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Analysis of Stroke Assistance in Covid-19 Pandemic by Process Mining Techniques

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Abstract. Medical assistance to stroke patients must start as early as possible; however, several changes have impacted healthcare services during the Covid-19 pandemic. This research aimed to identify the stroke onset-to-door time during the Covid-19 pandemic considering the different paths a patient can take until receiving specialized care. It is a retrospective study based on process mining (PM) techniques applied to 221 electronic healthcare records of stroke patients during the pandemic. The results are two process models representing the patient's path and performance, from the onset of the first symptoms to admission to specialized care. PM techniques have discovered the patient journey in providing fast stroke assistance.

Keywords. Process Mining, Stroke, Patient Journey

1. Introduction

Stroke is a non-communicable chronic disease that represents the second leading cause of mortality worldwide. Besides, it is considered the second leading cause of disability-adjusted life years loss globally and the main cause of hospitalization in the Brazilian Public Unified Health System[1]. In stroke treatment, a therapeutical window represents the best moment to intervene in the pathological process of cerebral ischemia and minimize damage to the central nervous system [2]. However, this window often lasts only a few hours, which implicates the need for fast medical assistance for people who experience an acute stroke. Furthermore, one of the intervals in this therapeutic window is the onset-to-door time, representing the interval between the onset of stroke symptoms and the patient's hospitalization [3].

Nevertheless, due to the Covid-19 pandemic, drastic and rapid changes have affected the daily operation of healthcare services, such as the suspension of programmed clinical activities during the lockdown period, significantly diminishing the search for emergency medical services caused by fear of contracting the SARS-CoV-2 coronavirus, which resulted in the postponement of appropriate treatment for cerebrovascular diseases. Besides, in this period, assistance to stroke patients suffered negative impacts worldwide, reflecting a sharp reduction in the number of hospitalizations for acute stroke and,

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consequently, in the number of patients receiving treatment within the therapeutic window [4].

Thus, the objective of this study was to identify the onset-to-door time through process mining techniques, considering the several paths within the healthcare network during the Covid-19 pandemic. This analysis is relevant because recognizing signs and symptoms and the early calling of emergency services can change the outcome of stroke patients, reducing possible sequelae. Furthermore, process mining (PM) techniques were used to identify and analyze the paths of stroke assistance and its outcomes. The application of PM is helpful since it allows manipulation of data from healthcare information systems, making it possible to analyze the flows and processes of a service, easing the recognition of eventual flaws, and allowing improved coordination of the patient's care [5,6].

2. Methodology

We performed a retrospective cross-sectional study by analyzing event logs from 221 electronic healthcare records of stroke patients in a public hospital in Joinville, Brazil, from March 17 to August 21, 2020. This initial date represents the start of Santa Catarina's social distancing measures. The Brazilian Ethics and Research Committee approved this study as report number 4.917.962, dated August 19, 2021.

The PM methodology applied to this study is composed of five stages (0 to 4) based on the "Process Mining Manifesto" [7]. Stage 0 includes planning and justification, according to our presentation in the Introduction of this research. Stage 1 embraces the data selection and extraction from the health information system [7]. The dataset consisted of the variables: date and time of the first symptoms, date and time when the patient sought help, where the assistance was requested, mode of transport to a hospital that is a reference for stroke assistance, data and time of hospitalization, and the modified Rankin Scale (mRS) of the patient at discharge. The mRS measures the degree of disability in daily activities. We grouped the mRS score according to the ranges: 0-1 (no disability and no significant disability), 2-3 (slight to moderate disability), 4-5 (moderate to severe and severe disability), and 6 (death) to simplify the presentation of results [8].

In Stage 2, after data extraction, data were pre-processed, excluding missing, incomplete, and undefined values in an Excel spreadsheet. The following variables were clustered: date and time of hospitalization and mRS score after discharge; this was grouped to understand the relationship between a patient's possible paths and outcome. An Excel file was input into the Disco software from Fluxicon to discover the process model, and after the file was imported, the columns were assigned to 'caseID,' 'timestamps,' and 'activity names.' The Disco Miner combined Fuzzy Miner with process metrics and modeling strategies[9]. In Stage 3, other process perspectives can be analyzed, such as date, time, and resources. Disco allows the analysis from an instance to a macro process. We presented only a macro process in this study. Finally, the models constructed in Stage 3 can be used in Stage 4 for making interventions, predictions, and recommendations [7]. In the Results of this paper, we presented Stage 2 and 3 outcomes.

3. Results

Figures 1 and 2 present the two discovered process models. These models represent the patient's path from the onset of symptoms to the moment of his admission to a public-stroke reference institution. In Fig. 1 and 2 legends, the inverted triangle indicates the start of the flowchart, the rectangles represent the events (which vary in color according to the number of patients that transit through them: the "lighter" color indicates fewer patients, and the "reddish" color indicates an increased number of patients transiting through that event), the arrows represent the path followed (which change in their width and color according to the intensity of patients transiting through that path), the numbers inside the rectangles or next to the arrows represent the number of cases, that is, the number of patients that went through that path, respectively. Finally, the square inside the red circle indicates the end of the flowchart.

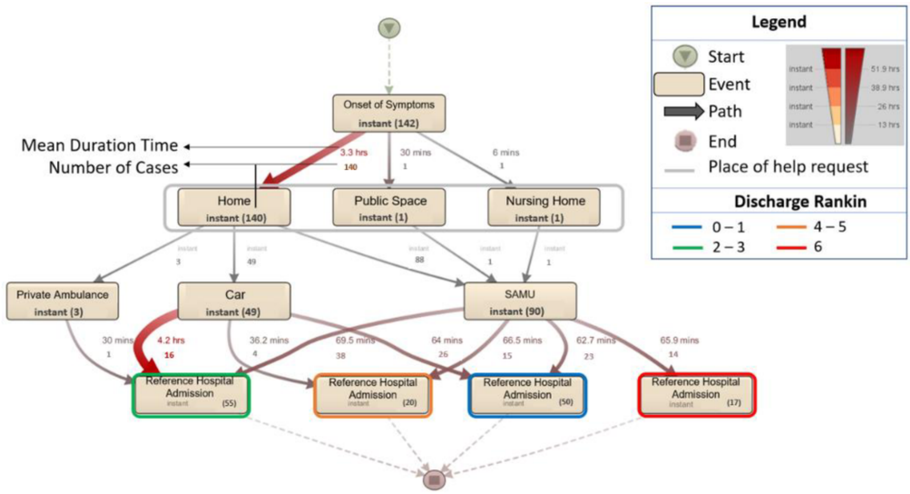

Figure 1. Model 1: Medical assistance requested from home, public space, and nursing home.

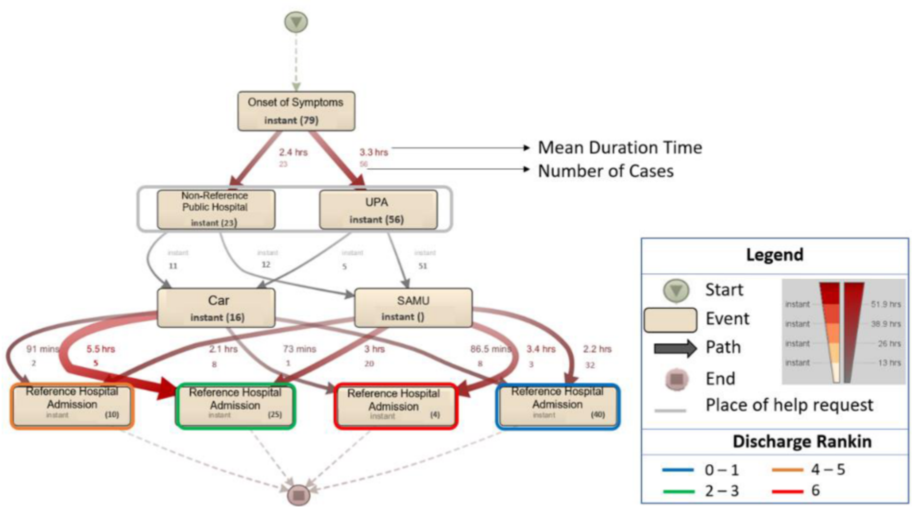

Figure 2. Model 2: The patient went to a Non-Stroke Reference-Public Hospital and UPA (emergency care units).

Fig. 1 presents events where the patient requested assistance at home, in public spaces and in nursing homes; Fig. 2 shows the patient already requested care and went to a Non-Stroke Reference Public Hospital and UPA (UPA are three local emergency care units) after the onset of symptom. In Fig. 1, 142 cases were analyzed, generating 568 events distributed into 11 activities. Some paths were hidden through filters to avoid incomprehensible models as performed in studies [10]. The mean onset-to-door time was 4.7 hours, and the median was 2 hours. Therefore, it is possible to conclude that the mean time between the onset and the assistance requested by patients at home (n = 140) was 3.3 hours, whereas to get to the stroke reference care: the majority used mobile emergency medical services (SAMU) (63%, n = 88), 35% (n = 49) used a private car, and the minority was transported via private ambulance (2%, n = 3). Post-assistance was also analyzed at discharge, 35% (n = 50) the patients evaluated as mRS 0-1, 39% (n = 55) evaluated as mRS 2-3, 14% (n = 20) evaluated as mRS 4-5 and 12% (n = 17) died.

The second model displays the flowchart of patients that, after experiencing the first stroke symptoms, sought help and were referred to public healthcare institutions other than the stroke reference hospital. In this model, 79 cases were analyzed and generated 316 events distributed into nine activities, making it feasible to display all the activities and routes followed by the patients until hospitalization. The mean onset-to-door time was 5.6 hours, and the median was 3.4 hours. Fig. 2 shows that the emergency care unit (UPA) (70%, n = 56) was most commonly sought was by the population among the public non-stroke reference institutions, followed by two other public hospitals (30%, n = 23), where there was 3.3 and 2.4 hours of mean medical assistance time, respectively. In these situations, 9% of the patients in UPA (n = 5) and 48% at the public non-stroke reference hospitals (n = 11) were not referred to the public stroke reference hospital via SAMU or fire-rescue squad but used their private cars.

When referring to the mode of transport compared to the patient's clinical outcome: a Rankin score of 0-1 refers to a mean interval of 2.2 hours (n = 32) via SAMU and 86 minutes (n = 8) via private car. A Rankin score of 2-3 refers to a mean interval of 3 hours (n = 20) via SAMU and 5.5 hours (n = 5) via private car. Rankin score of 4-5 with a mean interval of 2.1 hours (n = 8) via SAMU and 5.5 hours (n = 5) via private car, and Rankin score 6 with a mean interval of 91 minutes (n = 2) via SAMU and 73 minutes via private car.

4. Discussion and Conclusion

PM has made it possible to discover and analyze two process models: the first, the onset-to-door meantime, was 4.7 hours; and the second was 5.6 hours. The Teo et al. (2020) study compared the median stroke onset-to-door time before and during the Covid-19 pandemic, they noted that during the pandemic, the onset-to-door time was ≈1-hour longer than before the pandemic (154 versus 95 minutes, P=0.12), and the proportion of individuals with onset-to-door time within 4.5 hours was significantly lower (55% versus 72%, P=0.024) [11]. Leandro et al. (2022) realized that during the pandemic, the worsening of the patient health status during hospital admission, decreased hospitalization time, increased delay in receiving reperfusion therapies, and preference for the referral hospital over emergency services [6]. Although primarily, the onset-to-door time was maintained within the appropriate interval, it was identified that 36% of the population still sought non-reference-stroke institutions that increased the onset-to-door time, similar to the results found by Nguyen et al. (2021).

Most of the time, in this research, the patient's mode of transport did not influence the onset-to-door time; the patients remained within the therapeutic window of 4.5 hours. However, some medical assistance was not supplied within the therapeutic stroke window, either due to the failure to recognize stroke symptoms or seeking non-specialized care [12]. Therefore, it is necessary to promote campaigns to warn of the stroke signs and symptoms, stress the importance, and guide non-stroke reference hospitals. Even though our study was limited due to the small number of subjects, PM has proven to be a valuable tool for assisting managers in quicker identification of flows to reduce decision-making time.

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