REAL-WORLD APPLICATION OF PROCESS MINING TO THE EMERGENCY CARE PATHWAY IN A UK AMBULANCE TRUST

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1. INTRODUCTION

The UK ambulance service is in crisis. A report by the House of Lords in 2023 stated that "patients are delayed at every stage of trying to access emergency healthcare" exacerbating existing health problems[1]. The current emergency service pathway and its shortfalls must be understood before it can be improved, a task suited to process mining.

In this study, we apply PM2 process mining methodology to the Emergency Care Pathway in the East Midlands to[2].

- Discover the pathway.
- Check conformance to a target response time.
- Predict whether a patient will be transported to hospital from features available early on in an ambulance job cycle.

2. DATA SET DESCRIPTION

Data provided by East Midlands Ambulance Service (EMAS) included 224,559 ambulance callouts between the 1st of August and the 31st of December. The data included the patients that were seen and treated and seen and conveyed. In the UK these calls are split into the call categories of 1-5 based on severity with 1 being the most severe and 5 being the least severe. Category 2 makes up 68% of this call data. The mean target response time for Category 2 calls is 18 minutes, and given their frequency, it is a focus of EMAS to meet this target.

Filtering down to the Category 2 calls we are left with 152,525 calls. With an initial possible 18 activities ,we removed 4 activities due to data quality issues with their recording, and a further 7 "treatment" activities which were able to happen in any sequence. This leaves only the key events which make up an ambulance job cycle.

3. PROCESS DISCOVERY

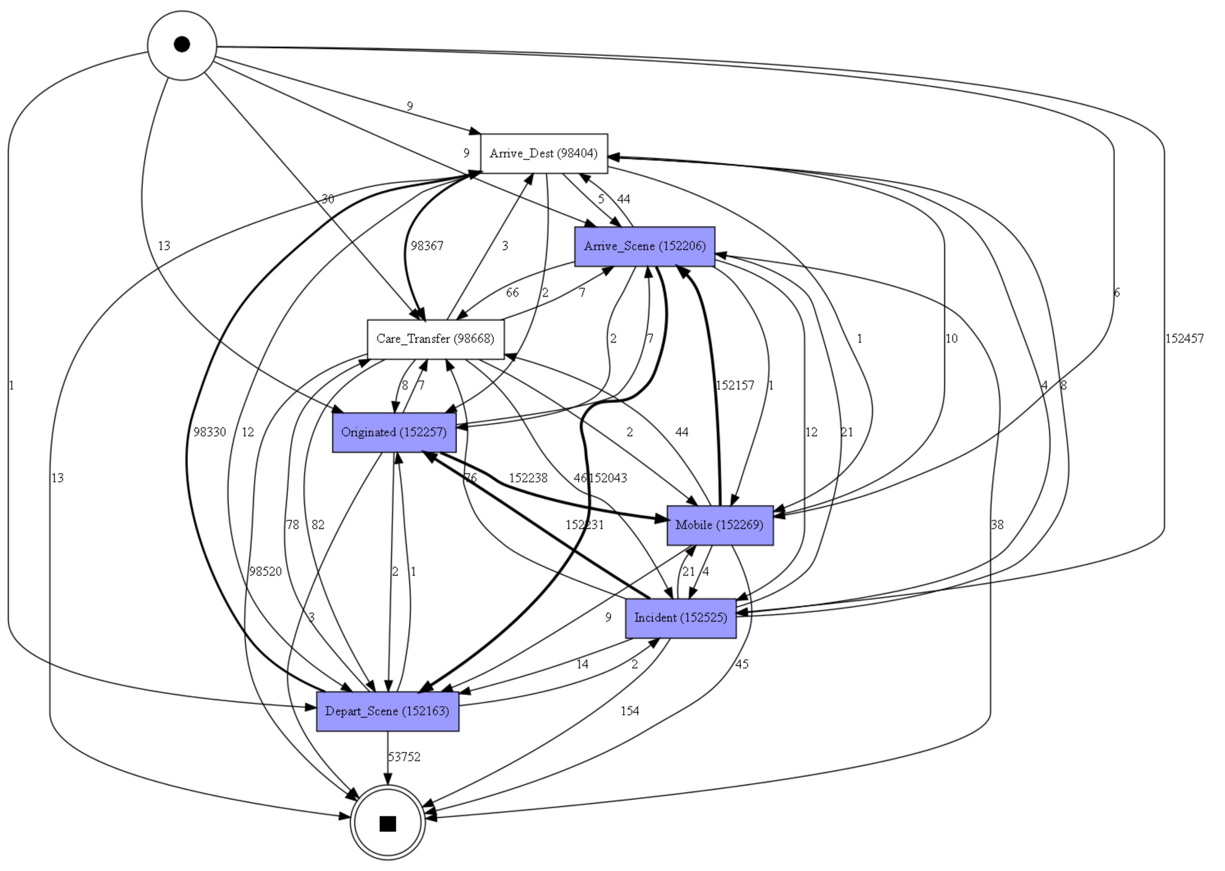

Figure 1: Directly Follows Graph (DFG) of category 2 ambulance job cycles with treatment and vitals signs recording events removed (Drug,IV,IO,NEWS etc). DFG made with the PM4PY package[3].

Having dropped the events relating to treatments and poorly recorded events we result in 86 possible variants of which 2 account for 99% of the log. The most common variant (65% of the log) represented people being seen and conveyed to hospital. The second most frequent variant (35% of the log) represented patients who were seen and treated on scene with no conveyance to hospital. These 2 traces covering the majority of the log are similar to the traces discovered by process mining of emergency pathways in Adana 2019[4].

Some activities were noted to be recorded out of the expected chronological order. After discussing this with the EMAS team we constructed business rules to remove these traces to help provide an expected path for our following conformance investigation.

4. CONFORMANCE

In process mining, conformance is usually used to measure how well a sequence of events conforms to an expected sequence using an algorithm such as token based replay (TBR). In an ambulance job cyle where there are few variant paths, TBR only validates Process Discovery's detection of these few variants with a high fitness value.

Of far more interest is a conformance to a target time such as the mean target response time of 18 minutes for Category 2 calls. The reported mean response time for August - December was 75 minutes. In Figure 2 we filter the log into those traces that have a response time greater than and less than 18 minutes to observe the effect it had on the larger job cycle.

5. CONFORMANCE TO TARGET 18-MINUTE RESPONSE TIME

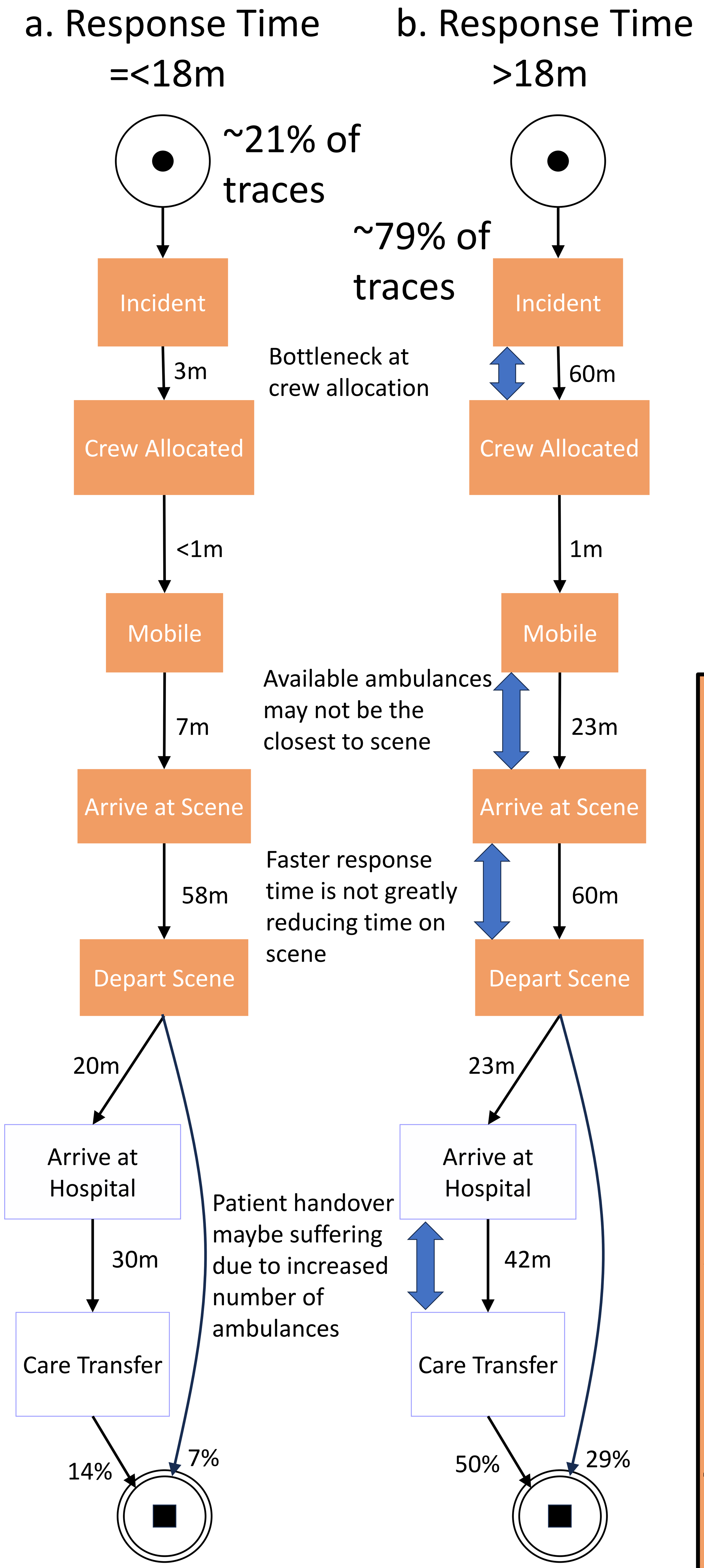

Figure 2: Directly Follows Graphs of top 2 variants for category 2 ambulance job cycles. Annotations of arcs indicate mean time between events. 2a. Shows the 21% of traces that have a response time (time between incident and arrival on scene) equal to or less than 18 minutes. 2b. Shows the 79% of traces that do not meet the target response time

7. PREDICTING ENDPOINT

If the endpoint of a patient (whether they need to be taken to hospital) could be predicted early on in a job cylce, this could be useful to clinicians on scene, whilst also learning which features most influence a patient's outcome.

A Classification and Regression Tree (CART) with a depth of 15 and minimum leaf size of 5 patients was trained using the Scikit Learn library to predict if a patient was to be treated and transported or not[5,6]. The treated and transported class dominated the class balance. Under sampling in the training set for a 50:50 split did not improve accuracy beyond the ratio of classes in the test set. Nevertheless, the feature importance's shown in Table 1 show which features were valued highest when making a classification for the model.

8. FEATURE IMPORTANCES

Table 1: Feature Importances from a Decision Tree predicting whether a patient was to be treated and taken to hospital using features available up to and including the first NEWS value of a patient being recorded

Feature	Importance
Initial Clinical Category of Call	0.29
First Recorded National Early Warning Score (NEWS)	0.23
Age of Patient	0.17
Hour of Arrival on Scene	0.10
Index of Multiple Deprivation (IMD) Decile at Incident Location	0.075
Day of the Week	0.065
Highest Qualification on Scene	0.038
Gender of Patient	0.022
Location of Incident (Home/Other)	0.015
Whether specific job cycle activities have occurred prior to arrival on scene	0.0013

TAKEAWAY

1. **Emergency service pathways have few variants with 99% of the log being accounted for in 2 variants.**
2. **A bottleneck between incident and crew allocation is causing the greatest delay in response time. However, a faster response time does not reduce the time spent on scene**
3. **Prediction of whether a patient will be transported to hospital requires more data than available in a single ambulance job cycle.**
4. **Future research should aim to measure the effect of ambulance availability and the performance of hospital emergency departments on the process pathway and how this effects patient outcomes.**

References

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This work uses data provided by patients and collected by the NHS as part of their care and support