A Bayesian Approach on Investigating Helicopter Emergency Medical Fatal Accidents

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INTRODUCTION: Helicopter Emergency Medical Service (HEMS) is a mode of transportation designed to expedite the transport of a patient. Compared to other modes of emergency transport and other areas of aviation, historically HEMS has had the highest accident-related fatality rates. Analysis of these accident data has revealed factors associated with an increased likelihood of accident-based fatalities. Here we report the results of an analysis on the likelihood of a fatality based on various factors as a result of a HEMS accident, employing a Bayesian framework.

METHODS: A retrospective study was conducted using data extracted from the NTSB aviation accident database from April 31, 2005, to April 26, 2018. Evidence from Baker et al. (2006) was also used as prior information spanning from January 1, 1983, to April 30, 2005.

RESULTS: A Bayesian logistic regression was implemented using the prior information and current data to calculate a posterior distribution confidence interval of possible values in predicting accident fatality. The results of the model indicate that flying at night (OR 3.06; 95% C.I 2.14, 4.48; PoD 100%), flying under Instrument Flight Rules (OR 7.54; 95% C.I 3.94, 14.44; PoD 100%), and post-crash fires (OR 18.73; 95% C.I 10.07, 34.12; PoD 100%) significantly contributed to the higher likelihood of a fatality.

CONCLUSION: Our results provide a comprehensive analysis of the most influential factors associated with an increased likelihood of a fatal accident occurring. We found that over the past 35 yr these factors were consistently associated with a higher likelihood of a fatality occurring.

KEYWORDS: HEMS, Bayesian, accidents.

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Helicopter Emergency Medical Services (HEMS) are a mode of transportation used to expedite the transport of a patient to a care facility. The inception of this program has its roots in the Vietnam war, in which the helicopter was a popular method of rapidly transporting the injured from rough or otherwise inaccessible terrain to field hospitals.[17] Since then, the use of helicopters in emergency transport has seen a steady increase in popularity from under 25,000 EMS helicopter flight hours in 1980 to nearly 600,000 flights hours in 2017.[6,7]

While the use of this technology for rapid transit is shown to decrease patient mortality rates,[16] controversy about the necessity of HEMS flights has been a contentious issue for decades. Specifically, medical professional consensus states that providing care within an hour of injury to trauma patients significantly increases their chances of survival. However, a review of the literature presents "little scientific evidence" that supports this position.[13] A review of the fatality and accident rates within the HEMS field reveals that EMS helicopters have nearly twice as many fatal accidents per 100,000 flight hours as any other form of aviation.[6] Although accident-related factors are associated with an increase in fatalities in HEMS accidents,[1] there is very little evidence of the factors that contribute to increased accident rates in HEMS. In other words, we know if lives will be lost due to a certain accident, but we have a poor understanding of the factors that are associated with an increased risk of an

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accident occurring. This paper intends to aggregate the past 35 yr of data on HEMS accident fatalities utilizing a Bayesian framework to best understand the conditions that are linked to loss of life in these accidents.

A number of studies have investigated and reviewed the state of HEMS and its risk factors;[1,3,4] however, the most recent of these comprehensive studies reviewing HEMS fatalities in the United States was published over a decade ago.[6] Our contributions in this paper include a review of HEMS accidents using data from 2005 to 2018 that is combined with previous research to strengthen the evidence of what contributes to an increased fatality likelihood. We achieve this by implementing prior evidence of the factors that contribute to HEMS accidents into a model with current data via the Bayesian framework. Due to the lack of research and evidence of any factors other than fatal HEMS outcomes, we are limited to what we can infer from prior information. As such, the scope of this paper focuses solely on what may affect the likelihood that any fatality occurs as the result of an accident by updating past evidence with current data.

Bayesian methodology is a framework that uses conditional probability and prior information on the probability of a condition occurring to inform and estimate the credibility that an event will occur or not. Essentially, it is a method of updating the credibility of an event based on previous information about said event. This framework is often expressed as its equation (Eq. 1). The left side of the equation represents the posterior probability or distribution, which is the updated probabilities when new information is merged with prior data. The right side of the equation represents the combination of the likelihood, or current data, and the prior information.

$$\textit{Likelihood Parameter} \propto \text{Posterior Parameter} \times \text{Prior Parameter} \quad \text{Eq. 1}$$

Below we discuss a few key differences of the Bayesian methodology that underlie its application in this study. First, and mainly, Bayesian methods do not utilize *P*-values to interpret significance of a viable model. Rather, various methods of identifying a variable influence on a model's ability to predict data are used. For the model developed in this paper, we identified any posterior that included zero in its 95% confidence interval and excluded it. In our application of Bayesian methodology, we use a combination of coefficient effects and their confidence intervals along with a priori theory to inform us of variable and model selection as well as hierarchical model comparison via a leave-one-out method of cross-validation.

The use of Bayesian methodology to update evidence is a popular technique applied in a multitude of fields to improve inferential power from the analyses conducted. For example, Solomon and King[18] presented a Bayesian application to studying the factors that are associated with accident rates for fire vehicles, and Miranda[15] applied a Bayesian framework to better understand Naval aviation mishaps. Similarly to these studies, we use prior information about the factors associated with higher likelihood of fatalities in HEMS accidents to update current data.

METHODS

A retrospective study of fatalities on HEMS related flights from April 31, 2005, to April 26, 2018, was conducted using information available from the National Transportation Safety Board (NTSB) aviation accident database. The inclusion criterion for an accident was that a helicopter designated for medical duties was involved in an unintended impact to any part of the aircraft or any unintended incident that led to the necessity of an NTSB investigation. A total of 131 HEMS accidents were extracted from the NTSB database. All information relevant to the accident reported in the NTSB's final report document was collected, organized, and concatenated for analysis. The prior distributions for the parameters of our model were based on previous research identifying the key factors that contribute to the likelihood of a fatality for HEMS accidents occurring between January 1, 1983, and April 30, 2005.[1]

Procedure

Bayesian inference is a method that incorporates both prior and current information into a model aimed at understanding conditional probabilities, i.e., the likelihood of two or more events happening together. This is accomplished using three main parameters of a model called the prior, likelihood, and posterior. The prior, or prior distribution, is the information from prior beliefs that is incorporated into the new model, or in other words, the currently known conditional probabilities between two events. After the current data, or likelihood, is entered into the model, we are given the posterior distribution, which is the distribution when the likelihood and prior parameters are combined. Each factor entered into a model (e.g., all input variables) is broken down into its parameters (i.e., mean, variance, etc.), which are assigned prior distributions which leads to a posterior distribution that contributes to the posterior prediction of the outcome. These aspects of Bayesian analysis are summarized in a graphical representation of Bayes' Formula (**Fig. 1**).

Deciding on the most appropriate prior is an important component of Bayesian statistics and generally receives the

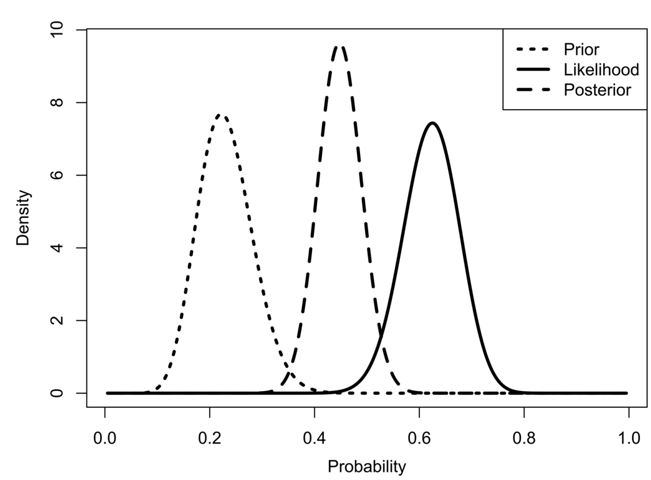

Fig. 1. Graphical representation of Bayes Theorem.

most scrutiny as a poorly formed prior can have as much influence on the outcome of the model as a diligently constructed one. As such, the use of three types of priors have been suggested: noninformed, weakly-informed, and informed. These are described below in order of least to most desirable, although this can depend heavily on the objective of the researcher.[9] The first, and oftentimes least desirable prior is noninformed, or a diffuse prior. This is essentially the assumption that no prior information is known about the conditional probability of a phenomena. Thus, any value of the parameter is possible, and findings are solely modeled on the current data. An example would be the first space shuttle accident, where there was no prior information from previous incidents to understand the probability of such an event occurring. The second type of prior is the weakly-informed prior which is used when a general effect direction of the parameter is known, but no specific information can be inferred. A semi-informative distribution may be represented by a standard normal distribution with a large confidence interval to cover the most likely event. An example for a weakly informed prior could be nuclear power plant accidents. Very few of these have occurred since the inception of the nuclear reactor, and reactors vary vastly in their construction and day-to-day activities, but information can be extracted from the few incidences that have occurred to understand general probabilities. Finally, there is the informed prior, which is used when specific prior information about a parameter is available. Our prior distributions are a representative example of this type of prior, where exact effect sizes and variances are used based on previously published data. Another example of this would be with a commercial aviation accident where a database of all commercial accidents in modern history can be accessed for understanding the probabilities of a particular incident.

Although there is a logical order to the quality of the type of prior it is important to note that poor application of any type of prior may lead to a deceptive posterior. However, when applied correctly, the Bayesian method updates can allow for previously inferred conclusions with new data to estimate a more accurate population-level effect. In the case of this study, we specifically examine whether fatalities occur as a result of a HEMS accident at a higher rate in concordance with other aspects of the flight such as environmental factors or pilot experience.

Statistical Analysis

Logistic regression is a technique under the generalized linear model that allows one to model predictions of dichotomous outcomes with continuous, multinomial, and dichotomous predictors.[19] When the predictors are put into the logistic regression model, they are processed through a logit function that then compares the effect of their presence on the odds that the outcome will happen or not. The output of the predictors of the logistic regression are the log odds. When exponentiated, log odds become the odds ratio, which is a measurement of an event occurring vs. an event not occurring based on the outcome of the dependent variable. The Bayesian framework of this model is similar in function with the exception that prior information interacts with the likelihood of each predictor to produce a posterior distribution of log odds for each variable. These posterior log odds represent an interval of possible values that attempts to classify the outcome of the variable.

We conducted a Bayesian logistic regression of whether a fatality occurred as the result of a HEMS accident predicted by a set of factors recorded in the associated NTSB reports. Our analysis utilized prior information of HEMS fatality occurrences from January 1, 1983, to April 30, 2005, by a previous study.[1] Three informative prior coefficients were derived from previous HEMS fatal accidents. The informative priors were extracted from a logistic regression odds ratio report, then converted back into logit and standard error coefficients. All binary variables were standardized with a mean of zero and a maximum of one as recommended by Gelman et al.'s[11] review of Bayesian logistic regression procedures.

The model was developed using multiple steps including variable selection, combining prior evidence with our current data (e.g., likelihood), using a Monte Carlo Markov Chain to calculate the posterior distribution for each parameter and for the model outcomes. Variable selection was conducted by analyzing all variables included in the NTSB reports for which they were extracted. These variables were then constructed into contingency tables or two-sample comparison tests and analyzed to determine whether a difference between the two conditions of the data (i.e., fatality or no fatality) existed. If no difference was detected, then the variable was left out of the model. We carried these analyses out using a permutation test, which is a popular nonparametric testing technique that does not suffer from the many assumptions (i.e., distribution limitations) that other nonparametric tests must adhere to. This test randomly resamples the distributions it is examining, while recalculating the test statistic (e.g., mean, median, etc.) which results in a stronger and more confident test of the differences between the two samples. This method was conducted due to the low event rate and irregular distributions (e.g., skewness and kurtosis) of the data included.

Combining prior and current evidence in the Bayesian framework often necessitates the use of advanced resampling methods as simulating and combining distributions can become complex with real-world data. Thus, an extra step in combining the information requires the use of various sampling techniques such as Monte Carlo Markov Chains (MCMC). Essentially, this works by estimating samples of the posterior distributions until an overall distribution is converged upon. However, as distributions are not always easily estimated, model diagnostics are available to determine if the sampled posterior distribution is reasonable.

We estimated model fit via the $\hat{R}$[10] (r-hat), the effective sample size and its ratio,[8] and the probability of direction (PoD)[14] statistics. The ratios of effective sample size can be interpreted as the number of independent samples used to calculate parameters of the posterior distribution over the number of samples used in the model. $\hat{R}$ is a measurement of MCMC convergence which compares the average variance of each draw of the MCMC to the variance of the pooled draws of all chains. It measures how consistent each sampled posterior distribution is to one another. If the models successfully converge to a common distribution (i.e., the posterior distributions parameters are similar) then $\hat{R}$ will be 1, indicating successful posterior draws. Probability of Direction is a calculation that describes the probability that an effect size will follow a particular direction. The PoD can be interpreted similarly to a P-value, where a 97.5 PoD represents a posterior effect in which 97.5% of all values will be in that direction. Finally, we calculated model comparison of fit via Pareto Smoothed Importance Sampling-Leave-One-Out (PSIS-LOO) cross-validation to communicate the strength of evidence about model fit. PSIS-LOO cross-validation using the *LOO* package in R[20] works by using the simulated data of the Bayesian model to predict a single data point, after being trained to predict the rest of the sample. This method has been shown to be effective in Bayesian model comparison with a wide array of sample sizes and consistently out-performs other Bayesian model fit methods.[21] Like with other model fit procedures (e.g., AIC, BIC, etc.) model comparison diagnostics are produced for interpretation, in this case with Expected Log Predictive Density (elpd) and its standard error. elpd is measured wherein the larger the number the better the fit, and in measuring the model comparison the larger the elpd is to its standard error, the better the fit of one model over the other.

RESULTS

HEMS accidents occurred with an average of 9.29 (N = 131, SD = 4.46) accidents per year, which is 1.19 more accidents per year compared to the previous review of HEMS accidents reported by Baker et al.[1] (N = 182, M = 8.1 per year). A one-sample t-test using the Baker et al.'s[1] sample of 8.1 accidents per year as a test value indicates that significantly more accidents occurred during the time frame between April 31, 2005, and April 26, 2018, as compared to January 1, 1983, and April 30, 2005.

A total of 398 people were involved in these accidents, 127 (31.90%) were killed and 94 (23.62%) incurred minor, or serious injuries. The pilots involved in these accidents had accumulated 601,497 (median = 5225, IQR = 3311; 7972) flight hours in total and 85,681.8 (median = 365.5, IQR = 126.25; 917.75) flight hours with their respective aircraft at the time of the accident. Further, the pilots had accumulated 4527 (median = 38, IQR = 28; 50.75) flight hours in the 90 d before the accident. Some 73 (77.66%) of the pilots from these accidents held a class 2 medical license and 51 (55.43%) held a medical waiver. There were 54 (45.38%) accidents which occurred at night, 78 (74.29%) accidents happened without a patient on board, 15 (15.30%) of the accidents happened in IFR weather, and 27 (26.21%) resulted in a fire. **Table I** provides a comparison between the demographic information garnered from our dataset compared to that of Baker et al.'s.[1] Missing data from incomplete or unavailable NTSB reports reduced our final sample size to 97 accidents for our logistic regression model.

Table I. Current and Prior Accident Demographics.

FACTOR	1983–2005		2005–2018	
	Fatal	Non-Fatal	Fatal	Non-Fatal
Pilot's Average Flight Hours	**5968**	**6230**	**6867**	**5974**
Fatal Crashes	71		45	
Deaths	184		127	
No to Moderate Injuries	373		271	

Relevant prior information extracted from Baker et al.[1] included the time of day of the flight, whether the conditions at the accident site were Instrument Flight Rules (IFR) or Visual Flight Rules (VFR), and if a post-crash fire occurred. Variable selection for our logistic regression was determined via multiple criteria. First, any variable that had an informed prior was included in the model (e.g., time of day, post-crash fire, and weather conditions). Any other factors extracted from the NTSB reports for which we could not identify an informed prior was organized into a contingency table for discrete data or two-sample comparisons for continuous data and then tested for differences (**Table II**). The two-sample comparisons of average pilot flight hours for fatal and nonfatal accidents (skewness = 1.23; 1.13, kurtosis = 0.54, 0.98) and average pilot flight hours in the accident helicopter for fatal and nonfatal accidents (skewness = 2.06; 4.04, kurtosis = 3.40, 17.91) suffered from significant skewness and kurtosis. Thus, each of these factors were compared via an independent sample permutation test.

In determining our sampling model convergence and fit (i.e., MCMC), we explore the effective sample size calculation and $\hat{R}$ calculation listed in **Table III**. Our Neff/N values for each parameter estimation of the model is greater than 0.1, indicating a strong effective sample size and confident estimation of the parameters of our logistic regression model. Additionally, the $\hat{R}$ of the posterior distributions all converged to 1 indicating that the posterior sample distributions successfully converged.

Our results show that flying at night (OR 3.06; 95% C.I 2.14, 4.48; PoD 100%), the occurrence of a post-crash fire (OR 18.73; 95% C.I 10.07, 34.12; PoD 100%), and flying under instrument flight rules (OR 7.54; 95% C.I 3.94, 14.44; PoD 100%) increased the odds of a crash being fatal. As logistic regression is a classification technique, we also test how well it classifies the outcomes compared to the original data as well as compared to the fitted model with a null model without predictors. In checking whether the predicted outcomes from the model match the original data, we can visually check for inconsistencies in a posterior predictive check. **Fig. 2** does not display any apparent deviance in posterior distributions (y rep) compared to the distribution of the original data (y). Next, we determine if the fitted model fits the data better than the null model without any variables. Essentially, we are testing if the fitted model that determines the outcome of an accident is doing so better than chance. A quantifiable means of comparing the models is to measure the degree of evidence in which the fitted model fits better than the null model (i.e., using PSIS-LOO). The comparison of fit results

Table II. Variable Comparison with Permutated *P*-values.

FACTOR	NOT FATAL	FATAL	*P*-VALUE (95% C.I.)
Passenger on Board			
Yes	6	3	*P* = 0.733 (0.721, 0.745)
No	57	38	
Medical Class			
2	42	31	*P* = 0.609 (0.596, 0.622)
1	14	7	
Patient on Board			
Yes	13	14	*P* = 0.174 (0.164, 0.184)
No	50	28	
Medical Waiver			
Yes	29	22	*P* = 0.830 (0.820, 0.839)
No	25	16	
NVG's Used			
Yes	5	3	*P* = 0.077 (0.079, 0.085)
No	3	11	
Avg. Pilot Total Flight Hours	median = 5380, Q1 = 3380;Q3 = 7928	median = 5092, Q1 = 3200;Q3 = 9260	*P* = 0.295 (0.283, 0.307)
Avg. Pilot Aircraft Flight Hours	median = 480, Q1 = 125;Q3 = 760	median = 315, Q1 = 130;Q3 = 1100	*P* = 0.11 (0.102, 0.118)

Table III. Final Model.

FACTOR	ODDS RATIO	POSTERIOR (LOGIT; 95% C.I.)	LIKELIHOOD (LOGIT; 95% C.I.)	PRIOR (LOGIT, SE)	EFF. SAMPLE SIZE	PoD	$\hat{R}$
Intercept		−2.15; −2.78, −1.58	−2.13; −3.25, −1.24	Cauchy (0,10)	4691	100	1
Night Flight	3.06	1.12; 0.76, 1.50	0.99; −0.15, 2.24	Normal (1.16, 0.211)	4192	100	1
Fire	18.73	2.93; 2.31, 3.53	3.39; 2.08, 5.02	Normal (2.77, 0.355)	4785	100	1
IFR Weather	7.54	2.03; 0.1.37, 2.67	1.86; 0.35, 3.57	Normal (2.079, 0.377)	5037	100	1

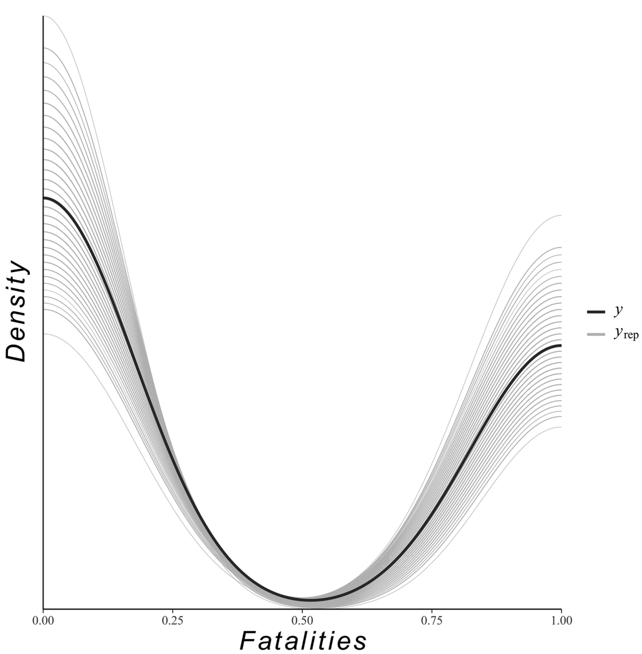

Fig. 2. Fitted model graphical posterior predictive density overlay.

for our fitted and null models resulted in an expected log predictive density indicating extreme evidence that the fitted model fits the data far better than the Null model, elpd = 22.7, SE = 5.4. In other words, the test shows there is substantial evidence that the model with the included factors (Table III) predicts fatal outcomes better than random.

Table III is a summary of the results of the Bayesian logistic regression model. It includes the odds ratio of the posterior distribution and the logits and 95% confidence intervals of the posterior, likelihood, and prior distributions, as well as the model convergence criteria of the Bayesian logistic regression model including effective sample size, probability of direction, and the $\hat{R}$ values.

DISCUSSION

Helicopter Emergency Medical Services (HEMS) expedites the transport of patients between care facilities or from remote accident sites to care facilities that may have specialized facilities. Proponents of HEMS cite the golden hour as evidence favoring the use of these services.[16] The golden hour refers to the finding that survival rates are highest if a patient receives care as soon as possible following a severe injury. However, researchers investigating the cost and benefit of HEMS transport have argued that these services are being utilized for patients with conditions that do not justify the cost or potential risk of this mode of transport. For instance, a meta-analysis showed that 61.4% of the patients who were transported via helicopter from a scene to a hospital only received minor injuries as a result of the original incident.[5]

Additionally, the trends in HEMS accidents should be cause for concern given the risk to passengers, aircrew, medical crew, and the patient as HEMS accidents have historically suffered from the highest fatality rate of any other aviation transportation method.[6,12] Our model offers insight into the factors that may influence increased fatalities given that an accident has occurred. The results show that a post-crash fire, flying in IFR conditions, and flying at night are more frequently associated with accidents involving fatalities. Further, due to the application of Bayesian inference, we were able to combine the measurable influence of information from prior analyses. The prior influences of post-crash fires, night flying, and flying in poor weather strengthened our inferences of their effects on the chance of a fatal accident due to the information they added to our model. Thus, as a result of our Bayesian specified model, we present a review analysis of the odds of these factors occurring during fatal accidents from January 1st, 1983, to April 26, 2018, which is the most extensive review of HEMS accidents to date. Additionally, inspection of the prior and current evidence of the included factors indicates that over these past 35 yr of HEMS accidents, the odds that a factor will increase the likelihood of a fatality as a result of an accident has barely changed (Table III). This indicates that the interventions and policies implemented in the United States, such as those suggested by the 2009 NTSB HEMS review forum,[6] may not have resulted in sufficient safety improvements in relation to the identified factors. However, this review is limited only to the prior information available to us and the data gathered from NTSB accident reports.

These results advance our understanding of the factors associated with the outcomes of HEMS flights. While the estimated rate of HEMS accidents is seemingly low given the number of flights per year, the risk of death, or injury, as a result of any of these accidents is high. Specifically, the environmental conditions included in the analyses (flying at night and in IFR weather) are shown to increase the risk of a fatal accident in both general aviation and HEMS but are also shown with high confidence to contribute to higher rates of fatalities.[1,2] One caveat is that the temporal order of these factors is not considered in this analysis. Specifically, flying in IMC weather or at night precede a post-crash fire, and thus may be considered causal factors. However, the analysis structure (e.g., choice and implementation of prior information) limited our ability to conduct such analyses.

The analysis has several limitations pertaining mainly to the lack of prior information. With respect to the priors, the field of HEMS accident investigation lacks data on a number of important issues including the identification of the factors associated with an increased number of fatalities as a result of an accident, factors associated with increased numbers of injuries as a result of an accident, and most importantly a comparison between factors associated with accidents and nonaccidents. The absence of flight data activity (i.e., yearly total of HEMS flights, environmental conditions on all HEMS flights) regardless of the outcome prevents us from understanding if the conditions present during a HEMS accident are unique to those incidents. Future research should explore the increased risk HEMS flights pose to patients, passengers, and care providers.

We presented a comprehensive analysis of what factors are associated with fatal HEMS accidents by combining prior evidence with current information to form a confidence interval of possible odds ratios associated with each factor. We found that over the past 35 yr post-crash fires, flying at night, and flying in inclement weather conditions were consistently associated with a higher likelihood of a fatality occurring. Further, we argue that the lack of data about various aspects of the HEMS community prevent us from understanding the risk a HEMS transport places on the patients, providers, and crew. Increasing patient safety during HEMS flights and ensuring provider and crew safety during flights is of paramount importance. A framework of research investigating the data-driven analysis of accident risk and added risk to patients should be the focus of future work.

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