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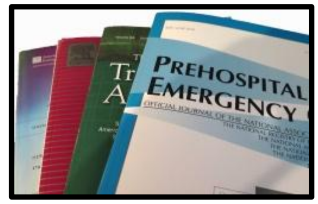

IPHMI Literature Review

Keeping You Up to Date with Current EMS Literature and Studies

Vol. 8.1

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1. Gender Differences in Defibrillator Practices in Out-of-Hospital Cardiac Arrest

Thompson K, Smith J, Tanski M, et al. *Prehospital Emergency Care* 2025;29:586–592

Studies have shown that there are differences in outcome after out-of-hospital cardiac arrest (OOHCA) between men and women. After initial recognition and activation of EMS, the second and third links of the cardiac arrest chain of survival involve direct, hands-on rescuer / patient interactions. Does initiation of high-quality CPR, specifically chest compressions and early defibrillation, differ based on patient gender? Are laypersons, in particular, and professional responders alike reluctant to bare the chest of females, to provide lifesaving procedures – specifically defibrillation?

The authors of this paper looked at adult (age $\geq$ 18) out of hospital cardiac arrests (OHCA) in the Northwest United States. They conducted an Oregon Health & Science University IRB approved, retrospective study with waived patient consent. Data from January 1st, 2018 through December 31st, 2021 were culled from the Portland Cardiac Arrest Epidemiologic Registry, a Portland, Oregon out of hospital cardiac arrest registry. They first looked at gender bias for layperson AED defibrillation and police first responder AED application when not previously deployed by laypersons. They also examined the time, by gender, of first defibrillation by EMS when encountering a patient without an AED already applied. Additionally, data was collected on patient age and location of arrest, public or private location.

The dataset was initially identified 3,843 non-traumatic OHCAs. That number was decreased to 3,049 (exclusions included 259 patients with Do Not resuscitate orders, 449 patient arrests witnessed by EMS and 83 with missing data points including gender). The final dataset consisted of 2,038 male and 1,011 female patients. Patient gender was grouped based on EMS assessed gender (on scene assumptions, patient legal documents and family information).

Overall, males had more pre-EMS AED applications than females (11.4% versus 7.6%). Police officers used an AED prior to EMS arrival on scene 36.2% of the time on males versus 23% of the time on females. EMS providers were also quicker to defibrillate shock treatable rhythms in male patients suffering from OHCA, without prior AED application, than females (4.6 minutes versus 5.5 minutes). The authors also discovered that female OHCA was more likely to occur in private versus public locations. This may have affected accessibility of an AED by laypersons.

There were limitations of this study. It was a retrospective observational study in nature and relied on data from one geographical area. EMS self-reporting elements may not have all been accurate including timing of interventions and gender. Additionally, they did not account for layperson accessibility of an AED.

Resuscitation from OHCA is dependent on the links in the chain of survival being performed quickly and efficiently by all members of the resuscitation team. Gender bias, possibly related to exposing an adult female's chest, might be understandable for the layperson. However, responders and medical providers understand the importance of preserving patient modesty but not at the expense of lifesaving care. This singular topic of baring a female's chest to apply and use an AED should be addressed in education programs for citizen responders and uniformed first responders.

2. **Disposition Outcomes Following Prehospital Use of Naloxone in a Large Metropolitan City in the United States.** Langabeer JR, Bakos-Block C, Cohen AS, et al. *Prehospital Emergency Care,* 2025:29:4, 361-366

Drug overdoses have surpassed trauma as the leading cause of injury-related deaths in the United States in recent years. In 2021, nearly 110,000 patients lost their lives to drug overdoses, the majority being from opioids. Despite the availability of Naloxone to the general population and its use by all levels of public safety responders, these numbers continue to rise. While some people will call 911 during an overdose crisis, many do not due to the worry of law enforcement and the criminal justice system interventions. The authors of this study examine the transport deposition of patients who receive EMS care and whether they refuse further treatment and transport to the Emergency Department.

The authors retrospectively examined data from opioid-related overdoses from January 1, 2018, to December 31, 2022 evaluated and treated by EMS in a single urban EMS system. A total of 6,582 cases were identified by a keyword search for possible opioid overdose. Of these, 5482 cases were included in the study cohort after exclusion criteria. Disposition information revealed 4984 (94%) patients were transported to an Emergency Department, with 304 (6%) patients refusing transport and 157 with undocumented final disposition and 37 in police custody.

The authors note limitations to the study that include multiple factors. The largest is the single city origin of the data. While the study took place in a large city (Houston), it may not be representative of other cities or regions. A secondary limitation noted was the "keyword" nature of the search. While keyword searches are a necessity when reviewing large blocks of data, they rely upon narrative reports from and data entered by field providers that may not yield all cases encountered during the study period.

The study demonstrated that patients in the study area were most likely to accept transport for further care and treatment at an Emergency Department after EMS care for narcotic overdose. EMS agencies should evaluate and understand the response, treatment, and transport complexities in their own communities.

3. **Associations Between Prenotification and Time to Management in Acute Stroke Patients Transported by Emergency Medical Services j**u Jeong, Y, Kim KH, Park JH, Ro YS, Song KJ, Do Shin S. Journal of Emergency Medicine 2025;74:77-85

Worldwide, stroke is the second most common cause of death. Time from symptom onset until definitive management is crucial to achieving a favorable outcome. This study looked at whether prehospital notification from EMS to the ED had an effect on the time to management for stroke patients.

The study population was all patients suffering acute ischemic stroke that were brought by EMS to an ED prepared with thrombolysis available between July 2020 and December 2021. Exclusion criteria were onset of symptoms greater than 24 hours, discharge from the ED, or transfer from another hospital. The study variable was whether or not EMS notified the receiving facility prior to arrival allowing for more prompt intervention. The primary outcome measures were the time to management in the ED, including stroke critical pathway (CP) activation, brain radiographic evaluation, intravenous thrombolysis, mechanical thrombectomy, and stroke unit admission."

The study population included 1,107 acute ischemic stroke patients, of which 742 patients were in the prenotification group and 365 patients in the non-notification group. The time to management was shorter in the prenotification group with CP activation at 10 vs 13.5 min. Radiographic evaluation of the brain was done within 27 min in the prenotification group vs 35 min in the group that did not include prenotification. Time to treatment also improved in the pre-notified group with thrombolysis being administered at 50.5 min vs 56.5 min in the non-pre-notified group and mechanical thrombectomy at 126.5 min vs 151 min. Time to admission was also better in the pre-notified group at 270.5 min vs 295.5 min.

The authors concluded that "in acute ischemic stroke patients, prehospital prenotification was found to be associated with shorter time to management."

The authors noted that the study had several limitations. The first was the potential for selection bias in the study subjects. They could not determine whether all acute stroke patients were eligible for the acute stroke management components mentioned. They noted that factors including medical history and underlying conditions might have caused delays in treatment. They also noted that delays in treatment due to prolonged onset of symptoms could not be assessed. Also, the study did not account for variations in the capabilities among the Eds participating in the study. The authors had confirmation of prenotification took place but not the content of the communications so they were unable to analyze this communication. Finally, they did not measure long-term neurologic outcomes which they admitted limits their ability to perform a detailed analysis. They also noted that the 26 Eds in the study were in a metropolitan area so their results might not be generalizable.

This study shows that there is a modest time savings when EMS personnel notify receiving hospitals of the likelihood of a stroke patient. Whether or not this is clinically significant cannot be determined given the lack of data on long-term neurologic function. Having said that, EMS personnel should, whenever possible, inform the receiving facility of their impending arrival with a likely stroke victim, just as they would for an acute trauma or myocardial infarction patient, to allow the ED staff to activate their internal resources and prepare for the patient's arrival.

4. **A Machine Learning Trauma Triage Model for Critical Care Transport.** Weidman AC, Malkouti S, Salcido DD, et al. *JAMA Network Open*. 2025;8(6):e259639. Full text available at: https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2835117

Current trauma triage guidelines are often unreliable, due partly to inclusion criteria that do not always reliably identify patients who require immediate lifesaving interventions (LSI). When faced with multiple casualties the task becomes even more difficult for the EMS provider when attempting to determine which patients will need LSI and other limited resources. Machine-learning (ML) analyses of patient physiologic factors could augment prehospital decision-making. Waveform analysis done in real time of physiologic factors such as heart rate and blood pressure and be analyzed into a predictive model to determine which patients would benefit from LSI. The authors developed a ML model capable of identifying single-patient LSI administration from a brief epoch of physiological waveform data. They examined how their model performs using standard ML metrics and per-patient overtriage and undertriage rates. They hypothesized that their model would perform on par with existing triage models while having overtriage and undertriage rates similar to the goals set in national trauma triage guidelines.

Patient data was collected from an aeromedical service in Pennsylvania from 2018-2021. Patients were included if they were classified as trauma, transported directly from the scene, and were aged 15-89. Pregnant patients and prisoners were excluded. A mean of 22.6 minutes elapsed between 911 dispatch and air transport crew arrival at the scene. No patient data from was recorded during this time. Once the air crew arrived, they began to record physiologic and waveform data, which was inputted into an electronic patient care reporting system. Data recorded included electrocardiography and heart rate; finger plethysmography and oxygen saturation; airway capnography and end-tidal carbon dioxide; and both invasive blood pressure (IBP, via arterial catheterization) and non-IBP (taken with a cuff). Data was analyzed for the first 15 minutes following arrival of the aeromedical crew to identify patients who most urgently required LSI. Each patient's physiologic waveform data was parsed into contiguous non-overlapping 2-minute epochs within the initial 15-minute period. Patients could have up to 8 epochs assessed during the 15-minute analytic period, with a final 1-minute epoch for some patients. Two-minute epochs allowed for time-specific predictions of patient LSI. Prehospital medical records and trauma registry data identified the occurrence of specific LSI treatments during this study period. The authors split LSI into 6 categories: airway interventions (e.g., endotracheal intubation), bleeding control (e.g., pelvic binder), blood transfusion, cardiovascular interventions (e.g. CPR), thoracic interventions (e.g. needle decompression), and vasopressor medication.

The authors used ML to predict prehospital LSI administration during each 2-minute epoch from physiological data recorded during the immediately preceding epoch. The authors used histogram gradient boosting (HGB), which involves fitting a series of decision trees to the data with each successive decision tree learning from the errors of the prior tree. Model performance was analyzed via the area under the receiver operating characteristics curve (AUROC). ML results were compared to prior prehospital over-and-undertriage rates. Undertriage is defined as those predicted to not need an LSI across all 2-minute epochs who did receive at least one LSI. Overtriage is defined as a patient predicted to need an LSI during one of the 2-minute epochs who did not receive any LSI. As per the field triage guidelines, the authors set the overtriage goal to be 35% and the undertriage rate at 5% or less.

A total of 2,809 patients were included in the study. The vast majority of patients have blunt injury (n=2535, 90%) and 202 had penetrating injury (7%). The remainder were either a combination of both or not recorded. LSIs occurred in 616 patients (21.9%). Good ML performance was observed. Model performance for airway intervention was strongest (AUROC of 0.910). Model performance for blood transfusion and vasopressor medication was moderate (AUROC 0.784 and 0.816). Model performance for bleeding control, thoracic interventions, and cardiovascular interventions was weaker (AUROC 0.580, 0.675, and 0.650 respectively). The model had a 21.3 undertriage rate (higher than the national goal of < 5%) and an overtriage rate of 34.9% (near the national goal of 35%).

The study has several limitations. A patient receiving an LSI doesn't necessarily mean it was indicated. Data were derived from a critical care database in which patients were transported by air. These results may not be applicable in other EMS systems and patient populations. LSI timestamps were taken from EMS records and are subject to recording errors. The authors only examined the first 15 minutes following medic arrival with the logic being that most LSIs would occur during this time period. The model may not predict intervention requirement during later states of transport.

This cohort study of trauma patients was analyzed with a machine learning model to identify single-patient need for LSI during 2-minute epochs in the first 15 minutes of medic arrival based on immediately preceding physiologic waveform analysis. It is an interesting concept and could have implications for prehospital triage during mass casualty events or in austere environments. As machine learning and artificial intelligence become more prevalent, it will be incumbent on the provider to be familiar with the strengths and limitations of the technology. This paper shouldn't alter practice, but will likely be the first of many studies in the coming years utilizing machine learning to predict treatment in critically ill patients.