Exploration with Process Mining on How Temperature Change Affects Hospital Emergency Departments

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Abstract. The way patients are treated in Hospital Emergency Departments changes during the year, depending on many factors. One key component is weather temperature. Some seasonal maladies are tightly related to temperature, such as flu in cold weather or sunburn in hot weather. In this study, data from a hospital in Valencia was used to explore how harsh weather changes affect the emergency department, obtaining information about probable impacts of global warming effects in healthcare systems. Process mining techniques helped in the discovery of changes in the Emergency Departments. Some illnesses, such as heat stroke, are more prevalent during heatwaves, but more interestingly, the time to attend patients is also higher. Rapid changes in temperature are also analyzed through Process Mining techniques.

Keywords: Process mining · Emergency · Weather conditions · Healthcare system.

1 Introduction

Emergency departments (EDs) work seven days, 24 hours a week. They are key departments that provide urgent care to the patients. Since many patients get further care after the ED's first response, they are regarded as the gateway to other hospital departments. The EDs aim to present urgent care to treat people recover from their illnesses or at least alleviate the symptoms. Well-performed and standard processes can accomplish this aim in the ED, where healthcare professionals collaborate systematically. The increasing number of patients causes a crisis of agglomeration in the gateway of hospitals [20]. Although it is well-known among professionals and literature that most EDs are frequently crowded, many questions wait for their answers [2]. Among these questions, one is how global warming affects emergency departments.

The Intergovernmental Panel on Climate Change (IPCC) points out that weather conditions will probably become hotter or colder frequently and intensely during the next years [12, 18]. Large parts of the World, especially Asia, Europe and Australia have encountered an increased recurrence of heatwaves [14]. Besides, human mortality rates related to extreme hot weather have raised with global warming [14]. Several reasons may affect the correlation between disease and global warming, such as local demographics, economic welfare, underlying disease risk or weather variability in seasons [8]. Another reason is that steep changes in daily temperature may have an impact on ED processes. For this consideration, more reliable intellection of disease conditions during temperature changes is an essential tool for health practitioners and the investigation of ED processes is gaining more and more attention [6, 9].

Despite progress in the analysis of ED processes, novel strategies are required because of complexity, diversity and non-adaptability reasons [1, 15]. ED processes are not adjustable or adaptable from another process model because of their nature and complexity. This complexity makes it hard to provide a clear representation of the patient flow. Hence, most investigations focus on the observations to discover the process model, which is time-consuming and unreliable. Process models are the central part of crowded ED problems. Therefore, they should represent real and reusable patient flows to find acceptable solutions. Process mining (PM) automatically creates process models using real data stored in the IT system as event logs [19]. By applying PM methods, the actual ED processes followed by patients can be discovered to see the effects of environmental temperature.

The studies presented in the following sections show the relation between higher temperatures and extra attention time, and explore the connection between patient cases and harsh, sudden temperature changes. This shows the potentiality of using PM in the study of global warming and healthcare.

2 Materials And Methods

For the study data was collected from 483,229 visits to the Emergency Department at Hospital General of Valencia. These were records from the years 2015 till 2018. The records included: patient ID; date and time of arrival; date and time of the start of the triage and its end; waiting queue assigned to the patient in the triage; the specific service that attended the patient (e.g. surgery, dermatology) and timestamp, both at the beginning and end of the attention to the patient; patient destination (e.g. home, hospitalization, another medical service); patient's date of birth; patient's diagnostic.

Daily temperature information was also available, including per day: average temperature, minimum temperature and maximum temperature. Across the years, subjects usually go to the hospital more than once. Specifically, 192,884 patients generated the 483,229 visits, with an average of 2.5 visits to the hospital per patient. Process Mining [19] solutions facilitate a clear understanding of the care process and it can help build models that can be understood by humans who can modify those processes according to their expert understanding of the processes. It also lets them measure changes objectively. The doctor or technician can thus understand the models that show their patients' behaviour.

When the user is set at the center, specifically the user with expert knowledge about the processes but with little to no PM abilities, interactive and visual tools are needed in what is known as Interactive Process Mining (IPM). PMApp[5] is an application that facilitates IPM. With PMApp and the PM algorithm PALIA, the processes with the data are represented as Timed Parallel Automata (TPA) and can be outlined visually in workflows with color gradients, or with other representations. In this case, workflows representing the different events in an ordered way, their connections, the time spent at each activity and the flow that was followed, all were summarized in a specific workflow, as seen in Figure 1. This powerful visualization is called an Interactive Process Indicator (IPI) and is explained in the following lines.

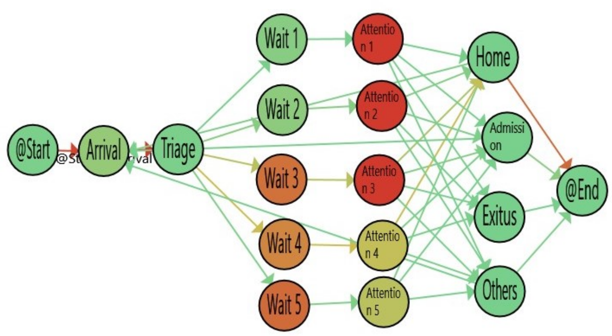


Fig. 1: IPI representing all the visits, including 393,963 traces after incorrect traces were discarded. Redder color in nodes, as opposed to green, represents higher time in that stage while redder color in transition means larger number of cases in that transition.

In Figure 1 a model of an ED is shown. The events (nodes) that exist, as seen in the IPI, are: 1. "Artificial" Start (@Start). Initial event, always present.

2. Arrival to the ED 3. Triage of the patient: Assessment of severity and urgency of the treatment 4. Wait 1-5, indicating the queue the patient was assigned to 5. Attention 1-5, indicating the attention associated to the corresponding queue 6. Final step, which can be Home, Admission into the Hospital, Exitus (decease) or Others (e.g. the patient ran away) 7. "Artificial" End (@End), always present.

In the IPI, it is observed that the patient can be assigned to different queues, different destintations, etc. A transition is needed so a visit can be traced e.g. a patient is assigned waiting queue 2 and then, after the attention, is sent home. This is represented by transitions (arrows) between the nodes.

There is key information that resides in the time spent at the nodes, and the different paths that the visits go through. Summarized information about e.g. waiting times, distribution of waiting queues, etc. can be seen through color gradients in the IPI for the nodes and transitions. In this specific study, there is a green-to-red gradient for the nodes that represents median duration in the node (e.g. time spent at waiting queue 1). As seen in Figure 1, waiting time is lower the lower the wait queue number. Conversely, attention time is higher the lower the attention number.

The same gradient color coding exists for the transitions and it represents the number of visits that went through any transition. Thus, all the 393,963 visits went from arrival to triage. Most visits were assigned to wait queues 3 and 4, as seen color-coded in the transition.

The Waiting 1 to 5 and Attention 1 to 5 nodes represent the queues (and level of emergency, top to bottom) that each patient is assigned after the arrival, at the triage step. After attention the patient usually returns home, though he or she could also be admitted into the hospital, or finish in *exitus*, among other possibilities. The Emergency Department modelling has been described elsewhere [7].

The IPI shown at Figure 1 comprises the whole dataset that generated the model.

2.1 Assigning Temperature to Cases and Discretization

With the help of PMApp, daily temperature information about Valencia city, where the hospital is located, was fused with the ED data, by assigning temperature to the date of each case. Average temperature information was then discretized, generating sub-groups of cases: 15-20°C, 20-25°C, 25-30°C, 30-35°C. Also, taking into account the average, minimum and maximum temperature, day to day steep temperature changes were selected and then divided into sudden temperature increases and sudden temperature decreases.

Inaccurate data (i.e. blank information, wrong dates) were removed, leaving 393,963 correct traces corresponding to visits to the ED. The other 89,266 traces either had empty values for any needed date or had an incorrect process flow (e.g. date of attention was prior to the date of arrival). PMApp let the user create groups dividing the TPA into groups by different patterns e.g. average temperature group, diagnosis, etc. and a combination of those.

Different models were explored relating temperature to diagnosis. Some of them did not show any interesting information. Others did and are exposed in the Results section. Firstly, high temperature and heat strokes was analyzed. An IPI for each temperature group was generated and inspected. In an exploratory way, correlations between diagnostics and temperature increases were also looked for and the otitis cases related to temperature are also shown. Finally, in order to study how sudden changes in the weather (a phenomenon related to global warming) affect the ED, harsh changes in day-to-day temperature were detected and those with a higher sudden change were selected and their processes were visualized and studied.

In order to select the days with higher changes, they were compared: Each day's minimum temperature was subtracted to the minimum temperature from the previous day. The same calculation was performed for the maximum and the average temperatures. Finally, those values were multiplied and a threshold of 100 was introduced, accounting for 14 days with increased temperature and 17 days with reduced temperature. Two groups were created according to temperature increase and decrease and an IPI was generated for each along with another one for stable temperature.

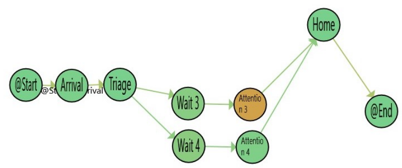
For the three mentioned IPIs, in order to assess the significance in the differences for specific nodes, the normality of each population of durations was assessed by the Kolmogorov-Smirnov test. In case both populations are normal, a Student T test is applied. Otherwise, a Mann-Whitney-Wilcoxon is applied. In any case, a p value is applied as a threshold to determine statistical significance between the populations. In this study a p value of 0.05 was set as the threshold for statistical significance. Yellow circles around nodes indicate a significant statistically difference between the duration in the population of days with a steep change compared to days without important changes in temperature. These are also shown in the results section.

3 Results

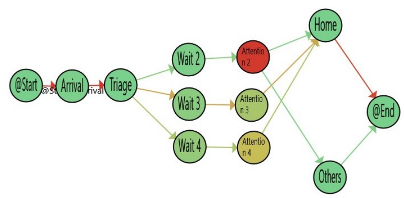
3.1 Temperature and Heat Strokes

The first study is related to daily weather temperature and heat strokes. As the WHO relates [21], heat is one important factor that affects mainly the elder population, causing cardiovascular and respiratory diseases. According to the same report, in 2003 an excess 70,000 elderly people died due to a heat wave.

IPIs were generated for each temperature range and it was visually observed that the attention of patients with heat stroke took longer the higher the temperature. The three IPIs corresponding to the ranges 20-25°C 25-30°C are shown in Figure 2. The color gradients are common for the three IPIs so it can be seen that attention time for the 25-30°C was highest, especially in Attention 2 (the following highest duration was Attention 3 from the range 25-30°C, then came Attention 4 from the range 25-30°C). The color for number of executions (coded in the transitions) was also common to all IPIs, so it can be observed that most of the visits corresponded to temperatures between 25ºC and 30ºC (mostly in Wait queue 3, then queue 4). There were very few cases in the 30-35ºC range, so they were not included in the Figure. Generally, waiting times were low compared to the time spent at Attention.



(a) 20-25ºC



(b) 25-30ºC

Fig. 2: Interactive Process Indicators (IPIs) with groups of average temperature per day, in Heat Stroke patients.

3.2 Otitis cases related to temperature

A high number of otitis (inflammation of the ear due to infection) cases were detected that related to high temperature. Their IPI is shown in Figure 3.

As can be seen in Figure 3, there were no otitis cases among the 568 diagnosed ones that were considered as serious, since none were triaged in the most urgent queues, 1 and 2. It was observed that the number of otitis patients related to the number of general patients increased with temperature, as seen in Figure 4. Although the attention of those patients took little time, their wait time was very high (as seen in Figure 3. This indicates a higher load of waiting rooms.

3.3 Harsh changes in temperature and ED

In the IPIs that compare to the baseline, greener means higher times while redder means lower (negative) subtracted times (Figures 6.b and 7.b).

The IPI that represents days without steep day-to-day changes in temperature is shown in Figure 5.

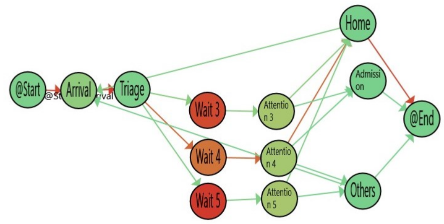


Fig. 3: IPI for otitis patients. Gradient colors represent the same durations as in Figure 1.

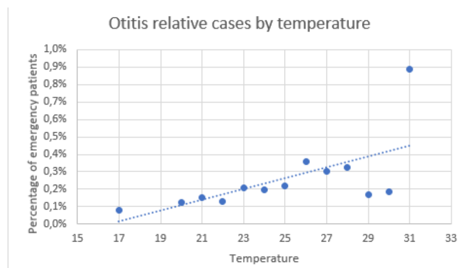


Fig. 4: Relative number of otitis cases (percentage of cases by general emergency patients), and its increase with temperature.

The comparison between days with a high change in temperature compared to the previous one, generally showed higher attention times. Specifically, for increases in temperature, attention in queues 2 and 3 took longer than days with no significant change in temperature (see Figure 6). The same situation happened for steep temperature decreases, with a higher attention time and wait time for patients classified in queue number 3, and wait time for queue 5 was also higher, along with the triage time (see Figure 7). These findings were statistically significant. There were no statistically significant reductions in time.

4 Conclusion and Discussion

This study considered data collected from an emergency department (ED) at a Hospital in Valencia city, from 2015 to 2018. 483,229 visits created by 192,884 patients were investigated for four years. The main goal of the study was to analyze a large dataset that had ED data along with weather temperature information through PM, specifically through a tool that allowed for visual inspection and surveillance of the processes discovered by PM, PALIA.

The effects of temperature on heat stroke and otitis cases are investigated in this study by analyzing process flows, along with a general investigation about the effects of steep changes in temperature on the Emergency Departments. Va-

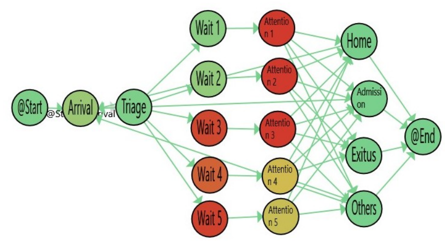
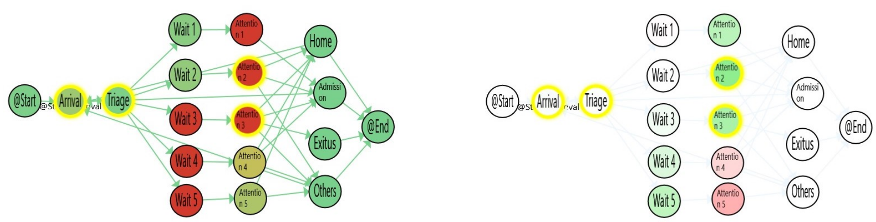
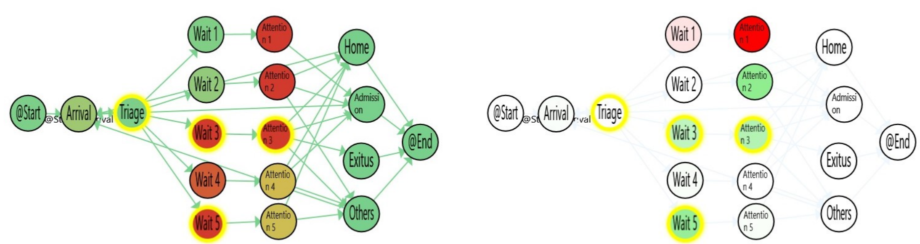


Fig. 5: IPI with information on days without harsh temperature changes. The redder the color, the longer the time at a node. Node colors (i.e. durations), are directly comparable between this Figure and Figures 6 and 7.



(a) IPI for harsh increase in temperature (b) Same IPI, compared to baseline

Fig. 6: IPIs for ED patients in days with steep increases in temperature.



(a) IPI for harsh decrease in temperature (b) Same IPI, compared to baseline

Fig. 7: IPIs for ED patients in days with steep decreases in temperature.

lencia is a warm Mediterranean coastal city, so the weather is generally mild. However, we could detect changes in the processes inside the Emergency Department that depended on weather temperature. This is especially interesting for our study, since extreme weather conditions such as heatwaves are more prevalent with global warming [4]. According to the Weather Meteorological Organization, heatwaves are the meteorological hazards that have created the maximum number of deaths in the recent years [22]. The effects of heatwaves and other steep temperature changes on the EDs can be observed and may be interpolated to places with more extreme weather conditions and to how attention may change in the future.

In the study, temperature data was categorized and linked to process cases to explore possible effects of heatwaves. Then PALIA algorithm created process flows of patients under categorized (discretized) temperature data. It was observed that Heat Stroke processes in EDs took longer the higher the temperature. There were also many more cases in the range of 25 to 30°C. The number of cases confirms the intuition that sunburns are more prevalent the higher the temperature (it should be considered that roughly 20% of days had an average temperature at or above 25°C, across the years of the study). The higher treatment time span per case could be thought of as intuitive too, but in this case the potential effect of global warming on the EDs is clear: with the increase of heatwaves, sunburns are expected to grow in number and EDs will have more cases that will need extra attention time. This is also compatible with the study by [10] where they analyzed the effect in a hospital during the most extreme heatwave in Melbourne. It was unexpected that wait time for these cases was very low compared to the usual wait times. In fact, heat stroke patients did not wait more in lower urgency waiting queues. This suggests that the ED treats those patients as soon as possible independently of the waiting queue.

In the case of otitis, this was an unexpected finding. It should be reviewed how much confounding factors played a role in the cases, such as infections due to longer times spent in swimming pools, as is usually the case during the summer vacations. This could nevertheless be attributed to overcrowded waiting rooms in humid areas with high temperatures.

The study also presented the effects of sudden changes in weather conditions to the ED. Generally, time spent at the waiting rooms and while being attended were longer for both sudden temperature increases and decreases. This exploration points in the direction that the more the sudden changes in temperature, the more collapsed EDs will be. And sudden changes in temperature are more and more frequent due to climatic change.

In future studies a correction for multiple condition tests should be added, such as a Bonferroni correction. The authors of PMApp have this in mind for the tool so these adjustments could be applied directly from the PM tool in future developments[7].

A formal definition of heatwave could have been used and the temperature ranges could have been defined accordingly. There are proposals for such a definition as in [17, 23]. However, the purpose of this study was mainly focused on the exploration, through PM, of the effects of temperature changes. Since the importance of heatwaves has been found, this require further refinement. The use of IPIs for the detection of changes in processes has been proposed in other realms such as Operating Rooms processes[11], Type 2 Diabetes Primary Care[3], etc. In fact, as stated in [16], it is important that there exist visual tools that let the care professionals analyze complex processes in a simple visual way, which are currently lacking. This would help and sometimes enable the user to interpret the outcomes of the PM techniques applied to their data.

Visual inspection, through IPIs, as shown through the figures, let us see differences in processes at a glance. In this study, duration in each node (e.g. a waiting queue) was accounted for by a color gradient where green meant 0 time and red the maximum duration in the specific graph. Another visual cue was the coloring of the transitions. The arrows were redder the higher the number of cases and greener the lower the number of cases. This turns the graphs into powerful visual tools that the doctor (or any other user) can manage easily. Furthermore, as shown in some figures, difference maps can also be created where colors represent the difference in duration for two process groups in the case of nodes, and the difference between the number of occurrences in the case of transitions. The information in the flows could be enhanced by adding a legend to the graphics, that would allow the user to see the exact amount of traces or the amount of time spent at a specific activity. These are things that will be incorporated to PALIA in future releases.

With the presented results, the study puts forwards that global warming may have a significant impact on Emergency Department processes. This is an exploratory study that shows how PM enables ED workers, mainly medical doctors and technicians, to explore ED event data related to weather. The incidence of global warming on the treatments has been analyzed by watching the cases related to high temperature and also through one key hazard that is caused by global warming: steep temperature changes (mainly heatwaves). Direct observation of year-to-year increase in temperature and its effect on EDs is not feasible, since the average increase of 0.18°C per decade since 1981 (according to the American National Oceanic and Atmospheric Administration)[13] per decade would take several decades of data to extract valuable information. However, although the year by year increase is out of the scope of this paper, the effects that global warming in the next decades can be analyzed showing how temperature affects the citizens' health in a critical service as ED. This information is central to make the scientific community aware of the effects of global warming on our health.

The study also highlights the power of visual tools to understand the dynamics of the processes in the EDs and how these tools can help the people working in the healthcare domain to inspect large amounts of event data in a friendly but comprehensive way.

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