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Ambulance dispatch prioritisation for traffic crashes using machine learning: A natural language approach

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ABSTRACT

Introduction: Demand for emergency ambulances is increasing, therefore it is important that ambulance dispatch is prioritised appropriately. This means accurately identifying which incidents require a lights and sirens (L&S) response and those that do not. For traffic crashes, it can be difficult to identify the needs of patients based on bystander reports during the emergency phone call; as traffic crashes are complex events, often with multiple patients at the same crash with varying medical needs. This study aims to determine how well the text sent to paramedics en-route to the traffic crash scene by the emergency medical dispatcher (EMD), in combination with dispatch codes, can predict the need for a L&S ambulance response to traffic crashes. Methods: A retrospective cohort study was conducted using data from 2014 to 2016 traffic crashes attended by emergency ambulances in Perth, Western Australia. Machine learning algorithms were used to predict the need for a L&S response or not. The features were the Medical Priority Dispatch System (MPDS) determinant codes and EMD text. EMD text was converted for computation using natural language processing (Bag of Words approach). Machine learning algorithms were used to predict the need for a L&S response, defined as where one or more patients (a) died before hospital admission, (b) received L&S transport to hospital, or (c) had one or more high-acuity indicators (based on an *a priori* list of medications, interventions or observations. Results: There were 11,971 traffic crashes attended by ambulances during the study period, of which 22.3 % were retrospectively determined to have required a L&S response. The model with the highest accuracy was using an Ensemble machine learning algorithm with a score of 0.980 (95 % CI 0.976–0.984). This model predicted the need for an L&S response using both MPDS determinant codes and EMD text. Discussion: We found that a combination of EMD text and MPDS determinate codes can predict which traffic crashes do and do not require a lights and sirens ambulance response to the scene with a high degree of accuracy. Emergency medical services could deploy machine learning algorithms to improve the accuracy of dispatch to traffic crashes, which has the potential to result in improved system efficiency.

1. Introduction

Demand for emergency ambulances is increasing at a rate that exceeds population growth, [1,8,14,19]. To manage this demand, emergency medical services (EMS) need to discriminate between those incidents that require the highest ambulance dispatch priority response, where lights and sirens (L&S) (hot response) are used on the way to the scene and those incidents that do not require a L&S ambulance response (cold response). EMS use a variety of systems to help identify and categorize (triage) patient needs (L&S or not) during the emergency phone call. However, for traffic crashes this is a particular challenge given that laypersons at the scene have limited ability to make medical observations and because there may be multiple callers, as well as multiple patients with different medical needs [16]. One way EMS categorize patient needs based on bystander reports during the emergency call is through standardized scripted systems, such as the Medical

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Priority Dispatch System (MPDS) [10]. Such systems assign traffic crashes into several different categories, each category then has an EMS pre-determined dispatch prioritisation. For example, a *rollover* might be pre-assigned as requiring a L&S response and the MPDS category of *no injuries confirmed* as not requiring a L&S response. Each EMS determines its standard response (L&S or not) for each category. However, these systems have been found to have limited predictive ability for identifying the ambulance response that traffic crashes require [7]. One possible reason for this is that crashes are complex events, with the different characteristics of the crash combining to make each crash unique. When a traffic crash is reduced to a single category, as when standardized scripted systems are used by EMS, important information may be lost [15]. However, advances in computational modelling offer new opportunities in the prioritisation of ambulance dispatch through the use of text the EMD keyed into the dispatch software.

During the emergency phone call, the caller will describe the scene of a traffic crash, in their own words, to the EMD. From this description, the EMD identifies information that is pertinent to the clinical needs of patients, such as the mechanism of injury involved (rollover, involving a motorcyclist etc.), as well as any additional information relating to scene safety, such as directions to find patients or the presence of other emergency services (police or fire). This pertinent information will then be entered into the dispatch software and automatically sent to the paramedics en-route to the crash. This text has the potential to be used to help identify those crashes that do/do not require a L&S as, unlike currently used dispatching systems that categorize a crash into a single category, it contains descriptive information that is more likely to capture the unique circumstances of that traffic crash.

The aim of this study is therefore to explore the predictive ability of EMD text, as well as MPDS determinant codes, for identifying traffic crashes that do/do not require a L&S ambulance dispatch.

2. Material and methods

2.1. Setting, population and design

This population-based retrospective cohort study was based in Perth, Western Australia from the 1st January 2014 to the 31st December 2016. The Perth metropolitan area had a population of approximately 2 million people (2016) and covers an area of 6,400 square kilometres [13]. All emergency medical services are provided by St John Western Australia (SJ-WA), which is the sole contracted provider of single-tier ambulance services in Perth. SJ-WA ambulances are staffed by two paramedics (sometimes one paramedic and a paramedic in training) who can perform advanced life support skills such as manual defibrillation and endotracheal intubation and are authorised to administer medications such as adrenaline (epinephrine), fentanyl and ketamine.

2.2. Data source

The data source comprised electronic patient care records for all traffic crashes attended by SJ-WA paramedics over the study period in the Perth metropolitan area. Each record includes computer-aided dispatch (CAD) data, together with patient care data entered by paramedics after attending the patient(s). The SJ-WA CAD data includes dispatch information recorded using the Medical Priority Dispatch System (MPDS) (v. 12) [11]. Traffic crashes comprise approximately 7,899 incidents each year in Perth for SJ-WA, which is around 3.7 % of all incidents, system wide [5].

Each patient record includes three data elements that we used as source data for our analysis: (a) a dispatch 'determinant' code, (b) EMD text data, and (c) patient care data entered by paramedics after attending the patient(s). The MPDS determinant or dispatch codes used in the study included any additional suffixes added to the code, such as those for multiple patients [11]. The EMD text was comprised as follows: using the Medical Priority Dispatch System (MPDS) (v. 12) [11], the EMD enters data for each incident, based on caller answers to scripted questions, that is used to assign a determinant code (e.g. '29D04') representing the nature and severity of the incident. In the case of traffic crashes, determinant codes are based on the scene characteristic (e.g. rollover, trapped victim, serious haemorrhage) that best describes potential clinical need or where any additional resources are required (e.g. concerning hazardous chemicals or a trapped patient). The determinant code is mapped within the SJ-WA response matrix which provides the Priority (1 – 3). The EMD text data used in this study is based on a text field stored in SJ-WA's computer-aided dispatch (CAD) system, which combines text that is auto-generated as a summary of the detailed MPDS dispatch coding, plus additional free-text typed by the EMD. Fig. 1 shows an example of EMD text data. Within that example, the text derived from the formal dispatch categorisation is '*YOU ARE RESPONDING TO A PATIENT INJURED IN A TRAFFIC INCIDENT. THE PATIENT IS A 41-YEAR-OLD FEMALE WHO IS CONSCIOUS AND BREATHING*.' This is then followed by free-text entered by the EMD: *'CALLER STATEMENT: VEH V PEDESTRIAN. POLICE OTW. 1X PT, SHOULDER & ABDO INJ, FACIAL INJURY, PREGNANT*.' This free-text component can relate to the caller statement in response to the MPDS prompt 'Tell me exactly what happened', but also other relevant information that becomes evident later in the call. The EMD text data can also include auto-formatted text that relates to structured fields (e.g. from EMDs populating check-boxes) that are unrelated to MPDS coding – e.g. '[84S ATTENDING]' flags that police are attending the incident. In addition to the MPDS determinant code and EMD text, paramedics complete an electronic patient care record (ePCR). The ePCR contains information about patient disposition, observations/vital signs and any medications or interventions that were given at the scene or during transport to the emergency department (ED).

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2.3. Data cohort

Our cohort was defined as incidents dispatched as "Traffic/Transportation incident" (MPDS Protocol 29) and which were identified by paramedics as a road crash. Aircraft/train/bicycle-only crashes, which are part of Protocol 29 were excluded.

2.4. Unit of measurement

The unit of measurement in this study was the traffic crash, given that ambulances dispatch priority is based on the needs of every-one at the crash, not an individual patient.

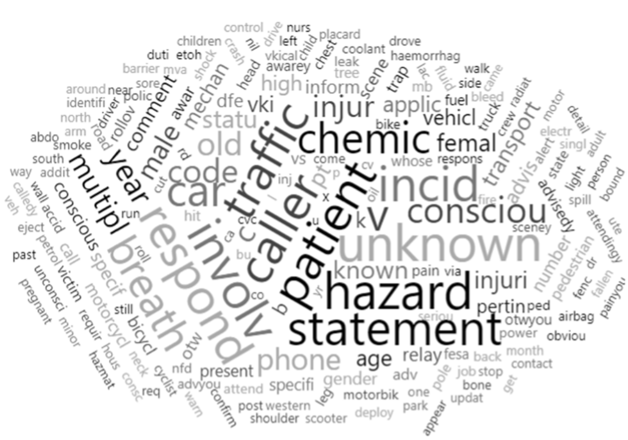

Fig. 1. Emergency medical dispatcher text word cloud.

2.5. Preparation of EMD text

A Bag of Words (BOW) approach is a Natural Language Processing (NLP) technique for converting text to numbers. The BOW approach was used to prepare the EMD text for analysis. Using this technique, the number of times a word appears in the text is counted. The process for preparing and converting the text to numbers was as follows. Firstly, all text was converted into lowercase. Punctuation (e.g. full stops and commas) and stop words were removed. Stop words are common use words that are not relevant to the analysis, such as: *as*, *and*, *is*, *that* and *was*. Commonly used medical and dispatch acronyms were standardized. Examples of these were *pts* into *patients* and *Hx* into *history*. Words were then stemmed. Stemming involves reducing a word to its root word and usually means removing the suffixes of a word. Examples of this are *stopped* in to *stop,* and *injuries* into *injur.* Porter's 2 stemmer algorithm, also known as the Snowball stemmer algorithm, was used to perform this step [21]. Words were then tokenized, where sentences were split into separated words, and the number of times a word appeared in the EMD text of each traffic crash was counted. Three examples are shown in Table 1. Words that occurred in less than 2 % of all EMD text words, such as individual street names and high-frequency words (e.g. hazard and statement) that had an inverse document frequency value (a measure of how common or rare a word is) of less than 0.6 were removed from the analysis (Robertson, 2004). Table 2..

2.6. Feature variables

Feature variables are input variables used to make predictions of the target variable. Features of the dataset were the MPDS determinant code and the counted BOW words from the EMD text. There were 9,224 input variables.

2.7. Target variable

The target variable is the outcome or the variable that is aimed to be predicted by the feature variables. The target variable measured was the crash-level need for a L&S ambulance response to the scene of a traffic crash, as a dichotomous variable (required, versus not required). A crash was retrospectively classified as having required a L&S ambulance response if any of the below indicators were present:

- Anyone had died on-scene or in transport to the emergency department (ED); or.

- The priority of the ambulance for anyone from the scene of the crash to an ED was L&S; or.

- Anyone had one or more L&S clinical indicators (Appendix 1). These indicators were based on a list developed previously by the SJ-WA Clinical Governance Department to retrospectively classify patients as high acuity. These included clinical interventions, medications administered and clinical observations that were recorded by paramedics (see Appendix 1).

Table 1
Example of emergency medical dispatcher (EMD) text conversion using word counts: Bag of words approach.

	Bag of Words (BOW)						
Original EMD text	patient	bleed	scene	police	head	leg	broke
The patient is bleeding. Head wound. Police on scene.	1	1	1	1	1	0	0
Police on their way. Two patients, 1x PTS with bleeding leg.	1	1	0	1	0	1	0
Bleeding has stopped. Patient with broken /bleeding leg. Police at scene.	1	2	1	1	0	1	1

Table 2
Ten most common root words in emergency medical dispatcher text.

patient
caller
involv
unknown
hazard
traffic
incid
respon
statement
vehic

2.8. Machine learning models

Data were randomly split into 60 % training and 40 % test datasets. The data were stratified such that each dataset (training and test) had a similar proportion of L&S crashes. K-fold cross-validation (10 folds) [2] was applied to the validation dataset.

The following machine learning models were chosen for their ability to predict and classify dichotomous outcome layers: Ensemble, K-nearest neighbours (k-NN), Naïve Bayes, Neural Network and Support Vector Machine [18]. Machine learning algorithms were optimized on the training dataset using standard optimization techniques [17].

Model performance was assessed using precision, recall, and F1 score. Precision is also known as a positive predictive value and recall as sensitivity. An F1 score is the harmonic mean of precision and recall which represents the models' overall performance. A perfect model would have a score of 1 for all these measures. The best performing model will be identified as that with the highest recall (or sensitivity) value. This is because, in practice in terms of patient safety, false negatives (crashes that required a L&S response but were predicted to not require a L&S response) are more important to identify than false positives (crashes that did not require a L&S response but were predicted to have required one). Binomial confidence intervals (95 %) were estimated for precision and recall, and bootstrap confidence intervals for the F1 score.

Data were cleaned in SAS/BASE (version 9.4). The EMD text was converted into a BoW using Orange (version 3.29). Machine learning algorithms were run in Matlab (version r2019) for all algorithms but the Neural Network (Weka version 3.9.5).

2.9. Ethics

This project was granted ethics approval by the Curtin University Human Research Ethics Committee (HR 128/2013) as part of the Western Australia Pre-hospital Record Linkage Project. The SJ-WA Research Governance Committee approved the research and the Main Roads Western Australia signed a Data Licensing Agreement.

3. Results

There were 11,971 traffic crashes attended by SJ-WA emergency ambulances in the three years from 2014 to 2016, involving 15,550 patients. Of these, 1,541 crashes (22.3 %) were retrospectively identified as having required a L&S response.

Features consisted of a single MPDS determinant code and 9,223 unique root words from the EMD text. The top three words were: *patient, caller* and *involve*. See Table 1. Fig. 1 shows the word cloud of EMD text with more common words shown in large font size.

The EMS from which the data for this manuscript was derived is St John Ambulance in Western Australia (SJ-WA). SJ-WA dispatch using

L&S to all road crashes they are notified of. Therefore, the baseline recall (sensitivity) is 1.0, the precision (PPV) is 0.1287 and the F1 score is 0.2281.

The classification performance results are shown in Table 3. The lowest precision (PPV), recall (sensitivity), and F1 scores were all found in models using MPDS determinant codes as the sole feature. The accuracy of these measures was: 0.122 (95 % CI 0.113–0.131), 0.012 (95 % CI 0.009–0.015) and 0.023 (95 % CI 0.017–0.030), respectively. Table A1..

The model with both the highest precision (0.975, 95 % CI 0.971–0.979) and F1 score (0.974, 95 % CI 0.964–0.979) was an Ensemble using the EMD text as the sole feature. The model with the highest recall was also an Ensemble model, however, this model used both MPDS determinant codes and EMD text (0.980, 95 % CI 0.976–0.984).

4. Discussion

This study explored the predictive ability of different methods for identifying traffic crashes that required a L&S ambulance dispatch response to the scene of a crash and those that did not. MPDS determinant codes, used by many EMS worldwide, were compared with EMD text (text the dispatcher sends to the paramedics en-route to the scene)

Table 3
Classification performance results for different machine learning algorithms with 95% confidence intervals.

		Precision (PPV)	Recall (sensitivity)	F1 Score
Medical Priority Dispatch System (MPDS) determinant codes				
	Ensemble	0.194 (0.183–0.205)	0.012 (0.009–0.015)	0.023 (0.017–0.030)
	k-NN	0.122 (0.113–0.131)	0.023 (0.019–0.027)	0.039 (0.031–0.048)
	Naïve Bayes	0.194 (0.183–0.205)	0.553 (0.539–0.567)	0.287 (0.274–0.310)
	Neural Network	0.209 (0.197–0.221)	0.076 (0.068–0.084)	0.111 (0.100–0.120)
	Support Vector Machines	0.124 (0.115–0.133)	0.721 (0.708–0.734)	0.212 (0.201–0.226)
Emergency medical dispatcher text				
	Ensemble	0.975 (0.971–0.979)	0.974 (0.969–0.979)	0.974 (0.964–0.979)
	k-NN	0.256 (0.244–0.268)	0.033 (0.028–0.038)	0.059 (0.052–0.066)
	Naïve Bayes	0.938 (0.931–0.945)	0.884 (0.875–0.893)	0.910 (0.900–0.919)
	Neural Network	0.869 (0.859–0.879)	0.865 (0.855–0.875)	0.867 (0.857–0.880)
	Support Vector Machines	0.786 (0.774–0.798)	0.303 (0.290–0.316)	0.437 (0.422–0.451)
Both MPDS & Emergency medical dispatcher text				
	Ensemble	0.940 (0.933–0.947)	0.980 (0.976–0.984)	0.960 (0.952–0.968)
	k-NN	0.786 (0.774–0.798)	0.864 (0.854–0.874)	0.823 (0.812–0.834)
	Naïve Bayes	0.939 (0.932–0.946)	0.885 (0.876–0.894)	0.911 (0.901–0.920)
	Neural Network	0.873 (0.864–0.882)	0.866 (0.856–0.876)	0.869 (0.859–0.880)
	Support Vector Machines	0.827 (0.816–0.838)	0.353 (0.339–0.367)	0.495 (0.480–0.509)
Baseline	**0.129**	**1.0**	**0228**	

Table A1
List of interventions/observations/medications indicating the need for a lights & sirens ambulance response.

Category	*Description*
Airway	Complete Obstruction
Airway	At-Risk/Unprotected
Airway	Soiled
Airway	Partial Obstruction
Airway	Stridor
Bleeding	Internal
Bleeding	External considered > 500mls
Breathing	Nil
Breathing	Shallow
Breathing	Slow
Breathing	Laboured
Breathing	Accessory Muscle Use
Breathing	Audible Wheeze
Burns	Full Thickness
Burns	Airway
Capillary Refill	> 2 Seconds
Clinical Interventions	Stroke Centre Delivery
Clinical Interventions	Mechanical CPR Device
Clinical Interventions	ST-Elevation Myocardial Infarction (STEMI)
Collapse	Ambulance Officer Witnessed
Collapse	Bystander Witnessed
Conscious State	Pain Response
Conscious State	Nil Response
Doctor at Scene	Intubated
E.C.G. Rhythm	Supraventricular Tachycardia (SVT)
Electrocardiogram (ECG/EKG)	Pulseless Electrical Activity (PEA)
Electrocardiogram (ECG/EKG)	Ventricular Tachycardia (VT)
Electrocardiogram (ECG/EKG)	Asystole
Electrocardiogram (ECG/EKG)	Bradycardia
Electrocardiogram (ECG/EKG)	Ventricular Fibrillation (VF)
Glasgow Coma Scale (GCS) Motor	1 None
Glasgow Coma Scale (GCS) Motor	2 Extension to Pain
Glasgow Coma Scale (GCS) Motor	3 Flexion to Pain
Glasgow Coma Scale (GCS) Total	Total less than 10
Glasgow Coma Scale (GCS) Verbal	1 None
Glasgow Coma Scale (GCS) Verbal	2 Incomprehensible
Head Gaze/Deviation	Present
Medications-Intervention	cefazolin
Medications-Intervention	packed red blood cells
Medications-Intervention	suxamethonium chloride
Medications-Intervention	epinephrine
Medications-Intervention	amiodarone
Medications-Intervention	atropine sulphate
Medications-Intervention	glucose 10 %
Medications-Intervention	heparin Sodium
Medications-Intervention	metaraminol tartrate (aramine)
Medications-Intervention	morphine & midazolam infusion
Medications-Intervention	rocuronium bromide (esmeron)
Medications-Intervention	tranexamic acid (TXA)
Other finding	Amputation
Other finding	Partial Amputation
Paediatric GCS Eye Opening	1 None
Paediatric GCS Eye Opening	2 To Pain
Paediatric GCS Motor Response	2 Extension to Pain
Paediatric GCS Verbal Response	2 Inconsolable, Agitated
Paediatric Motor Response	3 Abnormal Flexion to Pain
Post cardiac arrest	Return of Spontaneous Circulation (ROSC)
Post cardiac arrest	ROSC Temporary
Post defibrillation	No Rhythm Change
Post defibrillation	Rhythm Change
Pre-Ambulance Care	Ventilation Only
Pre-Ambulance Care	Cardiopulmonary Resuscitation (CPR)
Pre-Ambulance Care	Automated External Defibrillator (AED) - Shock delivered
Pulse	Nil
Pulse	Weak

(*continued on next page*)

Table A1 (*continued*)

Category	*Description*
Skills	Cardiopulmonary Resuscitation (CPR)
Skills	Oropharyngeal Airway
Skills	External Cardiac Pacing
Skills	Suction (of the airway)
Skills	Needle Thoracentesis
Skills	Cricothyrotomy
Skills	Defibrillator
Skills	Endotracheal Tube
Skills	Finger Thoracostomy
Skills	I-Gel Supraglottic Airway Device
Skills	Intraosseous Cannulation
Skills	Laryngeal Mask Airway
Skills	Magill Forceps
Skills	Rapid Sequence Induction
Skills	Synchronised Cardioversion
Skills	Ventilator
Skin Colour	Cyanotic
Splint/Dressing	Combat Application Tourniquet (CAT)
Splint/Dressing	Traction Splint

for predictive ability (requiring a L&S response or not). Predictive ability was measured using the F1 score, precision (PPV) and recall (sensitivity). Recall was the preferred measure of accuracy given the risk in ambulance dispatch of false negatives, where an ambulance is dispatched as not requiring a L&S response to a crash with patients(s) who do require L&S. The model with the highest recall score used both MPDS determinant codes and EMD text (0.980 95 % CI 0.976–0.984). This model also had both the second-highest precision (0.975 95 % CI 0.971–0979) and F1 score (0.960 95 % CI 0.925–0.968).

This is the first time that EMD text has been used to predict the need for a L&S response and the magnitude of the result certainly suggests that it has the potential to be used in practice. The models found here have used data from the past to predict whether a traffic crash had required a L&S response. These models can also be used prospectively to identify those crashes that require an L&S response or not. This is called model deployment, where the model derived from historical data is integrated into an existing production environment, such as that dispatching ambulances. In other words, EMD text could be used in real-time during the call to identify the appropriate ambulance response. Given that MPDS determinant codes alone are poor predictors of the need for an L&S response [9], the deployment of the Ensemble model found in this study could improve the accuracy of dispatching ambulances to traffic crashes. In particular, this could mean that the traffic crashes that require a L&S response receive one, and those crashes not requiring an L&S response do not receive one, freeing up ambulances as a resource for other calls for emergency medical assistance.

The use of machine learning and natural language processing of medical-related text is used with success in similarly complex domains. For example, Andrew et al [1] were able to use EMD text to predict transport to the emergency department of unconscious patients. Others have been able to predict patient disposition in the emergency department using triage notes [20], length of hospital stay using doctors notes [3] and cause of transient ischemic attacks using doctors notes on history at presentation [4]. One reason for dispatcher/medical text being able to predict different aspects of patient need is because of the level of detail often contained in the text. The EMD text contains detailed information that the dispatcher decides is most clinically relevant to paramedics. This contrasts with the MPDS system that is used by most EMS worldwide; which assigns a single category (determinant code) to each traffic crash that has an associated pre-determined level of ambulance response (L&S or not). Dispatching based on a single code has obvious limitations, especially when a crash is complex, such as that where there was a rollover, a pedestrian hit, and a patient haemorrhaging, all within the one crash.

5. Limitations

In some circumstances, EMD text is updated after the original text is entered. For example, in the case where the text is modified to include this information regarding police attendance. Also, police may arrive on-scene before any ambulances and update the EMD with information. This additional information has been included in this analysis. However, it would not be available in 'real-time' to prospectively identify the ambulance dispatch priority. However, this was not a concern, given that references to police were removed in the cleaning process of high-frequency words (See methods section).

The order of words has not been taken into account in this analysis. Consider the text, *the bleeding has stopped,* with the text, *she is bleeding.* In the BOW approach, the root word *bleed* would have been counted in these two examples. However, the text contains clinically opposite meanings. A Natural Language Processing approach that does take into account the order of words is *n*-grams [12]. *N*-grams involve joining multiple words after the removal of stop words such as *and* or *is*. In the example text, the created bigrams (the simplest form of *n*-gram using two consecutive words) would be *is bleeding-stopped* and *is not bleeding,* which maintains the meaning of the text. While *n*-grams were not a part of this study, the use of *n*-grams could further improve the predictive ability of the models.

An additional limitation is that this research was based on data partly derived using the MPDS version 12. We acknowledge that the latest version (13.3.3) has made some enhancement in regard to dispatch to crashes.

6. Future research

Future research could seek to explore whether the findings found here could be replicated in other EMS operating in different settings, as well as in fire and police emergency systems. Every EMS is different, with variances such as the number of ambulances per population, the skills of the paramedics or language colloquialisms. Additionally, every road environment is different such as traffic density, level of motorization and the average annual traffic crash fatality rate. Differences in road environment determine the types of crashes that happen and the subsequent needs of patients. Furthermore, a prospective study could assess the model in an operational setting, in real-time. A similar trial was conducted by [6]. This would enable assessment of processing speed, accuracy and general ease of use.

7. Conclusion

This study has shown that a combination of EMD text and MPDS determinate codes can predict which traffic crashes do and do not require a lights and sirens ambulance dispatch response to the scene. These findings have potential implications for how emergency medical services could dispatch ambulances to traffic crashes and presents an opportunity to make sure the right ambulance care is getting to those who need it through the use of real-time deployment of machine learning models.

8. Summary points

- Ambulance demand is increasing and it is important to identify what traffic crashes require the fastest ambulance response
- Traffic crashes are complex events and traditional methods for triaging during the call for emergency medical assistance have limitations
- Using natural language processing, EMD text has high predictive ability in identifying those crashes that require the fastest response and those that do not

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Author contributions:

EC, HT, SB, and JF developed the study. EC cleaned and prepared the data. EC analyzed and interpreted the results and drafted the manuscript. HT, SB, EB, DB, BP, AW, RB and JF helped write and review the manuscript. All authors approved submission.

Disclosure of Interest:

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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