

8-1-2017

Cardiac arrest risk standardization using administrative data compared to registry data.

Anne V. Grossestreuer

Beth Israel Deaconess Medical Center

David F. Gaieski

Thomas Jefferson University, david.gaieski@jefferson.edu

Michael W. Donnino

Beth Israel Deaconess Medical Center

Joshua I.M. Nelson

University of Pennsylvania

Eric L. Mutter

*Queen's University, Kingston, ON**See next page for additional authors*

[Let us know how access to this document benefits you](#)

Follow this and additional works at: <https://jdc.jefferson.edu/emfp>Part of the [Cardiology Commons](#), and the [Emergency Medicine Commons](#)

Recommended Citation

Grossestreuer, Anne V.; Gaieski, David F.; Donnino, Michael W.; Nelson, Joshua I.M.; Mutter, Eric L.; Carr, Brendan G.; Abella, Benjamin S.; and Wiebe, Douglas J., "Cardiac arrest risk standardization using administrative data compared to registry data." (2017). *Department of Emergency Medicine Faculty Papers*. Paper 62.

<https://jdc.jefferson.edu/emfp/62>

Authors

Anne V. Grossestreuer, David F. Gaieski, Michael W. Donnino, Joshua I.M. Nelson, Eric L. Mutter, Brendan G. Carr, Benjamin S. Abella, and Douglas J. Wiebe

RESEARCH ARTICLE

Cardiac arrest risk standardization using administrative data compared to registry data

Anne V. Grossestreuer^{1*}, David F. Gaieski², Michael W. Donnino^{1,3}, Joshua I. M. Nelson⁴, Eric L. Mutter⁵, Brendan G. Carr², Benjamin S. Abella⁴, Douglas J. Wiebe⁶

1 Department of Emergency Medicine, Beth Israel Deaconess Medical Center, Boston, Massachusetts, United States of America, **2** Department of Emergency Medicine, Thomas Jefferson University, Philadelphia, Pennsylvania, United States of America, **3** Department of Medicine, Division of Pulmonary and Critical Care Medicine, Beth Israel Deaconess Medical Center, Boston, Massachusetts, United States of America, **4** Department of Emergency Medicine, University of Pennsylvania, Philadelphia, Pennsylvania, United States of America, **5** Department of Emergency Medicine, Queen's University, Kingston, Ontario, Canada, **6** Center for Clinical Epidemiology and Biostatistics, University of Pennsylvania, Philadelphia, Pennsylvania, United States of America

* agrosses@bidmc.harvard.edu



OPEN ACCESS

Citation: Grossestreuer AV, Gaieski DF, Donnino MW, Nelson JIM, Mutter EL, Carr BG, et al. (2017) Cardiac arrest risk standardization using administrative data compared to registry data. PLoS ONE 12(8): e0182864. <https://doi.org/10.1371/journal.pone.0182864>

Editor: Chiara Lazzeri, Azienda Ospedaliero Universitaria Careggi, ITALY

Received: May 4, 2017

Accepted: July 25, 2017

Published: August 4, 2017

Copyright: This is an open access article, free of all copyright, and may be freely reproduced, distributed, transmitted, modified, built upon, or otherwise used by anyone for any lawful purpose. The work is made available under the [Creative Commons CC0](https://creativecommons.org/licenses/by/4.0/) public domain dedication.

Data Availability Statement: Due to ethical restrictions, the data underlying this study are available upon request to qualified researchers. The PATH registry, by nature of its agreements with member sites, imposes these restrictions. Sharing publicly a de-identified data set would violate the terms of the Data Use Agreements (DUA) and Business Associates Agreements (BAA) that are entered in by all PATH member hospitals. As a part of the BAA and DUA, data collected in PATH and utilized for research are not permitted to be disclosed. Any data requests could be routed to the

Abstract

Background

Methods for comparing hospitals regarding cardiac arrest (CA) outcomes, vital for improving resuscitation performance, rely on data collected by cardiac arrest registries. However, most CA patients are treated at hospitals that do not participate in such registries. This study aimed to determine whether CA risk standardization modeling based on administrative data could perform as well as that based on registry data.

Methods and results

Two risk standardization logistic regression models were developed using 2453 patients treated from 2000–2015 at three hospitals in an academic health system. Registry and administrative data were accessed for all patients. The outcome was death at hospital discharge. The registry model was considered the “gold standard” with which to compare the administrative model, using metrics including comparing areas under the curve, calibration curves, and Bland-Altman plots. The administrative risk standardization model had a c-statistic of 0.891 (95% CI: 0.876–0.905) compared to a registry c-statistic of 0.907 (95% CI: 0.895–0.919). When limited to only non-modifiable factors, the administrative model had a c-statistic of 0.818 (95% CI: 0.799–0.838) compared to a registry c-statistic of 0.810 (95% CI: 0.788–0.831). All models were well-calibrated. There was no significant difference between c-statistics of the models, providing evidence that valid risk standardization can be performed using administrative data.

Conclusions

Risk standardization using administrative data performs comparably to standardization using registry data. This methodology represents a new tool that can enable opportunities to

Legal Department at the University of Pennsylvania via the PATH Database Manager, David Buckler, who can be reached at 215-746-4630 or bucklerd@upenn.edu.

Funding: The authors received no specific funding for this work.

Competing interests: Dr. Grossestreuer received research support from the American Heart Association. Dr. Abella reports research funding from the National Institutes of Health, American Heart Association, Medtronic Foundation and CR Bard, as well as honoraria from CR Bard and advisory board membership with CardioReady. Dr. Gaieski reports research funding from CR Bard, as well as honoraria from CR Bard. Dr. Donnino serves as a paid consultant for the American Heart Association and reports research funding from the National Institutes of Health and the American Heart Association. Dr. Carr spends a portion of his time as the Director of the Emergency Care Coordination Center in the Office of the Assistant Secretary for Preparedness and Response. Dr. Wiebe, Dr. Nelson, and Dr. Mutter have disclosed no competing interests. These interests do not alter our adherence to PLOS ONE policies on sharing data and materials.

compare hospital performance in specific hospital systems or across the entire US in terms of survival after CA.

Introduction

Cardiac arrest (CA) is a widespread and unexpected clinical condition that represents a challenge to prevent, manage, and study. Differences in definitions,[1] termination-of-resuscitation rules,[2, 3] data collection[1, 4] and participation in registries,[5] as well as patient heterogeneity[6] make even capturing the incidence of CA difficult.[1, 4, 7] This diversity can lead to differences in outcomes that may be influenced by variations in care. [8–21] Recent initiatives to change both intra- and post-arrest care have led to improved outcomes,[22–28] highlighting the importance of performing these assessments. Additionally, the National Academy of Medicine has recently recognized as a priority the need for better CA data collection and outcomes improvement.[29]

An important step to better understand the management of CA involves comparing hospitals.[30] Unfortunately, many US hospitals do not participate in a registry that provides such outcomes; contributing can be prohibitive in terms of financial and time costs.[31, 32] As of 2016, out of the over 5000 hospitals in the United States[33], only 7% were contributing to the largest in-hospital cardiac arrest registry in the country[34], and about 40% were providing outcomes to EMS agencies regarding out-of-hospital cardiac arrest patients treated by that EMS agency and delivered to their hospital.[35] Additionally, because these registries are voluntary, participation may lead to selection bias and other systematic errors.[36] As registry data are the only current method for risk adjustment[37] in CA, there is no way to enable fair comparison of observed mortality relative to expected mortality given patient characteristics across all US hospitals treating CA.

Quality is compared nationwide through the Centers for Medicare and Medicaid Services using administrative-type claims data to risk standardize the patient case mix of individual hospitals, which potentially could point to an avenue through which to measure quality in CA. To our knowledge, no studies have investigated whether administrative data on CA, shown to be useful for risk standardization of sepsis patients[38] and potentially available for all hospitals in the U.S., could perform as well as registry data to accomplish risk standardization to study variability in CA outcomes. If administrative-type data perform as well as registry data in this population, we will have evidence that a tool for risk standardization potentially can be developed and applied to hospitals to compare quality across the US. We therefore aimed to develop a method for risk-standardizing hospital survival after CA using administrative data that is validated against one using registry data.

Methods

Data source

The registry data were from the Penn Alliance for Therapeutic Hypothermia (PATH) database. PATH is an internet-based registry established by the University of Pennsylvania in 2010. PATH includes CA data from pre-hospital, emergency department, and in-hospital settings. Potentially available to any US hospital, PATH supports the tracking of all patients who experience CA and receive cardiopulmonary resuscitation. CA is defined in PATH as a loss of pulse with subsequent chest compressions. Each patient record in PATH consists of 30 required data elements based on the Utstein template.[4, 39] One hundred additional data

elements are required for research participation. Further optional data elements are also available to address specific research questions. Data are entered via a secure website and maintained on a password-protected encrypted server at the University of Pennsylvania. Data are collected retrospectively at each of the participating institutions. Before entering data, data abstractors undergo structured training including mock case entry and case review. All participants are provided with a standardized data dictionary and are subject to a formal auditing process. PATH currently supports 34 member hospitals from 19 US states and includes data from over 5000 CAs. Exclusion criteria for this study were age <18 years, traumatic etiology of arrest, active do-not-resuscitate orders prior to arrest, and lack of administrative data.

Administrative data for this study were from the Penn Data Store, a research initiative at the University of Pennsylvania that integrates clinical data on all University of Pennsylvania Health System (UPHS) patients. All available administrative information on CA patients (defined as having an ICD-9 code of 427.5) seen at three UPHS hospitals, the Hospital of the University of Pennsylvania, Penn Presbyterian Medical Center, and Pennsylvania Hospital, was queried, and consisted of demographics, procedure codes, diagnosis codes, and drug and other orders. These data were then matched on medical record number to records from the PATH database. Only patients with both data in PATH and Penn Data Store were included in the risk standardization model building, creating a convenience sample of a granular dataset matched with administrative-type data. This study was approved by the University of Pennsylvania Institutional Review Board with a waiver of consent.

Model building

Recommended guidelines for conducting risk adjustment for trauma, another time-sensitive critical illness, have been published, allowing comparison of trauma center outcomes.[40] Using these methods as guidance, we applied and adapted that approach to develop two risk standardization models.

First, we developed a method for risk-standardization using registry data for in- and out-of-hospital CA patients using logistic regression with survival to discharge as the outcome. Cox regression was not used because our interest was not in time to the outcome of interest (death) but in whether death had occurred by hospital discharge. A total of 12 variables (Table 1) were modeled as potential independent, adjustor variables. The variables were selected to match, to the extent possible, the non-modifiable variables in the Utstein template. [4, 39] These variables were modeled through a backward stepwise variable selection process (using a $p < 0.25$ to enter the model)[41, 42] to generate the most parsimonious model and evaluate changes in predictive ability. Variables that did not contribute to prediction were excluded from the final model. The final model included race, whether the arrest was witnessed, initial rhythm, age, year of arrest, etiology of arrest, and whether the patient regained

Table 1. Variables explored for registry risk standardization.

Age*	Sex*	Race*
Location of arrest*	Etiology of arrest	Initial pulseless rhythm*
If patient was transferred*	Year of arrest*	If arrest was witnessed*
Duration of arrest	Bystander CPR provided*	Whether patient regained consciousness shortly post-arrest*

*variables with a univariate p-value with the outcome of interest of <0.25

<https://doi.org/10.1371/journal.pone.0182864.t001>

consciousness shortly post-arrest (defined as ineligibility for TTM due to purposeful following of commands). Significant missing data (more than 5% but no more than 15%) were addressed through multiple imputation, conducted using 20 iterations and then combined using the “mi estimate” Stata command.[40, 43, 44] A final logistic regression model generated the risk-adjusted predicted probability of death for each patient, ranging from 0 to 1, with higher values indicating a higher predicted probability that a given patient had died by hospital discharge. This final predictive model was assessed using conventional techniques including the Hosmer-Lemeshow goodness-of-fit statistic to assess calibration, calibration curves, c-statistic to assess discrimination, and Akaike information criterion value to compare model fit and composition across multiple models. The resulting model was considered the gold standard for risk adjustment for our study purposes. To accommodate multiple datasets created through multiple imputation, we used two strategies, after arriving at a final model, to derive a predicted probability for each patient: the predicted value of each imputed dataset averaged per patient and the predicted value of the imputed dataset closest to the median area under the curve with the better Hosmer-Lemeshow goodness-of-fit statistic.

Next, we developed a method for risk-standardizing hospital survival using administrative data. To identify candidate variables for exploration, we queried all available diagnostic codes, procedure codes, demographics, and orders for all patients with an ICD-9 code for cardiac arrest (427.5). We then isolated all unique diagnosis codes, procedure codes, and orders. These were assessed by two physician-fellows in resuscitation science to determine, by consensus, which of these should be explored as candidate variables due to their possible relationship to survival. Only the non-modifiable factors, as assessed by the physician-fellows, associated with CA were included. This was to limit controlling for features that are modifiable such as treatment with targeted temperature management could adjust away differences in care that are due to aspects of hospital performance that we would like to identify. Each identified candidate variable then was tested in univariate logistic regression against the outcome of interest (death at hospital discharge).

We next employed the same logistic regression methodology to the administrative data as was employed with the registry data, developing a logistic regression model using death at hospital discharge as the outcome. The administrative candidate variables were modeled as potential independent, adjustor variables through a manual forward stepwise variable selection process (using a univariate $p < 0.25$ to enter the model).[41, 42] Variables that did not contribute to prediction were excluded from the final model. Variance inflation factors were checked and collinear variables were collapsed or omitted. There was no missing data in the administrative data set that was greater than 1%. The final logistic regression model generated the risk-adjusted predicted probability of death for each patient; this model was used in comparison to the “gold standard” registry model.

Finally, we assessed the performance of the risk standardization done using administrative data to the performance of the “gold standard” risk standardization done using registry data. The results for both sets of analysis were reported as c-statistics, calibration plots, and Bland-Altman plots. To evaluate the models against each other, we used Bland-Altman plots to assess mean difference in predicted values and the percentage of values outside the limits of agreement, defined as two standard deviations of the mean difference,[45] a Hosmer-Lemeshow plot of the performance of the predicted values from each model compared to the observed values, and tests of the equality of receiver operating characteristic (ROC) areas between models. The last assessment, a test of the equality of ROC areas between models, was chosen a priori as the final determination for model comparison, with significance assessed at $p < 0.05$.

Results

Patient population

There were 2453 patients who had both administrative and registry data between 1/2000-4/2015 with 1820 (74.2%) having the outcome of interest. This cohort had a median age of 63 (IQR: 51, 74) years; 57.8% of these patients were male, 44.1% white, 24.8% had an initial shockable rhythm of ventricular fibrillation or pulseless ventricular tachycardia (VF/VT), 60.6% had a presumed cardiac etiology of arrest, 53.7% had an out-of-hospital CA (OHCA), 26.3% of OHCA patients received bystander CPR, 74.8% had a witnessed arrest, and 83.5% had intra-arrest epinephrine given, with a median dose of 2 (IQR: 0, 3) mg. The median duration of arrest was 11 (IQR: 5, 25) minutes, 62.5% had return of spontaneous circulation (ROSC), 19.8% of patients received TTM, 17.4% of patients regained arousal shortly post-ROSC, and 20.0% of patients had a favorable neurologic outcome (as defined as a Cerebral Performance Category [CPC] score of 1–2). [39, 46–48]

Registry risk standardization

There were 2622 cardiac arrests in PATH between 1/2000-4/2015 and 2453 of the arrests matched with administrative data (93.6%). The patients that did not match with administrative data were significantly more likely to have initial shockable rhythms, to be African-American, to have a cardiac etiology of arrest, to have an OHCA, to have a witnessed arrest, to not receive epinephrine intra-arrest and to receive a lower dose if given, to have a longer duration of arrest, to achieve ROSC, to not receive TTM, to regain consciousness shortly post-arrest, to survive to hospital discharge and to have an CPC score of 1 or 2 at hospital discharge (S1 Table).

The final registry risk standardization model, when limited to non-modifiable variables, contained six predictor variables (whether the arrest was witnessed, initial rhythm, age, year of arrest, and whether the patient regained consciousness post-arrest). Evaluating the risk standardization models using Bland-Altman plots, we found a much worse fit in terms of Pitman's test of difference in variance when using the model composed of the average predicted values from all imputations. Therefore, we chose to use the values from the median imputed dataset as the "gold standard." The c-statistic in the final model was 0.8097 (95% CI: 0.7882–0.8311) with a Hosmer-Lemeshow goodness-of-fit statistic of 0.51.

Administrative risk standardization

Penn Data Store included 5424 patients between 1/2000-4/2015 with an ICD-9 code of 427.5. These patients were 57.3% male, 50.1% white, and had a median length of hospital stay of 6 (IQR: 1, 17) days. Forty-five percent of the patients with an ICD-9 code for CA were matched with registry data. On these 5424 arrests, there were 1423 unique procedure codes, 2001 unique drugs, 5632 unique orders, and 4723 unique diagnosis codes (13,792 candidate variables including race, sex, and age).

A list of all unique procedure codes, drug orders, other orders, and diagnosis codes was compiled for assessment by two physician-fellows in resuscitation science involved in this study. Both fellows eliminated any variables assessed as irrelevant for predicting survival outcome in CA patients. Any variable eliminated by one fellow but not the other remained eligible for exploration. After the fellows' assessment, 1719 (12.5%) potential variables remained. Each of these was then analyzed in univariate logistic regression with survival to discharge as the outcome. Any variable with a p-value of <0.25 remained eligible for the model, which resulted in 317 variables. Using manual forward selection in order of lowest p-value to highest,

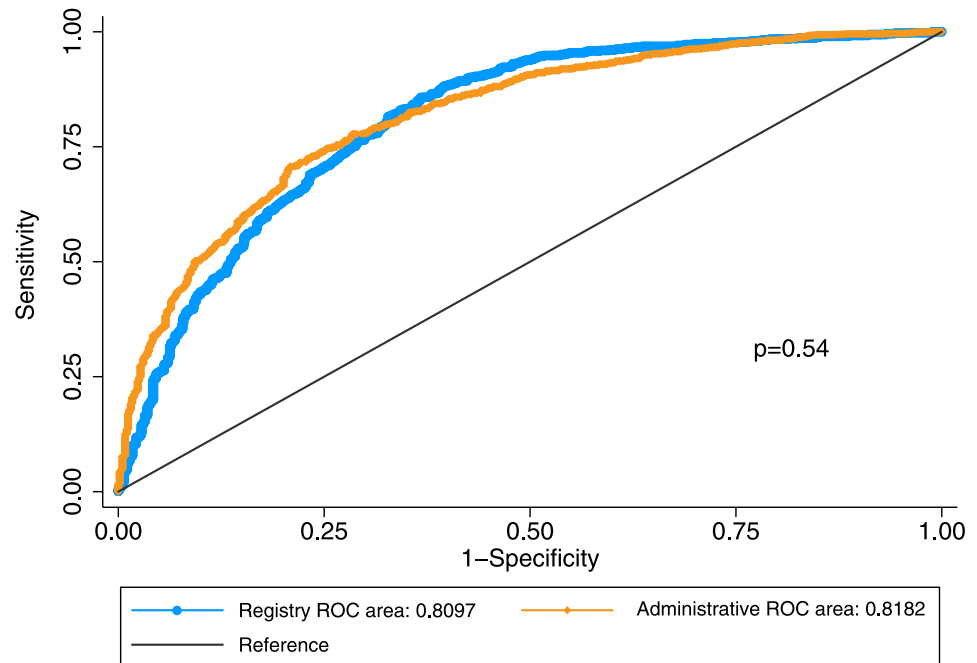


Fig 1. Comparison of ROC curves between registry and administrative data.

<https://doi.org/10.1371/journal.pone.0182864.g001>

variables then entered the logistic regression model. Variables remained in the model if they improved the predictive value and were removed if they worsened the predictive value or if it remained the same. Of the 317 candidate variables with a $p < 0.25$ in univariate association with death, 170 were identified as being non-modifiable. After analyzing these variables, 97 remained in the model (S2 Table) with a c-statistic of 0.8182 (95% CI: 0.7987–0.8377) and a Hosmer-Lemeshow goodness of fit of 0.11. Due to concerns of overfitting, we did a post hoc assessment of the minimal number of variables that would be required for a c-statistic of 0.8, which was 48 (S3 Table).

Comparing risk standardization models

Using the “rocgold” Stata command to compare the two models, there was an insignificant difference ($p = 0.542$; Fig 1). Controlling for trend with a Bland-Altman plot, we found that the mean difference between the two methods of risk standardization was -0.02 (95% CI: -0.06 – 0.02) with a non-significant Pitman’s test of difference in variance ($p = 0.13$), which we conclude represents good agreement; the line of equality falls within the confidence interval of the mean difference and only 1.81% of the data points lie outside the recommended range of two standard deviations of the mean difference (Fig 2). Both models had good calibration, as seen in Figs 3 and 4 and by non-significant Hosmer-Lemeshow goodness-of-fit statistics.

Discussion

In developing two risk standardization models with extremely small differences between their c-statistics (0.0085), we have identified that risk adjustment modeling for CA can be performed using administrative data, which are readily available and less costly [31, 32] and less challenging to compile and to access than registry data. We therefore have evidence that a tool developed using administrative data is feasible and has the potential to be used for quality

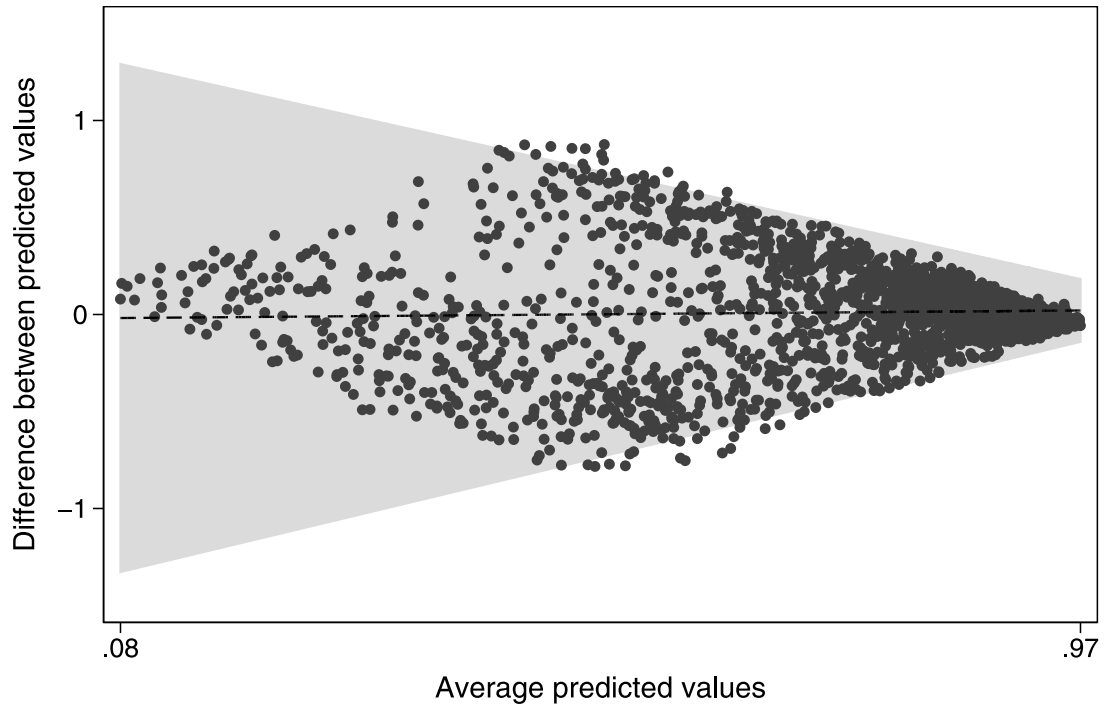


Fig 2. Bland Altman Plot of agreement between registry and administrative risk standardization models.

<https://doi.org/10.1371/journal.pone.0182864.g002>

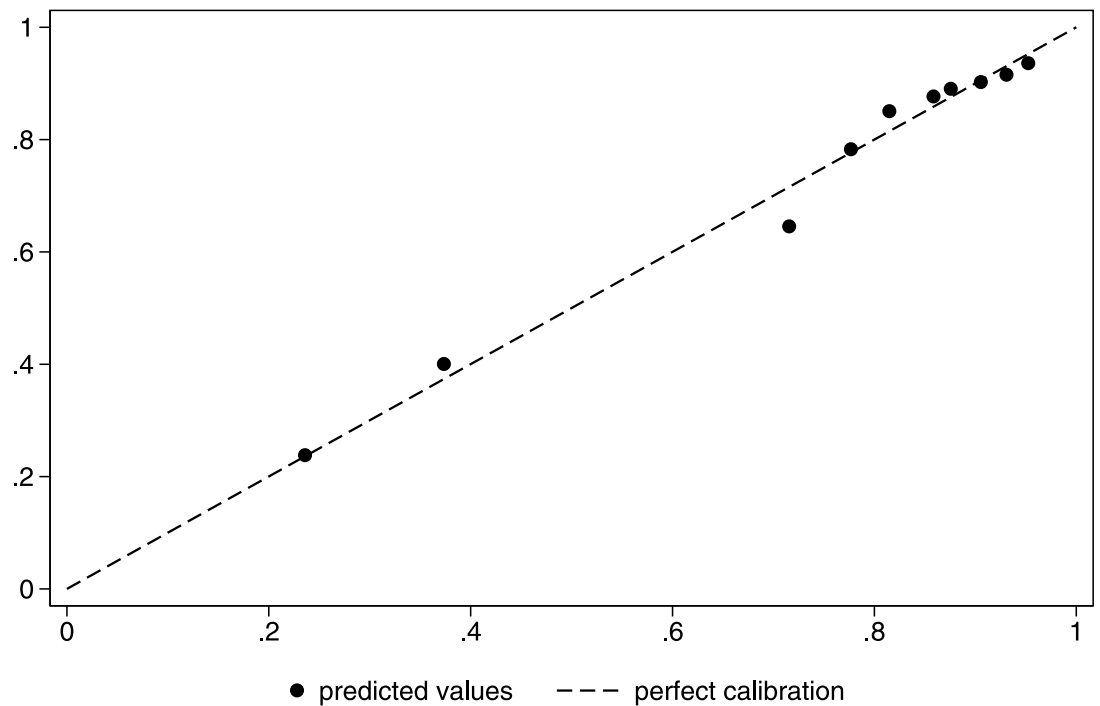


Fig 3. Calibration plot for registry data in all patients.

<https://doi.org/10.1371/journal.pone.0182864.g003>

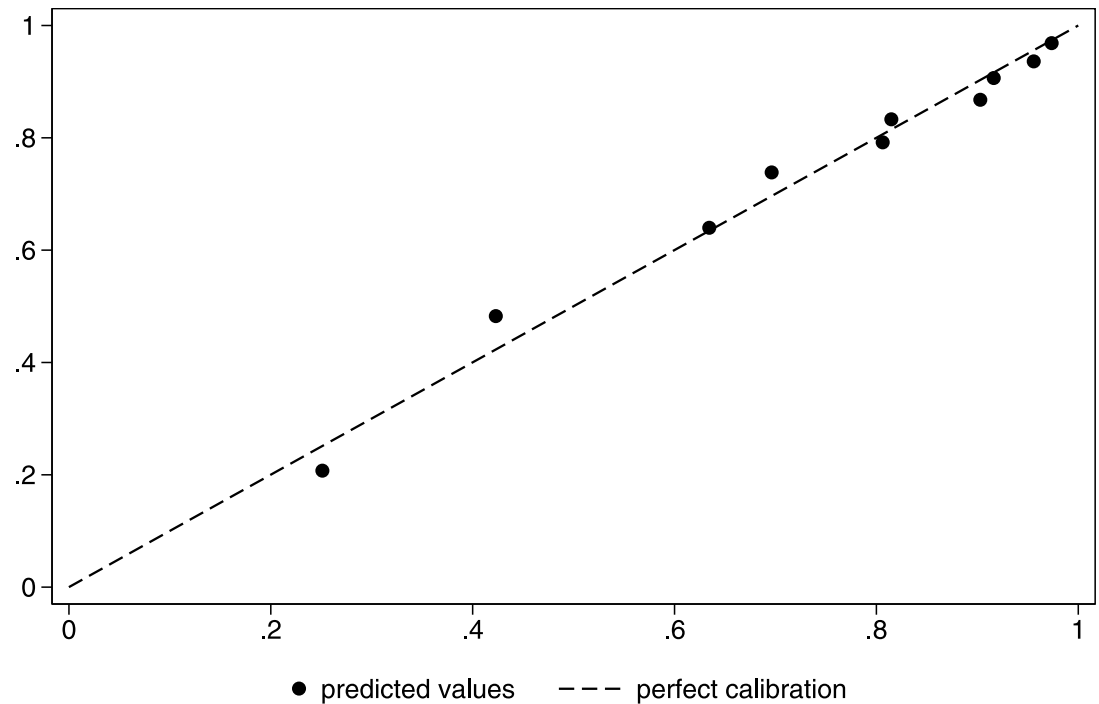


Fig 4. Calibration plot for administrative data in all patients.

<https://doi.org/10.1371/journal.pone.0182864.g004>

assessment in cardiac arrest. This tool also could be applied in research to identify variability in the management of CA and to learn from effective modalities and protocols to allow hospitals identify opportunities for improvement.

In the U.S., there is an estimated 42% difference in the odds of survival in in-hospital arrests by hospital even after risk adjusting the patient population for comparison.[49] Hospital-level interventions have been shown to be effective,[22–28] and hospitals that perform well with regard to in-hospital CA have also been found to be better at preventing CA.[50] Therefore, adequate comparisons, such as those provided using risk standardization, are vital to improve patient care and outcomes.

A recent study called into question the utility of administrative data for identifying out-of-hospital CA.[51] Investigators queried ICD-9 codes for cardiac arrest as well as VF, paroxysmal ventricular tachycardia, ventricular flutter, and respiratory arrest and found that only 40% of patients who had these ICD-9 codes had an out-of-hospital CA upon chart review. However, 94% of the CAs in our registry matched to administrative data, although there were some significant differences between the patients who were matched and those who were not. Despite our ability to risk standardize in a comparable way to registry data in our convenience sample of cardiac arrest patients, further work is needed to develop methods to identify this population in administrative datasets as well as to generalize to a larger sample from more than one health system.

The data from PATH have the limitations of data from any retrospective registry, including the use of predefined data points and the risk of data entry errors or inconsistencies. Additionally, while administrative data potentially are available from all institutions and can reflect “real world” situations, the information in these databases are not collected for research purposes, and often key variables are not recorded by administration, which have non-medical and non-research motivations for collecting information; these motivations can lead to

documentation that might not match with research documentation. Finally, the data collected by the University of Pennsylvania Health System may differ from that collected at other institutions, despite having many common elements, limiting generalizability.

This study serves as evidence that risk standardization using administrative data is comparable to that of registry data in the context of CA. The critical gap of only having information on the performance of a subset of hospitals that participate in a registry potentially could be addressed by providing support for a new method that may identify hospital performance and variability. Next steps include identifying a set of administrative variables that consistently provide discriminatory and well-calibrated risk standardization from a set that are most likely to be completely collected at hospitals and easily extractable for analysts performing research and quality comparisons. Future investigations into expanding this methodology to include more sites may lead to a new tool for nationwide risk standardization to allow benchmarking and comparison of hospitals in terms of expected to observed mortality to identify high- and low-performing hospitals.

Supporting information

S1 Table. Patient demographics in registry data.

(DOCX)

S2 Table. Administrative data elements used in risk standardization model.

(DOCX)

S3 Table. Administrative data elements used in risk standardization model with C-Statistic of 0.8.

(DOCX)

Acknowledgments

We would like to acknowledge the PATH members who entered the data that made this project possible. We would also like to acknowledge the Penn Data Store for their help with creating an administrative dataset.

Author Contributions

Conceptualization: Anne V. Grossestreuer, David F. Gaieski, Douglas J. Wiebe.

Data curation: Anne V. Grossestreuer, Joshua I. M. Nelson, Eric L. Mutter, Benjamin S. Abella, Douglas J. Wiebe.

Formal analysis: Anne V. Grossestreuer, Douglas J. Wiebe.

Investigation: Anne V. Grossestreuer, Douglas J. Wiebe.

Methodology: Anne V. Grossestreuer, Brendan G. Carr, Benjamin S. Abella, Douglas J. Wiebe.

Resources: David F. Gaieski, Benjamin S. Abella, Douglas J. Wiebe.

Supervision: David F. Gaieski, Michael W. Donnino, Benjamin S. Abella, Douglas J. Wiebe.

Writing – original draft: Anne V. Grossestreuer.

Writing – review & editing: Anne V. Grossestreuer, David F. Gaieski, Michael W. Donnino, Benjamin S. Abella, Douglas J. Wiebe.

References

1. Nishiyama C, Brown SP, May S, Iwami T, Koster RW, Beesems SG, et al. Apples to apples or apples to oranges? International variation in reporting of process and outcome of care for out-of-hospital cardiac arrest. *Resuscitation*. 2014 Nov; 85(11):1599–609. <https://doi.org/10.1016/j.resuscitation.2014.06.031> PMID: 25010784
2. Sasson C, Forman J, Krass D, Macy M, Kellermann AL, McNally BF. A qualitative study to identify barriers to local implementation of prehospital termination of resuscitation protocols. *Circ Cardiovasc Qual Outcomes*. 2009 Jul; 2(4):361–8. <https://doi.org/10.1161/CIRCOUTCOMES.108.830398> PMID: 20031862
3. Sasson C, Forman J, Krass D, Macy M, Hegg AJ, McNally BF, et al. A qualitative study to understand barriers to implementation of national guidelines for prehospital termination of unsuccessful resuscitation efforts. *Prehosp Emerg Care*. 2010 Apr-Jun; 14(2):250–8. <https://doi.org/10.3109/10903120903572327> PMID: 20144019
4. Jacobs I, Nadkarni V, Bahr J, Berg RA, Billi JE, Bossaert L, et al. Cardiac arrest and cardiopulmonary resuscitation outcome reports: update and simplification of the Utstein templates for resuscitation registries: a statement for healthcare professionals from a task force of the International Liaison Committee on Resuscitation (American Heart Association, European Resuscitation Council, Australian Resuscitation Council, New Zealand Resuscitation Council, Heart and Stroke Foundation of Canada, InterAmerican Heart Foundation, Resuscitation Councils of Southern Africa). *Circulation*. 2004 Nov 23; 110(21):3385–97. <https://doi.org/10.1161/01.CIR.0000147236.85306.15> PMID: 15557386
5. Sasson C, Rogers MA, Dahl J, Kellermann AL. Predictors of survival from out-of-hospital cardiac arrest: a systematic review and meta-analysis. *Circ Cardiovasc Qual Outcomes*. 2010 Jan; 3(1):63–81. <https://doi.org/10.1161/CIRCOUTCOMES.109.889576> PMID: 20123673
6. Cabanas JG, Brown LH, Gonzales L, Hinchey PR. Derivation and initial application of a standard population for out-of-hospital cardiac arrest (SPOHCA). *Resuscitation*. 2015 May; 90:30–4. <https://doi.org/10.1016/j.resuscitation.2015.02.008> PMID: 25708958
7. Morrison LJ, Nichol G, Rea TD, Christenson J, Callaway CW, Stephens S, et al. Rationale, development and implementation of the Resuscitation Outcomes Consortium Epistry-Cardiac Arrest. *Resuscitation*. 2008 Aug; 78(2):161–9. <https://doi.org/10.1016/j.resuscitation.2008.02.020> PMID: 18479802
8. Starodub R, Abella BS, Grossestreuer AV, Shofer FS, Perman SM, Leary M, et al. Association of serum lactate and survival outcomes in patients undergoing therapeutic hypothermia after cardiac arrest. *Resuscitation*. 2013 Aug; 84(8):1078–82. <https://doi.org/10.1016/j.resuscitation.2013.02.001> PMID: 23402966
9. Spaite DW, Bobrow BJ, Stolz U, Berg RA, Sanders AB, Kern KB, et al. Statewide regionalization of postarrest care for out-of-hospital cardiac arrest: association with survival and neurologic outcome. *Ann Emerg Med*. 2014 Nov; 64(5):496–506. <https://doi.org/10.1016/j.annemergmed.2014.05.028> PMID: 25064741
10. Carr BG, Kahn JM, Merchant RM, Kramer AA, Neumar RW. Inter-hospital variability in post-cardiac arrest mortality. *Resuscitation*. 2009 Jan; 80(1):30–4. <https://doi.org/10.1016/j.resuscitation.2008.09.001> PMID: 18952359
11. Carr BG, Goyal M, Band RA, Gaieski DF, Abella BS, Merchant RM, et al. A national analysis of the relationship between hospital factors and post-cardiac arrest mortality. *Intensive Care Med*. 2009 Mar; 35(3):505–11. <https://doi.org/10.1007/s00134-008-1335-x> PMID: 18936907
12. Lund-Kordahl I, Olasveengen TM, Lorem T, Samdal M, Wik L, Sunde K. Improving outcome after out-of-hospital cardiac arrest by strengthening weak links of the local Chain of Survival; quality of advanced life support and post-resuscitation care. *Resuscitation*. 2010 Apr; 81(4):422–6. <https://doi.org/10.1016/j.resuscitation.2009.12.020> PMID: 20122786
13. Kellum MJ, Kennedy KW, Ewy GA. Cardiocerebral resuscitation improves survival of patients with out-of-hospital cardiac arrest. *Am J Med*. 2006 Apr; 119(4):335–40. <https://doi.org/10.1016/j.amjmed.2005.11.014> PMID: 16564776
14. Hinchey PR, Myers JB, Lewis R, De Maio VJ, Reyner E, Licatase D, et al. Improved out-of-hospital cardiac arrest survival after the sequential implementation of 2005 AHA guidelines for compressions, ventilations, and induced hypothermia: the Wake County experience. *Ann Emerg Med*. 2010 Oct; 56(4):348–57. <https://doi.org/10.1016/j.annemergmed.2010.01.036> PMID: 20359771
15. Heffner AC, Pearson DA, Nussbaum ML, Jones AE. Regionalization of post-cardiac arrest care: implementation of a cardiac resuscitation center. *Am Heart J*. 2012 Oct; 164(4):493–501.e2. <https://doi.org/10.1016/j.ahj.2012.06.014> PMID: 23067906
16. Fredriksson M, Herlitz J, Nichol G. Variation in outcome in studies of out-of-hospital cardiac arrest: a review of studies conforming to the Utstein guidelines. *Am J Emerg Med*. 2003 Jul; 21(4):276–81. PMID: 12898482

17. Stub D, Smith K, Bray JE, Bernard S, Duffy SJ, Kaye DM. Hospital characteristics are associated with patient outcomes following out-of-hospital cardiac arrest. *Heart*. 2011 Sep; 97(18):1489–94. <https://doi.org/10.1136/hrt.2011.226431> PMID: 21693477
18. Stub D, Schmicker RH, Anderson ML, Callaway CW, Daya MR, Sayre MR, et al. Association between hospital post-resuscitative performance and clinical outcomes after out-of-hospital cardiac arrest. *Resuscitation*. 2015 Jul; 92:45–52. <https://doi.org/10.1016/j.resuscitation.2015.04.015> PMID: 25917263
19. Nichol G, Thomas E, Callaway CW, Hedges J, Powell JL, Aufderheide TP, et al. Regional variation in out-of-hospital cardiac arrest incidence and outcome. *JAMA*. 2008 Sep 24; 300(12):1423–31. <https://doi.org/10.1001/jama.300.12.1423> PMID: 18812533
20. Nichol G, Soar J. Regional cardiac resuscitation systems of care. *Curr Opin Crit Care*. 2010 Jun; 16(3):223–30. <https://doi.org/10.1097/MCC.0b013e32833985b5> PMID: 20463465
21. Chen TT, Ma MH, Chen FJ, Hu FC, Lu YC, Chiang WC, et al. The relationship between survival after out-of-hospital cardiac arrest and process measures for emergency medical service ambulance team performance. *Resuscitation*. 2015 Jun 14(97):55–60.
22. Weisfeldt ML, Sitalani CM, Ornato JP, Rea T, Aufderheide TP, Davis D, et al. Survival after application of automatic external defibrillators before arrival of the emergency medical system: evaluation in the resuscitation outcomes consortium population of 21 million. *J Am Coll Cardiol*. 2010 Apr 20; 55(16):1713–20. <https://doi.org/10.1016/j.jacc.2009.11.077> PMID: 20394876
23. Wissenberg M, Lippert FK, Folke F, Weeke P, Hansen CM, Christensen EF, et al. Association of national initiatives to improve cardiac arrest management with rates of bystander intervention and patient survival after out-of-hospital cardiac arrest. *JAMA*. 2013 Oct 2; 310(13):1377–84. <https://doi.org/10.1001/jama.2013.278483> PMID: 24084923
24. Fugate JE, Brinjikji W, Mandrekar JN, Cloft HJ, White RD, Wijdicks EF, et al. Post-cardiac arrest mortality is declining: a study of the US National Inpatient Sample 2001 to 2009. *Circulation*. 2012 Jul 31; 126(5):546–50. <https://doi.org/10.1161/CIRCULATIONAHA.111.088807> PMID: 22740113
25. Fothergill RT, Watson LR, Chamberlain D, Viridi GK, Moore FP, Whitbread M. Increases in survival from out-of-hospital cardiac arrest: a five year study. *Resuscitation*. 2013 Aug; 84(8):1089–92. <https://doi.org/10.1016/j.resuscitation.2013.03.034> PMID: 23583613
26. Iwami T, Nichol G, Hiraide A, Hayashi Y, Nishiuchi T, Kajino K, et al. Continuous improvements in "chain of survival" increased survival after out-of-hospital cardiac arrests: a large-scale population-based study. *Circulation*. 2009 Feb 10; 119(5):728–34. <https://doi.org/10.1161/CIRCULATIONAHA.108.802058> PMID: 19171854
27. Hollenberg J, Svensson L, Rosenqvist M. Out-of-hospital cardiac arrest: 10 years of progress in research and treatment. *J Intern Med*. 2013 Jun; 273(6):572–83. <https://doi.org/10.1111/joim.12064> PMID: 23480824
28. Tagami T, Hirata K, Takeshige T, Matsui J, Takinami M, Satake M, et al. Implementation of the fifth link of the chain of survival concept for out-of-hospital cardiac arrest. *Circulation*. 2012 Jul 31; 126(5):589–97. <https://doi.org/10.1161/CIRCULATIONAHA.111.086173> PMID: 22850361
29. Becker LB, Aufderheide TP, Graham R. Strategies to Improve Survival From Cardiac Arrest: A Report From the Institute of Medicine. *JAMA*. 2015 Jul 1; 314(3):223–4. <https://doi.org/10.1001/jama.2015.8454> PMID: 26132709
30. Donnino MW, Miller JC, Bivens M, Cocchi MN, Saliccioli JD, Farris S, et al. A pilot study examining the severity and outcome of the post-cardiac arrest syndrome: a comparative analysis of two geographically distinct hospitals. *Circulation*. 2012 Sep 18; 126(12):1478–83. <https://doi.org/10.1161/CIRCULATIONAHA.111.067256> PMID: 22879369
31. Khuri SF, Daley J, Henderson W, Hur K, Demakis J, Aust JB, et al. The Department of Veterans Affairs' NSQIP: the first national, validated, outcome-based, risk-adjusted, and peer-controlled program for the measurement and enhancement of the quality of surgical care. National VA Surgical Quality Improvement Program. *Ann Surg*. 1998 Oct; 228(4):491–507. PMID: 9790339
32. Render ML, Kim HM, Welsh DE, Timmons S, Johnston J, Hui S, et al. Automated intensive care unit risk adjustment: results from a National Veterans Affairs study. *Crit Care Med*. 2003 Jun; 31(6):1638–46. <https://doi.org/10.1097/01.CCM.0000055372.08235.09> PMID: 12794398
33. American Hospital Association. Fast Facts on US Hospitals. Health Forum LLC [Online] 2017. [Accessed June 20, 2017] <http://www.aha.org/research/rc/stat-studies/fast-facts.shtml>.
34. Truitt T. Personal communication. June 20, 2017.
35. Cardiac Arrest Registry to Enhance Survival. The CARES Report: May 2017. [Online] 2017. [Assessed June 20, 2017] <http://smemsc.org/wp-content/uploads/CARES-May-2017-Newsletter-.pdf>

36. Ferreira-Gonzalez I, Marsal JR, Mitjavila F, Parada A, Ribera A, Cascant P, et al. Patient registries of acute coronary syndrome: assessing or biasing the clinical real world data? *Circ Cardiovasc Qual Outcomes*. 2009 Nov; 2(6):540–7. <https://doi.org/10.1161/CIRCOUTCOMES.108.844399> PMID: 20031891
37. Chan PS, Berg RA, Spertus JA, Schwamm LH, Bhatt DL, Fonarow GC, et al. Risk-standardizing survival for in-hospital cardiac arrest to facilitate hospital comparisons. *J Am Coll Cardiol*. 2013 Aug 13; 62(7):601–9. <https://doi.org/10.1016/j.jacc.2013.05.051> PMID: 23770167
38. Lagu T, Lindenauer PK, Rothberg MB, Nathanson BH, Pekow PS, Steingrub JS, et al. Development and validation of a model that uses enhanced administrative data to predict mortality in patients with sepsis. *Crit Care Med*. 2011 Nov; 39(11):2425–30. <https://doi.org/10.1097/CCM.0b013e31822572e3> PMID: 22005222
39. Perkins GD, Jacobs IG, Nadkarni VM, Berg RA, Bhanji F, Biarent D, et al. Cardiac Arrest and Cardiopulmonary Resuscitation Outcome Reports: Update of the Utstein Resuscitation Registry Templates for Out-of-Hospital Cardiac Arrest: A Statement for Healthcare Professionals From a Task Force of the International Liaison Committee on Resuscitation (American Heart Association, European Resuscitation Council, Australian and New Zealand Council on Resuscitation, Heart and Stroke Foundation of Canada, InterAmerican Heart Foundation, Resuscitation Council of Southern Africa, Resuscitation Council of Asia); and the American Heart Association Emergency Cardiovascular Care Committee and the Council on Cardiopulmonary, Critical Care, Perioperative and Resuscitation. *Circulation*. 2014 Nov 11; 132(13):1286–300. <https://doi.org/10.1161/CIR.000000000000144> PMID: 25391522
40. Newgard CD, Fildes JJ, Wu L, Hemmila MR, Burd RS, Neal M, et al. Methodology and analytic rationale for the American College of Surgeons Trauma Quality Improvement Program. *J Am Coll Surg*. 2013 Jan; 216(1):147–57. <https://doi.org/10.1016/j.jamcollsurg.2012.08.017> PMID: 23062519
41. Maldonado G, Greenland S. Simulation study of confounder-selection strategies. *Am J Epidemiol*. 1993 Dec 1; 138(11):923–36. PMID: 8256780
42. Mickey RM, Greenland S. The impact of confounder selection criteria on effect estimation. *Am J Epidemiol*. 1989 Jan; 129(1):125–37. PMID: 2910056
43. StataCorp. *Stata Multiple Imputation Reference Manual: Release 13*. College Station, TX: 2013.
44. Cañette I, Marchenko Y. Combining results other than coefficients in e(b) with multiply imputed data. StataCorp [Internet]. 2013 [cited June 30, 2015].
45. Giavarina D. Understanding Bland Altman analysis. *Biochem Med (Zagreb)*. 2015 Jun 5; 25(2):141–51.
46. Nielsen N, Wetterslev J, Cronberg T, Erlinge D, Gasche Y, Hassager C, et al. Targeted temperature management at 33 degrees C versus 36 degrees C after cardiac arrest. *N Engl J Med*. 2013 Dec 5; 369(23):2197–206. <https://doi.org/10.1056/NEJMoa1310519> PMID: 24237006
47. Hypothermia after Cardiac Arrest Study Group. Mild therapeutic hypothermia to improve the neurologic outcome after cardiac arrest. *N Engl J Med*. 2002; 346(8):549–56. <https://doi.org/10.1056/NEJMoa012689> PMID: 11856793
48. Bernard SA, Gray TW, Buist MD, Jones BM, Silvester W, Gutteridge G, et al. Treatment of comatose survivors of out-of-hospital cardiac arrest with induced hypothermia. *N Engl J Med*. 2002 Feb 21; 346(8):557–63. <https://doi.org/10.1056/NEJMoa003289> PMID: 11856794
49. Merchant RM, Berg RA, Yang L, Becker LB, Groeneveld PW, Chan PS, et al. Hospital variation in survival after in-hospital cardiac arrest. *J Am Heart Assoc*. 2014 Jan 31; 3(1):e000400. <https://doi.org/10.1161/JAHA.113.000400> PMID: 24487717
50. Chen LM, Nallamothu BK, Spertus JA, Li Y, Chan PS, American Heart Association's Get With the Guidelines-Resuscitation (formerly the National Registry of Cardiopulmonary Resuscitation) Investigators. Association between a hospital's rate of cardiac arrest incidence and cardiac arrest survival. *JAMA Intern Med*. 2013 Jul 8; 173(13):1186–95. <https://doi.org/10.1001/jamainternmed.2013.1026> PMID: 23689900
51. Coppler PJ, Rittenberger JC, Wallace DJ, Callaway CW, Elmer J, Pittsburgh Post Cardiac Arrest Service. Billing diagnoses do not accurately identify out-of-hospital cardiac arrest patients: An analysis of a regional healthcare system. *Resuscitation*. 2016 Jan; 98:9–14. <https://doi.org/10.1016/j.resuscitation.2015.09.399> PMID: 26476197