed reduction, and decreased staff resources in a hospital stroke unit, and those results match this paper's findings showing the efficacy of PM in the healthcare field.

4.1. Limitations

Although this paper encompasses some phases of care, it was not the objective of this study to evaluate the transfer of all relevant information from one healthcare place to the following care location. This evaluation is necessary because when these elements are not effectively delivered to the following healthcare institution, the patient's safety is jeopardized (Wears et al., 2003). Furthermore, when the healthcare patient pathway is thoroughly analyzed, it is necessary to integrate and group data from different health information systems, which is not a trivial task (Yang & Su, 2014) since these systems are neither mutually integrated nor interoperable due to conceptual and terminological incompatibilities (Martínez-Costa et al., 2010; González-Ferrer et al., 2013). The use of interoperability standards such as HL7 and archetypes of openEHR has been recommended worldwide to solve these problems (Knaup et al., 2007). However, we did not address these issues in this paper.

4.2. Future works

To improve the journey of the stroke patient, PM techniques should be used to help administrators improve healthcare processes in the post-Covid period to make good decisions, for instance, investing in qualifications to the health professionals that work in Health Centers, to decrease the time of attendance and to transport for a Reference Hospital by SAMU improving the outcome for the patient. Furthermore, future work can implement an integrated suite, where data sources are connected, data are extracted, the event log is built, and the implemented PM techniques are applied considering all patient pathways. Furthermore, it should manage data and automatically suggest process improvement analytically.

5. Conclusion

PM techniques made it possible to discover two processes illustrating the patient pathway during stroke care before and during the Covid-19 pandemic. Sixty-eight pathways were discovered, making it possible to consider both contemplated periods; 26 happened only during the pandemic. The main discovered findings are: (1) users after the first symptoms of stroke started could not choose to seek UPA emergency services, but they went straight to the Reference Hospital by car or the SAMU public ambulance; (2) there was an extended care delay when the patient went to the Health Center; (3) the worsening of the patient's health status during their admission (from 'mRS: 0 and 1' to 'mRS: 2 and 3' in admission); (4) a long delay in calling the private ambulance service; (5) the reduction of hospitalization time during the pandemic; and (6) the increased delay after hospital admission to perform reperfusion therapies during the Covid-19 pandemic. The current pandemic scenario proved that PM helped identify and analyze patient pathways more rapidly, improving stroke patient safety. The methodology used in this study can be replicated in other healthcare studies.

Author Statement

The authors declare that there is no conflict of interest.

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