Curtin School of Nursing

Ambulance Dispatch Prioritisation of Road Crash Patients:

A Retrospective Study Using Population-Based Linked Data

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of

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Declaration

To the best of my knowledge and belief, this thesis contains no material previously published by any other person except where due acknowledgment has been made. This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Human Ethics

The research presented and reported in this thesis was conducted in accordance with the National Health and Medical Research Council National Statement on Ethical Conduct in Human Research. The proposed research study received human research ethics approval from the Curtin University Human Research Ethics Committee. Approval Number HR128/2013. The project was also approved by the St John WA Research Advisory Group (Research Governance) on 17 July 2017.

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20th June 2023

Abstract

Title: Ambulance Dispatch Prioritisation of Road Crash Patients: A Retrospective Study Using Population-Based Linked Data

Background: Road crashes contribute significantly to global mortality, ranking as the eighth leading cause of death, comprising 1.4 million fatalities annually. Emergency medical service (EMS) centres play a crucial role in reducing morbidity and mortality associated with crashes through the answering of phone calls for assistance and subsequent dispatch of emergency medical ambulances. Assigning the dispatch priority of the ambulance is a critical aspect of providing timely emergency assistance for road crashes. The highest priority response, known as a lights and sirens (L&S) response, is reserved for patients with potentially life-threatening conditions. Given that ambulances are a scarce resource, it becomes important to allocate them based on the highest level of need. However, dispatching ambulances to road crashes poses a challenge for many reasons including due to the varied nature of patient needs in crashes.

Primary aim: To investigate ways to identify, during the emergency call, which crashes require a L&S ambulance response and those that do not.

General methods: Six discrete studies comprise this thesis. I have published five in a peer-reviewed journal, and one is currently under review. One study was a systematic review; the others were retrospective cohort studies focusing on different aspects of ambulance prioritisation. I linked data from the emergency medical ambulance service and the police department of Perth, Western Australia (WA). This

made a comprehensive dataset of all road crashes (and patients) attended by emergency medical ambulance for the period 2014 to 2016.

Results and discussion:

Low prevalence of L&S: I confirmed that only a small portion of road crashes required a L&S response. This was consistent across all five analytical studies. Specifically, among the patients attended, 3.3% had a Glasgow Coma Scale score below 14, 2.1% had abnormal respiratory rates, and 0.7% had low blood pressure. When examining crashes, only a small percentage involved patients with the highest NEWS2 score of 20 (1.4%). Additionally, using high-acuity indicators, it was found that 22.3% of crashes required a L&S response. These findings hold significance for two reasons. First, there is a lack of research on the acuity of patients at crashes in terms of the requirement (or not) for a L&S response. Second, the current practice of dispatching ambulances as L&S to all reported road crashes by St John Western Australia (the local jurisdiction from which this thesis was derived) leads to significant over-triage, or dispatching ambulances in cases where it is unnecessary. This over-triage negatively affects EMS efficiency, potentially delaying responses to other time-critical patients.

Mixed results of ambulatory status as an indicator: I had varied results regarding the suitability of ambulatory status as a potential indicator of the need for a L&S response. I first found that non-ambulant patients had over 15 times higher odds of being high acuity than ambulant patients (OR 15.34, 95% CI, 11.48–20.49), making ambulatory status the strongest predictor of needing a L&S response in that study. Subsequently, I employed a simple decision tree to predict the need for a L&S response, but the tree with the most promising triage rates did not incorporate ambulatory status. Then, in a systematic review, I found insufficient evidence to conclusively link ambulatory status to the need for L&S response. The varied findings may be attributed to the bimodal distribution of ambulatory status I observed in a subsequent study. Further research is needed to determine the utility of ambulatory status as a crash characteristic with the potential to be used to identify dispatch priority at the scene of a crash.

Rollovers and prediction of the need for L&S: The suitability of vehicle rollover as a predictive crash characteristic for determining the need for a L&S response was investigated. Despite its use in field triage, its effectiveness for ambulance dispatch remains uncertain. The research revealed that only a small percentage of patients involved in rollovers (6.6%) required a L&S response. Similarly, of rollover crashes, it was found that the majority did not require a L&S response (11.4% and 15.9% respectively). Surprisingly, when acuity was considered as a continuous outcome measure rather than a dichotomous one (L&S or not), rollover cases exhibited a bimodal distribution. This distribution in acuity was also seen in other crash characteristics such as ejection, inability to ambulate, being trapped, and crashes occurring on hills. The presence of a bimodal distribution suggests that other crash characteristics may play a role in determining the need for a L&S response in rollovers. Factors like roof collapse and restraint use (seat belts) could influence the requirement for a L&S response. Considering the bimodal distribution observed across multiple crash characteristics, I concluded that combinations of characteristics, such as rollover and restraint use, might offer more accurate predictions for the need of a L&S response than any single crash characteristic.

Crash complexity: The thesis initially aimed to determine if crash characteristics could predict the need for a L&S response. The hypothesis was that combinations of crash characteristics could potentially create pre-scripted questions for emergency medical dispatchers (EMD) to prioritise ambulance responses. However, when using a simple decision tree algorithm, the accuracy of predicting the need for a L&S response was not satisfactory. The decision tree with the closest over/under-triage rates to recommended thresholds incorporated crash characteristics such as trapped individuals, involvement of vulnerable road users, ambulatory status, rainy conditions, and accident type. This decision tree achieved an 84.8% over-triage rate and a 2.7% under-triage rate and was deemed as a poor-performing model that would not have sufficient operational over/under-triage rates. Therefore, the analysis shifted towards utilising dispatcher free-text descriptions to incorporate a greater number of characteristics to improve prediction accuracy.

High accuracy of dispatcher text using a machine language technique: EMDs often type descriptive texts about crash scenes, which are relayed to ambulance crews for better situational understanding. In this study, I proposed a novel approach that involved converting these texts into computational vectors and applying machine learning algorithms to predict the need for a L&S response. A gradient-boosting model combining dispatch codes and dispatcher-recorded text achieved a high predictive ability, particularly in identifying crashes that required a L&S response. The model had a recall score (sensitivity) of 0.980. This model's remarkable predictive ability is notable when compared to previous literature on ambulance dispatch accuracy, where sensitivity values were typically much lower.

Conclusion: This thesis aimed to investigate methods for identifying the need for a lights and sirens (L&S) ambulance response to the scene of a road crash. The findings reveal that less than 20% of all road crashes attended by emergency ambulances require a L&S response. Unless emergency medical services (EMS) are willing to tolerate high rates of over-triage, which is increasingly challenging given

rising demand, a more precise approach to ambulance dispatch for road crashes is required. It was observed that the current dispatch system, relying solely on the Medical Priority Dispatch System (MPDS), exhibits inadequate predictive capability in discerning the need for a L&S response. As a result, novel machine learning-based predictive models were developed, incorporating EMD text data, which showed high accuracy in predicting the requirement for a L&S response. This thesis establishes that there is potential to enhance the efficiency of EMS dispatching for road crashes, ensuring appropriate care is delivered to the right patient, at the right time.

Acknowledgements

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This PhD would not have been possible without the supply of administrative and clinical data from St John Ambulance Western Australia and Main Roads Western Australia.

Copyright statement

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Acknowledgement of Country

We acknowledge that Curtin University works across hundreds of traditional lands and custodial groups in Australia, and with First Nations people around the globe.

We wish to pay our deepest respects to their ancestors and members of their communities, past, present, and to their emerging leaders. Our passion and commitment to work with all Australians and peoples from across the world, including our First Nations peoples are at the core of the work we do, reflective of our institutions' values and commitment to our role as leaders in the Reconciliation space in Australia.

Publications and Scholarships

Publications:

Study 1. Ceklic E, Tohira H, Finn J, Brink D, Bailey P, Whiteside A, Brown E, Brits, R, Ball, S. Can ambulance dispatch categories discriminate traffic incidents that do/do not require a lights and sirens response? International journal of emergency care. 2021, 10(3).

Study 2. Ceklic E, Tohira H, Ball S, Brown E, Brink D, Bailey P, Whiteside A, Finn J. Motor vehicle crash characteristics that are predictive of high acuity patients: an analysis of linked ambulance and crash data. Prehospital emergency care. 2021 Apr 20; 25(3):351-60.

Study 3. Ceklic E, Tohira H, Ball S, Brink G, Bailey P, Whiteside A, Finn J. A Systematic review of the relationship between ambulant status and the need for a lights-and-siren ambulance response to crashes. Annals of emergency dispatch & response. 2020; 7(3).

Study 4. Ceklic E, Tohira H, Ball S, Brown E, Brink D, Bailey P, Brits R, Finn J. A predictive ambulance dispatch algorithm to the scene of a motor vehicle crash: the search for optimal over and under-triage rates. BMC emergency medicine. 2022 Dec;22(1):1-1.

Study 6. Ceklic E, Ball S, Finn J, Brown E, Brink D, Bailey P, Whiteside A, Brits R, Tohira H. Ambulance dispatch prioritisation for traffic crashes using machine learning: A natural language approach. International journal of medical informatics. 2022 Dec; 1.

Manuscript submitted for publication:

Study 5. Ceklic E, Tohira H, Ball S, Brink D, Bailey P, Whiteside, A, Brits R, Finn J. Variation in on-scene patient acuity for different types of traffic crashes: a linked data study. Under review – Traffic Injury Prevention.

Scholarship:

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Author Attribution Statement

Ellen Ceklic, was the primary author of the following six studies. I contributed between 70% and 80% for each.

Table 1 Author contributions per study (%)

	Study					
	1	**2**	**3**	**4**	**5**	**6**
Ms Ellen Ceklic	70%	77%	80%	77%	70%	77%
Dr Hideo Tohira	5%	5%	10%	5%	10%	5%
Dr Stephen Ball	10%	5%	5%	5%	5%	5%
Dr Elizabeth Brown	2%	2%	n/a	2%	2%	n/a
Dr Paul Bailey	2%	2%	n/a	2%	2%	2%
Mr Austin Whiteside	2%	2%	n/a	2%	2%	2%
Mr Deon Brink	2%	2%	n/a	2%	2%	2%
Mr Rudolph Brits	2%	n/a	n/a	n/a	2%	2%
Professor Judith Finn	5%	5%	5%	5%	5%	5%

Ellen Ceklic

Dr Hideo Tohira

Dr Stephen Ball

Dr Elizabeth Brown

Dr Paul Bailey

Mr Austin Whiteside

Mr Deon Brink

Mr Rudolph Brits

Professor Judith Finn

List of Tables

Note that tables in the published manuscripts are not included in the above list.

List of Abbreviations

ACNS	Automatic Crash Notification Systems
ACSCOT	American College of Surgeons Committee on Trauma
AUROC	Area under the Receiver Operating Characteristic
CAD	Computer Aided Dispatch
CART	Classification and regression trees
CBDS	Criteria Based Dispatch System
CHAID	Chi-square Automatic Interaction Detector
CI	Confidence interval
CSS	Cincinnati Stroke Scale
ED	Emergency department
EMD	Emergency medical dispatcher
EMS	Emergency medical service
ePCR	Electronic patient care record
GCS	Glasgow Coma Scale
GP	General Practitioner
ICWA	Insurance Commission of Western Australia
IoT	Internet of things
IoV	Internet of vehicles
IQR	Inter-quartile range
k-NN	k-nearest neighbour
MPDS	Medical Priority Dispatch System
MCV	Motor vehicle crash
NEWS2	National Early Warning Score 2
NLP	Natural language processing
OECD	Organisation for Economic Co-operation and Development
SJ-WA	St John Ambulance Western Australia
SD	Standard deviation
TC	Traffic crash
TI	Traffic incident
WA	Western Australia
WHO	World Health Organisation

Table of Contents

Chapter 1: Introduction

1.1 BACKGROUND AND RATIONALE

Road crashes are the eighth leading cause of death globally, comprising around 1.4 million deaths each year.[1] Emergency medical service (EMS) call centres, which respond to the telephone call for assistance and dispatch emergency medical ambulances, play a central role in reducing the morbidity and mortality associated with crashes.[2] An important component in the provision of emergency assistance for road crashes is in determining the priority with which ambulances are dispatched to the scene. Ambulances should be dispatched at the highest priority, known as a lights and sirens (L&S) response, to patients with life-threatening conditions; and should be dispatched at a lower priority for all other conditions.

Road crashes are an unusual type of call for emergency medical assistance because of the varying acuity of patients, and therefore the varying required priorities of ambulances to the scene. Factors in the crash, such as the movement (for example, rear-end or head-on), or types of vehicles (for instance, sedan or truck), use of safety equipment (such as seatbelts or airbags), or the age and health of those involved, mean that some patients may die immediately, whereas others may be entirely uninjured.[3] This is consequently a challenge when dispatching to road crashes and the reason many EMS routinely dispatch ambulances using the highest priority L&S response. However, inaccuracy in ambulance dispatch can cause EMS inefficiencies. Over-triage, sending an ambulance using L&S to a patient(s) who does not require it, means that there is the opportunity cost, whereby the same ambulance could have been dispatched to a higher acuity incident elsewhere (that is not necessarily a road crash). [4] Besides the opportunity cost of over-triage, there is some evidence of the increased risk of ambulances being directly involved in a crash when driving L&S. [5] Conversely, under-triage, or not sending a L&S response ambulance to a patient(s) with life-threatening conditions, increases the risk of patient morbidity or mortality should there be a delay in the arrival of an ambulance on the scene. [6] Accuracy in dispatching ambulances is therefore important for both patient outcomes and ensuring EMS efficiency. [7]

My doctoral thesis sought to explore ways to accurately identify, during the emergency call, the required prioritisation (L&S or not) of the ambulance dispatch to the scene of a road crash.

I conducted a retrospective cohort study using EMS dispatch data sourced from St John Ambulance Western Australia (SJ-WA) [8] (a single-tier emergency ambulance service covering all WA) linked to detailed descriptive crash data sourced from composite collection from the Western Australia Police Department, Main Roads Western Australia, and the Insurance Commission of Western Australia. [9] Using these linked data, I firstly wanted to assess whether the system currently used by many EMS worldwide, known as the Medical Priority Dispatch System (MPDS), [10] could accurately identify the required dispatch priority of ambulances to the scene of a crash. To do this, I used the MPDS dispatch categories assigned during the call for emergency medical assistance and plotted their predictive ability on a Receiver Operating Characteristic (ROC) curve and assessed this ability to classify whether L&S were required according to the dispatch category. I then investigated alternative methods for the identification of ambulance dispatch priority to the scene. I explored this in three different ways: (1) using the MPDS and associated dispatch categories, (2) a simple decision-tree approach based on characteristics of crashes (e.g., head-on, at a roundabout, at night-time or involving a pedestrian) and (3) a machine-learning approach using emergency medical dispatch notes using natural language processing. The broad aims of my thesis were as follows:

1.2 AIM

Aim 1: To determine how well the Medical Priority Dispatch System (MPDS) [10] dispatch categories (codes) can discriminate between those road crashes that do/do not require a L&S response.

Aim 2: To describe the clinical, demographic, and crash characteristics of road crash patients attended by emergency ambulance.

Aim 3: To synthesise the reported evidence for whether ambulatory status can accurately inform the requirement for a L&S response to road crashes.

Aim 4: To determine whether combinations of characteristics of the crash, able to be described by a layperson at the scene, can identify those ambulance-attended road crashes that do/do not require a L&S response.

Aim 5: To describe the distribution of patient acuity at the scene of ambulance-attended road crashes according to different characteristics of crashes.

Aim 6: To determine (using natural language processing) how well text written in emergency medical dispatcher (EMD) dispatch notes can identify those ambulance-attended road crashes that do/do not require a L&S response.

1.3 RESEARCH OBJECTIVES

To address the above research aims, there were several specific research objectives. These are outlined in Table 2.

Table 2 Research aims linked to specific research objectives

Aim 1:	To determine how well the Medical Priority Dispatch System (MPDS) [10] dispatch categories (codes) can discriminate between those road crashes that do/do not require a L&S response.
i.	To undertake a retrospective cohort study in which MPDS dispatch codes for the Traffic/Transportation Chief Complaint are investigated for their ability to discriminate between L&S incidents.
ii.	To describe the proportion of L&S incidents within each MPDS dispatch category.
iii.	To determine whether MPDS dispatch categories can discriminate between those incidents that do/do not require a L&S response based on the sensitivity, specificity, and an AUROC.
iv.	To determine a threshold level of predictive models to identify those incidents that do/do not require a L&S response.
Aim 2:	To describe the clinical, demographic, and crash characteristics of road crash patients attended by emergency ambulance.
i.	To describe patient demographics and crash characteristics attended by emergency ambulance.
ii.	To determine factors associated with the need for a 'Priority One' (L&S) response.
Aim 3:	To synthesise the reported evidence for whether ambulatory status can accurately inform the requirement for a L&S response to road crashes.
i.	To conduct a systematic review of the published evidence for an association with ambulatory status and the need for a L&S response.
ii.	To evaluate the quality of the methods used in studies analysing the above association.
Aim 4:	To determine whether combinations of characteristics of the crash, able to be described by a layperson at the scene, can identify those crashes that do/do not require a L&S response.
i.	To derive decision-tree models to identify those crashes that do/do not require a L&S response using different combinations of MPDS dispatch codes and crash characteristics
ii.	To evaluate the predictability of the derived decision trees by over- and under-triage rates.
Aim 5:	To describe the distribution of patient acuity by characteristics of crashes and to identify those characteristics that have a bimodal distribution in the acuity of patients.
i.	To describe the distribution of the immediate on-scene acuity of patients using the NEWS2 score.
ii.	To determine the types of crashes that result in variation in patient acuity, particularly those that result in a bimodal distribution of acuity
Aim 6:	To determine how well text written in emergency medical dispatcher notes can identify those crashes that do/do not require a L&S response.
i.	To derive machine-learning models for predicting the need for a L&S response using both MPDS dispatch codes and features generated from free-text recorded by EMD.
ii.	To determine the best performance model using precision, recall and F1-score.

1.4 SIGNIFICANCE

The thesis seeks to make a positive contribution toward the accuracy of ambulance dispatch prioritisation with the goal that the findings will improve EMS system efficiency

1.5 THESIS APPROACH

This thesis takes a ‘hybrid model’ approach, which combines both published studies (or those submitted for review) and a written description of the work undertaken.

1.6 STRUCTURE OF THE THESIS

This thesis comprises eleven chapters, as follows in Table 3.

Table 3 Overview of thesis chapters

Chapter	Description	Aims
1	***Introduction***	
2	***Contextual Overview*** This chapter summarises existing literature regarding EMS and the dispatch of ambulances to the scene of road crashes.	
3	***General Methodology*** This chapter describes the general methodology for the six analytical studies, including data sources, variables, units of measurement, and analytical techniques.	
4	***Study 1 - Dispatch Codes and Ability to Discriminate*** This chapter gives a summary of the research conducted for the **published study** – *Ceklic E, Tohira H, Finn J, Brink D, Bailey P, Whiteside A, Brown E, Brits R, Ball S. Can ambulance dispatch categories discriminate traffic incidents that do/do not require a lights and sirens response? International Journal of Emergency Services. 2021 Dec 16.* Preceding this is a copy of the published version of the study.	1
5	***Study 2 – Crash Characteristics and High Acuity Patients*** This chapter gives a summary of the research conducted for the **published study** – *Ceklic E, Tohira H, Ball S, Brown E, Brink D, Bailey P, Whiteside A, Finn J. Motor vehicle crash characteristics that are predictive of high acuity patients: an analysis of linked ambulance and crash data. Prehospital emergency care. 2021 Apr 20;25(3):351-60.* Preceding this is a copy of the published version of the study.	2
6	***Study 3 – A Systematic Review of Ambulant Status*** This chapter gives a summary of the research conducted for the **published study** – *Ceklic E, Tohira H, Ball S, Finn J. A Systematic Review of the Relationship Between Ambulant Status and the Need for a Lights-and-Siren Ambulance Response to Crashes. Annals of Emergency Dispatch & Response. 2020;7(3).* Preceding this is a copy of the published version of the study.	3
7	***Study 4 – Decision Tree Dispatch Algorithm*** This chapter gives a summary of the research conducted for the **published study -** *Ceklic E, Tohira H, Ball S, Brown E, Brink D,*	4

	Bailey P, Brits R, Finn J. A predictive ambulance dispatch algorithm to the scene of a motor vehicle crash: the search for optimal over and under-triage rates. BMC emergency medicine. 2022 Dec;22(1):1-1. Preceding this is a copy of the published version of the study.	
8	***Study 5 - Variation in On-Scene Patient Acuity*** This chapter gives a summary of the research conducted for the **study submitted for review,** titled – *Variation in on-scene patient acuity for different types of traffic crashes: a linked data study.* Preceding this is a copy of the study submitted for review.	5
9	***Study 6 – Natural Language Processing Dispatch Algorithm*** This chapter gives a summary of the research conducted for the **published study -** *Ceklic E, Ball S, Finn J, Brown E, Brink D, Bailey P, Whiteside A, Brits R, Tohira H. Ambulance dispatch prioritisation for traffic crashes using machine learning: A natural language approach. International journal of medical informatics. 2022 Dec 1.* Preceding this is a copy of the published version of the study.	6
10	***Synthesis of Findings: Over and Under-triage Rates*** This chapter synthesises the findings from studies 1, 4 and 6 by providing comparative over and under-triage rates.	1,4,6
11	***Discussion*** This chapter provides a discussion synthesising the findings within the context of current literature and the research objectives. The significance of the findings, limitations, and suggestions for future research are presented.	

Chapter 2: Contextual Overview

This chapter aims to provide contextual information relating to road crashes and the role of EMS, particularly concerning the dispatch of ambulances.

2.1 BACKGROUND STATISTICS

Road crashes are the leading cause of injury worldwide, resulting in around 1.4 million deaths each year and about 35 million injuries.[1] While the road crash fatality rate (deaths per 100,000 population) varies considerably across countries, economic income groups and the road environment (urban or rural), the worldwide road crash fatality rate is estimated to be 15.1 deaths per 100,000 population. [11] This mortality rate is comparable to death due to diabetes, tuberculosis, and hypertensive heart disease.[1]

There are numerous methods to reduce the burden of road crashes, including enhancements to road infrastructure, enforcement of traffic laws, the development of safer vehicles and driving-related education. Emergency Medical Systems (EMS), which dispatch ambulances to the scene of a crash, are another available method to reduce the burden of deaths and injuries resulting from road crashes.

2.2 EMERGENCY MEDICAL SERVICES

An EMS, also termed an ambulance service, is defined as ‘the system that organizes all aspects of care provided to patients in the pre-hospital or out-of-hospital environment.’[12] ‘Pre-hospital’ is medical care given in the community, such as at the roadside (for road crashes), home, work, or school. This care may be given by doctors, nurses, paramedics, or emergency medical technicians (EMTs). The purpose of EMS is to provide timely care to patients with emergency medical needs, to mitigate the risk of death, long-term health consequences, physical pain or psychological distress.[13] For road crashes, EMS has a critical role in preventing road crash deaths and reducing the severity of injuries through accurate clinical assessment, provision of high-quality care, fast transport to definitive care (such as a hospital trauma centre) and coordination of other emergency services.[14] EMS are often the first point of contact with medical services for road crash patients and therefore they are viewed as the ‘gatekeepers’ for accessing further care, such as that provided in emergency departments (ED) and tertiary hospitals.[13 (p1)]

EMS are activated during phone calls for emergency medical assistance. For road crashes, this means calls from those directly involved in the crash or bystanders. In Australia, this involves a telephone call to the number ‘000’; [15] for the United States, this is ‘911’[16] and for the United Kingdom, ‘999’.[17] In Australia a call to ’000’ is initially directed to a centralised emergency call centre that also manages calls for other emergencies, such as for urgent police or fire brigade (also known as fire department) attendance.[17]

2.2.1 Dispatching Sequence of Events

An EMS' involvement with a medical emergency follows a sequence of events that starts with the incident and is followed by a telephone call (sometimes text) for emergency medical assistance[18] During the call for assistance, the emergency medical dispatcher (EMD) clarifies the reason for the call. This enables the triage priority to be established, for an ambulance (or ambulances) to be dispatched to the scene.[18] Other steps in the continuum involve ambulance arrival at the scene, assessment/treatment and potential transport to an ED. The steps involving the call to the EMS and subsequent dispatch of ambulances are the primary focus of this thesis.

2.3 AMBULANCE DISPATCH

The EMD answers the call for emergency medical assistance. They ask a set of questions (often scripted/pre-written) to determine the needs of the patient(s). Based on the information gathered during the call, the priority with which the ambulance is dispatched to the scene is determined.[19] Noting that the priority is also often pre-determined, for example, a crash involving a pedestrian might always have a pre-assigned priority as a L&S response. Given that ambulances are a scarce resource, with only a fixed number of ambulances available at any time, ambulances must be prioritised according to the medical needs of the patients.[20] Ambulance prioritisation directly relates to the urgency of the medical need of the patient(s) and the available resources (ambulance crew and ambulances), rather than a first come, first serve basis. Ambulance prioritisation aims to ensure the appropriate care reaches the appropriate patient(s) within the appropriate time. Patients requiring urgent care are categorised at the highest priority, where L&S are used by the ambulance on the way to the scene.

Alternatively, the patient's clinical needs may be categorised as a lower priority, therefore L&S are likely not used on the way.

2.4 LIGHTS AND SIRENS

L&S refers to using lights flashing on the ambulance and a warning siren sounding with the primary purpose to warn other drivers and request the right of way.[21] When L&S are used, drivers are warned of the approaching ambulance and are expected to clear its path (give way), enabling the ambulance to rapidly reach its destination.[22] When ambulances use L&S, they are often exempt from normal road rules (traffic laws). Such as they can drive through stop signs and red lights or exceed the posted speed limit (where it is safe to do so).[23]

2.4.1 Advantages of L&S

The major advantage of a L&S ambulance response is the reduction in travel time for the ambulance from the time of dispatch to its arrival on the scene.[24] This is because using L&S means that ambulances can exceed the posted speed limit and manoeuvre through traffic more efficiently. [22] Several studies found a reduction in travel time to the scene when using a L&S response, ranging from a reduction of 1 minute 46 seconds to 14 minutes. [24–29]

Reducing travel time to the scene can potentially improve patient outcomes. For instance, it was found that a response time below 4 minutes increased the chance of survival to hospital discharge[30] and reduced the likelihood of mortality across all calls for assistance, not just for road crashes.[31] However, many studies question whether a reduced response time produces clinically relevant results.[26,30,32,33] This is particularly the case in studies where L&S are used on the way to the scene for a low-acuity patient (one who does not require a time-critical intervention). While controversy undoubtedly exists regarding the effect of ambulance response time on patient outcomes across all calls for emergency medical assistance (for road crashes or otherwise), one study specifically concerning road crashes found that a 10-minute reduction in response time was associated with a one-third decrease in the probability of death following involvement in a crash.[6]

Given that a reduction in travel time to the scene is most frequently associated with positive patient outcomes for those requiring time-critical care, the opposite is also true: a prolonged response time can have negative consequences for the patient. A study conducted in the United States found that in trauma patients (including those in a road crash), a lengthy pre-hospital time was associated with the onset of pneumonia in hospital,[31] and a study of rural road crash patients found an increase in mortality because of a delayed response to the crash scene.[34] Overall, using L&S has positive outcomes for patients (who require care) due to reduced response times; equally, prolonged response times can risk patients' health.

An additional advantage of using L&S is that they may increase the safety of those driving the ambulance (e.g., doctors, nurses, or paramedics) and those around them, as drivers are warned of the oncoming ambulance. [35] Having a warning (through L&S) means that drivers can move out of the way of the ambulance, creating free driving space. This is sometimes termed as being 'required to yield.' [35] Having free driving space means that ambulances and other vehicles are less likely to make contact and crash. This is imperative when environmental conditions, such as high traffic congestion or wet roads caused by rain, may impede the speed of the ambulance to the scene. Notwithstanding the advantages of dispatching an ambulance to the scene using L&S, there are disadvantages and risks involved.

2.4.2 Disadvantages/Risks of L&S

One disadvantage associated with dispatching L&S is due to the relationship between speed and crash risk. When ambulances are dispatched using L&S, they may drive above the posted speed limit, potentially resulting in an increased risk of crashes involving ambulances. The premise that increases in driving speed are associated with an increase in the probability of a crash is based on the power model of speed. [33]

The relationship between speed and the probability of a crash is quantitatively explained by the power model of speed. The relationship was first described in a study combining the findings of 98 separate studies and has since been updated several times.[36–41] The model is as follows: any increase in mean traffic speed results in an increased probability of a crash; the greater the mean speed, the more likely is a fatal crash rather than a crash of lesser severity, such as one requiring hospitalisation. This model has been validated by hundreds of studies relating to road crashes among the general population.

A few studies have considered crash risk specifically for ambulances driving using L&S. A recent study found that during the ambulance response to the scene (for any type of call for emergency assistance, not limited to road crashes), the risk of crashing increased when L&S were used.[5] The study (based in the United States) estimated 4.6 crashes per 100,000 ambulance responses to the scene without L&S compared to 5.4 crashes per 100,000 responses to the scene with L&S (statistically significant difference). Conversely, others found this was not the case. One study from Alabama (United States) on the risks of police vehicles, fire trucks and ambulances crashing when using L&S found that ambulances were not at increased risk of crashing during this time.[34] Another study found no difference in the proportion of crashes when using L&S or not using L&S, [42] and a recent study from Japan found a low crash rate when using L&S. [43] More research is required to reach a clear conclusion regarding crash risk (versus clinical benefit) when ambulances drive with L&S.

The wake effect of ambulances, when using lights and sirens, refers to the phenomenon where other vehicles on the road respond to the presence of an approaching emergency vehicle by making way and yielding the right of way. The wake effect of ambulances using lights and sirens is a vital aspect of emergency response. It relies on the immediate and coordinated response of other road users to clear a path for the ambulance, allowing it to reach its destination quickly and provide critical medical assistance to those in need. This collective effort helps save lives by reducing response times during emergencies. However, this is some evidence that as vehicles make way for ambulances there is an increased probability of a crash. This disadvantage of using L&S has been reported by paramedics.[44]

Having discussed the benefits of responding using L&S (to arrive on the scene sooner to give potentially time-critical interventions) and the disadvantages (increased risk of ambulance crashes), another important consideration is relevant when understanding L&S use on the way to the scene; this relates to ambulances as a scarce resource.

2.5 AMBULANCES AS A SCARCE RESOURCE

In an EMS, an operationally prescribed number of ambulances is available, making ambulances a scarce, or limited, resource. This is important because sending an ambulance using L&S to the scene of a crash where it is not needed may mean that the ambulance is not free to respond using L&S to another incident that is a time-critical.

Usually, the number of available ambulances reflects the size of the population and the resources available to fund the EMS in terms of staff and operation costs. [45] The WHO recommends one ambulance per 50,000 population. [46] Having a fixed number of ambulances makes their allocation to patients even more difficult as ambulance demand increases. A recent study found that after controlling for population growth and seasonal changes, ambulance demand is increasing at a rate of 1.4% per year in Australia. [47] Some attribute this to an ageing population, [48] others have found that patients from lower socioeconomic groups, [47] younger patients, [47] or those with no pre-existing medical conditions [47] have contributed to increases in demand. Increases in ambulance demand combined with, in some jurisdictions, limited access to primary health care (general practitioners), insufficient community awareness of when to seek emergency care and the mainstreaming of mental health care, mean that delivering appropriate care to patients (L&S or not) is all the more important. [49] It is also important to appreciate that increases in ambulance demand have been found to impact ambulance response times directly and negatively. [50]

One way to manage an increase in ambulance demand is to ensure that appropriate care reaches patients and that only those requiring a L&S response receive it. EMS most commonly dispatch ambulances (as L&S or not) using standardised emergency medical dispatch systems to triage patients and determine dispatch priority (L&S or not).

2.6 EMERGENCY MEDICAL DISPATCH METHODS

Emergency medical dispatch systems are a unified and systematic approach to the triage response of ascertaining clinical needs and prioritising ambulance dispatch. [51,52] Emergency medical dispatch systems comprise various processes. These are not limited to but include standardising the call script, categorising calls into clinical need groups, ambulance dispatch prioritisation, and giving pre-arrival instructions. The systemised methods for determining the need for a L&S response are the focus of this thesis.

EMS worldwide use different systems to dispatch ambulances; these are mainly protocol-based or guideline-driven. One of the main proprietary systems is the Medical Priority Dispatch System (MPDS). [19]

2.6.1 Medical Priority Dispatch System

The MPDS[10] is a protocol-based system used mainly in Australia, the United Kingdom, the United States of America, and Canada. The MPDS protocol involves a set of scripted (pre-written) questions during the call for emergency medical assistance. These questions are asked by the EMD, often a layperson (non-medically) trained in receiving calls for emergency assistance and giving pre-arrival (before the ambulance arrives) instructions. Following the caller's response to the standardised EMD question of '*Okay, tell me exactly what happened*', [19] the EMD identifies the purpose of the call which then categorises the clinical urgency using a set of codes (categories), such as those representing a *cardiac arrest* or *drowning*. For road crashes, the EMD poses some further scripted questions concerning whether any hazardous chemicals are present, whether anyone is trapped or has been thrown from a vehicle and whether any serious bleeding is occurring. [53] The EMD then assigns the road crash to a category (termed a dispatch or determinant code). These categories classify the road crash into a single category, such as *rollover*, *trapped victim*, or *no injuries*. It is important to mention that the EMD chooses the category that best describes the need for emergency medical care. Using a single category to assign to a crash is noteworthy, as road crashes rarely fit one category, but most often fit many. An example is when a vehicle hits a truck carrying hazardous chemicals, the vehicle then rolls over, trapping the patient, who requires extrication. The EMD, using the MPDS, is required to choose a single category. In this example, this crash could be the MPDS category of a *rollove*r, a *trapped patient,* or a *hazardous chemical*. Each EMS has a predetermined ambulance priority associated with each MPDS category. For example, the category of a *rollover* might be pre-assigned as requiring a L&S response, whereas the MPDS category of *no injuries (confirmed)* is categorised as not requiring a L&S response. Noting that some EMS may assign a high priority L&S response to all road crashes they are notified of.

Despite the intention of MPDS to accurately prioritise patients to maximise EMS efficiency, some limitations exist regarding its ability to identify incidents or crashes that truly requiring a L&S response based on patient acuity. These limitations are mainly to do with the accuracy in identifying patient needs in terms of ambulance prioritisation.

2.6.2 Limitations of Dispatch Systems

Few studies have investigated the accuracy of emergency medical dispatch systems in identifying patients/incidents requiring a L&S response. A 2018 systematic review found that sensitivity (the proportion of those identified, over the phone, as requiring an urgent ambulance response, out of those who required it ranged from 78% to 93%. [7] Additionally, the specificity (the proportion of those identified as not requiring an urgent response, who did not require it) ranged from 48% to 87%.[7] When the under/over-triage rate is used as a measure of accuracy, the findings have a similarly broad range. Under-triage (the proportion of those who required a L&S response but did not receive one out of all those not prioritised as L&S) ranged from 3% to 5%. Conversely, over-triage (the proportion of those who did not require a L&S response but received one, out of all those who received a L&S response) ranged from 71% to 78%. [54,55] However, these studies, using sensitivity, specificity, and over/under-triage rates, were not specifically for road crashes but for the wider EMS. More research is needed to determine the accuracy of dispatch systems for identifying crashes that do/do not require a L&S response.

2.7 COMPLEXITY IN ROAD CRASHES

One reason emergency medical dispatch systems currently used by many EMS worldwide have limitations in identifying crashes requiring a L&S response is that crashes are complex events. [56] The Haddon matrix explains how elements relating to the person, vehicle and environment interact before, during and after a crash to determine the severity of the injuries of those involved. The unique combinations of these different elements (person/vehicle/environment and before/during/after) of a crash result in different severities of injuries, such as those that require or do not require a L&S response. Consider the criterion of a *rollover*. This characteristic of a crash is used by the MPDS to categorise and prioritise ambulances to the scene. However, the literature contains mixed findings regarding whether rollover should be used to predict patients who are severely injured and presumably require a L&S response. This is because some patients involved in a rollover are completely uninjured, whereas others die at the scene.[57] This variability could be due to combinations of other elements of the crash, such as whether the patient was wearing a seatbelt, the number of rotations, the strength of the vehicle and whether they were ejected. Using a single element, such as *rollover*, limits the accuracy of dispatch systems, and an alternative method should be explored.

2.8 NEED FOR EMS TO CRASHES

While not all those involved in a crash require a L&S response, for those patients who do, such a response (L&S) can have significant positive outcomes. A study specifically concerning EMS and road crashes found that a 10-minute reduction in the response time of the EMS was associated with a one-third decrease in the probability of death following involvement in a road crash.[6] Similarly, some note that the critical role of EMS in preventing road crash deaths is through accurate clinical assessment, provision of high-quality care and coordination of other emergency services.[14] Moreover, of deaths due to road crashes, using the internationally standard definition of death within 30 days of the crash, more than half occur at the scene, rather than in transit to the ED, in the ED, in the hospital or after discharge.[6] This reiterates the importance of a L&S response to the scene of a crash for time-critical patients.

2.9 ALTERNATIVE DISPATCH METHODS

Some researchers have sought to propose alternative methods to identify road crash patient needs. For example, crash scene characteristics have been used in decision trees to predict injury severity (different from the requirement for a L&S response). [58,59] Although these algorithms are not directly relevant to EMS as they often use crude ordinal outcome measures (died/injured/uninjured) or measured patient acuity well after the time of the crash (such as during the hospital stay) which are not directly applicable to EMS dispatch. However, they do propose the possibility of using combinations of crash characteristics, rather than a single crash feature, as in the MPDS. A single study did explore the use of combinations of crash characteristics to predict the need for a L&S response. [60] This study found that a combination of patient ambulatory status, the number of vehicles involved and the location of the crash, could accurately predict ambulance dispatch prioritisation. While many of these methods show promise, they either require further validation or have not used an outcome variable relevant to an EMS setting.

2.10 LOCAL CONTEXT

St John Western Australia (SJ-WA) is the single-tier, sole contracted provider of emergency medical services to Perth. Perth covers an area of around 6,400 square kilometres. [61] There are three expressways (those with limited access, also called freeways) and nine highways (those with intersections with other roads). [62] The road crash fatality rate is 3.6 per 100,000 people per year. [63] This is comparable to the cities of San Francisco (3.2 per 100,000) and Seattle (3.8 per 100,000). [64]

SJ-WA ambulances are generally staffed by two university-trained paramedics, although there may be an additional student on board. SJ-WA paramedics can perform advanced life-support skills such as manual defibrillation and endotracheal intubation. [65]

SJ-WA delivers emergency medical assistance to approximately 192,000 patients annually, across Western Australia (WA).[66] The local process for EMS is as follows: when the need for medical assistance arises, a telephone call will be made using the ‘000’ emergency call number. This call is answered by an Emergency Call Service Operator. The operator’s role, in Australia, is to distribute calls according to the required emergency service organisation: either medical (ambulance), police or fire.

Calls for emergency medical assistance are forwarded to the SJ-WA State Operation Centre located in Belmont, WA. The State Operation Centre uses the MPDS (version 12.1 over the study period) to categorise calls, with each category having a pre-assigned ambulance priority. In WA, the highest priority call is termed a Priority One, where L&S are used on the way to the scene and there is an operationally defined goal for the time to arrival (90% of Priority One answered calls to arrive on-scene within 15 minutes). Calls may also be categorised as Priority Two (90% of calls to arrive on-scene within 25 minutes) or Three (90% of calls to arrive on-scene within 60 minutes). For priorities Two and Three, L&S may not be used on the way to the scene.

Currently, SJ-WA assigns a L&S response to all calls for assistance to road crashes, due to the potential for life-threatening injuries and concerns that bystanders are unable to accurately assess clinical need. However, data derived from police crash records [67] suggests that only a small proportion of crashes require a L&S response, with 1.9% of those involved in a crash reported to police having either died or required hospitalisation. Although the number of people who require a L&S response to crashes remains unknown in Perth, the disproportionate percentages of people who died/were hospitalised versus those who were uninjured suggests SJ-WA does not need to send L&S responses to all crashes.

Not limited to a SJ-WA locally relevant issue, the variability of the acuity of patients at road crashes and the associated priority of ambulance directly relates to the local EMS from which this PhD derives. Therefore, exploring evidence-based approaches for identifying the prioritisation of an ambulance to the scene of a crash is the main aim of this thesis.

Chapter 3: General Methodology

This chapter describes the analytical methods commonly used in this thesis. The methods for the systematic review is reported within that study.

3.1 RESEARCH DESIGN AND SETTING

This retrospective cohort study was based on road crashes attended by paramedics from the 1st of January 2014 to the 31st of December 2016, in the Perth metropolitan area of Western Australia. In 2016, Perth had a population of approximately 2.02 million people. [68] Around 77% of the population were aged over 18 years, and there was a median age of 36.0 years. [68]

3.2 DATA SOURCES

There were two data sources used to conduct the research for the analytical studies of this thesis - ambulance data and crash data.

3.2.1 Ambulance Data

The ambulance data were extracted for all crashes where the dispatch code was related to transport (MPDS Protocol 29: Traffic/Transportation Incidents)[10] or where a road crash was identified in an electronic patient case record (ePCR) by paramedics on the scene.

The following cases were excluded from the ambulance data:

(1) those involving emergency medical helicopters, as these are not routinely used in the Perth metropolitan area.

(2) those where a patient was assessed (visually or verbally but no observations were taken) and did not require any transport or treatment.

(3) where the patient could not be located on arrival, such as if the patient left the scene or there was a hoax call.

(4) where the patient did not require emergency care, such as inter-facility transfers.

The ambulance data contained information collected during the emergency telephone call (recorded by the computer-aided dispatch system, or CAD) and ePCRs, completed by paramedics. There was a separate record (ePCR) for every patient, and this record may be attached to one or more CAD records. For example, where there were multiple callers (or CAD records) for the same patient. Similarly, there may be multiple ePRCs for the same patient, attached to one or more CAD records. For example, where a patient was assessed or treated by more than one ambulance crew and had multiple callers for emergency medical assistance, including both bystanders or those directly involved. These complex combinations of 'many-to-many relationships' in the ambulance data required me to spend considerable time cleaning records to create one unique record for every patient that contained all collected information.

As well as creating a unique person record, I also create a unique crash record. Sometimes, multiple calls may be received for the same crash, but different circumstances and geographies are described by the caller. This could cause the CAD system to not recognise that these calls were for the same crash and associated patients. The cleaning of data and subsequent identification of unique crashes and patients were essential for the process of linkage to occur to police crash data.

3.2.2 Police Crash Data

Police crash data contained detailed information describing the crash. This included information on the persons involved, their role in the crash, the vehicle details, the crash, the sequence of events surrounding the crash and the road environment.

Police crash data is a combination of data collected by:

(1) The Western Australia Police officers who attended the scene of a crash for all crashes above a certain threshold, defined as grievous bodily harm or serious injury.

(2) The Insurance Commission of Western Australia (ICWA), who collects information derived from those people who were involved directly in the crash and are legislatively required to report the crash (where the value of the damage exceeded AUD$3,000, where someone was injured or if the owner of damaged property was not present).

(3) Main Roads Western Australia, who add detailed temporal (day, time, weather) and environmental information (road environment) besides that collected by Police and ICWA.

The following cases were excluded from the Police crash data:

(1) crashes not on a gazetted road (such as private road or property).

(2) Those that resulted from an intentional act (such as suicide, murder, or a deliberate crash by police to halt a driver); or

(3) Those that resulted from a force of nature (such as a flood, tree falling or a lightning strike).

3.3 DATA LINKAGE

The linking of ambulance and police data was an important part of this thesis, with studies 1, 2, 4, 5 and 6, using linked data (correspondingly chapters 4, 5, 7, 8 & 9).

Data linkage allowed me to have access to a broad scope of variables for analysis that were not available in simply one dataset. However, the linking of ambulance and police data was a difficult and lengthy process because of the complexity of the many-to-many relationships in the ambulance data.

The data were linked using a deterministic and then probabilistic approach. Firstly, ambulance data were linked to crash data based on geographical proximity and date of the crash. This was further refined using vehicle license plate numbers, and demographics (age in years and sex). Lastly, the SPEDIS technique, [69] a fuzzy name-matching algorithm, was used to estimate the likelihood that the first/last name in the ambulance data were a probable match to the first/last name in the police data.

Records were linked between the ambulance and the police data using a left outer join, where the final included records for analysis were: (1) all ambulance records and (2) only police records that had a matching ambulance record. This is because the focus of the thesis was ambulance-attended crashes. There were some records in the ambulance data that did not have a corresponding police record (<5%), this could be where the driver neglected to report the crash. As the primary interest of this thesis was in ambulance dispatch priority, all road crash ambulance records were retained whether there was a matching police record. Conversely, there were many crashes recorded in the police data, such as crashes where no one was injured and only damage to vehicles occurred, that did not have a corresponding ambulance record. Given that no one was injured, a corresponding ambulance record was not expected. These records were excluded, as there was no corresponding ePCR or dispatch information. The linkage rate was 66.6%.

Data were linked using SAS BASE 9.3 [70] and Fine-Grained Records Integration and Linkage Tool (Emory University, US).

3.4 OUTCOME MEASUREMENT

The primary outcome of interest (dependent variable) was the need for a L&S response. Initially, I defined this as either (1) or (2) see below (used in Study 2), however during the course of my thesis a high acuity indicator was developed, after which I defined the need for a L&S response as either (1), (2) or (3) (used in studies 1,4 and 6).

(1) Anyone died on scene/in transit, or

(2) Anyone went L&S from scene to ED, or

(3) Anyone had any high acuity retrospective indicators.

The third indicator above (3) was based on criteria developed by a clinical reference group at SJ-WA (initially for internal purposes within SJ-WA that were independent of this PhD). This reference group created a list of high acuity indicators in 2019 to support system-wide analysis of patient acuity regarding dispatch categories, as part of a review of the response priorities assigned to each dispatch code. These indicators include observation metrics, administered medications and clinical interventions. See Chapter 7, Study 4, Supplementary material, for a complete list. A similar methodology was employed by Ambulance Victoria, also as part of a review of dispatch priorities. [71]

Some examples of observations identifying the need for a L&S response include having a Glasgow Coma Scale verbal score of 1 (none) or 2 (incomprehensible), or a consciousness state as nil response to pain. Interventions included cardiopulmonary resuscitation and automated external defibrillator - shock delivered. Medication in the indicator list included packed red blood cells and epinephrine.

For the fifth study, I required the outcome measure (representing patient acuity and the need for a L&S response) to be continuous, rather than a binary variable. Therefore, I used the New Early Warning Score (NEWS2). The NEWS2 is a clinical tool used to assess a patient's illness severity and identify those at risk of deterioration. The NEWS2 assigns scores based on vital signs and clinical observations. I derived the NEWS2 from the initial vital signs and clinical observation collected by paramedics at the scene.

3.5 ANALYTICAL TECHNIQUES

As well as descriptive and univariate techniques (counts, percentages, medians standard deviations and inter-quartile ranges) a variety of different analytical methods were used, encompassing both traditional statistics and machine learning approaches. Each of these analytical techniques was chosen to reflect the aim of that study.

Techniques included:

(1) the plotting of sensitivity/specificity thresholds on the receiver-operating characteristics (ROC) curve to find the optimal performance of sensitivity versus specificity. This technique was used a study that sought to assess whether MPDS dispatch categories could be used to discriminate between those crashes that required a L&S response and those that did not. This technique was suitable as it allowed me to plot the sensitivity against specificity and assess whether these values would be acceptable in an EMS context. See Study 1 in Chapter 4.

(2) crude odds ratios and 95% confidence intervals. This technique was chosen for the study that initially explored the concept of using crash characteristics to predict the need for a L&S response. Odds ratios was chosen due to the data types, with the dichotomous dependant variable (required or did not require a L&S response) and categorical independent variables (such as road user type: driver, passenger, motorcyclist, pedestrian and bicyclist, or crash type: head one, sideswipe etc). See Study 2 in Chapter 5.

(3) a Chi-square Automatic Interaction Detector technique (CHAID) to develop decision trees. This technique was used in the study that explored whether

crash characteristics, which could potentially be described by someone at the scene of a crash, could be used to identify the need for a L&S response. This technique was chosen because decision trees are easy to visualize and interpret, such as for application as a simple bystander description into a prediction about L&S requirements. Additionally, the CHAID decision tree was chosen over other decision tree types, as it allows for use of both numeric and categorical data types, which was important as I wanted to use all the available variables (both numerical and categorical) to maximise the potential for accuracy. See Study 4 in Chapter 7.

(4) the Kolmogorov-Smirnov test, Bi-modality coefficient and Hartigan's dip test were used to detect the presence of bimodal or multimodal distributions in data. These tests were used to explain the findings from Study 4, where crash characteristics were unable to predict the need for a L&S response, with the idea that this night be attributable to the distribution of acuity across different crash characteristics. These tests have both advantages and disadvantages and are therefore best used in conjunction. See study 5 in Chapter 8.

(5) machine learning techniques including ensemble, k-nearest neighbour (k-NN), Naïve Bayes, neural network, and support vector machine. Machine learning can be better suited for data that has a varied distribution because it can effectively model complex relationships between input variables (called independent variables in traditional statistics) and the target variable, (otherwise known as the dependent variable). See Study 6 in Chapter 9.

Table 4 Differences in methods across analytical studies

Chapter	Study	Data source/s	Unit of measurement	Predictor/Independent variables	Outcome/Dependant variables	Analytical technique
4	*Study 1: Can Ambulance Dispatch Codes Discriminate those traffic incidents*	Ambulance	Incident (MPDS Protocol Transportation/Traffic)	MPDS dispatch codes	Required a L&S response as (1) Died on scene/in transit or (2) L&S from scene to ED (3) High acuity retrospective indicators	Sensitivity/specificity ROC curve
5	*Study 2: Motor Vehicle Crash Characteristics that are Predictive of High Acuity Patient*	Ambulance & crash	Patients	Clinical, Demographic, Crash characteristics	High acuity as (1) Died on scene/in transit or (2) L&S from scene to ED	Crude odds ratios and 95% confidence intervals
6	*Study 3: A Systematic Review of Ambulant Status*	n/a	n/a	n/a	n/a	n/a
7	*Study 4: A predictive Dispatch Algorithm to the Scene of a Motor Vehicle Crashes*	Ambulance & crash	Crash	Crash characteristics and MPDS dispatch codes	Required a L&S response as (1) Died on scene/in transit or (2) L&S from scene to ED (3) High acuity retrospective indicators	Decision tree: Chi-square Automatic Interaction Detector technique
8	*Study 5: Variation in On-scene Patient Acuity for Different Types of Traffic Crashes*	Ambulance & crash	Patients ≥ 16 years	Crash characteristics	Initial on-scene acuity (NEWS2)	Kolmogorov-Smirnov test, Bi-modality coefficient & Hartigan's dip test
9	*Study 6: Ambulance dispatch prioritisation for traffic crashes using machine learning*	Ambulance & crash	Crash	Crash characteristics and MPDS dispatch codes	Required a L&S response as (1) Died on scene/in transit or (2) L&S from scene to ED (3) High acuity retrospective indicators	Machine learning techniques

Chapter 4: Dispatch Codes and the Ability to Discriminate

4.1 OVERVIEW AND RATIONALE

My first study aimed to determine whether the Medical Priority Dispatch System (MPDS), [19] a proprietary dispatch system used by many EMS globally, could be a suitable tool to determine the required priority of ambulances to the scene of a crash. Therefore, I set out to see if dispatch categories—as defined by the MPDS—could distinguish between crashes that require a L&S response and those that do not.

Ambulance data from the period 2014 to 2016 were used in a retrospective cohort analysis. The predictor variable was the dispatch categories for the traffic/transportation MPDS Chief Complaint (Protocol 29) [19] assigned during the call for emergency medical assistance. Whether a crash required a L&S response (defined as: whether anyone died on scene/in transit, or whether L&S was used from scene to ED, or whether anyone included any high acuity retrospective indicators) was the outcome variable. The potential cut-off threshold was calculated for each trade-off between the true positive rate (sensitivity) and the false positive rate (specificity).

My findings are described in the following manuscript which was published in the International Journal of Emergency Services in 2022.

Ceklic E, Tohira H, Finn J, Brink D, Bailey P, Whiteside A, Brown E, Brits R, Ball S. Can ambulance dispatch categories discriminate traffic incidents that do/do not require a lights and sirens response? *International Journal of Emergency Services*. 2022 Aug 9;11(2):222-34.

4.2 STUDY 1

Title

Can ambulance dispatch categories discriminate traffic incidents that do/do not require a lights and sirens response?

Abstract

Purpose: Traffic incidents vary considerably in their severity, and the dispatch categories assigned during emergency ambulance calls aim to identify those incidents in greatest need of a lights and sirens (L&S) response. The purpose of this study was to determine whether dispatch categories could discriminate between those traffic incidents that do/do not require a L&S response.

Method: A retrospective cohort study of ambulance records was conducted. The predictor variable was the Traffic/Transportation dispatch categories assigned by call-takers. The outcome variable was whether each incident required a L&S response. Possible thresholds for identifying dispatch categories that require a L&S response were developed. Sensitivity and specificity were calculated for each threshold.

Findings: There were 17,099 patients in 13,325 traffic incidents dispatched as Traffic/Transportation over the study period. 'Possible death at scene' 'had the highest odds (OR 22.07, 95% CI 1.06-461.46) and 'no injuries' the lowest odds (OR 0.28 95% CI 0.14-0.58) of requiring a L&S response compared to the referent group. The area under the ROC curve was 0.65, 95% CI [0.64, 0.67].

Conclusion: We found that Traffic/Transportation dispatch categories allocated during emergency ambulance calls had limited ability to discriminate those incidents that do/do not require a lights and sirens response to the scene of a crash.

Originality: This research makes a unique contribution as it considers traffic incidents not as a single entity but rather as a number of dispatch categories which has practical implications for those emergency medical services dispatching ambulances to the scene.

Introduction

Background/Rationale

The emergency ambulance response for patients involved in traffic incidents begins with a phone call to emergency medical services (EMS). One of the key decisions made by a dispatch centre is what priority to send the ambulance. For traffic incidents where patients have sustained injuries requiring time-critical interventions, dispatching an ambulance at the highest priority, with lights and sirens (L & S) used on the way to the scene, may significantly improve patient outcomes by minimising response times (Kupas et al. 1994; O'Brien, Price, and Adams 1999; Petzäll et al. 2011). However, assigning a L&S response also carries potential risks, by increasing the likelihood that ambulances themselves are involved in serious crashes (Watanabe et al. 2019), or the potential opportunity cost, whereby the same ambulance could have been more appropriately dispatched to an incident elsewhere (not necessarily a traffic incident) (Chuanliang, Zefu, & Yanqiu, 2012).

Many EMS worldwide use dispatch systems to categorise emergency ambulance calls in relation to the need for urgent care. (Clawson, Boyd Dernocoeur, and Murray 2015) A key aspect of the Medical Priority Dispatch System (MPDS) (Clawson et al. 2015) is that using a structured method, each call is allocated to one of a number of dispatch categories, which are used to assign a priority dispatch level. The assigned priority determines whether L & S are used on the way to the scene and the response time target (target for the time interval from the call being received to the ambulance arriving on the scene). For example, a cardiac event, where a patient is unconscious, would be assigned the highest dispatch category, where L & S are used on the way to the scene. Similarly, EMS may assign different types of traffic incidents to different dispatch categories, such as to a rollover, a traffic incident involving a pedestrian or where a patient is trapped. However, within dispatch categories for traffic incidents there exists a large amount of unobserved heterogeneity, otherwise conceptualised as information not received by EMS that may contribute to variation in the need for urgent ambulance care within a dispatch category (Mannering, Shankar & Bhat, 2016). For example, some people involved in a rollover incident do not require any ambulance care, however, some may require a L&S response (Haan et al., 2009). This variability may be due to elements of the crash that are difficult to determine at the time of ambulance dispatch, such as the curve of the road (Islam, Hossain& Barnett, 2016). This variation in patient acuity within individual dispatch codes increases the complexity of predicting the need for a L&S response. To assist in triage, it may therefore be useful to undertake retrospective analyses to measure the observed association between dispatch codes and acuity. Several studies have demonstrated the value of a data-driven approach to measuring the association between ambulance dispatch codes and patient acuity. For example, MPDS dispatch codes for chest pain were found to accurately predict on-scene cardiac arrest and L&S transport to an emergency department (Clawson et al. 2008). Among patients dispatched for falls, "not alert" dispatch codes accurately predicted severe patient outcomes (Clawson et al. 2010). However, some studies have found dispatch codes to be poor predictors of acuity. For example, Sporer et al (2010) found that high priority dispatches were not associated with advanced clinical interventions on-scene, such as for dispatches for fainting and chest pain which had had high false-positive and low false-negative rates (Sporer, Youngblood, and Rodriguez 2007).

We are aware of only one published example of this retrospective data-driven approach being applied to traffic incidents. Streeter et al (2019) found that "higher" (MPDS Delta) level calls were associated with more severe injuries. In this case, severe injuries were identified as final patient disposition, whether the patient was transported from the scene to ED or not, and the priority to the final destination. While previous studies have shown that MPDS dispatch codes can predict patient acuity for both traffic and calls for other incidents types, there exists a knowledge gap in assessing MPDS dispatch codes for traffic incidents ability to predict the need for a L&S response to the scene. This research will fill the knowledge gap as to whether dispatch categories are able to discriminate traffic incidents that do/do not require a L&S response. This may be applicable to other jurisdictions currently using the MPDS.

Aim

The aim of this study was to determine whether MPDS dispatch categories assigned to traffic/transportation incidents could discriminate between those incidents that do/do not require a lights and sirens response.

Methods

Setting/Study Design

This study was a population-based retrospective cohort study of traffic incidents attended by St John Western Australia (SJ-WA), in Perth, Western Australia between 1st January 2014 and 31st December 2016. Metropolitan Perth covers an area of approximately 6,400 square kilometers (Department of Agriculture 2019) and a population of around 2.0 million in 2016 (Australian Bureau of Statistics, 2017). SJ-WA is the sole provider of EMS (ambulance) in Perth. All ambulances are staffed by paramedics.

Data source

The data used in this study were based on SJ-WA electronic EMS records (recorded by call-takers/dispatchers) and combined with patient care data (recorded primarily by paramedics). Dispatch information included the dispatch category assigned using MPDS (v12.1), as part of SJ-WA's computer-aided dispatch system. Patient care data were recorded on electronic patient care records (ePCRs) and included data on patient clinical observations and interventions.

Predictor variables

The predictor variable was the allocated Traffic/Transportation MPDS dispatch categories (v12.1). Using the MPDS, call-takers allocate each call to one of 32 Chief Complaints (e.g. Falls, Headache, Traffic/Transportation), representing the primary nature of the patient's medical problem. Then, asking a set of questions that are specific to each Chief Complaint, the EMS allocates each call to one of a number of dispatch categories. The Traffic/Transportation Chief Complaint classifies traffic incidents into discrete dispatch categories within the SJ-WA system, including rollover, involving a trapped victim or no injuries. See Table I for the full list of MPDS Traffic/Transportation dispatch categories. While these dispatch categories are dispatched as mutually exclusive, in reality, the circumstances of a traffic incident may cross over more than one dispatch category. For example, a traffic incident could be both a 'rollover' and involve patients with 'serious haemorrhage.' However, dispatchers identify the dispatch category that best describes the need for care of the incident, for example a dispatcher will choose a higher mechanism over another category, such as a low mechanism.

{Insert Table I}

Outcome variables

The outcome variable in this study was the need for a L&S response (yes/no binary variable) to a traffic incident. We operationally defined an incident as having retrospectively needed an

L&S response where one or more patients (1) died on scene or died in transit, or (2) were transported L&S to hospital, or (3) had one or more high-acuity indictors. The list of high acuity indicators was developed in 2019 by SJ-WA using a clinical reference group, to enable system-wide analysis of patient acuity in relation to dispatch categories. The list of indicators (see Appendix I) comprises medications administered, clinical interventions and observation parameters, as recorded by paramedics in the ePCR and were agreed by the reference group to be indicative of a high-acuity incident, and for which a L&S response is appropriate. The development of the high acuity indicators at SJ-WA based on a similar approach to that used by Ambulance Victoria (Andrew et al., 2019)

Statistical methods

Descriptive statistics included counts and percentages. For each MPDS dispatch category, crude odds ratio (ORs) and 95% confidence interval (CIs) were used to measure the odds of the need for L&S, relative to a reference category (vehicle versus pedestrian). We chose this as the reference category as it had a high number of incidents and good face validity. Sensitivity/specificity and the area under the receiver operator curve (AUROC) were used to assess whether MPDS dispatch categories can discriminate between those incidents that do/do not require a L&S response. The AUROC was chosen as the assessment method in this study as it is the standard way that a diagnostic tool (such as we are proposing the MPDS dispatch codes are here) is assessed for its ability to discriminant a dichotomous variable (such as required an L&S response/did not require an L&S response) (Fawcett 2006; Ward-Powers 2007). Furthermore, it is anticipated that use of the AUROC will help us identify a threshold for which dispatch codes could be used to identify the need for an L&S response.

Possible threshold or cut-off points, for identifying which dispatch categories require a L&S response to a traffic incident were developed for each MPDS dispatch category. Firstly, the proportion of L&S incidents within each MPDS dispatch category were calculated and categories were ranked in ascending order, according to this proportion. See Table I. These proportions then became thresholds, as dispatch categories were divided into two groups, those with a higher than or equal proportion (or threshold) of L&S incidents (positive group), and those with less than the threshold (negative group). True positives were incidents requiring a L&S response in the positive group. True negatives were incidents which did not require a L&S response in the negative group. The predicted condition was the dispatch scenario should all incidents be dispatched as L&S within the threshold and above. Sensitivity was then calculated as the proportion of true positives in total incidents which actually required a L&S response, while specificity was calculated as the proportion of true negatives in total incidents which actually did not require a L&S response.

At each threshold, the predicted sensitivity and specificity were calculated and plotted on a receiver-operating characteristics (ROC) curve. The ROC curve allowed us to determine the effect of modifying which dispatch categories were dispatched as L&S in terms of sensitivity and specificity for different thresholds. The true condition was the outcome variable as either required a L&S response (the incident was identified as having a life-threatening emergency) or did not require a L&S response (the incident was not a life-threatening emergency).

An example of the method is as follows: for the dispatch category of 'train', 65% of incidents were retrospectively found to have required an L&S response to the scene. Therefore, if the threshold is set at 65%, where 'train' and all categories with 65% or greater L&S incidents ('train' and 'possible death at scene') are sent with L&S to the scene, the number of true positives would be n=15 and the number of true negatives would be n=11,556. The number of false positives (n=7), would be calculated as if we predicted all those incidents within the 65% threshold were dispatched as L&S, minus the true positives. Conversely the number of false negatives would be n=1,747. See Table II.

We are undertaking a subsequent study to look at combinations of environmental, incident and MPDS codes using a decision tree approach. This study will explore the different over/under triage rates associated with different combinations (models) of the predictor variables.

{Insert Table II}

SAS/BASE software (version 9.4) was used to prepare the data (clean and manipulate) and perform statistical analysis (counts, percentages, ORs and the AUROC).

Ethics

Ethics approval for this study was granted by the Curtin University Human Research Ethics Committee (HR 128/2013), as a sub-study of the Western Australia Pre-hospital Record Linkage Project. Approval to conduct the study was also obtained from the SJ-WA Research Governance Committee.

Results

There were 17,099 patients in 13,325 traffic incidents dispatched as Traffic/Transportation incidents using the MPDS in the three years to the 31^{st} December 2016, in Perth Western Australia. Table I shows the number/proportion of incidents by MPDS dispatch category.

Of the 13,325 incidents dispatched as the Traffic/Transportation Chief Complaint, 1,762 (13.2%) were deemed to have required a L&S ambulance response to the scene. Of these 1,762 incidents, 31 had a patient die on scene or in transit and 824 incidents were transported L&S to hospital. All incidents transport L&S to hospital had a high acuity indicator and all but one incident were a patient died on scene or in hospital, had a high acuity indicator. In this case, paramedics recorded limited observations, and no medications or interventions were given due to injuries being incompatible with life.

As shown in Table I, the dispatch category with the highest proportion of incidents that required a L&S response was 'possible death at scene' (100%, although representing 2 incidents), followed by 'train' (65.0%, involving 20 incidents). Of all incidents determined to have required a L&S response, the highest number of L&S events were in the dispatch categories 'injuries' (348 incidents) and 'unknown status/other codes not applicable' (270 incidents). There were no incidents dispatched as 'vehicle off bridge/height' or 'sinking vehicle' over the study period.

A number of dispatch categories had a higher likelihood of requiring a L&S response than the reference category of 'vehicle v. pedestrians.' The likelihood of an incident having required a L&S response were 22.07 times higher for those incidents dispatched as 'possible death at scene' (OR 22.07, 95% CI 1.06-461.46), 8.21 times higher for those dispatched as 'train' (OR

8.21 95% CI 3.24-20.84) and 1.89 times higher for 'not alert' (OR 1.89 95% CI 1.51-2.36) when compared to incidents dispatched as 'vehicle v. pedestrian.' See Table III.

The odds of being classified as requiring an L&S response were 72% lower for those incidents dispatched as 'no injuries (confirmed)' (OR 0.28 95% CI 0.14-0.58), 64% lower for 'unknown status/other codes not applicable' (0.36 95% CI 0.30-0.45), and 56% lower for 'hazardous materials' (OR 0.44 95% CI 0.23-0.86). See Table III.

{Insert Table III}

Sensitivity and specificity were calculated for each threshold for the construction of the ROC curve. See Table IV. The area under the ROC curve was 0.65, 95% CI [0.64, 0.67], as shown in Figure I, representing a poor discriminator according to Hosmer & Lemeshow (2013).

{Insert Table IV}
{Insert Figure I}

Discussion

Accuracy in the identification of which traffic incidents require/do not require a L&S response, is important for a number of reasons, including optimising patient outcomes. This study assessed whether MPDS dispatch categories, used by many EMS around the world, could make this discrimination.

We found that some dispatch categories had higher or lower odds of requiring a L&S response than the referent group, (vehicle versus pedestrian), such as 'train' (OR 8.21 95% CI 3.24-20.84) and 'no injuries' (OR 0.28 95% CI 0.14-0.58), but for most dispatch categories, there was no association between the odds of requiring a L&S response/not requiring a L&S response, as compared to the referent group. Additionally, MPDS dispatch categories for the Traffic/Transportation Chief Complaint were found to be poor discriminators of incidents requiring an L&S response according to the area under the ROC curve (0.654, 95% CI 0.64-0.67). Hosmer & Lemeshow (2013) suggest that any value for the area under the ROC curve between 0.5 and 0.7 is a poor discriminator. Additionally, for an EMS to have good discriminating ability it would be expected that there would be a threshold that optimized sensitivity and specificity. While there is no universally accepted goal for the sensitivity when discriminating L&S incidents, the American College of Surgeons Committee on Trauma recommends an acceptable sensitivity of 95% (termed as an under-triage rate of 5%) for treatment at a trauma centre (American College of Surgeons, 1990). In this study, in order to reach 95% sensitivity, a threshold of sending L&S to all incident categories with a proportion of 0.09% L&S incidents or more would be required. At this threshold, the system would have 99.99% sensitivity and 0.0% specificity - in other words, sending L&S to nearly all incidents.

While this study did not find the MPDS to be a useful discriminator of L&S incidents, conceptualizing the MPDS like a diagnostic test has been previously used, for example, to determine MPDS dispatch category thresholds for firefighter first response to 911 incidents (Craig, Verbeek, & Schwartz, 2009), diagnostic characteristics to include in a hospital trauma triage protocol (Henry, 2006) and predictor variables to identify non-transport of older fallers (Simpson et al, 2014).

Interestingly, the dispatch category 'no injuries (confirmed)', where we could reasonably expect to see no L&S incidents, had 8 incidents (out of a total of 134 incidents) that required a L&S response. These incidents were examined in detail based on paramedic case notes, and included the following high-acuity indicators: slow pulse, C-Spine fitted, poor Glasgow Coma Scale Score (due to conditions related to collapse or witnessed syncope) and chest pain (some of the incidents had more than one of these). Therefore, although the dispatch category was correctly identified at the point in time of dispatch, given that there were no obvious injuries from the lay-caller's perspective, this seemingly low acuity dispatch category cannot be used to identify those patients who definitively do not require a L & S response.

While it is not the specific intention of the MPDS to be used to discriminate according to need for an L&S response (Clawson, Boyd, Dernocoeur & Murray, 2015), these findings have significance for EMS using the MPDS who currently prioritize according to MPDS dispatch categories. EMS managers and researchers may like to use the findings here regarding specific dispatch categories and apply this to their own jurisdictions, recognizing that each EMS will have a context relevant level of risk they are willing to take for the accuracy of dispatch. We recognize that categories within the Traffic/Transportation Chief Complaint have an additional purpose, that being to provide information not related to identifying the requirement for a L&S response. This includes identification of where multiple resources are required (such an in an event involving a multi-car pile-up), where additional support is required (such as where a trapped patient is requiring mechanical extrication) or where there is the potential for hazardous chemicals.

While the purpose of this paper was to assess the current EMS's potential to discriminate those incidents that do/do not require L&S, further variables might be included to improve discrimination. For example, Isenberg et al., (2012) developed a three-step dispatch rule to identify those incidents requiring an L&S response to the scene. While MPDS dispatch categories were not used, they determined that where any patient was not ambulatory, or the traffic crash involved a single vehicle, or the crash occurred on a highway or interstate, that the rule could predict requiring L&S with suitable sensitivity and specificity. Isenberg et al's., (2012) findings demonstrate that there is the potential to use alternative traffic crash indicators to identify those incidents requiring an L&S response to the scene. Future research could consider exploring combinations of MPDS dispatch categories as well as additional crash scene information, such as ambulatory status, age or speed limit, to improve the reliability of dispatch categories to identify those traffic incidents requiring a L&S response.

Additionally, there is currently no consensus for an acceptable threshold for the sensitivity and specificity of the ability of a dispatch system to accurately recognise those incidents that require a L&S response (Mann et al., 2004). Future research could consider what threshold values might meaningfully be.

It is important to note that some studies have similarly found that the MPDS is more sensitive than specific, given that it was "purposefully designed that way – placing patient care and safety first" (pg. 298, Clawson *et al.,* 2008). These studies include for high acuity patients (Hinchey et al., 2009), cardiac arrest calls (Kay et al., 1995), patients requiring advanced life care (Bailey, O'Connor, & Ross, 2000) and cardiac arrest in seizure patients (Clawson *et al.*, 2007). This is not surprising given that EMS are said to be “front loaded” where a low specificity (or high over-triage) is used as safety rule to protect patients (Bohm & Kurland, 2018).

Limitations

We recognize that MPDS dispatch variables are not mutually exclusive, in the sense that a single traffic incident can, for example, be a rollover, include a patient with a serious haemorrhage and involve a motorcyclist. Given that assignment of dispatch categories is not precise, additional information on traffic incidents and cross-over of dispatch categories could provide further useful information in discriminating those incidents that do/do not require an L&S emergency ambulance response.

While some MPDS dispatch categories had many traffic incidents over our study period, some had few or no incidents at all, such as ‘sinking vehicle’ and ‘vehicle off bridge/height’. We were unable to assess these categories for their potential to determine the need for a L&S response due to this low count. It is possible that these dispatch categories could be used to identify those traffic incidents requiring a L&S response. It is therefore suggested that increasing the study period could improve the scope of these findings, however, it would be expected that these categories would remain a low proportion of all L&S incidents.

Conclusion

Identifying which traffic incidents require a L&S response is important for many reasons, not limited to the optimization of patient outcomes. We assessed whether MPDS dispatch categories could discriminate between those incidents that do/do not require a L&S response. We found dispatch categories to be poor discriminators, with an associated high sensitivity and low specificity. We recognize that the MPDS has many purposes and is not limited to that for identifying L&S incidents, however, we think these findings will have practical implications for those jurisdictions currently using the MPDS. Alternative methods of identifying L&S traffic incidents may improve sensitivity/specificity.

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Figure I. The area under the receiver operating (ROC) curve for the prediction rule to discriminate between Traffic/Transportation dispatch categories requiring a lights and sirens response.

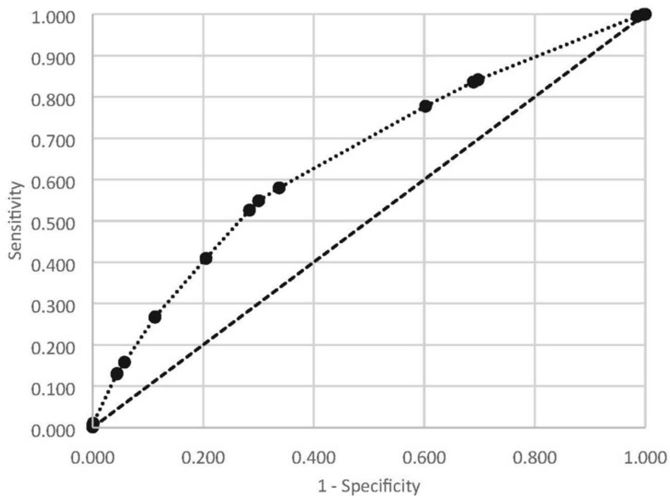

Table I. Incidents ranked by the proportion of lights and sirens responses within each MPDS dispatch category

		L&S (n)	Not L&S (n)	L&S (row%)	L&S (col%)
D2r	Possible death at scene	2	0	100.0%	0.1%
D1d	Train	13	7	65.0%	0.7%
D2k	All terrain/snow mobile	3	6	33.3%	0.2%
D5	Not alert	210	492	29.9%	11.9%
D1a	Aircraft	2	5	28.6%	0.1%
D2n	Ejection	48	156	23.5%	2.7%
D4	Trapped victim	192	635	23.2%	10.9%
D2o	Personal watercraft	2	7	22.2%	0.1%
D2l	Vehicle v. bicycle/motorcycle	249	1,063	19.0%	14.1%
D2m	Vehicle v. pedestrian	206	911	18.4%	11.7%
B2	Serious haemorrhage	40	192	17.2%	2.3%
D2p	Rollovers	55	429	11.4%	3.1%
B1	Injuries	348	3,062	10.2%	19.8%
B3	Other hazards	103	999	9.3%	5.8%
D3	HAZMAT (hazardous materials)	10	100	9.1%	0.6%
B4	Unknown status/Other codes not applicable	270	3,327	7.5%	15.3%
Ω1	No injuries (confirmed)	8	126	6.0%	0.5%
D1e	Watercraft	1	17	5.6%	0.1%
A1	1st party caller with injury to not dangerous body area	0	18	0.0%	-
D1b	Bus	0	6	0.0%	-
D1c	Subway/metro	0	1	0.0%	-
D1f	Multi-vehicle (≥ 10 pile up)	0	4	0.0%	-
D2q	Vehicle off bridge/height	0	0	-	-
D2s	Sinking vehicle	0	0	-	-
	TOTAL	**1,762**	**11,563**	**13.2%**	**100.0%**

Table II. Confusion matrix demonstrating the calculations involved for a threshold of 65% lights and sirens incidents

n=13,325	Predicted: Required L&S	Predicted: Did not Require L&S
Actual: Required L&S	15 (2+13)	1,747 (3+210+2+48+192+2+249+206 +40+55+348+103+10+270+8+1)
Actual: Did not require L&S	7 (0+7)	11,556 (6+492+5+156+635+7+1,063+911+192+429 +3,062+999+100+3,327+126+17+18+6+1+4)

Table III. Odds ratios (ORs) of being classified as Requiring a lights and sirens response, relative to Vehicle v pedestrian (referent group)

	OR (95% CI)	
Possible death at scene	**22.07***	**(1.06 to 461.46)**
Train	**8.21**	**(3.24 to 20.84)**
All terrain/snow mobile	2.21	(0.55 to 8.91)
Not alert	**1.89**	**(1.51 to 2.36)**
Aircraft	1.77	(0.34 to 9.18)
Ejection	1.36	(0.95 to 1.94)
Trapped victim	**1.34**	**(1.07 to 1.67)**
Personal watercraft	1.26	(0.26 to 6.13)
Vehicle v. bicycle/motorcycle	1.04	(0.84 to 1.27)
Vehicle v. pedestrian (referent group)	***1***	
Serious haemorrhage	0.92	(0.63 to 1.34)
Rollovers	**0.57**	**(0.41 to 0.78)**
Injuries	**0.50**	**(0.42 to 0.61)**
Other hazards	**0.46**	**(0.35 to 0.59)**
HAZMAT (hazardous materials)	**0.44**	**(0.23 to 0.86)**
Unknown status/Other codes not applicable	**0.36**	**(0.30 to 0.45)**
No injuries (confirmed)	**0.28**	**(0.14 to 0.58)**
Watercraft	0.26	(0.03 to 1.97)
1st party caller with injury to not dangerous body area	0.12*	(0.01 to 1.99)
Bus	0.34*	(0.019 to 6.05)
Subway/metro	1.47*	(0.06 to 36.25)
Multi-vehicle ($\geq$ 10 pile up)	0.49*	(0.03 to 9.15)
Vehicle off bridge/height	-	-
Sinking vehicle	-	-

*Haldane effect (adding 0.5 to zero values) (Lawson, 2004).

Categories in bold font have 95% confidence intervals that do not overlap with the referent group.

Table IV. Sensitivity and specificity for each threshold* of sending a lights and sirens response

Threshold	Sensitivity	Specificity
1.00	0.1%	100.0%
0.65	0.9%	99.9%
0.33	1.0%	99.9%
0.30	12.9%	95.6%
0.29	13.1%	95.6%
0.24	15.8%	94.2%
0.23	26.7%	88.7%
0.22	26.8%	88.7%
0.19	40.9%	79.5%
0.18	52.6%	71.6%
0.17	54.9%	70.0%
0.11	58.0%	66.2%
0.10	77.8%	39.8%
0.09	83.6%	31.1%
0.09	84.2%	30.3%
0.08	99.5%	1.5%
0.06	99.9%	0.4%
0.06	100.0%	0.3%
0.00	100.0%	0.0%

*Threshold represents the proportion of L&S incidents required within each dispatch category, to be included in that threshold.

Appendix I. List of interventions/observations/medications representing the need for a lights & sirens ambulance response

Category	Description
Pre-Ambulance Care	Ventilation Only
Pre-Ambulance Care	Cardio-pulmonary Resuscitation (CPR)
Pre-Ambulance Care	Automated External Defibrillator (AED) - Shock delivered
Collapse	Ambulance Officer Witnessed
Collapse	Bystander Witnessed
Conscious State	Pain Response
Conscious State	Nil Response
Glasgow Coma Scale (GCS) Verbal	1 None
Glasgow Coma Scale (GCS) Verbal	2 Incomprehensible
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
Paediatric GCS Eye Opening	1 None
Paediatric GCS Eye Opening	2 To Pain
Paediatric GCS Verbal Response	2 Inconsolable, Agitated
Paediatric GCS Motor Response	2 Extension to Pain
Paediatric Motor Response	3 Abnormal Flexion to Pain
Glasgow Coma Scale (GCS) Total	Total <10
Head Gaze/Deviation	Present
Electrocardiogram (ECG/EKG)	Asystole
Electrocardiogram (ECG/EKG)	Bradycardia
Electrocardiogram (ECG/EKG)	Ventricular Tachycardia (VT)
Electrocardiogram (ECG/EKG)	Ventricular Fibrillation (VF)
Electrocardiogram (ECG/EKG)	Pulseless Electrical Activity (PEA)
Burns	Full Thickness
Burns	Airway
Bleeding	External considered > 500mls
Bleeding	Internal
Splint/Dressing	Traction Splint
Doctor at Scene	Intubated
E.C.G. Rhythm	Supraventricular Tachycardia (SVT)
Clinical Interventions	Mechanical CPR Device
Clinical Interventions	ST-Elevation Myocardial Infarction (STEMI)
Clinical Interventions	Stroke Centre Delivery
Breathing	Nil

Breathing	Shallow
Breathing	Slow
Breathing	Laboured
Breathing	Accessory Muscle Use
Breathing	Audible Wheeze
Splint/Dressing	Combat Application Tourniquet (CAT)
Airway	At Risk/Unprotected
Airway	Soiled
Airway	Partial Obstruction
Airway	Complete Obstruction
Airway	Stridor
Skin Colour	Cyanotic
Capillary Refill	> 2 Seconds
Pulse	Nil
Pulse	Weak
Post cardiac arrest	Return of Spontaneous Circulation (ROSC)
Post cardiac arrest	ROSC Temporary
Post defibrillation	No Rhythm Change
Post defibrillation	Rhythm Change
Medications-Intervention	Epinephrine
Medications-Intervention	Amiodarone
Medications-Intervention	Atropine Sulphate
Medications-Intervention	Cefazolin
Medications-Intervention	Glucose 10%
Medications-Intervention	Heparin Sodium
Medications-Intervention	Metaraminol Tartrate (Aramine)
Medications-Intervention	Morphine & Midazolam Infusion
Medications-Intervention	Packed Red Blood Cells
Medications-Intervention	Rocuronium Bromide (Esmeron)
Medications-Intervention	Suxamethonium Chloride
Medications-Intervention	Tranexamic Acid (TXA)
Skills	Needle Thoracentesis
Skills	Cardio-pulmonary Resuscitation (CPR)
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	Oropharyngeal Airway
Skills	External Cardiac Pacing
Skills	Rapid Sequence Induction

Skills	Suction (of the airway)
Skills	Synchronised Cardioversion
Skills	Ventilator
Other finding	Amputation
Other finding	Partial Amputation

4.3 INTERPRETATION

The main finding from this study was that MPDS dispatch categories were not useful discriminators between those incidents that do or do not require a L&S response. While there is no universally accepted target for sensitivity/specificity values in an EMS setting, the American College of Surgeons Committee on Trauma (ACSCOT) recommends sensitivity as 95% (otherwise known as an under-triage rate of 5%). [72] However, I found a threshold of sending L&S to all incident categories with a percentage of 0.09%, in order to meet the ACSCOT value for sensitivity. In other words, the system would dispatch L&S to almost all incidents at this level since it would have approximately 99% sensitivity and 1% specificity. While I recognise that the MPDS serves many objectives, I do not think it is a good discriminator when determining retrospectively whether a particular road crash was a L&S incident or not and is therefore unlikely to be a suitable tool to be used prospectively. These findings may have practical implications for any EMS jurisdiction currently using the MPDS to identify the priority of ambulances to the scene of a crash.

As an extension to this study, further exploration could involve repeating the area under the ROC curve calculation after excluding the MPDS categories with relatively low numbers of incidents such as ‘death on scene’ or ‘subway incident'.

Chapter 5: Crash Characteristics and High Acuity

5.1 OVERVIEW AND RATIONALE

Given the findings from my previous study (Study 1), I sought to explore alternative methods (to the MPDS) to identify the required dispatch priority of ambulances to the scene of a crash. The proposed method was to use descriptive characteristics of the crash, such as if an airbag was deployed or the location of the crash. I wanted to assess whether these characteristics were associated with crashes with high acuity patients; thereby suggesting the possibility that such characteristics could be used by laypersons at the scene to describe crashes to EMDs and potentially improve the accuracy of ambulance dispatch.

All road crash patients attended by SJ-WA ambulance in Perth between 2014 and 2016 were the subject of a retrospective cohort analysis. Police crash data and ambulance data were linked. Patient acuity was the key outcome variable, and high acuity was defined as either (1) an on-scene death or (2) an ambulance transfer on priority one (lights and sirens) from the site to the hospital. Crude odds ratios and 95% confidence intervals were used to identify crash characteristics that indicated high acuity (need for a L&S response).

My findings are described in the following manuscript that was published in Prehospital Emergency Care in 2021. The 'author accepted manuscript' version, as allowed due to copyright, is the version provided

Ceklic, E., Tohira, H., Ball, S., Brown, E., Brink, D., Bailey, P., ... & Finn, J. (2021). Motor vehicle crash characteristics that are predictive of high acuity patients: an analysis of linked ambulance and crash data. *Prehospital emergency care*, *25*(3), 351-360.

5.2 STUDY 2

Title

Motor vehicle crash characteristics that are predictive of high acuity patients: an analysis of linked ambulance and crash data.

Abstract

Background: Motor vehicle crashes (MVCs) comprise a significant component of emergency medical service workload. Due to the potential for life-threatening injuries, ambulances are often dispatched at the highest priority to MVCs. However, previous research has shown that only a small proportion of high-priority ambulance responses to MVCs encounter high acuity patients. Alternative methods for triaging patients over the phone are required to reduce the burden of over-triage. One method is to use information readily available at the scene (e.g. whether a person was a motorcyclist, ejection status or whether an airbag deployed) as potential predictors of high acuity.

Methods: A retrospective cohort study was conducted of all MVC patients in Perth attended by St John Western Australia between 2014 and 2016. Ambulance data was linked with Police crash data. The outcome variable of interest was patient acuity, where high acuity was defined as where a patient (1) died on-scene or (2) was transported by ambulance on priority one (lights & sirens) from the scene to hospital. Crash characteristics that are predictive of high acuity patients were identified by estimating crude odds ratios and 95% confidence intervals.

Results: Of the 18,917 MVC patients attended by SJ-WA paramedics, 6.4% were classified as high acuity patients. The odds of being a high acuity patient was greater for vulnerable road users (motorcyclists, pedestrians and cyclists) than for motor vehicle occupants (OR=3.19, 95% CI, 2.80-3.64). A not ambulant patient had 15 times the odds of being high acuity than ambulant patients (OR=15.34, 95% CI, 11.48-20.49). Those who were trapped in

a vehicle compared to those not trapped (OR 4.68, 95% CI, 3.95-5.54); and those who were ejected from the vehicle compared to those not ejected (OR 6.49, 95% CI, 4.62-9.12) had higher odds of being high acuity patients.

Discussion: There were two important findings from this study: (1) few MVC patients were deemed to be high acuity; and (2) several crash scene characteristics were strong predictors of high acuity patients.

Introduction

Background/Rationale

Recent studies have shown that motor vehicle crashes (MVCs) make up a significant component of the workload in emergency medical services (EMS) (1, 2). Emergency calls relating to MVCs are one of the ten most common call types for ambulance services (1, 2, 3), yet have relatively high non-transport rates (4). This discrepancy arises from a difficulty for emergency call-takers (dispatchers) to determine patient acuity at the scene of a crash, based on the details provided by the caller, often a bystander. Decisions about the ambulance priority at dispatch are commonly based on the mechanism alone, i.e. 'traffic incident', 'vehicle versus pedestrian' (5, 6), however, there is a considerable range in injury severity and patient acuity in MVCs. Some patients may die immediately on impact, whereas some patients may be entirely uninjured (7). This variability is a reason many EMS routinely dispatch ambulances to MVCs at the highest priority (6), where lights and sirens (L&S) are used while driving to the scene of the crash in an attempt to minimize response times.

Such 'erring on the side of caution' when dispatching ambulances to MVCs often results in 'over-triage' – defined as a priority one ambulance response where the patient's condition was not time critical (8). Assigning the highest priority dispatch to every MVC risks a misallocation of scarce EMS resources if the injury is minor or the patient does not require emergency care from ambulance paramedics. A potential way to determine ambulance dispatch priority to MVCs is by using additional information from the scene of a crash. Some studies have shown that crash scene variables can be used to predict injury severity (9,10). For example, an on-scene injury prediction algorithm found that seatbelt usage (belted/unbelted), location (urban/rural), age and speed limit could predict an anatomical measure of severity (the Injury Severity Score) (11). However, such studies have limited utility in informing dispatch priority, as the outcome measures of interest do not adequately reflect the need for a priority one response. They are either too broad (serious/non-serious), limited to either anatomical (Injury Severity Score) or physiological scales (Glasgow Coma Scale) (which are not assessable by bystanders) or reflect the outcome of the crash not the patient condition at the scene (12,13).

Aim

The aim of this study is to describe patient and crash characteristics of MVCs attended by emergency ambulance in Perth, Western Australia, and to identify patient/crash characteristics that are predictive of high acuity patients.

Methods

Design, setting, and population

A population-based retrospective cohort study was conducted consisting of all MVC patients attended by St John Western Australia (SJ-WA) paramedics in Perth, Western Australia (WA) from 1st January 2014 to 31st December 2016. The Perth metropolitan area has a population of around 2.02 million, with 77% aged 18 years or older (14). The road environment consists of three expressways (those with limited access) and nine highways (those with many crossing/merges with other roads) (15). The MVC fatality rate in Perth is 3.6 per 100,000 persons per year (16), similar to San Francisco (3.2 per 100,000) and Seattle (3.8 per 100,000) (17). Emergency ambulance response times to MVCs in Perth (18) are comparable to urban areas of the United States (17) and the United Kingdom (19) (targeted to be within 15 minutes for priority one in Perth).

SJ-WA is a single-tier ambulance service that is the contracted provider of emergency road ambulances in Perth. Within Perth, SJ-WA ambulances are staffed by two crew members, at least one of whom is a qualified paramedic. During the study period, SJ-WA used the Medical Priority Dispatch System (MPDS v12.1) to categorise emergency calls for help (6). The MPDS assigns determinant codes to each category (i.e. stroke or traffic/transportation) however, it is at the discretion of each emergency medical system (including SJ-WA) to determine their own response regarding the priority of ambulances. Currently, all emergency ambulance calls relating to MVCs in WA are assigned a priority one dispatch response, whereby lights and sirens can be used on the way to the scene (lights and sirens cannot be used for Priority 2 or 3 responses). SJ-WA's operational target is that 90% of priority one responses arrive within 15 minutes of dispatch (20).

Data sources

Two sources of data were used for this study: SJ-WA data (ambulance data) and Main Roads WA/Police crash data (crash data). The ambulance data contain information collected during the emergency telephone call (computer-aided dispatch) and electronic patient case records (ePCRs) completed by paramedics. Ambulance data were extracted for all cases where the dispatch code was motor vehicle related (MPDS Protocol 29: Traffic/Transportation Incidents) (6) or identified in the ePCR by paramedics on-scene as a MVC. To be included in the study, patients had to be involved in a MVC that included a moving vehicle fitted with an engine (car, truck, motorbike). Cases of single-bicycle or single-pedestrian events were excluded, for example, where a bicyclist fell on the road but where there was no crash with a vehicle. All deaths relating to ambulance cases were included (i.e. including records where a patient died at the scene and the patient's name could not be ascertained by the paramedic). Ambulance records were excluded if a patient could not be located on arrival (e.g. hoax calls, or where patients leave the scene) or for cases that did not require a primary emergency response (e.g. inter-facility transfers).

The crash data consists of information collected on all those persons involved in a reportable road crash as defined by the WA Police (21). These data contain detailed information describing the crash such as the location, vehicles' movements (i.e. right turn), and demographic details of people involved. These data are collected from people involved directly in the crash, and are recorded by police officers who attended the crash (for some crashes), the Insurance Commission of WA, and by the state authority responsible for transport and road infrastructure (Main Roads/MRWA).

Data Linkage

Records in the ambulance data were linked to crash data in a staged approach. First, records were linked using Fine-Grained Records Integration and Linkage Tool (v2. 1.5, Emoly University, U.S.) for records where the geographic coordinates (latitude/longitude) of the dispatch location of the MVC (ambulance data) were within one kilometer (0.62 miles) of the reported location of the crash (crash data), and within one calendar day. Matches were programmatically identified where there was a match on surname, first name, date of birth and vehicle registration number, using SAS Base 9.3, with the SPEDIS function (22) used to allow for fuzzy matches on close spelling of surname and first name.

Patient and crash variables

Patient characteristics included: clinical characteristics, which were based on the Guidelines for Field Triage of Injured Patients (23) (Glasgow Coma Scale Score (GCS), systolic blood pressure (SBP) and respiratory rate (RR)); demographics (age, sex) and road user type (motor vehicle occupant, motorcyclist including pillion, cyclist and pedestrian). Crash characteristics were selected as on-scene characteristics that had the potential to be used at dispatch to prioritize ambulances. Our criteria for choosing these variables were: they be associated in the literature with injury severity and potentially observable and reportable to EMS dispatch by a layperson at a crash scene. Crash characteristics included whether any patient was in a vehicle rollover, was ejected, or trapped (either mechanical or physical), whether the crash was at an intersection, or between intersections (midblock), airbag deployment, time of day, weather and speed zone. Paramedic clinical notes (examination text) in the ePCR were searched (using code-based search of keywords), to supplement data not already recorded in the pre-defined ambulance or crash data fields.

Outcome variables

The outcome variable of interest was patient acuity. High acuity was defined as patients who (1) died on-scene or (2) were transported by ambulance on priority one (L&S) (high priority) from the scene to hospital. Conversely, we defined low acuity as patients who (1) did not die on-scene and (2) were either not transported to hospital or were transported to hospital at a priority lower than priority one (not L&S).

Statistical analysis

Univariate statistics were used to describe the cohort. Continuous data were described using medians and interquartile ranges. Group differences were assessed using the Kruskal-Wallis test for continuous variables. Categorical data were summarised as counts and percentages. To examine factors associated with the need for a priority one response (i.e. a high acuity patient), crude odds ratios (ORs) and 95% confidence intervals (CIs) were calculated. We decided *a priori* to restrict the scope of this study to calculating univariate effect estimates. We considered that, due to the potential for collinearity between predictors, it was beyond the scope of this study to use multivariate modelling (e.g. logistic regression).

Ethics

Ethics approval was granted as a sub-study of the Western Australia Pre-hospital Record Linkage Project by the Curtin University Human Research Ethics Committee (HR 128/2013). The St John Research Governance Committee approved the conduct of the research. The researchers and Main Roads Western Australia signed a Data Licensing Agreement for the use of the crash data.

Results

Cohort selection

There were 23,589 records associated with a MVC in the ambulance data. A total of 3,129 ambulance records were excluded prior to linkage (20,460 remaining for linkage). The main reasons for exclusion was empty records. This occurs where there was no electronic record of any assessment, intervention, or clinical case notes due to a patient not meeting a paramedic assessed need for care/assessment/intervention (n=2,051). Other reasons are where no patient could be found (n=532), or records that were not for a MVC emergency, such as those cases incorrectly classified as an MVC (n=486).

Data Linkage

Of the 20,460 ambulance records, 12,872 records (62.9%) had a matching record in the crash data. We did not expect a 100% linkage rate between the two datasets because not all people involved in a reportable road crash (crash data) necessarily require an ambulance (e.g. where there is damage to property, but no significant injuries); and conversely, not all people using an ambulance after a MVC must report their crash to government authorities. Figure 1 details the linkage process.

Of the 20,460 ambulance records, there were 18,917 unique patients, with some patients having more than one record of care, such as when they were attended by more than one ambulance crew. During the study period, there were 20,428 ambulance attendances for 18,917 patients in 14,846 road crashes. Most patients had one attending crew (92.5%); some had two crews (7.0%), three crews (0.4%) or four crews (0.1%).

Patient characteristics

As shown in Table 1, for the 18,917 MVC patients in the ambulance data the median age was 34.0 years (IQR: 23 to 53), with ages ranging from less than 1 to 101 years. There was a statistically significant difference between the median age for males compared to females ($p<0.01$), with males being slightly younger than females (median age 34.0 years compared to 36.0 years respectively). Patients were mainly occupants of a vehicle (60.7%). A small proportion were motorcyclists (9.4%), pedestrians (4.0%) or cyclists (3.4%). Data on road user type was not available for 22.5% of cases. Cyclists had the highest median age (40.0 years) and pedestrians the lowest (29.0 years). A very small proportion of patients had a Glasgow Coma Scale score of less than 14 (3.3%), a systolic blood pressure of < 90mmHg (0.7%) or a respiratory rate of <10 or >29 breaths per minute (2.1%).

Characteristics of high acuity versus low acuity patients

There were 1,214 high acuity patients (6.4% of all patients). Of these, 50 people died on-scene and 1,164 were transported from the scene to hospital at priority one.

Clinical, demographic and crash characteristics for high acuity patients were compared with those defined as low acuity patients (Table 1). A higher proportion of males (8.7%) versus females (3.7%) were classified as high acuity. A higher percentage of vulnerable road users (motorcyclists, cyclists, and pedestrians) were classified as high acuity than motor vehicle occupants (MVOs), with 15.1% of pedestrians, 14.9% of motorcyclists and 9.2% of cyclists being high acuity compared to 4.8% of MVOs. Of the crash characteristics explored in this study, the category of being ejected (from a vehicle) had the highest proportion of high acuity patients (30.1%). This rate was similar to those patients who were not ambulant at the scene (26.3% high acuity) and for those trapped in a vehicle (21.8% high acuity). High acuity patients comprised only 6.6% of vehicle rollovers and 3.9% of cases where airbags where deployed. Conversely, of high acuity patients, 46.1% were middle aged (25-64 years), 36.2% were vulnerable road users and 29.5% were at an intersection.

Unadjusted odds ratios (ORs) of high acuity (relative to the odds of low acuity) were calculated according to demographic and crash characteristics (Table 2). The OR of a person involved in a MVC being a high acuity patient were 39% lower for those aged 17-24 years (OR=0.61, 95% CI, 0.51-0.73), 40% lower for those aged 25 to 64 years (OR=0.60, 95% CI, 0.52-0.69) and 47% lower than those aged 65 years and over (OR=0.53, 95% CI, 0.43-0.67) when compared to those aged 16 years or less.

The odds of being classified as a high acuity patient were significantly greater for pedestrians (OR=3.56, 95% CI, 2.86-4.42) and motorcyclists (OR 3.49, 95% CI 2.98-4.08) than for motor vehicle occupants (MVOs). Not ambulant patients had 15 times the odds of being high acuity than ambulant patients (OR=15.34, 95% CI, 11.48-20.49). Patients who were ejected from the vehicle, compared to those not ejected, (OR 6.49, 95% CI, 4.62-9.12); and those who were trapped compared to those not trapped, had higher odds of being high acuity patients (OR 4.68, 95% CI, 3.95-5.54) – see Table 2.

Discussion

The aim of this study was to describe and identify patient/crash characteristics associated with high acuity. Specifically, we sought to identify those factors that could be reported to an ambulance dispatcher by a bystander during the emergency phone call. Ambulance data was linked with police crash data, comprising n=18,917 unique patients, with 6.4% of patients being classified as high acuity (defined here as priority one transport the hospital, or died at the scene).

There are two important findings from this study. The first reflects the imbalanced proportion of high compared to low acuity patients at the scene of MVCs. Nearly all patients attended by paramedics to motor vehicle crashes were of low acuity in this study, with 93.6% of patients neither dead on-scene, nor transported priority one to a to hospital. While the imbalanced nature of MVCs towards being primarily low severity is well known (24), some of the research in this field uses crude ordinal categories (fatality/hospitalization/minor injury/property damage) that reflect the outcome of injuries in a crash and do not adequately translate to describing the need for a priority one ambulance response to MVCs (13). Therefore, as patient acuity described in this study relates to the need for a priority one ambulance response to the scene of a crash, this study makes a unique contribution to confirming the disparity between high and low acuity patients in regards to urgent need for an ambulance.

The second main finding of our study was similar to that identified by Lerner et al. (25), namely that 'not all crash scene characteristics are created equal'. We found a number of scene characteristics that were strongly associated with patient acuity, while other scene characteristics showed almost no association. The strongest predictor was ambulation, with not ambulant patients having more than 15 times the odds of high acuity than ambulant patents (OR=15.34, 95% CI, 11.48-20.49). Significant associations were found for other variables, including whether a patient was ejected from the vehicle (OR 6.49, 95% CI, 4.62-9.12) or trapped in vehicle (OR 4.68, 95% CI, 3.95-5.54). One crash scene characteristic with some contention as to its relevance to be used in triage is vehicle rollover (26–28). Vehicle rollover has been used to aid in triage in different settings, including ambulance dispatch (6) and transport from the field to trauma centers (23). This study found that being in a vehicle rollover did not significantly increase the odds of being classified as a high acuity patient (OR=1.04; 95% CI, 0.75-1.43), while others have found that vehicle rollover is a criterion with suitable predictive ability (for trauma team activation) (29). Previous studies have suggested that the use of rollovers as a dispatch criterion to identify the acuity of patients could be improved when combined with other crash characteristics (30) such as whether the patient remained in the vehicle or was ejected (31). The crash characteristics identified in this study need to be further explored with respect to their suitability to be used to determine ambulance dispatch priority.

This study has affirmed that using a single crash scene variable to represent patient acuity is not likely to be reasonable, as MVCs vary in their nature including the type of road users involved and the movement of vehicles. For example, not all vehicles have airbags and not all crashes involve a rollover. Isenberg, Cone and Stiell (32) have suggested that a dispatch rule where one of the following needed to occur for a priority one response: a MVC occurred on a highway/interstate or involved a single vehicle or the patient was not ambulatory. It is therefore suggested that used selectively and in combination, crash scene variables have the potential to improve the sensitivity and specificity of ambulance dispatch to MVCs. This approach had been adopted by algorithms used by Automatic Crash Notification Systems, such as URGENCY (33). However, many variables used in these algorithms would not be able to be described by a bystander during the emergency phone call to the ambulance dispatcher (e.g. speed at collision, steering wheel deformation, vehicle intrusion depth).

Limitations

A limitation of this study was that there are currently no validated criteria that explicitly determine the need for a priority one ambulance dispatch. We therefore used a proxy measure defined as (1) death at the scene or (2) priority one transport from the scene to hospital.

While this proxy measure is indicative of the severity of injuries sustained by the MVC patient, it is possible that some conditions that are potentially life-threatening can be managed by paramedics at the scene and therefore not have required a priority one transport to hospital. These could have included conditions such as an obstructed airway and bleeding, which all require urgent paramedic intervention at the scene but not necessarily urgent transport to hospital.

The road user status (i.e. motor vehicle occupant, motorcyclist, cyclist, pedestrian) is a variable of interest to this study as it reflects the level of protection that a patient has in the crash and therefore the potential need for a priority one ambulance response. Yet, for around a quarter of patients in this study, the road user status was unknown (22.5%). However, where the road user status was unknown, nearly all these patients were low acuity (94.7%) and nearly half were not transported anywhere from the scene (49.3%). Therefore, it is expected that the primary cohort of interest in this study ('high acuity' patients) were not disproportionately represented in this unknown road user group. This assessment was made and the same conclusion reached for other crash variables investigated.

There is a possibility that there were other persons involved in the MVCs attended by paramedics, but because they were clearly not injured, an e-PCR was not completed. There is no way of enumerating this in a retrospective study – however, it is not envisaged that the numbers would be large and in any case would further reduce the percentage of high acuity patients.

Future Research

Future research could consider how on-scene crash characteristics might be incorporated for use in determining ambulance dispatch priority. While it is not feasible for ambulance emergency call-takers to ask bystanders about physiologic or anatomic criteria (34), we suggest that future research investigate the potential to use combinations of on-scene crash characteristics (and possibly environmental characteristics) to develop reliable algorithms to distinguish between those MVCs that do and do not require a priority ambulance response.

Conclusion

While motor vehicle crashes can result in serious injuries and even death, over 93% of MVC patients attended by ambulance paramedics in Perth, WA were classified as low acuity. We found that some crash scene characteristics (including ambulation, person ejected, trapped, or involving a vulnerable road user) were significant predictors of high acuity. In addition, a crash characteristic currently used in dispatch systems to triage for MVCs (whether the vehicle rolled over) appears to be a weak predictor of patient acuity. There is a need to further investigate the potential for crash scene characteristics, as identified by bystanders, to be incorporated into algorithms to determine ambulance dispatch priority.

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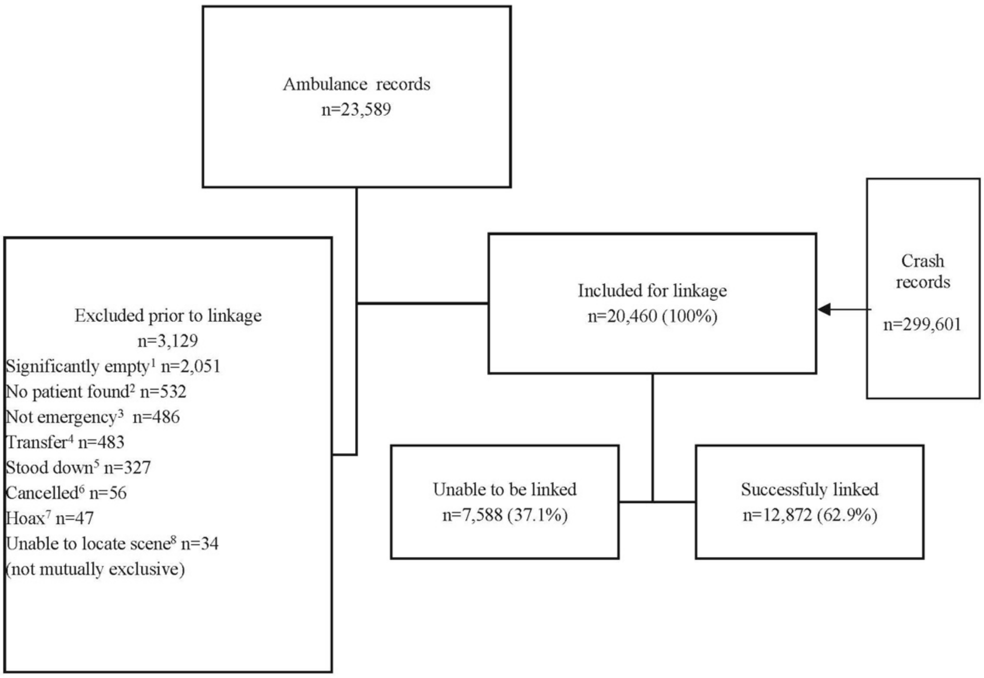
Figure 1. Flow diagram of included/excluded patient records and linkage process between ambulance dispatch record and road crash notification records



[1] No electronic record of assessment, intervention, or clinical case notes; [2] Paramedics arrived on-scene but there was no patient present (e.g. patient absconded); [3] Use of the ambulance for other than delivering patient care, such as transport of equipment; [4] Patient transfer between hospitals; [5] Ambulance dispatched but then received a higher priority job or another crew was closer to the scene; [6] Individual calls from the scene and states they no longer require the ambulance; [7] Call for an ambulance is falsely and deliberately made; [8] Ambulance is sent but cannot locate the MVC.

Table 1. Characteristics of MVC patients by 'high/low acuity'[1]

	n (%)	n (%)	n (100%)
Total	**17,703 (93.6%)**	**1,214 (6.4%)**	**18,917**
Clinical characteristics (1st observation)			
Glasgow Coma Scale <14	170 (27.5%)	449 (72.5%)	619
Systolic blood pressure <90 mmHg	58 (42.6%)	78 (57.4%)	136
Respiratory rate <10 or >29 breaths per minute	181 (44.6%)	225 (55.4%)	406
Demographic characteristics			
Age - years			
<=16	3,281 (90.7%)	336 (9.3%)	3,617
17-24	3,179 (94.1%)	198 (5.9%)	3,377
25-64	9,160 (94.2%)	566 (5.8%)	9,726
65+	2,083 (94.8%)	114 (5.2%)	2,197
Sex			
Male	8,735 (91.3%)	837 (8.7%)	9,572
Female	7,557 (96.3%)	290 (3.7%)	7,847
Road User			
Motor vehicle occupant	10,925 (95.2%)	584 (4.8%)	11,473
Motorcyclist	1,521 (85.1%)	266 (14.9%)	1,787
Cyclist	581 (90.8%)	59 (9.2%)	640
Pedestrian	639 (84.9%)	114 (15.1%)	753
Other/unknown	4,037 (94.7%)	227 (5.3%)	4,264
Crash characteristics (patient-level)[2]			
Vulnerable road user[3]	2,741 (86.2%)	439 (13.8%)	3,180
Other road users	10,925 (95.2%)	548 (4.8%)	11,473
Not ambulant	263 (73.7%)	94 (26.3%)	357
Ambulant	5,922 (97.7%)	138 (2.3%)	6,060
Rollover	592 (93.4%)	42 (6.6%)	634
Other crash type	17,112 (93.6%)	1,171 (6.4%)	18,283
Ejected	114 (69.9%)	49 (30.1%)	163
Not ejected	17,589 (93.8%)	1,165 (6.2%)	18,754
Trapped	708 (78.2%)	198 (21.8%)	906
Not trapped	16,995 (94.4%)	1,016 (5.6%)	18,011
Intersection	6,774 (95.0%)	358 (5.0%)	7,132
Mid-block (not intersection)	4,254 (90.3%)	455 (9.7%)	4,709
Airbags deployed	4,623 (96.1%)	185 (3.9%)	4,808
Airbag not deployed	13,080 (92.7%)	1,029 (7.3%)	14,109
Rainy weather	543 (93.3%)	39 (6.7%)	582
Fair weather	5,857 (90.2%)	635 (9.8%)	6,492
Dawn/dusk	715 (94.2%)	44 (5.8%)	759
Not dawn/dusk	9,908 (93.0%)	750 (7.0%)	10,658
Night-time (7:30pm-5am)	2,669 (88.6%)	342 (11.4%)	3,011
Day-time (5am-7:30pm)	15,034 (94.5%)	872 (5.5%)	15,906

[1] High acuity was defined as patients who (1) died on-scene or (2) were transported by ambulance on priority one (L&S) (high priority) from the scene to hospital. Low acuity was defined as patients who (1) did not die on-scene and (2) were either not transported to hospital or were transported to hospital at a priority lower than priority one (not L&S).
[2] Categories may not sum to the total where the crash characteristic was unknown.
[3] Vulnerable road users were either motorcyclists (incl. pillion), cyclists or pedestrians.

Table 2. Odds Ratios (OR) of being classified as a 'high acuity patient' (with Referent group)[1]

	OR (95% CI)
Age group (years)	
0-16	*1.00*
17-24	0.61 (0.51-0.73)
25-64	0.60 (0.52-0.69)
65 and over	0.53 (0.43-0.67)
Sex	
Male	*1.00*
Female	0.40 (0.35-0.46)
Road user group	
Motor vehicle occupant	*1.00*
Motorcyclist	3.49 (2.98-4.08)
Cyclist	2.02 (1.53-2.68)
Pedestrian	3.56 (2.86-4.42)
Vulnerability[3]	
Not-vulnerable (MVO)	*1.00*
Vulnerable	3.19 (2.80-3.64)
Ambulatory status	
Ambulant	*1.00*
Not-ambulant	15.34 (11.48-20.49)
Vehicle rollover status	
Not a rollover	*1.00*
Rollover	1.04 (0.75-1.43)
Patient ejection status	
Not ejected	*1.00*
Ejected	6.49 (4.62-9.12)
Trapped status	
Not trapped	*1.00*
Trapped	4.68 (3.95-5.54)
Road position	
Not an intersection	*1.00*
Intersection	2.02 (1.75-2.34)
Airbag status	
Airbags not deployed	*1.00*
Airbags deployed	0.51 (0.43-0.60)
Weather	
Not rainy weather	*1.00*
Rainy weather	0.66 (0.47-0.93)
Light	
Not dawn/dusk	*1.00*
Dawn/Dusk	0.81 (0.59-1.11)
Day/Night	
Not night-time	*1.00*
Night-time (7:30pm-5am)	2.21 (1.94-2.52)
Speed zone (km/h)	
50km/h or less	*1.00*
60km/h	0.85 (0.69-1.04)
70km/h	1.20 (0.97-1.47)
80km/h	1.31 (1.03-1.68)
90km/h	3.03 (2.04-4.48)
100km/h	1.00 (0.71-1.41)
110km/h	1.49 (0.71-3.13)

5.3 INTERPRETATION

The purpose of this study (Study 2) was to explore the potential of crash characteristics to be used to prioritise ambulances. I found that there was considerable variability in the predictive ability of characteristics, with some being highly predictive and others not. As with other crash severity prediction models in the literature, [73] I reasoned that combinations of characteristics were more likely to provide reliable prediction models. Therefore, in a subsequent study (study 4), I investigated a decision tree approach that I thought might reflect the need for combinations of characteristics.

Interestingly, I found that ambulation was the strongest predictor of high acuity, with not ambulant patients having over 15 times the odds of being high acuity than ambulant patients. This is remarkable because ambulation status is not a criterion commonly used by EMS. In the next study I sought to explore this crash characteristic in the context of existing literature.

Chapter 6: A Systematic Review of Ambulant Status

6.1 OVERVIEW AND RATIONALE

Given the finding from my previous study, it was hypothesized that the ambulatory status of the road crash patient (i.e., whether they can walk) might potentially assist ambulance dispatch prioritisation. The goal of this systematic review was to review all published research to see whether the ambulatory status of people involved in a road crash could predict the requirement for a L&S ambulance response. A systematic review was therefore undertaken with the aim to address the question "is ambulatory status of those involved in a road crash associated with the need for a lights and sirens (L&S) ambulance response?".

I searched the following databases: EBSCO CINAHL, Ovid EMBASE/MEDLINE, Scopus, Cochrane Library, and grey literature. Studies that met the following criteria were considered: 1) ambulatory status was recorded as a predictor variable, 2) the need for a L&S ambulance response was an outcome variable, 3) restricted to comparative studies, 4) involved road crash patients. The risk of bias in studies was examined.

My findings are described in in the following manuscript that was published in the Annals of Emergency Dispatch in 2020.

Ceklic E, Tohira H, Ball S, Finn J. A Systematic Review of the Relationship Between Ambulant Status and the Need for a Lights-and-Siren Ambulance Response to Crashes. *Annals of Emergency Dispatch & Response*. 2020;7(3).

6.2 STUDY 3

A Systematic Review of the Relationship Between Ambulant Status and the Need for a Lights-and Siren Ambulance Response to Crashes

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Keywords
Motor Vehicle Crashes; Lights-and-Siren; Ambulant Status; Ambulation; Emergency Dispatch Priority; Emergency Dispatch Triage

Citation
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ABSTRACT

Introduction: Motor vehicle crashes (MVCs) can result in life-threatening injuries, and ambulances are therefore often dispatched at the highest priority response of lights-and-siren (L&S). However, assigning L&S ambulance response based on type of incident alone may result in over-triage, meaning that the patient's condition did not warrant L&S ambulance response. Potentially, the ambulatory status of the MVC patient at the scene (i.e., whether they can walk) could help inform the ambulance dispatch priority, given that ambulation reflects both a person's physical ability to walk and their conscious state. The objective of this systematic review is to examine published studies to determine whether ambulatory status of those involved in an MVC can predict the need for L&S ambulance response.

Methods: A systematic review of the literature was conducted. The following databases were searched: Ovid MEDLINE, Ovid EMBASE, EBSCO CINAHL, Scopus, Cochrane Library and grey literature from inception until April 2, 2019, were searched. Studies meeting the following criteria were included: 1) comparative study; 2) patients involved directly in an MVC; 3) ambulatory status reported as an exposure; and 4) the need for L&S ambulance response reported as an outcome. Studies were assessed for risk of bias.

Results: The search strategy yielded 2,856 unique citations, including one study that directly addressed the review question. This study found that non-ambulation was a strong predictor of the need for L&S ambulance response (OR 0.13; 95% CI 0.07-0.24) based on field triage guidelines.

Conclusion: There was insufficient evidence to reach a conclusion regarding the utility of ambulatory status as an indicator of the need for L&S ambulance response. Further research in this field is required.

INTRODUCTION

Motor vehicle crashes (MVCs) are the leading cause of injury-related death worldwide.[1] Due to the potential for life-threatening traumatic injuries in an MVC, many emergency ambulance dispatch systems assign the highest priority response of lights-and-siren (L&S).[2] However, routinely assigning L&S ambulance response for all MVCs may not be the best utilization of limited emergency medical service (EMS) resources, since it is likely to result in over-triage – i.e. a high priority ambulance response to a low acuity patient. Furthermore, L&S ambulance response poses an inherent increased risk of a traffic accident involving an ambulance.[3] In contrast, under-triage by dispatchers could mean that some patients do not receive the timely emergency care they require, potentially resulting in poorer patient outcomes.[4]

Previous research has found that factors relating to the physical force involved in a crash, such as vehicle intrusion depth and speed at time of collision, can predict the severity of patient injuries.[5] However, these factors may be difficult for bystanders to accurately describe to emergency ambulance dispatchers during the emergency call.[6] A novel dispatch criterion to identify patients who require a high priority ambulance response could be ambulatory status at the scene. Being ambulant refers to "walking or able to walk," which depends on both the movement of the legs and the ability to coordinate balance and posture.[7] As the ability to walk has been used to indicate a non-urgent triage priority,[8] ambulation has the potential to be a diagnostic criterion for the need for L&S ambulance response.

Ambulation is seen as an important basis for triaging trauma patients in a range of settings. In mass casualty disasters, the "walking wounded" are given a non-urgent status for care,[9] and in emergency departments (ED), ambulatory status has been used to identify patients with minor injuries.[10] The similarity of these situations to MVCs (multiple trauma patients in one location) suggests that ambulatory status could help ambulance dispatchers to discriminate between patients requiring L&S response and those who do not in MVCs. However, there are situations where a patient may be walking after an MVC, but their condition is likely to still require L&S response. For example, a patient with an intracranial hemorrhage may be able to walk after an MVC, but require urgent care due to the high risk of mortality and importance of timely in-hospital treatment.[11] This study sought to systematically review the published evidence for whether ambulatory status can accurately inform the requirement for L&S ambulance response in MVCs.

METHODS

The Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) statement was followed for this systematic review.[12] Details of the protocol were registered on PROSPERO (CRD42018097283) and can be accessed at https://www.crd.york.ac.uk/prospero/display_record.php?RecordID=97283.

Study question

Is the ambulatory status of those involved in an MVC associated with the need for L&S ambulance response?

Eligibility criteria

To be included in this review, studies needed to meet four criteria: 1) the study must be a comparative study, including randomised controlled trials, cohort studies, cross-sectional studies, case-control studies; 2) study participants must be people directly involved in an MVC; 3) the study must report ambulatory status of the patient at the scene as an exposure; and 4) the study must report the need for L&S response as an outcome.

An MVC was defined in this review as a crash on a public road or highway. Vehicle types of cars, buses, trucks, motorcycles, bicycles, and scooters were included; however, larger transport types (e.g. trams and trains) were excluded. All road user types were included (such as drivers, passengers, motorcyclists, bicyclists, and pedestrians). However, crashes in which no vehicles were involved, such as a single-pedestrian incidents, were excluded.[13]

Ambulation was defined as walking or being able to walk.[14] Entrapped patients were assumed to be non-ambulant (even though sometimes patients may be able to walk if extricated). An operational definition of the need for L&S ambulance response was not pre-specified. Reviews, conference abstracts, letters, editorials, case studies, and all other commentaries were excluded. The literature search was not limited by language or publication date.

Information sources

Ovid MEDLINE, Ovid EMBASE, EBSCO CINAHL, Scopus, Cochrane Library and grey literature via Mednar from inception date up to April 2, 2019 were searched. Review articles were used to find other relevant articles, and reference lists from articles were used to identify additional sources.

Search strategy

Our search strategy involved three key concepts: ambulation, motor vehicle crashes, and the need for L&S ambulance response (see Appendix 1). Keywords relating to these three concepts were combined with the boolean operator 'AND.'

Study selection

Author EC performed the database searches and conducted an initial review based on title and abstract to select potentially relevant papers. All identified studies were then independently assessed by authors EC and HT to ensure the eligibility criteria were met. Discrepancies were resolved by consensus.

Data collection process and data items

Data items were extracted by EC onto an electronic spreadsheet relating to the year of publication, research design, sample size, the population of interest, predictor and outcome measures; and double-checked. Authors were contacted when further information was required to determine the eligibility of studies.

Risk of bias in individual studies

Methodological quality of the studies was independently assessed by two authors (HT and EC) using the Newcastle-Ottawa Scale (NOS) for cohort studies.[15] This scale comprised nine items relating to the selection of the exposure and outcomes, comparability of groups, and how the outcome was assessed and followed up. Consensus about the risk of bias was reached by discussion.

Statistical analysis and synthesis of results

Odds ratios comparing odds for the requirement of L&S ambulance response in ambulating participants to the odds in non-ambulating participants were computed. Heterogeneity between studies was assessed using the I^2 statistic, with the rule that results would not be pooled if I^2 exceeded 50% (high heterogeneity).[16] It was planned that funnel plots would be examined for potential publication bias.

RESULTS

Our search strategy yielded 2,856 unique citations. The titles and abstracts were screened, identifying seven potentially relevant articles.[17-23] The full text of these articles was then reviewed for eligibility according to the inclusion criteria. One article[17] remained after full texts were reviewed (Fig. 1); therefore, only a narrative summary of results is provided.

Study characteristics

The characteristics of the one included study (Isenberg et al.[17]) are summarised in Table 1. This was a cohort study conducted in

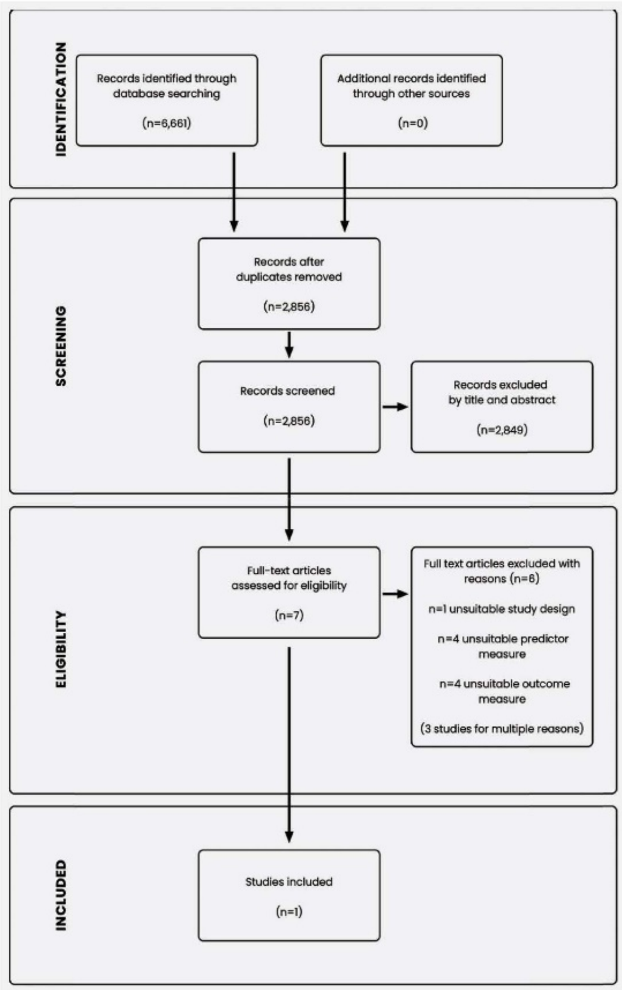

Figure 1. PRISMA flow diagram

Study ID/ Country	Year	Study Design	Population	Age group	Total (n)	Predictor	Outcome
Isenberg et al.[17] USA	2012	Retrospective observational study	Motor Vehicle Crash patients transported to a Level I trauma center	All ages	509 (205 not ambulant)	Ambulation v non-ambulation	Criteria of the Guidelines for Field Triage of the Injured Patient (patient did/did not meet the criteria)[24]

Table 1. Characteristics of Included Study

the USA that evaluated on-scene ambulatory status related to people transported to a Level I Trauma Center who had been in an MVC. Isenberg et al. [17] attempted to identify MVC characteristics (including ambulatory status) that could easily be identified by emergency callers and were associated with the need for an ambulance L&S response. Isenberg et al.[17] defined the need for L&S ambulance response according to the published "Guidelines for Field Triage of Injured Patients,"[24] which involved consideration of physiologic, anatomic, and mechanistic criteria. The first author of the included study was contacted to clarify how ambulatory status was determined, who confirmed that this was based on a review of each patient's ambulance chart (D. Isenberg, personal communication, 7th June 2018).

Methodological quality

The study scored 7 out of a possible 9 on the Newcastle-Ottawa Scale,[15] and was deemed to be good quality. Points were deducted for comparability of cohort (limited information on adjustment of confounders).

Results of individual studies

Isenberg et al.[17] found that of 509 MVC patients, n=304 (60%) were ambulant at the scene; and of these 15 (4.9%) required L&S ambulance response; in comparison, of the 205 patients (40%) who were not ambulant, 58 (28.3%) required L&S response. Based on these data, there was an 87% lower odds of requiring L&S ambulance response for ambulant compared to non-ambulant MVC patients (OR 0.13; 95% CI 0.07-0.24).

Synthesis of results

Given that a single study met the inclusion criteria a meta-analysis was not undertaken.

Characteristics of excluded studies

Table 2 shows the characteristics of excluded studies. The reasons for exclusion were: unsuitable type of study design (n = 1);[23] unsuitable measurement of ambulatory status (n = 4)[19-22] and unsuitable measurement of a need for L&S response (n=4).[18,20-22] Three studies were excluded for multiple reasons.[20-22]

DISCUSSION

Despite ambulation being seen as an important basis for triaging trauma patients in emergency-department and mass-casualty environments,[9,10] there is limited evidence of its value for triaging ambulance calls for MVCs. In this systematic review, there was only one study that specifically addressed our review question and met our inclusion criteria.[17] Isenberg et al.[17] found that the ambulatory status of patients at the scene of an MVC was a strong predictor of the need for L&S ambulance response. However, despite this strong effect size (OR=0.13), the Isenberg et al. [17] study indicates that using ambulatory status alone as an indicator of the L&S response in MVCs would lead to both under-triage (5% of ambulatory patients required L&S), and over-triage (72% of non-ambulatory patients did not require L&S). In relation to this, it is important to note that the optimal prediction

Study ID/Country	Year	Primary Reason for Exclusion
Loza[23]/USA	2013	Conference abstract.
McCoy[18]	2017	Outcome measure (Glasgow Coma Scale score and spinal injury) did not adequately represent the need for a lights & sirens response.
Merlin[19]/USA	2013	No comparison group for ambulation.
Ryb[21]/USA	2011	Ambulatory status of patients was not clearly defined. The authors compared characteristics among those ejected, self-exited, exited with assistance, removed from the vehicle with decreased mental status, removed due to perceived serious injury and removed for other reasons. A large proportion of patients (25%) had unknown mobility. The outcome measure was also not adequately reported.
Ryb[20]/USA	2011	Ambulatory status not clearly defined. The authors used scene mobility information as follows: ejection, removed due to decreased mental status, self-exited, exited with assistance, removed due to perceived serious injury. Outcome measure not adequate (ISS>15).
Scheetz[22]/USA	2007	Ambulatory status of patients was not clearly defined. The authors compared the characteristics of those fatal when removed, unconscious/disorientated, serious injury, exit own way, exit some assist, ejected. Outcome measure not adequate (ISS>15).

Table 2. Characteristics of Excluded Studies

model developed by the authors of this paper (Isenberg et al.[17]) used ambulation in combination with two other variables (whether the MVC was on an interstate road/highway; whether the MVC involved more than one car). Thus, the limited evidence to date suggests that while ambulation is a strong predictor of the need for L&S response in MVCs, its value as a predictor may require that it is used in combination with other predictors.

Systematic reviews finding few papers serve an important purpose in identifying research gaps.[25,26] Higgins and Green eloquently distinguish between "evidence of no effect" and "no evidence of effect,"[27] and it is the latter that is relevant here. Systematic reviews that find few papers with strong effect provide valuable information to researchers and funding institutions regarding gaps in knowledge and directions for research.[28] It is suggested that future research should be undertaken in this field.

A study of Cochrane Systematic Reviews proposed three reasons for a systematic review finding few or no papers, namely: the area of study is relatively new and can be considered immature; the study question was narrow in focus, or the criteria for inclusion/exclusion were overly restrictive.[25] However, in our review one reason for exclusion of studies was the predictor variable of interest was not sufficiently specific to identify if people were ambulant after a crash. Two of the excluded studies[21,22] used data derived from the National Automotive Sampling System Crashworthiness Data System (NASS-CDS). The NASS-CDS collects information on a representative sample of police-reported MVCs in the United States. This system records "occupant mobility status," which on face value appears to be a measure of ambulatory status; however, a closer inspection of the variable revealed it was unsuitable. "Occupant mobility status" classifies people according to how they exited their vehicle after a crash, with categories of ejected, self-exited, exited with assistance, removed from the vehicle with decreased mental status, removed due to perceived serious injury or removed for other reasons.[29] The categories do not necessarily indicate ambulatory status. For example, a patient could self-exit a vehicle, but not be ambulant after this action. Data from the NASS-CSC is therefore unsuitable for this kind of study.

Although there was only one study that met the inclusion criteria for our review, there have been other papers published that have considered using ambulatory status for ambulance dispatch triage in MVCs.[30] For example, a descriptive (non-comparative) study which did not meet our inclusion criteria due to study design concluded that ambulatory status could not be reliably used to triage patients after an MVC, as some patients who were ambulant also had serious injuries or required hospitalization.[19] A further study by McCoy et al.[18] reported that non-ambulant patients were more likely to have reduced GCS scores or be at risk of spinal injury than ambulant patients. However, it was determined that while these outcomes measures are suggestive of the need for L&S response, they were not sufficient to determine this outcome.

Limitations

Despite searching for grey literature, a limitation of this study could be the non-identification of unpublished literature. Publication bias or the "file drawer effect" is thought to occur with the favoring of positive results for publication.[31] It is possible that research concluding that ambulation was not a suitable triage criterion have systematically been excluded from publication and resulted in the findings here. However, with only one study identified, the potential for publication bias through a funnel plot could not be assessed.

CONCLUSION

A single study identified in this systematic review suggests that ambulatory status has the potential to be a useful criterion to identify patients who require a lights-and-siren ambulance response at the scene of an MVC. However, this study also indicates that using ambulatory status alone would lead to high rates of under-triage and over-triage, and that it may be necessary to use ambulatory status in combination with other predictors. The key finding of this paper is the gap in existing literature and therefore it is hoped that these findings will stimulate research in this field. Methodological considerations for future research could include improved identification of the ambulatory status of patients and accurate measurement of those requiring a lights-and-siren ambulance response.

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#	Medline terms	Results (n)
1	(road OR traffic OR motor$ OR vehicle OR MVA OR MBA OR driver OR passenger OR pedestrian OR scooter OR bicyc$ OR cyclist OR truck) AND (crash OR accident) .mp.	21,246
2	accidents, traffic.sh OR automobile driving.sh,xm OR motor vehicles.sh,xm OR automobile driving.sh OR bicycling.sh OR pedestrian.sh	64,584
3	1 or 2	71,782
4	(triage OR over?triage OR under?triage OR urgen* OR acuity OR patient condition OR injury OR Glasgow coma score OR GCS OR abbreviated injury score OR AIS OR injury severity score OR ISS OR survival risk ratio OR severity OR SRR OR light?*siren? OR L&S OR dispatch or ambulance or emergency or severe).mp.	2,275,409
5	triage.sh. OR wounds and injuries.sh,xm. OR health status indicators.sh,xm. OR critical care.sh. OR patient acuity.sh OR injury severity score.sh or "severity of illness index".sh OR trauma severity indices.sh OR ambulatory care.sh,xm. OR ambulances.sh. OR emergency medical services.sh,xm. OR emergency medical technicians.sh.	507,642
6	4 or 5	2,400,033
7	(ambulat* or ambulant or walk* or self?extricat* or mobil*).mp.	582,736
8	walking.sh. OR ambulation.sh.	29,693
9	7 or 8	582,736
10	3 and 6 and 9	1,354
11	rehabiliation.sh	19,312
12	10 not 11	1,342

Appendix 1. Search strategy (Medline)

6.3 INTERPRETATION

This systematic review determined that there was insufficient evidence to reach a definitive conclusion about the potential for ambulatory status as a dispatch criterion for road crashes. One study found that a 'not ambulant' status of patients at the scene of a road crash was a strong predictor of the need for a L&S ambulance response. [60] Another reported that non-ambulant patients were more likely to have a reduced Glasgow Coma Scale score than ambulant patients, leading to a greater need for a L&S ambulance response. [74]

The paucity of research found in this systematic review contrasts with the findings from my previous study where ambulatory status was the strongest predictor of high acuity patients. I therefore suggested that future research could explore this crash characteristics further.

Since the publication of this systematic review, no new studies have been published that provide additional information (up until June 2023).

Chapter 7: Decision Tree Dispatch Algorithm

7.1 OVERVIEW AND RATIONALE

Given the findings from my second study, that some crash characteristics were associated with the need for a L&S response, I sought to determine whether combinations of crash characteristics could be used to develop an algorithm to identify the required ambulance response to the scene of a road crash. This algorithm could then potentially be used to construct a set of questions to ask of the layperson at the scene to identify the need for a L&S response.

A retrospective cohort study using ambulance and police data from 2014 to 2016 was conducted. The predictor variables included crash characteristics and MPDS dispatch codes, while the outcome variable was the need for a L&S ambulance response. Using the Chi-square Automatic Interaction Detector technique, decision trees with over/under-triage rates were constructed. The optimal model aimed to have a 5% under/over-triage rate and a 25-35% over-triage rate.

My findings are described in the following manuscript that was published in BMC Emergency Medicine in 2022.

Ceklic E, Tohira H, Ball S, Brown E, Brink D, Bailey P, Brits R, Finn J. A predictive ambulance dispatch algorithm to the scene of a motor vehicle crash: the search for optimal over and under-triage rates. *BMC emergency medicine*. 2022 Dec;22(1):1-

7.2 STUDY 4

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BMC Emergency Medicine

RESEARCH ARTICLE Open Access

A predictive ambulance dispatch algorithm to the scene of a motor vehicle crash: the search for optimal over and under triage rates

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Abstract

Background: Calls for emergency medical assistance at the scene of a motor vehicle crash (MVC) substantially contribute to the demand on ambulance services. Triage by emergency medical dispatch systems is therefore important, to ensure the right care is provided to the right patient, in the right amount of time. A lights and sirens (L&S) response is the highest priority ambulance response, also known as a priority one or hot response. In this context, over triage is defined as dispatching an ambulance with lights and sirens (L&S) to a low acuity MVC and under triage is not dispatching an ambulance with L&S to those who require urgent medical care. We explored the potential for crash characteristics to be used during emergency ambulance calls to identify those MVCs that required a L&S response.

Methods: We conducted a retrospective cohort study using ambulance and police data from 2014 to 2016. The predictor variables were crash characteristics (e.g. road surface), and Medical Priority Dispatch System (MPDS) dispatch codes. The outcome variable was the need for a L&S ambulance response. A Chi-square Automatic Interaction Detector technique was used to develop decision trees, with over/under triage rates determined for each tree. The model with an under/over triage rate closest to that prescribed by the American College of Surgeons Committee on Trauma (ACS COT) will be deemed to be the best model (under triage rate of ≤ 5% and over triage rate of between 25–35%.

Results: The decision tree with a 2.7% under triage rate was closest to that specified by the ACS COT, had as predictors—MPDS codes, trapped, vulnerable road user, anyone aged 75 +, day of the week, single versus multiple vehicles, airbag deployment, atmosphere, surface, lighting and accident type. This model had an over triage rate of 84.8%.

Conclusions: We were able to derive a model with a reasonable under triage rate, however this model also had a high over triage rate. Individual EMS may apply the findings here to their own jurisdictions when dispatching to the scene of a MVC.

Keywords: Ambulance, Dispatch, Lights, Sirens, Motor vehicle crash

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Background

Calls for emergency ambulance assistance for motor vehicle crash (MVCs) patients substantially contribute to the demand on emergency medical services [1]. Triage by emergency medical systems (EMSs) is therefore important to ensure the right care is provided to the right patient, in the right amount of time [2]. EMS must determine the priority of the ambulance response. The highest priority (usually where it is recognised there is an immediate risk of death to one or more of the patients at the scene), is where lights and sirens (L&S) are used on the way to the scene. In this setting, over triage can be defined as dispatching an ambulance using L&S to a low acuity MVC. Conversely, under triage involves dispatching an ambulance not using L&S to a MVC, where patients are at immediate risk of death. Under triage is a concern because of the risk of death, or another adverse patient outcome should there be a delay in the arrival of an ambulance on-scene [3]. Over triage, in the context of limited EMS resources, could result in ambulances not being available for other, more time-critical patients as well as the additional risk of an ambulance crashing [4].

An ideal system would match patient need with ambulance dispatch priority. With MVCs people on the scene are usually not medically trained and cannot provide reliable information about medical need. Therefore, there are various methods used by EMS for prioritizing ambulance dispatch to MVCs. Some use codes assigned through a systemized dispatch system, such as the Medical Dispatch Priority System (MPDS); which uses criteria related to the number of resources needed (such as for multi-vehicle crashes), the potential for danger (such as for those involving hazardous chemicals) or those involving high mechanisms of injury (such as rollovers) [5]. However, these codes have been found to have poor predictive ability to identify those patients who require a L&S ambulance response to the scene of a crash [6, 7]. An alternative is to use additional information and characteristics of the MVC that laypersons can easily report at the scene and therefore able to be derived through a set of questions prompted by the dispatcher within the EMS during the call for emergency ambulance services. These characteristics could include road features, speed zone or how many vehicles were involved. While it is not a novel idea that crash characteristics be used to predict injury severity [8, 9], there is a scarcity of research exploring whether crash characteristics could improve the dispatch accuracy in identifying those MVCs that do/do not require an ambulance L&S response to the scene.

Aim

To develop an algorithm to identify cases for which a L&S ambulance response is required, using MVC characteristics.

Methods

A population-based retrospective cohort study was conducted on all MVCs attended by St John Western Australia (SJ-WA) ambulance paramedics in the Perth metropolitan area, Western Australia, from 1st Jan 2014 to 31st Dec 2016. Perth had a population of approximately 2 million people and covers an area of 6,400 square kilometres [10]. The road environment is built-up/urban with mandated speeds ranging from 50 km/h in residential areas to 110 km/h on motorways [11]. SJ-WA is the sole, contracted provider of single-tier advanced life support EMS in Perth.

Data sources

We used two data sources in this study (1) SJ-WA ambulance data and (2) Main Roads Western Australia (MRWA) crash data. The ambulance data comprised information collected during the emergency phone call, as logged through a computer-aided dispatch system (CAD) using the Medical Priority Dispatch System (MPDS) (v. 12) [12], and electronic patient care records (ePCRs) entered by paramedics. This includes event date and time, geographical coordinates of the location of the MVC, dispatch code, main problem for which an ambulance was requested (as determined by paramedics), dispatch priority to the scene, priority from the scene to a hospital, patient vital signs, interventions provided (e.g., medications, splinting) and patient disposition (left at scene, died at scene, or transported to hospital).

The study cohort was defined as those MVCs where an ambulance was dispatched as a Traffic/Transportation incident (MPDS Protocol 29), and where paramedics coded the incident as Motor Vehicle Accident. This was to exclude incidents that did not include a motor vehicle (such as single bicycle crashes, as those involving an aircraft or train) within the Traffic/Transportation MPDS category.

The MRWA crash data is a composite dataset of information collated from Western Australian Police (who attended all fatal and critical injury crashes); and drivers involved in the crash. Data includes information pertaining to the crash (such as location, weather and road environment details), as well as information to do with the vehicle (such as make, model, year of manufacturing and safety features) and persons involved (age, sex, role in the crash and injury severity). We limited records in the crash data to those defined as a reportable road crash [13], with crashes that result in damage costing < $5,000 AUD or not resulting in injury, not being required to be legally reported.

Data linkage

We linked the ambulance study cohort (defined above) to the MRWA crash data using first and last name, sex, date of birth and vehicle registration number. We used Fine-Grained Records Integration and Linkage Tool (version 2, Emory University, US) and SAS (version 9.4. SAS Institute Inc., Cary, NC, USA) for this purpose. Crash records without a corresponding ambulance record were excluded from the final dataset. The linkage rate was 66.7%, representing the proportion of ambulance records with a corresponding crash record. See Fig. 1. It was not expected that there would be an exact match between the datasets as not all people with ambulance care after a MVC report their crash to MRWA or involve Police.

Predictor variables

Predictor variables were defined as characteristics of the crash, derived from either the ambulance or crash data, and that bystanders could reasonably describe at the scene, and be coded by EMS. See Table 1 for a full list of the variables included.

MPDS dispatch codes for the Traffic/Transportation Chief Complaint (Protocol 29) that were routinely assigned during each call were also included as predictor variables. MPDS dispatch codes are automatically assigned (through the use of the ProQA software) immediately following a set of scripted questions from the emergency medical dispatcher to the caller at the scene. MPDS dispatch codes are those that best describe the incident, such as the code for rollover (D2p), HAZMAT (D3) or sinking vehicle (D2s) [5]. These MPDS dispatch codes were 'forced' as the first variable in some of the models to more closely reflect 'usual state' should an EMS continue to use the established MPDS.

Outcome variables

The outcome variable was the need for a L&S ambulance response to the scene of a crash. In SJ-WA a L&S response is the highest priority ambulance response, where L&S are used on the way to the scene. This is also

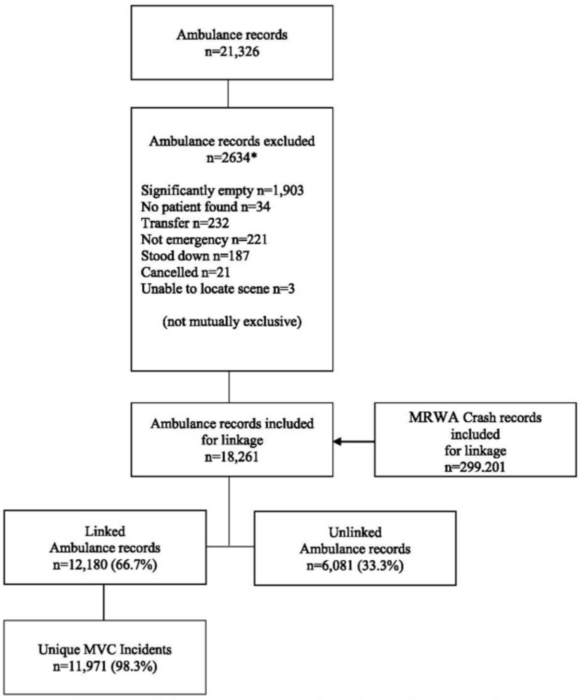

Fig. 1 Flow diagram of linkage process between ambulance and motor vehicle crash records.*Significantly empty: no electronic record of assessment, intervention, or clinical case notes;. No patient found: Paramedics arrived on-scene but there was no patient present (e.g. patient absconded); Patient transfer between hospitals; Not emergency: Use of the ambulance for other than delivering patient care, such as transport of equipment; Stood down: Ambulance dispatched but then received a higher priority job or another crew was closer to the scene; Cancelled: Individual calls from the scene and states they no longer require the ambulance; Unable to locate scene: Ambulance is sent but cannot locate the MVC

Table 1 Description of decision tree variables

Variable name	Variable type	Brief description
Accident type	Dichotomous	Intersection/Midblock
Airbag deployed	Dichotomous	Any airbag deployed/No deployed
Anyone ejected	Dichotomous	Anyone ejected (incl. partial)/Everyone not ejected
Anyone not ambulant	Dichotomous	Anyone not ambulant/Everyone ambulant (able to walk)
Anyone trapped	Dichotomous	Anyone trapped in a vehicle/Everyone not trapped
Atmosphere	Nominal	Smoke, Clear, Overcast, Raining, Fog
Child	Dichotomous	Anyone aged ≤ 12 years/Everyone aged ≥ 13 years
Day of the week	Nominal	Day of the week Sunday = 1 etc
Lighting	Nominal	Daylight/Dawn or dusk/Dark with lights on/off/not provided
MPDS dispatch code	Nominal	Medical Priority Dispatch System dispatch codes for Protocol 29
Older	Dichotomous	Anyone aged ≥ 75 years/Everyone aged ≤ 74 years
Raining	Dichotomous	Raining/Clear
Road alignment	Dichotomous	Curved/Straight
Road grade	Nominal	Level/Crest of hill/Slope
Road surface	Dichotomous	Sealed/Unsealed
Rollover	Dichotomous	Any vehicle rolled over/No vehicle rolled over
Single v. Multi-vehicle	Dichotomous	Single vehicle/2 or more vehicles
Speed limit	Ordinal	Posted speed limit (km/h)
Time of day	Continuous	hh:mm
Traffic control	Nominal	Traffic lights/Stop sign/ Give way sign/Zebra crossing/ Railway crossing/ School crossing/No signal or control
Type of intersection	Nominal	4-way/3-way (T-junction)/Roundabout/Bridge/Rail Crossing/Driveway
Vulnerable road user	Dichotomous	Involved vulnerable road user (cyclist, motorcyclist or pedestrian)/No vulnerable road user involved

termed a priority one or hot response in some jurisdictions. In SJ-WA there is an operationally defined time to arrive within 15 min for 90% of L&S responses and L&S are not permitted to be used for lower priority responses, such as priority two, three or four. In this study, a L&S response was a binary: yes/no. A MVC was retrospectively determined to have potentially required a L&S response for the following conditions:

- The ambulance priority from the scene to an emergency department was L&S; or.
- Anyone was dead on-scene or in transit; or.
- Anyone had one or more L&S dispatch indicators (described below).

The L&S dispatch indicators were developed by the SJ-WA Clinical Governance Department. The indicators included specific clinical interventions, administered medications and patient clinical observations recorded by paramedics (see Supplementary material).

Statistical analysis

We analysed data using the Chi-square Automatic Interaction Detector (CHAID) [14] technique for branching using SPSS (version 26. IBM Corp. Armonk, NY,). This decision tree technique was chosen as it allowed for a multi-way split on variables (as opposed to a binary split using a CART technique) and both categorical and numerical variables can be used in the tree.

A CHAID technique splits data into groups based on the relationship between the predictor variables (in our case, MPDS code ± on-scene crash characteristics) and the outcome variable (whether the crash was classified as having required a L&S response). To minimize error rates, misclassification costs were used to penalize incorrectly classified cases. Both the levels and misclassification costs were varied to identify the best decision tree model. Misclassification cost ratios were incrementally increased from 1 until the under triage rates were at 0%, which represents assigning all MVCs as L&S. Misclassification costs allowed us to preference those MVCs that required a L&S response over those that did not. Model A was set to include only MPDS dispatch codes (and therefore could have only a depth of one). Model B included MPDS dispatch codes at the first level and any combination of crash characteristics as other levels. For this model, levels were limited to three. Model C included only crash characteristic and levels were limited to three. Model D included MPDS dispatch codes as the first level and any combination of crash variables, with

Table 2 Motor vehicle crash incidents by medical priority dispatch Code (MPDS) and lights and sirens ambulance (L&S) response

MPDS dispatch code	Brief descriptor	Not L&S n	L&S n	Total n	Total Col %
29D1	Major incident	7	1	8	0.1%
29D1V	Major incident, multiple patients	2	0	2	0.0%
29D1b	Major incident—bus	5	1	6	0.1%
29D1d	Major incident—train	1	2	3	0.0%
29D1f	Major incident—multiple vehicle (≥ 10) pile-up	4	0	4	0.0%
29D2	High mechanism	257	78	335	2.8%
29D2k	High mechanism—all-terrain/snowmobile	2	0	2	0.0%
29D2l	High mechanism- vehicle v. bicycle/motorcycle	905	247	1,152	9.6%
29D2m	High mechanism—vehicle v. pedestrian	672	169	841	7.0%
29D2n	High mechanism—ejection	80	34	114	1.0%
29D2p	High mechanism—rollovers	377	67	444	3.7%
29D2r	High mechanism—possible death at scene	0	1	1	0.0%
29D3	HAZMAT	67	10	77	0.6%
29D3U	HAZMAT, unknown number of patients	3	1	4	0.0%
29D3V	HAZMAT, multiple patients	19	3	22	0.2%
29D3X	HAZMAT, unknown number of patients and additional response required	1	0	1	0.0%
29D3Y	HAZMAT, multiple patients and additional response required	3	0	3	0.0%
29D4	Trapped victim	338	126	464	3.9%
29D4U	Trapped victim, unknown number of patients	59	23	82	0.7%
29D4V	Trapped victim, multiple patients	124	64	188	1.6%
29D4X	Trapped victim, unknown number of patients and additional response required	3	2	5	0.0%
29D4Y	Trapped victim, multiple patients and additional response required	28	21	49	0.4%
29D4n	Trapped victim, ejection	3	0	3	0.0%
29D5	Not alert	325	153	478	4.0%
29D5U	Not alert, unknown number of patients	5	2	7	0.1%
29D5V	Not alert, multiple patients	47	21	68	0.6%
29D5X	Not alert, unknown number of patients and additional response required	0	1	1	0.0%
29D5Y	Not alert, multiple patients and additional response required	3	2	5	0.0%
29D5m	Not alert, vehicle v. pedestrian	0	2	2	0.0%
29D5n	Not alert, ejection	2	4	6	0.1%
29B1	Injuries	2,098	237	2,335	19.5%
29B1U	Injuries, unknown number of patients	41	8	49	0.4%
29B1V	Injuries, multiple patients	470	56	526	4.4%
29B1X	Injuries, unknown number of patients and additional response required	6	1	7	0.1%
29B1Y	Injuries, multiple patients and additional response required	57	5	62	0.5%
29B2	Serious haemorrhage	126	31	157	1.3%
29B2V	Serious haemorrhage, multiple patients	23	3	26	0.2%
29B2X	Serious haemorrhage, unknown number of patients and additional response required	1	0	1	0.0%
29B2Y	Serious haemorrhage, multiple patients and additional response required	5	3	8	0.1%
29B3	Other hazards	589	76	665	5.6%
29B3U	Other hazards, unknown number of patients	71	8	79	0.7%
29B3V	Other hazards, multiple patients	214	29	243	2.0%
29B3X	Other hazards, unknown number of patients and additional response required	6	2	8	0.1%
29B3Y	Other hazards, multiple patients and additional response required	33	4	37	0.3%
29B4	Unknown status/Other codes not applicable	2,054	185	2,239	18.7%
29B4U	Unknown status/Other codes not applicable, unknown number of patients	429	36	465	3.9%
29B4V	Unknown status/Other codes not applicable, multiple patients	442	37	479	4.0%
29B4X	Unknown status/Other codes not applicable, unknown number of patients and additional response required	29	4	33	0.3%
29B4Y	Unknown status/Other codes not applicable, multiple patients and additional response required	31	5	36	0.3%
29A1	1st party caller with injury to not dangerous body area	16	0	16	0.1%
29A1V	1st party caller with injury to not dangerous body area, multiple patients	1	0	1	0.0%
29O1	No injuries (confirmed)	116	6	122	1.0%
Total		**10,200**	**1,771**	**11,971**	**100.0%**

Table 3 Motor vehicle crash incidents, by crash characteristics and lights and sirens (L&S) response

	Not L&S n	L&S n	Total n	Total Col %
Accident Type				
Intersection	4,230	653	4,883	40.8%
Midblock	2,513	586	3,099	25.9%
Airbag deployed				
Any airbag deployed	3,280	571	3,851	32.2%
No airbag deployed	6,920	1,200	8,120	67.8%
Alignment				
Curve	861	206	1,067	8.9%
Straight	4,669	850	5,519	46.1%
Atmosphere				
Clear	3,207	694	3,901	32.6%
Dust/Smoke	5	1	6	0.1%
Fog/Mist	12	3	15	0.1%
Fog/smoke/dust	0	1	1	0.0%
Overcast	277	90	367	3.1%
Raining	358	55	413	3.5%
Day of the week				
Monday	1,384	189	1,573	13.1%
Tuesday	1,481	261	1,742	14.6%
Wednesday	1,537	234	1,771	14.8%
Thursday	1,552	271	1,823	15.2%
Friday	1,683	297	1,980	16.5%
Saturday	1,360	258	1,618	13.5%
Sunday	1,203	261	1,464	12.2%
Ejected				
Anyone ejected	63	62	125	1.0%
No one ejected	10,137	1,709	11,846	99.0%
Grade				
Crest of hill	78	18	96	0.8%
Level	3,321	668	3,989	33.3%
Slope	666	186	852	7.1%
Lighting				
Daylight	4,867	824	5,691	47.5%
Dawn/Dusk	479	75	554	4.6%
Dark—street lights on	1,095	257	1,352	11.3%
Dark—Street Lights Off	19	6	25	0.2%
Dark—Street Lights Not Provided	69	46	115	1.0%
Not ambulant				
Anyone not ambulant	140	116	256	2.1%
Everyone ambulant	10,060	1,655	11,715	97.9%
Older				
Any aged ≥ 75 years	739	120	859	7.2%
Everyone aged ≤ 74 years	9,461	1,651	11,112	92.8%
Single versus Multi-vehicle				
2 or more vehicles	5,314	689	6,003	50.1%
Single vehicle	1,423	326	1,749	14.6%

Table 3 (continued)

	Not L&S n	L&S n	Total n	Total Col %
Surface				
Sealed	3,321	668	3,989	33.3%
Unsealed	78	18	96	0.8%
Rollover				
Any vehicle rolled	377	67	44	0.4%
No vehicle rolled	9,823	1,704	11,527	96.3%
Trapped				
Anyone trapped	444	303	747	6.2%
No one trapped	9,756	1,468	11,224	93.8%
Under				
Anyone ≤ 12 years	455	92	547	4.6%
Everyone ≥ 13 years	9,745	1,679	11,424	95.4%
Vulnerable				
Motor vehicle occupant	6,866	854	7,720	64.5%
Vulnerable	1,943	536	2,479	20.7%
Total	**10,200**	**1,771**	**11,971**	**100.0%**

[*] Components may not sum to the total due to missing data

levels as unlimited. Lastly model D could include any crash variables with unlimited levels.

Over triage rate was defined as the proportion of crashes where a L&S response was determined to have not been required among those for which a decision tree predicted L&S was required (i.e. 1 – positive predictive value). Under triage rate was defined as the proportion of MVCs where a L&S response was determined to have been required, among crashes where the decision tree predicted that L&S was not required (i.e. 1 – negative predictive value). The model with an under/over triage rate closest to that prescribed by the American College of Surgeons Committee on Trauma (ACS COT) was deemed to be the best model: that being an under triage rate of 5% or below and an over triage rate of between 25–35% [15].

Ethics

Curtin University Human Research Ethics Committee granted approval for this study, as a sub-study of the Western Australia Pre-hospital Record Linkage Project (HR 128/2013). A data licensing agreement was signed with Main Roads Western Australia for use of the crash data. SJ-WA Research Governance Committee gave approval to conduct the study using ambulance data.

Results

There were 11,971 MVCs attended by SJ-WA emergency medical ambulances in Perth WA during the three years to the 31st of December 2016. Of ambulance records, 66.7% had a matching crash record. (see Fig. 1).

Within the study cohort, the following MPDS dispatch codes has the highest proportion of MVCs attended: 29B1-injuries (19.5%), 29B4 – unknown status/other codes not applicable (18.7%) and 29D2l – High mechanism, vehicle v. bicycle/motorcyclist (9.6%). See Table 2.

For crash characteristics the categories of no one ejected (99.0%), everyone ambulant (97.9%) and no

Table 4 Dispatch decision tree by depth, model, misclassification costs and Over/under triage rates*

Depth	Model	Misclassification costs	Over triage (%)	Under triage (%)
1	A	1:1	85.2%	0.0%
3	B	1:1	36.0%	14.1%
3	B	1:2	52.4%	13.0%
3	B	1:3 to 1:4	66.0%	10.6%
3	B	1:5	71.9%	9.4%
3	B	1:6	73.8%	8.9%
3	B	1:7	75.6%	8.5%
3	B	1:8	76.9%	8.2%
3	B	1:9 to 1:12	82.3%	6.8%
3	B	1:13 to 1:18	84.7%	4.8%
3	B	1:19	85.2%	0.0%
3	C	1:1	40.5%	14.0%
3	C	1:2	53.5%	13.0%
3	C	1:3	64.9%	11.3%
3	C	1:4	66.3%	11.0%
3	C	1:5 TO 1:8	72.7%	10.1%
3	C	1:9	85.2%	0.0%
Unlimited (7)	D	1:1	35.4%	13.8%
Unlimited (7)	D	1:2	51.6%	12.7%
Unlimited (7)	D	1:3	61.7%	11.4%
Unlimited (7)	D	1:4	67.7%	9.9%
Unlimited (7)	D	1:5	70.7%	9.3%
Unlimited (7)	D	1:6	72.0%	9.0%
Unlimited (7)	D	1:7	76.2%	8.0%
Unlimited (7)	D	1:8	78.0%	7.4%
Unlimited (7)	D	1:9	78.6%	7.2%
Unlimited (7)	D	1:10 to 1:12	80.0%	6.7%
Unlimited (7)	D	1:13	82.6%	6.1%
Unlimited (7)	**D**	**1:21**	**84.8%**	**2.7%**
Unlimited (7)	D	1:22	85.2%	0.0%
Unlimited (7)	E	1:1	42.1%	13.6%
Unlimited (7)	E	1:2	52.5%	12.5%
Unlimited (7)	E	1:3	56.7%	12.1%
Unlimited (7)	E	1:4	69.8%	9.9%
Unlimited (7)	E	1:5 to 1:6	70.5%	9.7%
Unlimited (7)	E	1:7 to 1:8	73.5%	9.4%
Unlimited (7)	E	1:9	83.4%	7.8%
Unlimited (7)	E	1:10 to 1:11	83.5%	7.7%
Unlimited (7)	E	1:12	85.2%	0.0%

* Model A variables were: MPDS dispatch codes

Model B variables were: MPDS dispatch codes, anyone trapped, vulnerable road user, airbag deployed, atmosphere, road surface

Model C variables were anyone trapped, vulnerable road user, anyone not ambulant, atmosphere, accident type

Model D variables were: MPDS dispatch codes, anyone trapped, vulnerable road user, anyone aged ≥ 75 years, day of the week, single v. multi-vehicle, airbag deployed, atmosphere, road surface, lighting, accident type

Model E variables were: MPDS dispatch codes, anyone trapped, vulnerable road user, anyone aged ≥ 75 years, day of the week, single v. multi-vehicle, airbag deployed, atmosphere, road surface, lighting, accident type vehicle rolled (96.3%) had the highest proportion of MVCs attended. See Table 3.

As shown in Table 4, under triage rates ranged from 0% (where all incidents were dispatched at L&S) to 14.1%, in a decision tree with three levels using MPDS dispatch codes along with anyone trapped, vulnerable road use, airbag deployed, atmosphere and road surface. See Table 4, and Fig. 2.

CHAID decision tree models had over triage rates that ranged from 35.4% in a decision tree with 3 levels using splits based on MPDS dispatch codes, anyone trapped, vulnerable road user, airbag deployed, atmosphere, and road surface; to 85.2% for multiple decision trees based on different combinations of MPDS dispatch and crash characteristics. See Table 4 and Fig. 2.

Figure 3 shows the decision tree that had under/over triage rates closest to the maximums proposed by the ACS COT [15], with 2.7% under triage and 84.8% over triage. This model had seven levels, with 58 nodes and 32 terminal nodes (Fig. 3).

Discussion

A CHAID decision tree technique was used to explore different crash characteristics that had the potential to identify those MVCs that required a L&S ambulance response to the scene of a crash. Several decision trees predicted the need for a L&S response. A decision tree that would require one to ten questions asked by the EMS dispatcher of the layperson at the scene was able to predict the need for a L&S response with the lowest under triage rate. The first level of this tree was the MPDS dispatch code, followed by a combination of whether anyone was trapped, a vulnerable road user was involved, anyone was aged 75 or over, the day of the week, whether the crash involved a single or multiple vehicles, airbag deployment, the atmosphere, road surface, lighting and type of accident.

Our model had an under triage rate of 2.7% and an over triage rate of 84.8%. While not specifically for a prehospital setting, the ACS COT suggests a 5% under triage and a 25% to 35% over triage rate, as acceptable for trauma team activation at any emergency department [13]. However, EMSs are said to be 'front loaded', where a low under triage rate is prioritised higher than that of over triage rates [6]. A review of triage accuracy of dispatch systems for trauma patients found under triage rates varied from 1.1% to 68.0% and over triage from 4.7% to 98.8% [17]. Therefore, while this model does not reach the over triage rate set by the ACS COT, when compared to other prehospital trauma triage systems, it is within

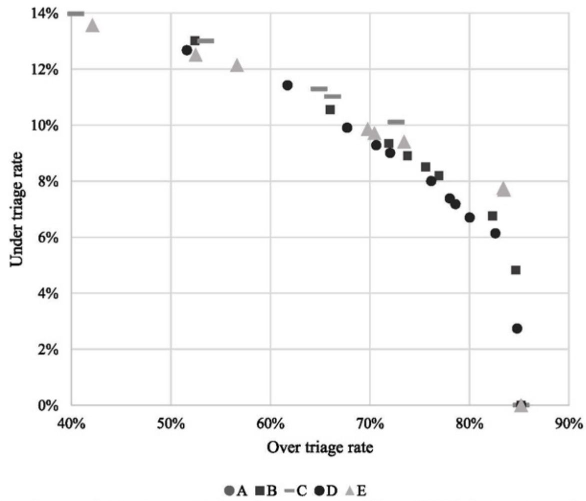

Fig. 2 Over/under triage rates of various decision trees. + Each marker represents a different CHAID decision tree, as listed in Table 4. *Model A variables were: MPDS dispatch codes. Model B variables were: MPDS dispatch codes, anyone trapped, vulnerable road user, airbag deployed, atmosphere, road surface. Model C variables were anyone trapped, vulnerable road user, anyone not ambulant, atmosphere, accident type. Model D variables were: MPDS dispatch codes, anyone trapped, vulnerable road user, anyone aged ≥ 75 years, day of the week, single v. multi-vehicle, airbag deployed, atmosphere, road surface, lighting, accident type. Model E variables were: MPDS dispatch codes, anyone trapped, vulnerable road user, anyone aged ≥ 75 years, day of the week, single v. multi-vehicle, airbag deployed, atmosphere, road surface, lighting, accident type

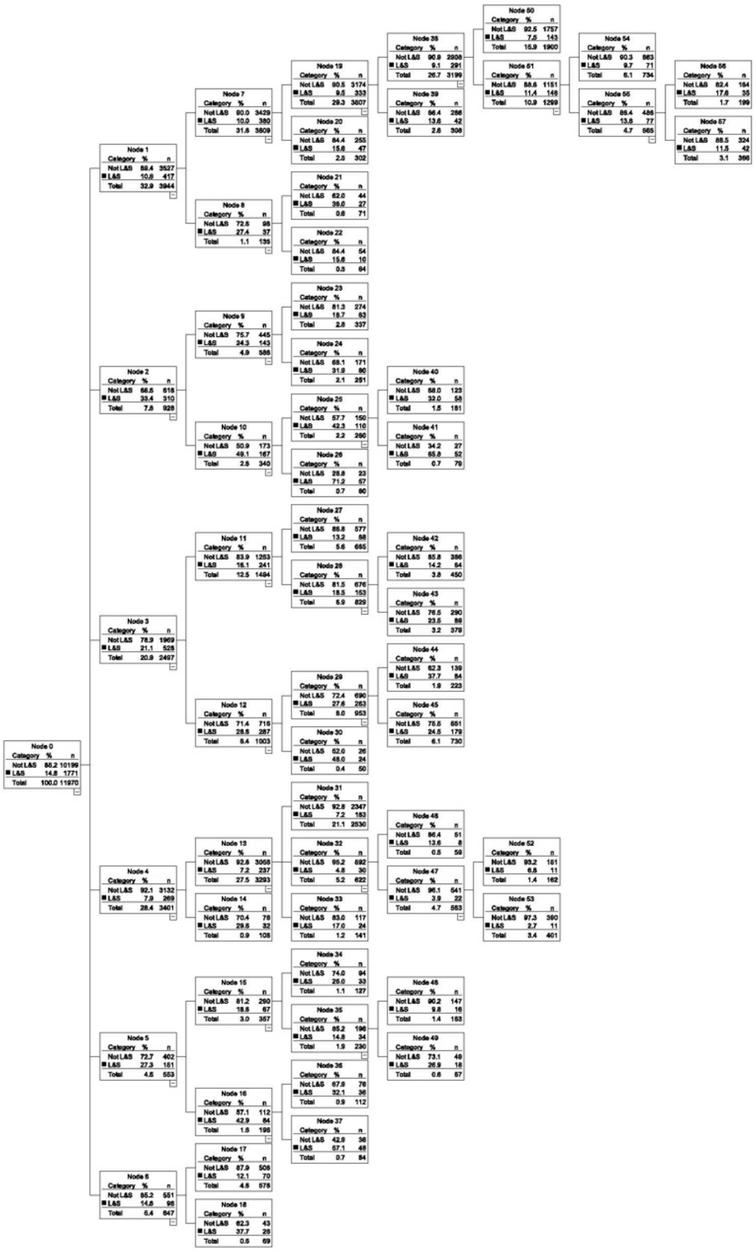

Fig. 3 CHAID decision tree model with 84.8% over triage and 2.7% under triage rate

the range of what is commonly present. Additionally, it is interesting to note that this model shares some crash characteristics with the findings of others who produced similar models [8, 9, 18]. For example, a model where all patients are ambulatory, multiple vehicles involved and on a highway/interstate was able to predict the need for a L&S response to MVCs [18]. Due to differences related to ambulance availability, demand and road conditions, each EMS must define their acceptable level of risk when deciding the prioritization of ambulances [19] and may deem the under/over triage rates presented here as operationally acceptable. The importance of this variation between each EMS is aptly captured in the notion that "if you have seen one EMS, you have seen one EMS" [20].

Advanced automatic collision notification systems (AACNS) that involve in-vehicle sensors and geographic locating are progressively being included in vehicle designs [21]. AACNS provide a promising future in reducing MVC morbidity and mortality due to improved identification of injury severity and reduced response time [22]. These systems use indicators such as intrusion depth, change in velocity at impact and restraint use, to automatically relay information to EMSs regarding the predicted injury severity of the involved in the crash. These AACNS have been found to predict injury severity with under triage rates of between 5 to 13% [23]. While the number of vehicles fitted with AACNS has been limited to luxury vehicles, legislative changes, such as the eCall in Europe from 2018 [21], will provide the opportunity for EMS to improve their triage accuracy to MVCs.

Another avenue to explore improving the accuracy of identifying those MVCs that require a L&S response is through the use of machine learning algorithms. Machine learning algorithms, such as Random forest or XGBoost, are similar to the decision tree methods proposed here, although they differ in their complexity. The decision trees in this paper has a maximum depth of 7, whereas a Random forest may represent several decision trees (a forest of decision trees). While using such machine learning algorithms means the algorithms become uninterpretable, there is the potential to improve accuracy. For example, there has been some success in predicting anatomical injury (the Injury Severity Score) using crash characteristics and a machine learning methods [24]. This approach could similarly be used to predict the need or a L&S response.

Limitations

There currently exists no standard method of retrospectively classifying those patients who required a L & S response in MVC. Our study used a composite index based on whether anyone died on scene or in transit, the priority from the scene and any medication/interventions/observations considered as requiring a L&S response. Future research could assess the utility of this measure. However, a similar method for identifying L&S has undergone preliminary validation, where detailed clinical profiling compared those who did/did not require a L&S response using a similar indicator [25]. Likewise, there exists no standard metric for EMS accuracy. Although we have used the ACS COT model, which was designed for trauma patients in a pre-hospital setting, the model was not specifically derived for decisions about EMS dispatching ambulances. It is possible that our results would have been different were a specific measure for dispatch accuracy available [16].

Conclusions

We conclude that we were able to derive a model with a reasonable under triage rate, however, this model had an associated high over triage rate. Individual EMS, when considering their own level of risk in the prioritization of ambulances, may apply the findings here to their own jurisdictions when dispatching to the scene of a MVC. It is anticipated that the implementation of future technologies such as AACNS will improve the accuracy of identification of those MVCs that require a L&S response.

Abbreviations

AACNS: Advanced automatic collision notification systems; ACS COT: American College of Surgeons Committee on Trauma; CAD: Computer aided dispatch; CHAID: Chi-square Automatic Interaction Detector; ePCR: Electronic patient card record; EMS: Emergency medical system; HAZMAT: Hazardous materials; L&S: Lights and sirens; MRWA: Main Roads Western Australia; MPDS: Medical Priority Dispatch System; MVC : Motor vehicle crash; SJ-WA: St John Western Australia.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12873-022-00609-5.

Additional file 1: Supplementary material. List of interventions/observations/medications representing the need for alights & sirens ambulance response

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Authors' 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, RB and JF helped write and review the manuscript. All authors approved submission.

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Availability of data and materials
The datasets generated during and/or analysed during the current study are not publicly available due to patient confidentiality. Deidentified datasets may be available after seeking relevant ethical/administrative approval from the data custodians.

Declarations

Ethics approval and consent to participate
Ethics approval has been granted as an amendment to the Western Australian Pre-hospital Record Linkage Project by the Curtin University Human Research Ethics Committee (HR 128/2013) under which there is waiver of patient consent consistent with The Australian National Statement on Ethical Conduct in Human Research. A data licensing agreement was signed with Main Roads Western Australia for use of the crash data. SJ-WA Research Governance Committee gave approval to conduct the study using ambulance data.

Consent for publication
Not applicable.

Competing interests
EB, DB, PB, RB and AW are employed by St John Western Australia (SJ-WA). JF and SB hold adjunct research positions at SJ-WA. JF receives research funding from SJ-WA.

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Publisher's Note

Supplementary material: List of interventions/observations/medications representing the need for a lights & sirens ambulance response

Category	Description
Pre-Ambulance Care	Ventilation Only
Pre-Ambulance Care	Cardiopulmonary Resuscitation (CPR)
Pre-Ambulance Care	Automated External Defibrillator (AED) - Shock delivered
Collapse	Ambulance Officer Witnessed
Collapse	Bystander Witnessed
Conscious State	Pain Response
Conscious State	Nil Response
Glasgow Coma Scale (GCS) Verbal	1 None
Glasgow Coma Scale (GCS) Verbal	2 Incomprehensible
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
Paediatric GCS Eye Opening	1 None
Paediatric GCS Eye Opening	2 To Pain
Paediatric GCS Verbal Response	2 Inconsolable, Agitated
Paediatric GCS Motor Response	2 Extension to Pain
Paediatric Motor Response	3 Abnormal Flexion to Pain
Glasgow Coma Scale (GCS) Total	Total <10
Head Gaze/Deviation	Present
Electrocardiogram (ECG/EKG)	Asystole
Electrocardiogram (ECG/EKG)	Bradycardia
Electrocardiogram (ECG/EKG)	Ventricular Tachycardia (VT)
Electrocardiogram (ECG/EKG)	Ventricular Fibrillation (VF)
Electrocardiogram (ECG/EKG)	Pulseless Electrical Activity (PEA)
Burns	Full Thickness
Burns	Airway
Bleeding	External considered > 500mls
Bleeding	Internal
Splint/Dressing	Traction Splint
Doctor at Scene	Intubated
E.C.G. Rhythm	Supraventricular Tachycardia (SVT)
Clinical Interventions	Mechanical CPR Device
Clinical Interventions	ST-Elevation Myocardial Infarction (STEMI)
Clinical Interventions	Stroke Centre Delivery
Breathing	Nil
Breathing	Shallow
Breathing	Slow
Breathing	Laboured
Breathing	Accessory Muscle Use
Breathing	Audible Wheeze
Splint/Dressing	Combat Application Tourniquet (CAT)
Airway	At-Risk/Unprotected

Airway	Soiled
Airway	Partial Obstruction
Airway	Complete Obstruction
Airway	Stridor
Skin Colour	Cyanotic
Capillary Refill	> 2 Seconds
Pulse	Nil
Pulse	Weak
Post cardiac arrest	Return of Spontaneous Circulation (ROSC)
Post cardiac arrest	ROSC Temporary
Post defibrillation	No Rhythm Change
Post defibrillation	Rhythm Change
Medications-Intervention	epinephrine
Medications-Intervention	amiodarone
Medications-Intervention	atropine sulphate
Medications-Intervention	cefazolin
Medications-Intervention	glucose 10%
Medications-Intervention	heparin Sodium
Medications-Intervention	metaraminol tartrate (aramine)
Medications-Intervention	morphine & midazolam infusion
Medications-Intervention	packed red blood cells
Medications-Intervention	rocuronium bromide (esmeron)
Medications-Intervention	suxamethonium Chloride
Medications-Intervention	tranexamic acid (TXA)
Skills	Needle Thoracentesis
Skills	Cardiopulmonary Resuscitation (CPR)
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	Oropharyngeal Airway
Skills	External Cardiac Pacing
Skills	Rapid Sequence Induction
Skills	Suction (of the airway)
Skills	Synchronised Cardioversion
Skills	Ventilator
Other finding	Amputation
Other finding	Partial Amputation

7.3 INTERPRETATION

Decision trees using crash characteristics as the node/branches were used to predict the need for a L&S response. A decision tree that would require between one and ten questions asked of the layperson at the scene by the EMD (to identify ambulance dispatch priority) had an under-triage rate of 2.7% and an over-triage rate of 84.8%. The ACSCOT suggests a 5% under-triage and a 25% to 35% over-triage rate for trauma team activation at any emergency department. While the results are not unusual compared to other dispatch methods, [7] the high over-triage rate represents considerable system inefficiency, as ambulances are sent using L&S to those crashes that do not require it.

The findings from this study were surprising to me, I had expected at the beginning of my thesis to have found more promising under/over-triage rates using crash characteristics. My fifth study sought to explore the reason this method did not produce the desired results and my sixth offered an alternative, novel method, for identifying the need for a L&S response.

Chapter 8: Variation in On-Scene Patient Acuity

8.1 OVERVIEW AND RATIONALE

My second study demonstrated that some crash characteristics have high predictive ability in terms of the need for a L&S ambulance response. My fourth study suggested that combinations of crash characteristics might improve prediction, however simple combinations of crash characteristics could not predict the need for a L&S response with suitable accuracy. This study, therefore, aimed to explore the kinds of crash characteristics that result in variation in the acuity of patients and thereby provide an explanation for the simple decision tree having unsuitable accuracy in terms of the need for a L&S response prediction.

In Perth, Western Australia, a retrospective cohort study was conducted on all road crash patients who were attended by emergency ambulance paramedics between 2014 and 2016. The New Early Warning Score 2 (NEWS2) [75] was used to assess the initial on-scene patient acuity, which was based on the paramedics' initial clinical observations. The study involved performing the Bimodality statistic, Hartigan's dip statistic, [70,76] and visually inspecting the data to assess for the variation in acuity for crash characteristics.

My findings are described in the following manuscript which is currently under review. The 'author accepted manuscript' version, as allowed due to copyright, is the version provided

5. Ceklic E, Tohira H, Ball S, Brink D, Bailey P, Whiteside, A, Brits R, Finn J. Variation in on-scene patient acuity for different types of traffic crashes: a linked data study. Under review – Traffic Injury Prevention.

8.2 STUDY 5

TITLE

Variation in on-scene patient acuity for different types of traffic crashes: a linked data study

ABSTRACT

Objective: Traffic crashes (TCs) are the leading cause of traumatic injury. Through dispatching ambulances, emergency medical services (EMSs) play an important role in reducing the burden of TCs. While callers at the scene of a TC have limited medical knowledge, they do have the ability to describe the characteristics of a crash. These characteristics could include if there was a vehicle rollover, the location and the type of intersection. Crash characteristics have an established relationship with patient acuity which could be used by EMS to identify those crashes that require the fastest ambulance response to the scene, known as a lights and sirens (L&S) response, and those that do not. However, there is some debate in the literature about variation in acuity for some crash characteristics. This study aims to explore the kinds of crash characteristics that result in variation in the acuity of patients. Methods: A retrospective cohort study of all TC patients in 2014-2016 attended by emergency ambulance paramedics in Perth, Western Australia was conducted. The initial on-scene patient acuity was measured as the New Early Warning Score 2 (NEWS2), based on initial clinical observations recorded by paramedics. The Bimodality statistic, Hartigan's dip statistic and a visual inspection of the data were conducted. Results: Paramedics attended 11,492 patients over the three years to 2016. Most had an immediate on-scene low NEWS2 score of 0 (41.1%). A small proportion had the highest NEWS2 score of 20 (1.4%). The crash characteristics of crest/slope, cyclist, ejected, midblock, motorcyclist, not ambulant, pedestrian, raining, speed zone ≥ 90 km/h, and trapped were bimodal. Conclusions: Initial on-scene patient acuity is low for most crash characteristics. However, some characteristics have a strongly

bimodal distribution in patient acuity. Emergency medical systems dispatching ambulances to the motor vehicle crash may find this of interest.

KEYWORDS

NEWS2, on-scene acuity, ambulance, dispatch, traffic crash.

INTRODUCTION

Traffic crashes (TCs), which are the leading cause of traumatic injury worldwide, result in around 1.5 million deaths each year (World Health Organisation, 2020). Emergency medical services (EMS) play an essential role in reducing the burden of TCs by dispatching ambulances. Once a call ('000 in Australia like '911' in the United States) from the scene of a crash arrives, the EMS has to decide whether the crash requires the faster lights and sirens (L&S) response or slower ambulance response (not L&S). Although callers on-scene cannot accurately assess patient need due to limited medical knowledge, they can describe the characteristics of a crash (Heidari et al. 2019), such as whether there was a rollover, what the weather was at the time (e.g., raining, clear, fog), the type of road (e.g., traffic lights, 4-way intersection, curved) and the road users involved (e.g., bicyclists, motorcyclists, pedestrians). These characteristics are important because of the direct relationship between crash characteristics and patient acuity. This relationship may be used to identify the need for emergency medical assistance and determine the ambulance response required (L&S or not) because unlike medical observations (such as vital signs), crash characteristics are easily describable by laypersons.

Crash characteristics may be used to prioritise ambulance responses; however, there is some contention in the literature about variations in patient acuity. Patient acuity is referred to here as the need for time sensitive care, with a high acuity patient requiring a faster ambulance response than those with low acuity (Daly and Brennan 2009). It can be argued that for some crash characteristics most patients are either high or low acuity (minimal variation in acuity). Whereas for other characteristics there may be a mix both high and slow (variation in acuity). For example, in high-speed crashes or those where a passenger is ejected from the vehicle, there is almost always a high risk of high patient acuity (Schoettker et al. 2001; Elvik 2013). This makes high-speed crashes a potential candidate for ambulance prioritisation. Conversely, with other crash characteristics, the likely acuity varies. Consider the contention in the literature regarding the suitability of vehicular rollover to be a standalone indicator of high acuity patients (Champion et al. 2009; Haan et al. 2009). This is because, in rollovers, some patients are unharmed, whereas others do not survive the event. This makes rollover a potentially less suitable candidate for ambulance prioritisation.

An additional issue with the existing evidence and its suitability to be used to prioritise ambulances is that much of the research does not apply directly to an EMS setting. This is because the measures of patient acuity used are usually outcome-related (lived/died) or specific (such as the Glasgow Coma Scale score for the level consciousness or the Injury Severity Score for anatomical injuries). Measures of acuity applicable to an EMS setting need to be taken as close in time to the crash itself and reflect the need for emergency medical assistance. This study, therefore, seeks to explore the kinds of crash characteristics that result in variation in patient acuity. This information may be useful to the EMS when dispatching ambulances (Candefjord et al. 2016).

METHODS

Design, setting and population

We conducted a retrospective cohort study of all TCs attended by St John Western Australia (SJ-WA) paramedics in the Perth metropolitan region of Western Australia from the 1st January 2014 to the 31st December 2016. The population of Perth during this period was approximately 2 million (Australian Bureau of Statistics 2017). SJ-WA is the sole contracted provider of emergency medical ambulances in Perth. All ambulances are staffed by at least one qualified paramedic, with a second crew member who may be in training or qualified. All paramedics can provide advanced life support.

Data sources

There were two sources of data. The first was SJ-WA ambulance data recorded during computer-aided dispatch (CAD), which logs information during the call for emergency medical help (in Australia as “000” alike “911” in the USA), along with electronic patient care records (ePRCs) documented by paramedics who attended TC patients at the scene. Data was restricted to those patients that were both identified during the call as Transportation/Traffic (in the Medical Priority Dispatch System as Protocol 29 (Clawson et al. 2014)) and identified by paramedics at the scene as a TC.

The second source of data was from Main Roads Western Australia (MRWA) which comprised information recorded by police who attended a crash (for fatalities or those injured to the equivalent of grievous bodily harm), or by drivers involved in the crash. Crashes in this dataset reflect those defined as a reportable road crash, with crashes associated with deliberate intent excluded (e.g. police chase or suicides) and those crashes not on a gazetted road, such as those on private property.

Data were linked using a stepped approach using both deterministic and probabilistic linkage methods. SJ- WA ambulance data was linked to the MRWA crash data. Records were linked using FRIL (Fine-Grained Records Integration and Linkage Tool, v2. 1.5 Emory University, U.S.) using matches based on latitude/longitude of the dispatch location within one kilometre of the MRWA crash data location, and within one calendar day. SAS Base 9.4 (SAS Institute Inc. SAS, Cary, NC, USA) was used to probabilistically match on surname, first name, date of birth and vehicle registration number. Names were matched using the SPEDIS function (Sloan and Lafler 2018).

The linkage rate was 66.6%. Given that not all crashes require emergency ambulance care, a higher linkage rate was not expected. See Figure 1.

{Insert Figure 1}

Unit of measurement

The unit of measurement was the patient at a traffic crash attended by an emergency ambulance during the study period.

Predictor variables

The predictor variables are the crash characteristics that relate to the TC the patient was involved in. Crash characteristics that the patient will share with everyone in the TC were: crest/sloped road, dawn/dusk, intersection, midblock, raining, rear-end, rush hour, signalized intersection, roundabout, speed zone <=50km/h and speed zone >=90 km/h. Crash characteristics that the patient will share with everyone in the same vehicle as that patient are: airbag deployed and rollover. Crash characteristics that relate to the patient only are: cyclist, ejected, motorcyclist, not ambulant, pedestrian, motor vehicle occupant and trapped.

Crash characteristics were derived from either or both of the datasets. The following were derived from the ambulance data: ejected (when a vehicle occupant is partially or fully thrown from the vehicle), patient(s) not ambulant (unable to walk), rollover (when a vehicle tips onto its roof or side), rush hour (8am-10am and 4pm-6pm) and trapped (patient is unable to exit the). The characteristics of dawn/dusk, intersection (crossroads), midblock (between intersections), raining, rear-end, roundabout (traffic circle), signalized intersection (with traffic lights), crest/sloped road, speed zone <=50km/h, and speed zone >=90 km/h were from the MRWA crash data. From either data source: the characteristics of airbag deployed, cyclist, motorcyclist, pedestrian, rush hour, and motor vehicle occupant, were derived.

Outcome variable

The initial on-scene patient acuity, measured close to the point in time just proceeding the TC, was the outcome variable of interest. This was estimated using the New Early Warning Score 2 (NEWS2) which is an indicator of the need for urgent medical care in patients (Kolic et al. 2015). The NEWS2 score is derived from the first examination/observations of the patient as recorded by paramedics on-scene at the MVC. NEWS2 is a composite score derived from respiration rate (breaths/minute), oxygen saturation (SaO2%), supplementary oxygen, systolic blood pressure (mmHg), pulse (beats/minute), consciousness (GCS) and temperature (°C). Each parameter is given a score from zero to three and is summed to form a total NEWS2 score. NEWS2 scores can range from 0 to 20, with scores of seven or more (or any parameter with a score of 3) considered as requiring urgent clinical intervention (Royal College of Physicians 2012).

We calculated the NEWS2 score based on the first clinical observations recorded on the e-PCR by the first paramedics who arrived on-scene. Where temperature was not recorded, it was assumed to not be clinically relevant and therefore given a normal score. Glasgow Coma Scale scores (GCS) were converted into the NEWS2 conscious 'AVPU' equivalent scale using a prescribed method where a GCS of 15 = A, a GCS of ≤ 14 = C, V, P or U (Zaidi et al. 2019). 'AVPU' is a composite score of the measure of the patient's level of consciousness where A = alert, V = verbal, P = pain and U = unresponsive (Alam et al. 2015).

If patients were dead on-scene or had injuries incompatible with life (such as patients who were incinerated) and paramedics recorded no observations, then the maximum NEWS2 score was given for these patients. Patients <16 years were excluded as the NEWS2 score is not recommended for children. Similarly, NEWS2 is not recommended for pregnant women, however, we could not reliably identify pregnancy in our study cohort.

Statistics Analysis

Two tests for variation were conducted. These were

(1) The Bimodality coefficient;

(2) Hartigan's dip test.

These tests were chosen as they have applicability to dispatch of ambulances which would require identification of either a multi (or bi) modal distribution, as distinct from a strongly skewed distribution.

It is recommended these two methods of assessment of variation be used in combination in addition to the Kolmogorov-Smirnov test (Pfister et al. 2013). Variation was identified in this study where the distribution of patient acuity (NEWS2) for a crash characteristic was non-normal (according to the Kolmogorov-Smirnov test) and was bimodal in the two modality tests (Bimodality coefficient and Hartigan's dip test) and where variation was evident in the histograms.

The Bimodality co-efficient was used to assess for bimodality (SAS Institute 2012). This is calculated:

$$b = \frac{g^2 + 1}{k + \frac{3(n-1)^2}{(n-2)(n-3)}}$$

Where n is the size of the population, g is the skewness and k is the excess kurtosis (three minus kurtosis). A value of 5/9 or greater indicates bimodality.

Hartigan's dip statistic is based around the concept that if a continuous variable has a bimodal distribution it will have a dip in the middle between the two peaks. The test measures the maximum difference between an empirical (sample) distribution function from our data and that of a unimodal distribution function. Hartigan's dip statistics tests with a value of less than 0.05 are considered strongly bimodal, those between 0.06 and 0.1 as marginally bimodal and those with a value about 0.1 as unimodal.

To display the distribution of NEWS2 by crash characteristics we constructed a smoothed polygon histogram of percentages for each NEWS2 score, as a proportion of the total count of NEWS2 scores for that crash characteristics. We sorted the smoothed histograms according to the Bimodality coefficient.

Data were analysed using SAS/BASE software version 9.4 (SAS Institute Inc. SAS, Cary, NC, USA.), the Bimodality coefficient and Hartigan's dip test were conducted in RStudio version 1.4.1717 (RStudio, Integrated Development for R. RStudio, PBC, Boston, MA) and histograms were visualized using SPSS software version 27.0 (IBM Corp. Released 2020. IBM SPSS Statistics for Windows, Armonk, NY: IBM Corp) and Matlab (R2009. B.Mathwords Inc.).

Ethics

The Western Australia Pre-hospital Record Linkage Project was granted ethics approval by the Curtin University Human Research Ethics Committee (HR 128/2013). The Research Governance Committee at St John also approved the research. A Data Licensing Agreement was signed with MRWA.

RESULTS

Demographic and clinical characteristics

There were 11,492 patients attended by paramedics at the scene of TCs over the three years to 2016. The median age was 38 years (IQR: 24 to 52), with ages ranging from 16 to 97. The median values for initial clinical characteristics were: respiration rate of 16 breaths/minute; peripheral oxygen saturation of 99%, temperature of 36.7 °C; systolic blood pressure of 132 mmHg and heart rate of 84 beats per minute. Demographic and clinical data are shown in Table 1.

{Insert Table 1}

NEWS2

Most patients had an immediate on-scene NEWS2 score of 0 (41.1%), followed by a score of 1 and 2 (25.8% and 10.2% respectively). A small proportion of TC patients had the highest NEWS2 score of 20 (1.4%), of these 27 patients were dead on arrival. Table 2.

{Insert Table 2.}

The crash characteristics with the highest proportion of TC patients were motor vehicle occupant (69.3%), intersection (42.8%), and airbag deployed (32.8%). Characteristics with the lowest proportion patients were ejected (0.9%), not ambulant (1.9%) and roundabout (3.3%). See Table 3.

{Insert Table 3}

Crash characteristics and variation

Bimodality coefficients for NEWS2 scores ranged from $b = 0.23$ to $b = 0.86$. Crash characteristics that indicate bimodality (with $b \geq 55$) were: ejected ($b = 0.88$), trapped ($b = 0.87$), not ambulant ($b = 0.87$), motorcyclist ($b = 0.86$), crest/slope ($b = 0.86$), pedestrian ($b = 0.85$), midblock ($b = 0.79$), speed zone >=90 km/h ($b = 0.72$), raining ($b = 0.61$), rollover ($b = 0.56$) and cyclist ($b = 0.55$). See Table 4.

{Insert Table 4}

Hartigan's dip statistic ranged from 0.02 to 0.12. Not ambulant, trapped, ejected, midblock, pedestrian, motorcyclist, rush hour, roundabout, cyclist, raining, speed zone ≥ 90km/h and crest/slope had a dip statistics of d=0.05, indicating a bimodal distribution. See Table 4.

From a visual inspection of smoothed histograms, all the crash characteristics showed one positively skewed mode (peak) and many showed a bimodal distribution. A few crash characteristics showed three or more modes, these were speed ≥ 90km/h, cyclist and roundabout. See Figure 2.

{Insert Figure 2}

DISCUSSION

Identifying patient need over the phone during an EMS call is difficult due to the limits of a layperson's medical knowledge. However, there is an established relationship between patient acuity and the characteristics of crashes that may be used by EMS to get more information about patient need. This study investigated the variation in initial on-scene acuity of patients for different crash characteristics. We found that the majority of patients (92.4%) had an initial on-scene acuity considered low clinical risk (Klepstad et al. 2019), scoring on the NEWS2 between 0 and 4. A small proportion of patients had a score of 7 or above, indicating high clinical risk (3.1%) (Klepstad et al. 2019). This finding is not surprising given that only a small proportion of TCs result in serious injury or death (Washington et al. 2014). Interestingly, we found that several crash characteristics showed evidence of a strongly bimodal distribution. Crest/slope, cyclist, ejected, midblock, motorcyclist, not ambulant, pedestrian, raining, speed zone ≥ 90 km/h and trapped were bimodal according to the indicators used (the bimodality coefficient and Hartigan's dip test), suggesting variation in patient acuity for these characteristics.

Within the literature, a finding of bimodal distribution of the NEWS2 in any setting (TCs or otherwise) is unusual, with most studies reporting a positively skewed distribution (Smith et al. 2013; Bilben et al. 2016; Spagnolli et al. 2017; Pedersen et al. 2018; Barker et al. 2019). However, variations (including bimodal distributions) are common within TC research. Traffic crash research uses data derived primarily from two types of jurisdictions: police and road construction. This data is biased towards the purpose of those jurisdictions, namely for law enforcement and safe road design (Abdulhafedh 2017). It is therefore expected that characteristics to do with the crash that are not routinely collected (e.g., speed at collision and number of rotations) contribute to the variation and bimodality found here.

Describing acuity in terms of the first on-scene examination is relevant to EMS for several reasons. First, describing acuity in terms of outcome measures, such as acuity at presentation to the emergency department (ED), omits important changes that might have happened between the time of the crash to arrival at the ED. This includes prehospital interventions, such as pelvic splinting (Lee and Porter 2007), fluid infusion (Cotton et al. 2009) and airway manoeuvres (Crewdson and Lockey 2016), which improve patient acuity at the time of the intervention. Second, the EMS dispatches based on potential patient acuity measure in as close a time as possible to the TC. Therefore, this paper may be of interest to the EMS in identifying patient need in terms of the ambulance response and dispatch required. For example, crash characteristics that have a strongly bimodal distribution should receive the fastest ambulance response due to the presence of both high and low acuity patients.

It is relevant to note that many EMSs worldwide use a scripted set of questions during the call for emergency medical assistance to classify TCs into categories to determine the type of ambulance response required (Clawson et al. 2014; Dami et al. 2015). Some of these categories are the same as those presented here, such as trapped, ejected, motorcyclist, cyclist and pedestrian. Given that these crash characteristics were bimodal with groups of low and high acuity patients, these types of crashes are likely to require a L&S response.

Future Research

Further research may investigate crash characteristics that explain the bimodal distributions identified here. Bimodal distribution suggests that there are additional factors that determine patient acuity. In the case of the characteristic of trapped, low acuity patients may be mechanically trapped (damage to the vehicle limits exist), and high acuity patients may be physically trapped (unable to exit the vehicle due to trauma to the body). Therefore, using a combination of crash characteristics (such as speed being trapped with the cause – mechanic or physical) for bimodal distributions may provide additional predictive power in identifying patient need.

Limitations

There are two potential limitations with the outcome measure of this study. Firstly, we could not measure initial on-scene patient acuity at the point just after the crash and used first observations recorded by paramedics instead. It is likely that for some crash characteristics, patient acuity is stable over time, whereas for other characteristics, patients may improve or deteriorate quickly. However, given that the expected arrival time of the ambulance on-scene at the TC in this jurisdiction is within 15 minutes from the call for emergency medical assistance, we think that this measure is reasonable. Secondly, it is possible that a patient could still be in need of prompt attention with a NEWS2 score. For example, an open fracture or compound is a clinical situation that needs attention – but in any otherwise healthy adult – it may not cause an adverse effect on any of the six physiological parameters that comprise the NEWS 2 scoring system.

An additional limitation is that the statistics we used (the bimodality coefficient and Hartigan's dip test) could only test for bimodality. It is possible that some crash characteristics (such as roundabout) had a multimodal distribution with more than two modes (peaks) in the data. While the statistics we used did not indicate bimodality for roundabouts, the histogram (see Figure 2) showed a second peak close to the main peak. This is not surprising given that unmeasured crash characteristics, such as roundabout diameter (with larger diameters increasing patient acuity) (Elvik 2003) or number of lanes (with double carriageway roundabouts resulting in increased patient acuity), influence patient acuity (Polders et al. 2015). However, there are no existing statistics that indicate multimodality.

Conclusion

We conclude that some crash characteristics have a bimodal distribution, whereas others do not. This is evidence of variation. Among crash characteristics that have a bimodal distribution, multiple crash characteristics are required to be able to explain and predict patient acuity. This bimodal distribution may interest the EMS in terms of dispatching ambulances based on similar crash characteristics.

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Figure 1. Flow diagram of linkage process between ambulance and motor vehicle crash records

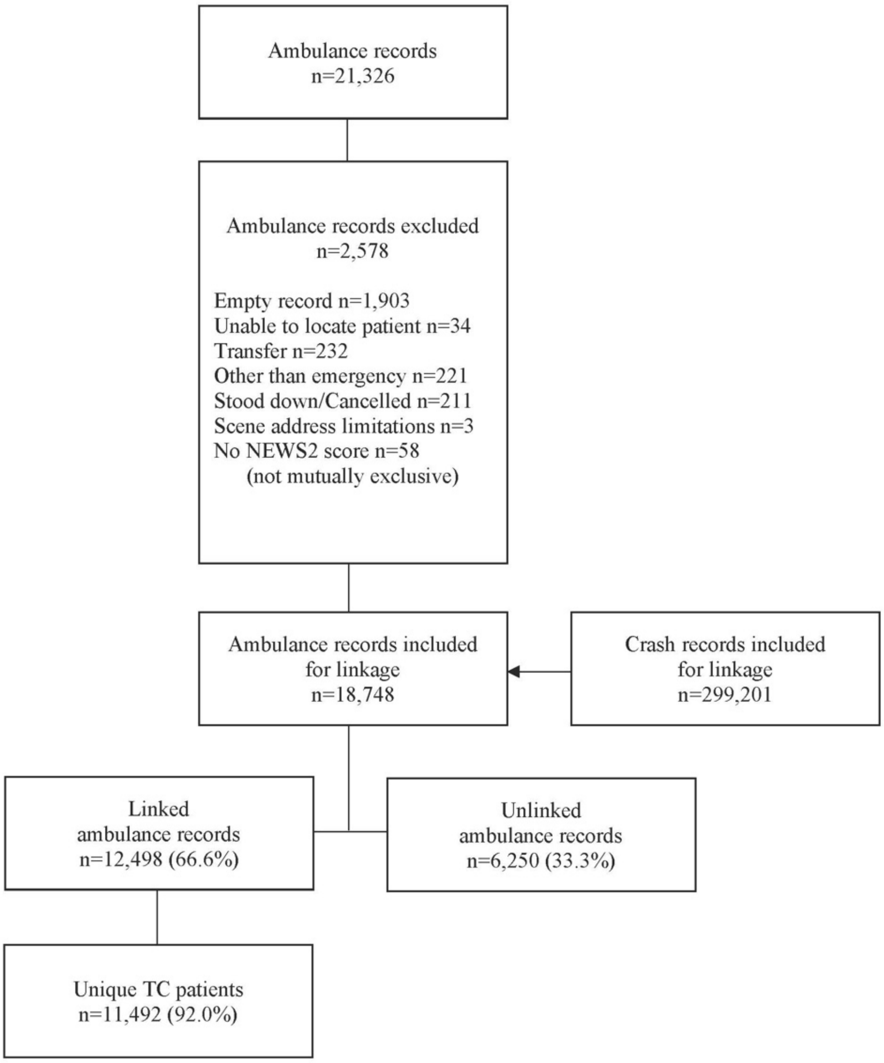
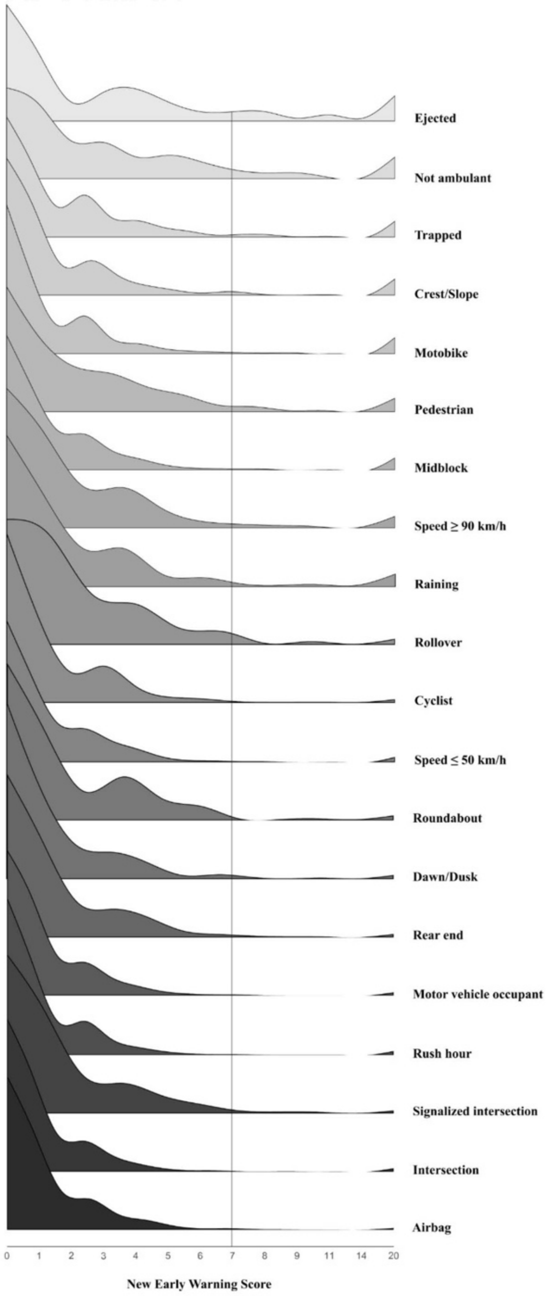


Figure 2. Ridgeline diagram showing the percentage of patients for each NEWS2 score for each crash characteristic *



*The figure shows a smoothed polygon histogram of percentages for each NEWS2 score, as a proportion of the total count of NEWS2 scores (y-axis) for that crash characteristic.

Vertical mid-line indicates NEWS2 score at 7, above which patients are deemed to be high clinical risk (Klepstad et al. 2019).

Crash characteristics are ordered by the Bimodality coefficient.

Table 1. Demographic and clinical profile of study population using initial paramedic on-scene observations

Total patients (n)	11,492
Sex (%)	
Female	5,437 (47.3%)
Male	6,054 (52.7%)
Age, median (IQR)	38 (24-52)
Respiration rate (breaths/minute), median (IQR)	16.00 (15.00-18.00)
Oxygen saturations (%), median (IQR)	99 (98-100)
Use of supplementary oxygen (n)	2
Temperature (°C), median (IQR)	36.7 (35.8-37.2)
Systolic blood pressure (mm Hg), median (IQR)	132 (119.5-144.5)
Heart rate (beats/minute), median (IQR)	84 (74.5-93.5)

Table 2. Number of patients for individual New Early Warning Score (NEWS2)

NEWS score	Number of patients (n)	Proportion of patients (col %)
1	4,726	41.1%
2	2,968	25.8%
3	1,174	10.2%
4	1,129	9.8%
5	636	5.5%
6	352	3.1%
7	156	1.4%
8	70	0.6%
9	46	0.4%
10	36	0.3%
11	15	0.1%
12	9	0.1%
13	8	0.1%
14	1	0.0%
15	2	0.0%
16	6	0.1%
17	0	0.0%
18	0	0.0%
19	1	0.0%
20	157	1.4%
	11,492	**100%**

Table 3. Number of patients by crash characteristics

Crash characteristic	n	Col %
Total all patients	**11,492**	
Airbag deployed	3,765	32.8%
Cyclist	409	3.6%
Dawn/Dusk	535	4.7%
Ejected	109	0.9%
Intersection	4,915	42.8%
Midblock	3,094	26.9%
Motorcyclist	1,330	11.6%
Motor vehicle occupant	7,967	69.3%
Not ambulant	221	1.9%
Pedestrian	452	3.9%
Raining	409	3.6%
Rear-end	1,744	15.2%
Rollover	433	3.8%
Roundabout	377	3.3%
Rush hour	4,527	39.4%
Signalized intersection	2,783	24.2%
Crest/sloped road	881	7.7%
Speed zone <=50 km/h	2,134	18.6%
Speed zone >=90 km/h	711	6.2%
Trapped	704	6.1%

Rush hour is 06:00-10:00 to 15:00 to 19:00 on weekdays.

Table 4. Crash characteristics by measure of modality

Crash characteristic	**Bimodality co-efficient**	**Hartigan's dip statistic**
Airbag deployed	0.23	0.09
Crest/sloped road	0.86^{+}	0.04^{+}
Cyclist	0.55^{+}	0.04^{+}
Dawn/Dusk	0.43	0.12
Ejected	0.88^{+}	0.02^{+}
Intersection	0.24	0.06
Midblock	0.79^{+}	0.03^{+}
Motorcyclist	0.86^{+}	0.03^{+}
Motor vehicle occupant	0.39	0.08
Not ambulant	0.87^{+}	0.02^{+}
Pedestrian	0.85^{+}	0.03^{+}
Raining	0.61^{+}	0.04^{+}
Rear-end	0.40	0.09
Rollover	0.56^{+}	0.05
Roundabout	0.44	0.04^{+}
Rush hour	0.31	0.04^{+}
Signalized intersection	0.30	0.12
Speed zone ≤ 50 km/h	0.49	0.07
Speed zone ≤ 90 km/h	0.72^{+}	0.04^{+}
Trapped	0.87^{+}	0.02^{+}
Total all patients	**0.54**	**0.13**

$^{+}$ Indicates a bimodal distribution.

8.3 INTERPRETATION

This study found that most patients had a low initial on-scene NEWS2 score of 0 (41.1% representing low acuity patients), whereas only a small proportion had the highest score of 20 (1.4% representing high acuity patients). Crash characteristics such as crest/slope, cyclist, ejected, mid-block, motorcyclist, not ambulant, pedestrian, raining, speed zone ≥ 90 km/h, and trapped exhibited a bimodal distribution. The study concludes that while most crash characteristics have a low initial on-scene patient acuity, certain characteristics show a strongly bimodal distribution. These findings could be operationally useful for EMS dispatching ambulances to motor vehicle crashes. For my thesis, I concluded crash characteristics are not a useful predictor to be used for dispatch, which was the initial aim of this thesis. I therefore sought to find alternative methods with greater predictive accuracy (than my fourth study), and which could take advantage of the complexity of crashes (demonstrated in my sixth and final study).

A suggestion for further research is to confirm the applicability of the NEWS2 in a pre-hospital setting, given that the NEWS2 was developed to be applied in an ED setting. Confirmation of its applicability could strengthen these findings.

Chapter 9: Natural Language Processing Dispatch Algorithm

9.1 OVERVIEW AND RATIONALE

This study sought to investigate whether the descriptive text typed by emergency medical dispatchers (EMDs) and conveyed automatically to paramedics on the way to the scene of a road crash, could predict the requirement for a L&S ambulance response to the scene. The rationale for this study was taken from my previous two studies that found a simple decision tree using traditional statistics could not predict the need for a L&S response with the required accuracy (the fourth study) and that one reason for this could be the distribution of acuity for different crash characteristics (the fifth study). Therefore, I wanted to use the dispatcher text to increase the number of elements that described the crash (from around 200 crash characteristics to 9,000 unique dispatcher root words) and to take advantage of the features of machine learning. Machine learning algorithms are adept at discovering patterns in data that may not be apparent using traditional statistical methods. This is because machine learning algorithms find complex patterns and relationships in data, whereas traditional statistical methods may only identify simple linear relationships. The existence of these complex patterns was suggested in the findings of the fifth study.

My findings are described in the following manuscript which was published in the International Journal of Medical Informatics in 2022.

Ceklic E, Ball S, Finn J, Brown E, Brink D, Bailey P, Whiteside A, Brits R, Tohira H. Ambulance dispatch prioritisation for traffic crashes using machine learning: A natural language approach. *International journal of medical informatics*. 2022 Dec 1; 168:104886.

9.2 STUDY 6

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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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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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9.3 INTERPRETATION AND APPLICATION

Overall, machine learning techniques offer significant advantages over traditional statistical methods, particularly in their ability to handle large and complex data, discover patterns, and achieve higher accuracy. All these features were evident in the findings of this study, which was with an ensemble machine learning algorithm using both MPDS dispatch codes and dispatcher text. This model could predict the need for a L&S response with 98% accuracy. I concluded that implementing machine learning algorithms by EMS (using MPDS dispatch categories and dispatcher text) has the potential to enhance the accuracy of dispatching to road crashes and ultimately lead to improved EMS efficiency.

Chapter 10: Synthesis of Models

To compare the findings from my three studies which offer a model and method to identify the need for a L&S response, I calculated the under and over-triage rates, as a shared measure of model accuracy.

Under and over-triage rates are terms commonly used in emergency medicine and triage to assess the accuracy of patient prioritisation. Under-triage (also known as the false positive rate) refers to the situation where a patient with a serious condition is classified as having a lower priority (under-estimating), while over-triage (also known as the false positive rate) occurs when a patient with a less severe condition is assigned a higher priority (over-estimating). [77,78] Under/over-triage are two important measures of the accuracy of a trauma triage system. In the context of ambulance dispatch over-triage occurs when crashes that do not require a L&S response receive it, potentially delaying care for other incidents (crashes and otherwise) that truly need it. Under-triage occurs when crashes that require a L&S response do not receive it, leading to delayed or inadequate care and potentially poorer outcomes for patients at these crashes. Minimising both over-triage and under-triage is therefore important to optimise the operational efficiency and clinical effectiveness of EMS.

Table 5 shows a confusion matrix as applied to under/over-triage rate calculation for the dispatch of ambulances by EMS. A confusion matrix is a table used to describe the performance of a classification model.

Table 5 Confusion matrix for over/under-triage rate calculation

	Actual not L&S	Actual L&S
Prioritised L&S	False positive	True positive
Prioritised not L&S	True negative	False negative

Over-triage and under-triage can be calculated using the following formulas: [79]

Over-triage rate = (number of false positives / total number of positives) x 100

Under-triage rate = (number of false negatives / total number of negatives) x 100

Using the above calculation methods and categories derived from Table 5, the below table provides a comparison across studies in this thesis.

Table 6 Comparison of study outcomes

	Over -triage rate	Under -triage rate
Thesis findings		
Study 1: MPDS Chief Complaint 29 Traffic/Transportation existing dispatch accuracy Dispatch categories using the ROC curve (mean across curve) Dispatch categories using the ROC curve (range across curve)	 86.9% 39.3% 0.0%-100.0%	 0% 50.1% 0.0%-99.9%
Study 5: Crash characteristics CHAID simple decision tree	84.8%	2.7%
Study 6: MPDS & dispatcher text Machine learning	52.6%	6.1%
Recommendation for trauma (not dispatch)		
Recommendation: ACSCOT Recommended rates[80]	25-35%	5.0%

Study 1 found that the existing dispatch accuracy (for road crashes) of the St John WA EMS, which dispatches using L&S to all road crashes they are notified of, is 86.9% over-triage and 0% under-triage. Of the models I proposed, I found the following over-triage values: 39.3% (study 1: using MPDS dispatch categories as thresholds), 52.6% (study 6: using EMD text) and 84.8% (study 5: using simple crash characteristics).

Under-triage rates were: 2.7% (study 5: simple crash characteristics), 6.1% (study 6: using EMD text) and 50.1% (study 1: using MPDS dispatch categories). While each of the three proposed models represents an improvement on the existing 86.9% over-triage rate (for SJ-WA), both over and under-triage need to be considered together. For example, while study 5 using simple crash characteristics in a decision tree had the lowest under-triage rate of any of my models (2.7%), it also had the highest over-triage rate (84.8%). At these values, there is little improvement in system efficiency as compared to the existing dispatch accuracy (similar over-triage rates) and an increased risk to clinical effectiveness (increased under-triage rate). The model that provides a balance between over and under-triage rates is study 6 using machine learning to predict the need for a L&S response using words derived from EMD text. (and MODS categories) This model had a reasonable under-triage rate (6.1% compared to the 5% recommended by the ACSCOT) with an associated over-triage rate, which although higher than that recommended by the ACSCOT, represents an improved system efficiency (52.6% compared to an existing 86.9%).

Chapter 11: Discussion

11.1 INTRODUCTION

The primary purpose of my doctoral research was to identify potential methods by which EMS could determine which road crashes require a L&S ambulance response to the scene of a road crash, and those that do not. This investigation resulted in the formation of six studies (five of which have been published and one under review), of which I am the primary author. In this chapter, I will synthesise the findings of these studies within the context of the existing literature. After this I will discuss the real-world implications of these findings for EMS, I will then evaluate the strengths and limitations of my doctoral research and make suggestions for future research, before drawing a conclusion.

11.2 OVERVIEW OF MAJOR FINDINGS

11.2.1 Low Prevalence of L&S

I found that of all road crashes responded to by EMS, only a small proportion required a L&S response. This small proportion was found in all five of the analytical studies of this thesis, despite differences in the units of measurement (patients/incidents/crashes) or how the cohort, or population was identified (MPDS Protocol 29 and/or paramedic-identified road crash).

Specifically, of all patients attended, 3.3% had a Glasgow Coma Scale score of less than 14, 2.1% had a respiratory rate of <10 or >29 breaths per minute, 0.7% had a systolic blood pressure of < 90mmHg. Of all crashes, only a small proportion had any patient with the highest NEWS2 score value of 20 (1.4%). Similarly, when I used a set of high-acuity indicators (medications, interventions and observations suggesting the need for a L&S response), I found that 13.2% of incidents (dispatched as MPDS Protocol 29) and 22.3% of crashes (paramedic-confirmed) required a L&S response.

These findings are important for two reasons. First, there is a paucity of research about the acuity at the scene of a road crash in terms of the need for a L&S response. [60] The second reason is that only a small proportion of crashes require a L&S response. St John Ambulance Western Australia (the local jurisdiction from which this thesis was conceptualised) currently dispatches ambulances using a L&S response to all road crashes they are notified of. This presents a significant over-triage (dispatching ambulances using L&S to crashes that do not require it). Over-triage in EMS can result in reduced system efficiencies such as the ability to respond quickly to other patients of high acuity. This justifies the purpose of my thesis, to find methods to accurately identify the need for a L&S response.

11.2.2 Ambulatory Status

Ambulatory status, which refers to a patient's ability to walk or move around, was one factor considered as a prognostic indicator of the need for a L&S response. In the context of crashes, it refers to a crash where either everyone was ambulant or whether any one patient was not ambulant (not ambulant versus ambulant crash). In an earlier study I found that the strongest predictor of requiring a L&S response, as compared to other crash characteristics, was ambulatory status (not ambulant patients having over 15 times the odds of being high acuity than ambulant patients (OR 15.34, 95% CI, 11.48–20.49). I consequently conducted a systematic review to determine whether the relationship between ambulatory status and the need for a L&S response had been identified in previously published studies. However, I concluded that the evidence did not draw a conclusion regarding the use of ambulatory status as an indicator of the need for a L&S response. I, therefore, included ambulatory status in subsequent analyses using a decision tree. While one decision tree did use ambulatory status, it was not the decision tree with optimal over/under-triage rates. One possible reason for these varied findings regarding ambulatory status could be due to its bimodal distribution (I found a strong bimodality coefficient value of 0.87). Having a bimodal distribution in the context of road crashes suggests that there is distributed acuity or need for a L&S response. Such a distribution could arise from a combination of multiple underlying processes or multiple subpopulations within a larger population. For example, an explanation for this is that ambulatory status may be an indicator of functional status and mobility, [81] but may not reflect the severity or complexity of underlying medical conditions. Additionally, a patient's ambulatory status can be affected by a wide range of factors such as pain, [82] fatigue, [83] and medications, [84] which can all impact the road crash patient's ability to move around. This multi-causal nature of ambulatory status could explain why it was a useful indicator in a decision tree model but had mixed findings a stand-alone indicator. Further research is required before any conclusion can be reached about this crash characteristic's utility for EMS dispatch.

11.2.3 Medical Priority Dispatch System

The MPDS is a propriety tool comprised of a set of scripted questions that the EMD asks of the caller at the scene. [19] I sought to assess whether the dispatch category generated from the MPDS used by SJ-WA could identify those road crashes that require a L&S response. The MDPS allows EMDs to assign a road crash to a single category from a list of around 24 different categories (with additional suffixes). These categories are termed determinant codes (or dispatch codes), and these indicate characteristics of incidents/crashes, for example, *rollover, ejection* and *sinking vehicle*. I found that MPDS dispatch codes were poor discriminators of the need for a L&S response (AUROC 0.65, 95% CI 0.64-0.67), where an AUROC value from 0.5 to 0.7 is deemed to be poor discriminator between categories. [85] A pertinent example is that for the dispatch code representing *no injuries confirmed*, where I would have expected to see few incidents that required a L&S response, I found that 5.9% of the incidents needed a L&S response. While the total number of incidents in this category was relatively small (n=134), this result was unexpected.

The finding that the MPDS, when used alone, was a poor discriminator of the need for a L&S response is significant because the MPDS is a widespread tool used to determine the priority with which ambulances are dispatched worldwide. [86] The MPDS is used in approximately 50 countries and has been translated into 19 different languages/dialects. [86] This finding suggests that an alternative method of determining the priority with which ambulances are dispatched to road crashes is required, such as that outlined in later sections of this discussion.

It is important to note that while I found that the MPDS used alone is not a useful tool to predict the need for a L&S response to road crashes, it has other important purposes in this context. Road crashes often involve multiple vehicles and patients. The MPDS has a suffix added to the end of any dispatch code that identifies whether multiple vehicles/patients are involved. This is important where dispatch of more than one ambulance is required or if scene control might be needed (such as by a police or fire department). [87] Also, by enabling identification of rollovers, trapped persons, or hazardous chemicals, the potential need for additional equipment such as that for extrication or vehicle recovery, can be obtained.

11.2.4 Rollovers and crash prediction

I explored whether vehicle rollover was a potential predictive crash characteristic for identifying the need for a L&S response. While involvement in a rollover is used as a criterion in many field triage guidelines, there is also considerable debate in the literature regarding its suitability. [88–90] I found that very few patients involved in a rollover (6.6%) required a L&S response. Likewise, I found that being in a vehicle rollover did not increase the odds of requiring a L&S response (OR 1.04; 95% CI, 0.75–1.43). Similarly, when the cohort of my research was limited to incidents identified in the MPDS's dispatch codes as a *rollover*, 88.6% of rollover incidents did not require a L&S response. Similarly, when the cohort was limited to crashes where there was a vehicle rollover, 84.1% of crashes did not require a L&S response. One could reasonably expect that due to the forces involved in flipping a vehicle, most rollovers would result in the need for a L&S ambulance response. However, I found that patient acuity had a bimodal distribution in rollover cases. In fact, this was the finding for many crash characteristics, including being *ejected* (b=0.88), *unable to* *ambulate* (*b*=0.87), *trapped* (*b*=0.87) and the crash having occurred on the *crest/slope* of a hill (*b*=0.86). Where a crash characteristic has a bimodal distribution, it suggests that there are potential other crash characteristics causing this bimodality. For example, in the case of rollovers, whether the roof collapsed, or the wearing of a restraint (seat belt), could impact whether a person involved in a rollover requires a L&S response or not. [91] Given my finding that many crash characteristics had a bimodal distribution, I hypothesized that combinations of characteristics (e.g., rollover and restraint use) could more accurately predict the need for a L&S response.

11.2.5 Complexity in Crashes

At the onset of this thesis, I envisaged crash characteristics could be used to predict the need for a L&S response (as an alternative to the MPDS) and that combinations of these crash characteristics could form a set of pre-scripted questions for the EMD ("was there a rollover?" or "was the crash on the crest of a hill?") to determine ambulance priority to the scene. This notion was developed from a study by Isenberg et al. (2012) who developed a "simple three-step dispatch rule." [60(p1)] This rule could predict the need for a L&S response using three crash characteristics, which were: whether anyone was not ambulatory, whether the crash occurred on a freeway, or whether it involved only a single vehicle. I hypothesised that additional crash characteristics derived using the linked data sources could improve the accuracy of the findings of Isenberg et al. This hypothesis appeared promising in predicting a L&S response when crash characteristics were investigated as standalone predictors (in my second study). For example, non-ambulant patients had more than 15 times the odds of requiring a L&S response (measured as high acuity patients) of ambulant patients (OR 15.34, 95% CI, 11.48–20.49). Similarly, patients who were trapped compared to those not trapped (OR 4.68, 95% CI, 3.95–5.54) and patients who were ejected from the vehicle compared to those not ejected (OR 6.49, 95% CI, 4.62–9.12) had greater odds of requiring a L&S response. However, when I used combinations of crash characteristics in a simple decision-tree algorithm (an algorithm where information is split to reach a decision), the derived decision tree failed to achieve a suitable accuracy in identifying those crashes that required a L&S. The decision tree that achieved over/under-triage rates closest to those thresholds recommended by ACSCOT used the following crash characteristics: whether anyone was trapped, whether a vulnerable road user was involved (motorcyclist, bicyclist, or pedestrian), whether anyone was not ambulant, whether it was raining, and the type of accident (such as side-on, head-on and run off the road). The algorithm based on this decision tree would have required the EMD to ask a caller two to six questions to determine whether the crash required a L&S response. This algorithm was able to predict the need for a L&S response with an 84.4% over-triage and 2.7% under-triage rates. While there is presently no standard for over/under-triage rate goals in an EMS setting, the ACSCOT recommends an over-triage rate of between 25-35% and an under-triage rate of 5% or below. [80] A potential reason I did not have as accurate a prediction as Isenberg et al., is due to the difference in how the need for a L&S response was measured. Isenberg et al., used two umbrella criteria to retrospectively determine the need for a L&S response, which were the activation of trauma centre resources (a trauma team who are ready to accept trauma patients at ED) and the guidelines for triage of trauma patients at the scene (a set of anatomical, physiological or mechanistic criteria).[80] I used different criteria, as follows: whether anyone died on scene or in transit, whether L&S was used from the scene to an ED or whether any high acuity indicator was present (specific observations, medications or interventions). While I shared some similarities with Isenberg et al., for example in using vital signs as indicators (Glasgow Coma Scale score of < 14, respiratory rate of <10 or >29 breaths per minute, systolic blood pressure of < 90mmHg), Isenberg et al included many mechanistic criteria (such a pedestrian or bicyclist thrown) as well as anatomic criteria (such as long bones fractures). Whereas my identification of the retrospective need for a L&S response, in addition to vital signs, used paramedic skills (such as needle thoracentesis and thoracostomy) and medications (such as packed red blood cells and tranexamic acid).

While it is not in scope of this thesis to explore the meaning of this difference, I can conclude that despite having detailed crash data sourced from the linked ambulance and police data, with more than 200 available crash characteristics, combinations of these characteristics could not predict the need for a L&S response with a suitable accuracy (over/under-triage rates).

Reflecting on the finding that combinations of around 200 crash characteristics (those that described the crash scene) could not predict the need for a L&S response, due to the complexity of road crashes as an open system, taking a machine-learning approach formed the basis for my analysis of dispatcher free-text descriptions. [92] These free-text descriptions dramatically increased the number of characteristics used to describe the crash from around 200 to more than 9,000. (derived from dispatcher derived free-text words).

11.2.6 High Accuracy of Prediction Using Dispatcher Text

Emergency medical dispatchers (EMDs) in many EMSs record descriptive texts that are automatically relayed to the ambulance crew on the way to the crash so that the ambulance crew can get a better understanding of the scene they will soon arrive at. An example of this text could be: *"You are responding to a patient injured in a road crash. The patient is a 67-year-old male. The patient is breathing and conscious. Multiple vehicles are involved. Rollover. The patient has suspected spinal injury. Police are on the way."* I proposed a novel approach of using this text, converting it to vectors for computation, and then applying machine-learning algorithms to predict the need for a L&S response. I found that a gradient boosting model (otherwise known as a forest of decision trees), combining both MPDS dispatch codes and dispatcher-recorded text, had a high predictive ability to identify and discriminate between those crashes that do and those that do not require a L&S response. This model was identified as it had the highest recall (sensitivity) score of 0.980 (95% CI 0.76-0.98). A recall score, in this context, is the proportion of correct L&S predictions out of all those who required a L&S response. This score is important in an EMS setting where it is more important to identify patients who have time-critical injuries (who require a L&S response), than it is to correctly identify those that do not have such injuries (who do not require a L&S response). This is because the consequences of failure to identify crash patients with time-critical conditions, as compared to patients without time-critical conditions, could result in death for the former but not for the latter. Additionally, when over/under-triage rates were subsequently calculated this method of identifying whether a crash required a L&S response had the most favourable balance between rates, having an over-triage rate of 52.6% and an under-triage rate of 6.1%.

This compares to the CHAID simple decision tree model derived from crash characteristics (with over-triage at 84.8% and under-triage at 2.7%) and the MPDS dispatch categories using a ROC curve (with over-triage at 39.3% and under-triage at 50.1%).

While it is essential to strike a balance between under-triage and over-triage to optimize the use of resources and ensure appropriate care, the emphasis is typically placed on minimising under-triage to prioritise timely and accurate responses to those in urgent need of medical assistance. Therefore, while the model using MPDS dispatch categories has a suitable (according to the ACSCOT) over-triage rate, the associated under-triage rate of 50.1% would likely present an unacceptable risk for most EMS. Additionally, while the model using crash characteristics has a suitable under-triage rate of 2.7%, the associated over-triage rate (84.8%) is high enough, that it could make an EMS consider, at SJ-WA do, whether to send all ambulances using L&S to road crashes. Therefore, the model using EMD dispatcher text has the values for over and under-triage closest to that recommended by the ACSCOT.

One reason for the possible improvement in rates between the crash characteristics model (simple decision tree) to that using EMD text (ensemble) is that a decision tree is a single model, while a random forest is an ensemble of decision trees. Random forests tend to have better predictive accuracy than individual decision trees, as they are less prone to overfitting and can capture more complex patterns in data. [93]

My finding is however similar in accuracy to previous machine learning research concerned with used of medically related text notes used to predict medical needs. For instance, doctors' medical progress notes have been used to predict the length of stay in hospital [94,95] and re-admission of geriatric patients, [96] clinical paramedic notes have been used to improve stroke diagnosis, [97] and clinician notes have been used to predict mortality for patients with diabetes. [98]

I have showed that it is possible to identify the need for a L&S response to road crashes with high accuracy. This has practical implications for EMS that may currently dispatch ambulances with L&S to all crashes, such as SJ-WA, but also for those EMS that want to improve the accuracy of their current dispatch methods. Accuracy in identifying patients requiring a L&S response is important in dispatch, as with increases in demand for emergency ambulance services, [47] over-triage can pose a burden to EMS. This burden could be in the form of increases in ambulance ramping and hospital-bed waiting time, or ambulances not being available to those who need them. I, therefore, suggest that SJ-WA and other EMS worldwide might benefit from the use of prospective dispatcher text to identify the need for a L&S response to road crashes.

11.3 STRENGTHS

A strength of my doctoral research is its use of detailed ambulance and police crash data. Ambulance data comprised the computer aided dispatch (CAD) data collected during the call for emergency medical assistance and ePCR data collected by ambulance crews at the scene. Police data comprised information about the crash, including the people and vehicles involved, the location and temporal information about the day, and detailed information about both the road environment and the crash itself. The ambulance data comprised around 200 unique variables (measurements), and the police data around 150. Given the range of modelling approaches I applied to these data, this gives me confidence in reaching the conclusion that crash characteristics, detailed numerously in the ambulance and police data, are not sufficient to predict the need for a L&S response.

Another strength of the study was the novel measurement of the need for a L&S response for road crashes. Crashes were retrospectively identified as requiring a L&S response, based on: (1) whether anyone died on scene or in transit, and/or (2) whether the ambulance used L&S from the scene to ED or (3) whether patients had an indicator representing the need for a L&S response. This indicator identified whether certain medications had been administered (such as fentanyl), whether certain observations were made by ambulance crews (e.g., a capillary refill of > 2 seconds or cyanotic skin colour) and whether certain interventions were performed (e.g., endotracheal tube intubation or cardiopulmonary resuscitation). The addition of this indicator was important because it captured those patients whose condition may have improved on-scene due to paramedic intervention. The indicator was developed by a clinical reference group of experts, including the General Manager of SJ-WA Clinical Services, a Duty Manager of the WA State Operations Centre (call-taking/dispatch centre) of SJ-WA, two senior SJ-WA paramedics, and an emergency physician from Royal Perth Hospital. This bespoke indicator is noteworthy as prior research has tended to use approximate indicators to suggest the need for a L&S response. These indicators include the necessity for trauma team activation,[99] on-scene trauma triage guidelines,[99] injury severity score, [100,101] delta-v (change in force) [102] and the principal direction of force. [103] While these alternative indicators are certainly valid to be used as approximates to measuring the need for a L&S response, my research used an indicator that was specifically designed for such a purpose. This gives weight to the validity of my findings.

11.4 LIMITATIONS

11.4.1 Generalisability

Generalisability is an inherent limitation of retrospective cohort studies, including those presented here. [104] Data in these studies was derived from road crashes attended by ambulance in Perth, Western Australia from 2014 to 2016. From a road safety perspective, Perth is like many other urban cities with comparable fatality and motorisation rates. For Perth fatality rate for 2015 was 3.6 per 100,000 population. [63] This compares to the OECD (Organisation for Economic Co-operation and Development) median of 5.5 per 100,000 population among its 38 member countries, which makes the generalisation of the findings here to other OECD member nations and those with a similar road crash fatality rate, appropriate. However, there are other differences, particularly those across different EMS that may limit the generalisability of this research, such as: what is or is not typically included in the dispatcher free text, the acuity with which road crashes are attended (for example in some jurisdictions paramedics will attend for only severely injured patients), or the role of police and fire emergency services in road crashes.

11.4.2 Bias Toward More Sever Crashes

There is a potential bias in the SJ-WA collection of records of patients at crashes that were of slightly higher severity than the whole population of people injured in a crash in Perth. This is because the completion of an ePCR was only done by paramedics when people reached a certain acuity level (although still a relatively low acuity). While only one study reported at the patient level, my other studies were at the crash (or incident) level. This means that the severity of the crash was determined to be the severity of the highest injured patient. It is reasonable to assume there were people at the scene of a crash visually assessed by paramedics, determined to be very low acuity (slightly or not injured). Therefore, an ePCR was determined as unnecessary and not completed. Furthermore, in instances of cancellations or where the patients could not be found, these likely low low-acuity patients were excluded from the analysis. Therefore, there was a bias toward more severely injured patients in this context. However, since this bias is in favour of including high acuity patients (who required a L&S response), who were the primary group of interest here, I considered this bias acceptable.

11.5 SUGGESTIONS FOR FUTURE RESEARCH

11.5.1 Prospective Text

The machine-learning model identified in this thesis as having a high predictive ability to identify crashes requiring a L&S response requires further research. For example, dispatcher text is likely to vary across jurisdictions, countries, and standards. Using abbreviations and colloquialisms, in this context, needs to be explored. More importantly, the model requires prospective evaluation. This means that the model needs to be deployed in an operational, real-time, and real-world environment, to explore outcomes such as processing time, predictive accuracy and any limitations that evolve, and any evolving limitations.

11.5.2 Further clarification of the need for a L&S response

The identification of the need for a L&S response was varied throughout this thesis but primarily was identified where anyone died on the scene, a patient was transferred using L&S from the scene to an ED or where any one of a list of clinical indicators were recorded by paramedics in their assessment or treatment of a patient. While the use of a list of clinical indicators is not a novel approach [71] further research could refine and expand this list using data analysis of the clinical indicators derived from ambulance systems, a review of medical literature, expert input or further retro or prospective studies.[105] Or alternative measures, such as trauma team activation, could be explored.

11.5.3 Need for a Consensus Definition on a Standard Measure of Dispatch Accuracy

I found no universally accepted standard exists by which to assess the accuracy of emergency medical dispatch. While the ACSCOT makes recommendations for the over and under-triage rates for the triage of patients in the field, this is not directly applicable to accuracy for ambulance dispatch. [80,106] Notably, a recent systematic review over/under-triage rates in multiple types of medical settings found a wide variation in the reported rates. [107] There are many alternative measures of clinical accuracy that could be applied to an emergency medical dispatch such as sensitivity/specificity, positive predictive value (and negative predictive value), the number needed to treat or number needed to harm, as well as machine-learning measures such as those I have used (precision, recall, and F1 score). [7,108–110] Additionally, MPDS categories could be used as comparators for different types of incidents.

One possible reason for the existing lack of a gold standard is due to there being important differences between EMS, aptly captured in the phrase "if you have seen one EMS, you have seen one EMS." [111(p1)] Differences to do with acceptable levels of risk, staffing, the number of ambulances per capita and ambulance demand, all contribute to a lack of homogeneity. For example, at the Neely Conference in 2004, a committee of 31 experts met to establish a standard for over/under-triage rates to be used in EMS research. However, the committee was unable to reach an agreement on this heterogeneity among EMS. [112] Despite this, I think that the development of a standard measure of dispatch accuracy and an associated goal for that accuracy, is fundamental for the progression of research in this field and will make comparison of research findings in this field comparable.

11.5.4 Vulnerable road users

Vulnerable road users (motorcyclists, pedestrians and cyclists) are a distinct group of road users from motor vehicle occupants due to the limited physical protection during a road crash. Therefore, the injuries sustained by vulnerable road users and motor vehicle occupants can vary significantly in terms of severity, type, and likelihood. For example, pedestrians often suffer from severe injuries, including fractures, head injuries, internal injuries, and soft tissue injuries. Future research could separate data for analysis based on these two distinct groups (vulnerable road users and motor vehicle occupants) with the aim of improving accuracy for a decision tree approach to ambulance dispatch.

11.5.5 Additional Information Available to Dispatchers

With advances in technology, further information may become available to EMSs to assist in deciding what crashes do or do not require a L&S response. Future research could explore these alternative sources of information relevant to dispatch, such as through use of crash detection software in vehicles, or smart watches. One example of these examples is vehicles fitted with automatic crash notification systems (ACNS) that can provide a real-time prediction of the probability of death/serious injury of vehicle occupants following a crash. [113] While ACNS have been around for several years, they have been limited by the requirement for nationwide mandates (legislation requiring ACNS to be fitted in all new vehicles), whereas the internet of vehicles (IoV) is a promising avenue with the potential to be more effective than ACNS for EMS. The IoV is based on the principles of the Internet of Things (IoT), whereby physical objects (such as vehicles, roads, ambulances, or traffic lights) are fitted with communication and computing capabilities. [114] In the IoV, it is envisaged that vehicles will be able to communicate with each other, as well as other systems such as EMS. Rather than being limited to information collected by the vehicle involved in the crash, as with ACNS, the IoV would gain information from additional sources and this information could be in different formats such as predictive injury scales, vision, or audio. [115] While this may seem like a distant possibility, urban designers in Saudi Arabia are currently planning the world's first "cognitive and smart city" [116(p1)] called

Neom, which will be built with an IoV enabled. Further research is required to scope the potential for the IoV and its applicability to be used to identify the need for a L&S response.

11.6 CONCLUDING REMARKS

This thesis aimed to explore methods to identify the need for a L&S ambulance response to the scene of a road crash during the call for emergency medical assistance. In doing so, I found that less than a fifth of all road crashes attended by emergency ambulance required a L&S response. This means that unless EMS are willing to have high over-triage rates, which in an environment of increasing ambulance demand is becoming more difficult, a more accurate method of ambulance dispatch to crash patients is required. Furthermore, I determined that the current system used to dispatch ambulances (the MPDS alone) had poor predictive ability to identify the need for a L&S response. Consequently, I derived predictive models with a novel machine machine-learning approach, incorporating EMD text that could predict the need for a L&S response with high accuracy. My thesis has led me to conclude that it is possible for EMS dispatching to road crashes to improve system efficiency, and to get the right care, to the right patient, at the right time.

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