Hospital Recovery Study

Statistical analysis plan

1. Overview

This document provides an overview of our planned statistical analysis of the hospital recovery study. This analysis plan will facilitate the methodological decisions surrounding handling of primary data source, analysis of primary and secondary outcomes as well as transparent reporting of the study results and will limit biases associated with exploratory post hoc analyses.

2. Background and goal

The COVID-19 pandemic unveiled prevailing inadequacies in the ability of US hospitals to deliver care effectively during public health emergencies. Surging caseloads of patients strained many hospitals and disrupted the standard of care. Nearly 1 in 4 COVID-19 deaths were potentially attributable to caseload strain and resulted in diagnostic delays, iatrogenic complications, and resource rationing which harmed all hospitalized patients. In a pandemic aftermath characterized by persistent staffing shortages, exhausted hospital resources, and financial strain, there remains concern for ongoing suboptimal healthcare delivery and worse patient outcomes, particularly in care settings with baseline vulnerabilities. This proposed work aims to catalog residual impacts of the COVID-19 pandemic on US hospitals and identify paths to recovery and resilience. We will conduct investigations using large publicly available and proprietary administrative and electronic health record (EHR) datasets to assess variation in performance across hospitals in the aftermath of the pandemic and identify factors linked to poor performance. Performance will be measured using modified standardized mortality ratios and compared with expected outcomes on a pre-pandemic population and adjusted for case-mix and secular changes. This investigation could help localize care settings and hospital types as targets for improvement and identify clinical and policy solutions to address modifiable vulnerabilities, minimize disparities in care delivery and improve future outcomes.

3. Study design and data source

We will perform a retrospective cohort study of all adult non-COVID-19 patients hospitalized in acute care US hospitals. We will leverage the longitudinal, nationally representative, multicenter PINC-AI Database (formerly “Premier Healthcare”), a de-identified all-payer administrative database from over 1000 hospitals, and other secondary data sources to understand how care-delivery performance varies across US hospitals post-pandemic and which factors might contribute to poor performance.

4. Study aims and hypotheses

Aim: Determine variation in hospital performance after the pandemic and identify hospital factors associated with lower-than-expected performance.

Hypothesis: We hypothesize that post-pandemic performance of hospitals has deteriorated compared to pre-pandemic times and the extent of performance deterioration varies considerably across hospitals.

5. Study time period and relevant timelines

Admitted within Jan 1, 2018 – May 31, 2023 (65 months) with discharge charge dispositions 60 days from patient discharge.

Following pandemic wave definitions will be used:
Period A, Pre-pandemic: Jan 1, 2018- Feb 29, 2020 (26 months)
Period B, Pandemic: March 1, 2020- Dec 30, 2022 (34 months)

- Wave 1: March 2020 – May 2020
- Wave 2: June 2020 – September 2020
- Wave 3: October 2020 – June 2021
- Delta wave: July 2021 – December 2021
- Omicron: Jan 2022 – April 2022 (based on CDC net data on hospitalization trends)

Period C, Post pandemic duration: May 2022 - May 31, 2023 (13 months)
End to International Public Health Emergency (WHO announcement): May 5, 2023
US Public health emergency end declaration: May 11, 2023.

The start of the "post pandemic" or recovery period was determined by visualizing the nadir of caseload in US hospitals during the Omicron surge which occurred on or around April 2022 based on the CDC net data on hospitalization and death trends.

6. Study hospitals

The primary study hospitals will consist of all acute care US hospitals in PINC-AI database that are continuously reporting with at least one inpatient encounter in each week of the study period. Continuous reporters will be assessed for each of the conditions of interest cohort separately. Freestanding emergency departments and facilities which do not admit inpatients will be excluded. We will exclude all long-term care, psychiatric, substance abuse, rehabilitation and children hospital.

7. Study cohort

The study cohort will include one random encounter per patient for all adult (age ≥18years) encounters. All inpatients (**Patient type code 08**) with inpatient/outpatient indicator of **'I'** in the Premier healthcare database and those patients who were admitted under observation status (**Patient type code 29**) and expired in the hospital or those who presented acutely to the emergency department (**Patient type code 28**) and died in the emergency department will be considered as inpatients for the purpose of this study as per prior precedence in including such patients. (Rhee, 2017, JAMA; 318(13):1241-1249)

All pediatric inpatients, skilled nursing facilities inpatients, long term acute care inpatients, rehabilitation facility inpatients, psychiatric inpatients, hospice inpatients, chemical dependency unit inpatients and deceased organ donor inpatients are excluded after applying encounter level exclusion criteria from this inpatient cohort. Application of this encounter level exclusion will also preferentially exclude any children hospitals, skilled nursing facilities, acute long term care facilities, psychiatry hospitals, inpatient hospices and chemical dependency units.

8. Study patients:

Study patients will include non-COVID-19 patients within select five primary diagnoses of acute myocardial infarction, stroke, heart failure, pneumonia, and chronic obstructive pulmonary disease in alignment with the Centers for Medicare and Medicaid Service's (CMS's) condition-specific mortality measures reporting. To select patient cohort with these diagnoses, we will first identify all non-COVID-19 cases after excluding all the COVID-19 primary and secondary diagnoses as outlined in the steps below. Patients admitted with primary nonCOVID-19 diagnoses who has a prior history of admission for COVID-19 during the study period and their date of admission will also be curated as below.

a. All non-COVID19 cases codes: All those patients who did not have primary or secondary SARS-CoV-2 admission diagnosis codes. For the purpose of this study, SARS-CoV-2 diagnosis codes are defined as:
   - March 2020 only legacy code: B97.29 + one of the following: 'J12.89','J12.81','J12.9','J18.0','J18.1','J18.2','J18.8','J18.9','J20.8', 'J20.9','J40','J22','J98.8','J98.9','J98.0','J98.01','J98.09','J98.1','J98.11', 'J98.19','J80','J96','J96.0','J96.00','J96.01','J96.02','J96.2','J96.20','J96.21', 'J96.22','J96.9','J96.90','J96.91','J96.92'
   - March 2020 onwards: U07.1 or J12.82 diagnosis codes. U49

b. Select five common conditions of interest as defined by CMS, (see supplemental condition specific excel sheet located in NIH sharepoint)
   i. Acute myocardial infarction 2024_AMI_Mortality_v1.0.xlsx (sharepoint.com)
   ii. Stroke 2024_Stroke_Mortality_v1.0.xlsx (sharepoint.com)
   iii. Pneumonia 2024_PN_Mortality_v1.0.xlsx (sharepoint.com)
   iv. Heart failure 2024_HF_Mortality_v1.0.xlsx (sharepoint.com)
   v. Chronic obstructive pulmonary disease 2024_COPD_Mortality_v1.0.xlsx (sharepoint.com)

c. History of COVID-19
   i. J12.82, U07.1, U09.9, Z86.16
   ii. Date of history of COVID-19 if reported

9. Primary outcome
   Our primary outcome will be based on a composite measure of in-hospital mortality or discharge to hospice as determined by discharge status code. The primary outcome will itself be expressed as a modified standardized mortality ration (mSMR) calculated as mean-shrunken number of observed deaths or discharge to hospice divided by the expected number of deaths or discharge to hospice for a center in that post-pandemic month assuming the effects of a typical center in the pre-pandemic era.

10. **Statistical approach:**

This analysis will measure post-pandemic performance using modified standardized mortality ratios based on expected mortality modeled from pre-pandemic times and corrected for a time factor. Using patient level PINC-AI data from 2018 to 2023, we will identify patients admitted to US hospitals and fit generalized linear mixed models (GLMMs) which accounts for within-hospitals clustering to estimate the pre-pandemic and post-pandemic age, sex and case-mix

Commented [S[1]: How do we feel about changing the moniker "mSMR"?

Also, I think we might need to change this graphic because the numerator will not be RAW observed outcomes but mean-shrunken observed outcomes. I suppose we could leave it too...

Commented [N[2R1]: @Swihart, Bruce (NIH/CC/CCMD) [E] sounds good Bruce. Please feel free to change/delete. Anything that you suggest instead of mSMR?

adjusted mSMRs and their associated uncertainty intervals for each hospital. mSMRs for each of the hospital will be computed as a ratio of the number of observed deaths to the number of expected deaths. Expected deaths will be derived on Jan 2018 - Feb 2020 data controlling for case-mix and correcting for a time factor by projecting secular trends in mortality up until post-pandemic times. This analysis will be conducted individually for five common conditions of interest (acute myocardial infarction, stroke, pneumonia, heart failure and chronic obstructive pulmonary disease) for which Centers for Medicaid and Medicare Services also publish their performance statistics as well as an aggregated measure for these five principal admission diagnoses. We will then rank the hospitals based on their post-pandemic performance to display variation after reliability adjustment to minimize effects of very low volume outliers on impressions of variation. Next, we will test how post-pandemic performance relates to specific modifiable and non-modifiable factors such as clinical infrastructure, rurality, bed capacity, patient volume, payor distribution, critical access status, health system affiliation, and historical factors such as cumulative pandemic caseload strain and their association with post-pandemic performance. We will use a machine learning approach called “elastic net” to objectively select candidate variables and account for multicollinearity before entering them into the GLMM risk-factor model. Patients transferred in from other hospitals will be excluded but examined in sensitivity analysis.

Commented [S[3]: There's a smidge of 2020 in there -- should we change to "Period A" (?)

10.1 Statistical modeling

The statistical modeling approach will facilitate describing the variability of the mSMRs across centers and their interval of uncertainty akin to the league table approach [ref] in Statistical Analysis 1 (SA1). In Statistical Analysis 2(SA2), we relate the mSMRs to center-level variables (section 10.3) to identify center-level associations impacting mSMRs.

Statistical Analysis 1 (SA1):

Conducting a CMS-type (aka league table) analysis -- where the distributions of the mSMRs for each and every center are procured -- would be informative and potentially elucidating for how hospital recovery is taking place, allowing the display of the variation and uncertainty of mSMRs (i.e., a catepillar plot). The CMS-type analysis requires a sophisticated bootstrapping algorithm, and we will follow their (CMS) algorithm with a few crucial adaptations. Within each bootstrap iteration, a denominator and numerator are calculated for each center for each month of the post-pandemic era. The underlying models for each, as well as the data to which those models are fitted, are distinct for each the *denominator* and *numerator*. For each bootstrap iteration:

Step 0:

Sample hospitals with replacement. This means there will be duplicates. Give them a new, unique id in the models so the variances are calculated correctly.

Step 1:

Denominator: The expected number of deaths will be calculated per calendar month within each center. First, a mixed-effects logistic regression fitted to the bootstrap sample’s longitudinal patient-level pre-pandemic data will yield

estimates for the pre-pandemic era's effects. A tractable and interpretable parameterization for temporal trends will be used: an effect for each calendar month along with an overall linear effect over time. This parameterization allows for seasonality in addition for multiyear overall trend that hospital mortality. The month-to-month effects are not super-imposed from period A to period C, but rather fit as an extrapolation (this has the interpretation/assumption that the trends happening in Period A continued through Period C *as if the pandemic never happened*). Notably, the fixed effect estimates from this fit will be applied to the post-pandemic data of the unique hospitals along with the simulated random intercept of the numerator model (more details below in the *Numerator* section) in the bootstrap sample to yield fitted values (the probability of dying) for patients of the post-pandemic era. These probabilities of dying are then summed within month to represent the expected number of deaths for a center in that post-pandemic month using the effects of a *that* center in the pre-pandemic era. In this regard, each hospital from Period A serves as its own reference.

Numerator: The procedural flow is the same as the denominator: estimates from a model fitted to data, predictions with model estimates fitted to data, and then sum predictions within month within center. A mixed-effects logistic regression fitted to bootstrap sample's longitudinal patient-level post-pandemic data (as opposed to pre-pandemic for the denominator) to yield estimates for this era's effects. Note, different variables can be used in the numerator model (i.e., history of covid, history of covid vaccination, etc) that will not appear in the distinct model for the denominator. A (tractable and interpretable) parameterization, similar to that of the denominator model, will be used for temporal trends. Whereas the model for the denominator was an extrapolation of Period A effects into Period C, the numerator model uses the Period C trend. Notably, the fixed effect estimates and random effects from this fit will be applied to post-pandemic data of the unique hospitals in the bootstrap sample to yield fitted values (the probability of dying) for patients of the post-pandemic era. These probabilities of dying are then summed within month to represent the expected number of deaths for a center in that post-pandemic month assuming the effects of *this particular center* in the *post-pandemic era* (as opposed to *the same center of the pre-pandemic era operating in the post-pandemic era* as in the denominator calculations). Worth noting is that the random effects are simulated for the set of unique hospitals based on the mean and covariance of the random effects of the bootstrap sample in the numerator model.

Step 2:

Calculate mSMR as numerator mean-shrunk observed deaths divided by denominator expected deaths for the unique hospitals in the bootstrap sample. Store them under their unique, original id.

Step 3:

Repeat Steps 0-1 for *B* iterations, where *B* is reasonably large. Large enough where there will be *B/2* stored estimates for each hospital in the entire original population of

Commented [S[4]: REVISIT this. 2024-08-08 project meeting we decided to explore hopkins being hopkins' own baseline as opposed to a typical center being its baseline. The "perception" of this change might be substantial and beneficial and statistically/algorithmically is a relatively small change.

hospitals. This is crucial because not every hospital will get a result from each bootstrap iteration due to sampling with replacement.

The bootstrap iterations will be embarrassingly parallelized with each iteration's results written to file in high computing cluster environment. They will then be gathered so the distributions can be visualized and tabulated. Ninety-five percent interval estimates (or alternative interval estimates) for the hospital-standardized outcome can be computed by identifying the 2.5th and 97.5th percentiles of randomly half of the B estimates (or the percentiles corresponding to the alternative desired intervals). The variances can be taken on the same random half sample and used in *SA2*.

To conclude, the choice of denominator (the patient-level effects of the pre-pandemic era applied to post-pandemic data in calculating the expected deaths) is a choice that shapes the interpretation of the SMR and enables the commentary of whether a hospital has recovered in terms of monthly mortality. This is a modification to the commonly understood SMR which is standardized to a "typical hospital" in the same time era. Therefore, to honor this distinction, we denote this performance metric mSMR (modified SMR). Consequently, the mSMR is the center-size mean-shrunk observed values for a month for a center divided by the expected value for the same month and center. From the resultant 95% confidence intervals on the B/2 samples, a 95% CI where the lower bound is larger than 1 means the center had not returned to pre-pandemic levels and had higher mortality. A 95% CI where the upper bound is less than 1 means the center has significantly lower mortality in the post-pandemic month than what would have been expected of that center in the pre-pandemic era (Period A). A 95% CI containing 1 means there's is not a statistically significant difference detected.

Statistical Analysis 2 (SA2):

As we can see, a lot of effort goes into being able to calculate the mSMRs within a bootstrap iteration. Once the mSMRs for the bootstrap sample are constructed, the (bootstrap) variance will be calculated for the outcomes within center. These will be used in an inverse variance weighted linear mixed model relating the monthly post-pandemic mSMRs and/or log(mSMR)s to center level covariates *during the pandemic* (note: that is, distinctly between the pre- and post-pandemic data that was used in *SA1*), as calculated on the original, non-bootstrapped data. The inverse variance weights will account for the different center sizes in this aggregate analysis. This analysis will answer if center level covariates or summaries thereof, such as max-surge, during the pandemic era had effects on the monthly mSMRs of the post-pandemic era. As the effects in such a model can be a weighted-average of cross-sectional and longitudinal effects, parameterizing effects as recommended in Fitzmaurice's Applied Longitudinal Analysis (Chapter 9) will be used in the analysis.

The primary analysis will use binary variable of dead / discharge to hospice (y=1) vs not (y=0).

10.2 Patient level covariates

The cohort will be restricted to adults >= 18 years and patient level variables for case-mix adjustment will include age, sex, race/ethnicity, payor type, admission source, admission type, Elixhauser comorbidity index, high risk comorbidities present on admission, acute organ failure

present on admission, do not resuscitate order present on admission, principal admission diagnosis, history of COVID-19. We will also control for seasonality as well as temporal secular changes in outcomes over time.

As the observed outcomes and expected outcomes are assessed in patients admitted over different time periods before and after the pandemic, the model to calculate the **observed outcomes (numerator)** in post-pandemic period will also adjust for 'history of COVID-19' besides the remaining patient level covariates that will be used to estimate the expected outcomes using pre-pandemic model fit on post-pandemic period (denominator).

Commented [S[5]]: moreover, I can't control for admission month in the denominator model because I can't extrapolate the admission month from Period A to Period C. Do you want me to account for admission date in the numerator model? Or forget admission year-month altogether? We can discuss.

Commented [S[6]]: did I say this? We're already breaking this down to a monthly level for discharge...this might be too much.... Just a note to ourselves.

10.3 Hospital level covariates

Commented [S[7]]: (these may be considered only once we have the mSMRs, I think...the CMS report made a big deal about whether to include hospital level covars in observed and expected deaths models...)

All hospital level covariates will be used in the risk factor model to assess the association between hospital characteristics that are associated with either poor or better performance post pandemic. These will include variables like hospital or provider ID, urban/rural status, teaching/nonteaching status, pre-pandemic bed size, hospital US census region, 3 digit-zip code of hospital and 3-digit zip code related 2020 CDC social vulnerability index. Additional hospital level covariates based on certain procedural volume (e.g. mechanical ventilation tertiles) will be added to assess their influence on outcomes. Hospital level covariates will not be included in the within-hospital case-mix adjustment model to estimate observed and expected deaths.

10.4 Associating cumulative surge burden to hospital performance

Commented [S[8]]: This is going to be important. I'm glad you and Alex are thinking about it. Basically we need summarize what was happening in Period B at hospital level...

Cumulative surge burden across hospitals will be calculated by adding monthly COVID-19 surge index for each of the hospital from the start of the pandemic to the end of the Delta wave of the pandemic in the US, i.e., from March 2020 to December 2021. Severity weighted COVID-19 surge index normalized to pre-pandemic hospital bed capacity will be calculated for each of the hospital month and numerically added to calculate the cumulative surge burden experienced by each of the hospital. Surge exposure during the Omicron phase (Jan 2023 and onwards) will be excluded due to heterogenous patient presentation as well as non-uniform hospital surge across US regions during that period of the pandemic.

11. Secondary outcomes

Rates of potential inpatient complications (PICs): PICs are complications developed during the hospital stay which may reflect the performance changes post pandemic due to circumstances observed during the pandemic. List of PICs will be curated as has been done previously using Premier Healthcare Database as reported in Korvink et al. Med Care, 2023. For each of the patient, we will calculate the cumulative number of PICs developed during their inpatient stay, which would be a sum of individual counts of PICs out of the list of 74 total possible PICs. Eventually, observed and expected rate of PICs normalized to the length of stay will be calculated with analysis restricted to within hospitals after adjusting for patient level covariates. Subsequently, risk factor model will include hospital level factors to assess association of these

factors to aggregate rates of PICs in the cohort to identify factors associated with better or poor performance post pandemic.

12. Sensitivity analyses

We will perform several sensitivity analyses to examine the robustness of our study results.

a) Analyse in overall cohort of all diagnoses without restriction to five conditions.
b) Inclusive of all patients including those transferred from other hospitals.
c) Substituting high risk comorbidities present on admission in lieu of Elixhauser comorbidity.
d) Extending the start of post-pandemic caliper from Jan 2023 to an earlier date such as September 2022 (to yield 9 months of 'post-pandemic' data), or May 2022 (to yield 12 months of 'post-pandemic' data). (refer to CDC net graph for nadir of April 02, 2022)
e) Adding eSOFA values in the patient level case-mix adjustment model to calculate the observed and expected. While performing this analysis, we will also check for multicollinearity between eSOFA components and acute organ failure score components and one of the collinear variables will be excluded. eSOFA and its individual component score will be based on Rhee et al. CCM, 2019 (PMID: 30768498) as shown in the table in Appendix 1.

13. Other considerations
    a. We will additionally assess if rates of any procedures performed in hospitals have returned to pre-pandemic level or not during the post pandemic times. This will be expressed as total number of any procedures divided by the number of total hospitalizations times the sum of length of stay. Cumulative counts of all procedures will be obtained from the variable icd_diag_proc indicating "P" for procedure codes.

14. Role of the funder

This work is supported by the Intramural Research Program of the NIH Clinical Center.

Appendix 1

The Sequential Organ Failure Assessment Score (SOFA) and eSOFA Criteria

Organ System	SOFA Score	eSOFA
Cardiovascular[a]	1 - Mean Arterial Pressure <70 mmHg 2 –DA ≤ 5 mcg/kg/min or Dobutamine (any dose) 3 - DA > 5 or EPI ≤0.1 or NE ≤0.1 mcg/kg/min 4 - DA > 15 or EPI >0.1 or NE >0.1 mcg/kg/min	Vasopressor initiation
Pulmonary	1 - PaO2/FiO2 300–399 2 - PaO2/FiO2 200–299 3 - PaO2/FiO2 100–199 and ventilated 4 - PaO2/FiO2 ratio <100 and ventilated	Mechanical ventilation initiation (>1 calendar day required between vent episodes)
Renal[b]	1 - Creatinine 1.2–1.9 mg/dL 2 - Creatinine 2.0–3.4 mg/dL 3 - Creatinine 3.5–4.9 mg/dL or UOP <500 cc/day 4 - Creatinine >5.0 mg/dL or UOP <200 cc/day	↑2x Creatinine or ↓≥50% of eGFR relative to baseline (excluding patients with end-stage renal disease)
Hepatic	1 - Bilirubin 1.2–1.9 mg/dL 2 - Bilirubin 2.0–5.9 mg/dL 3 - Bilirubin 6.0–11.9 mg/dL 4 - Bilirubin >12.0 mg/dL	Bilirubin ≥ 2.0 mg/dL and ↑2x from baseline
Coagulation	1 - Platelets 100–149 cells/μL 2 - Platelets 50–99 cells/μL 3 - Platelets 20–49 cells/μL 4 - Platelets <20 cells/μL	Platelet count <100 cells/μL and↓ ≥50% decline from baseline (baseline must be ≥100 cells/μL)
Neuro	1 - Glasgow Coma Scale score 13–14 2 - Glasgow Coma Scale score 10–12 3 - Glasgow Coma Scale score 6–9 4 - Glasgow Coma Scale score <6	*None* Perfusion dysfunction: Lactate ≥2.0 mmol/L

	all	Pre-pandemic	Pandemic	Post pandemic
covid	1,228,735	511 (0.0%)	1,162,711 (94.6%)	65,513 (5.3%)
non-covid	28,313,672	12,359,817 (43.7%)	13,772,741 (48.6%)	2,112,650 (7.5%)
cms_mort_AMI	967,394	401,885 (41.5%)	490,195 (50.7%)	72,248 (7.5%)
cms_mort_COPD	5,075,240	2,208,202 (43.5%)	2,472,177 (48.7%)	377,651 (7.4%)
cms_mort_HF	5,992,406	2,425,545 (40.5%)	3,060,802 (51.1%)	486,782 (8.1%)
cms_mort_PN	3,417,473	1,365,738 (40.0%)	1,785,798 (52.3%)	248,163 (7.3%)
cms_mort_Stroke	822,246	322,717 (39.2%)	433,959 (52.8%)	63,106 (7.7%)

Appendix 2:
List of Potential inpatient complications (PICs)

1. Air Embolism
2. Accidental Laceration or Puncture
3. Acid-Base Disturbance
4. Acute Myocardial Infarction
5. Acute Necrosis of the Liver

6. Acute Necrosis of the Liver with Coma
7. Acute Pancreatitis
8. Acute Pulmonary Edema
9. Acute Renal Failure
10. Acute Renal Failure with Delivery
11. Acute Respiratory Failure
12. Adverse Drug Event (ADE)
13. Amputation Stump Complications
14. Anaphylactic Reaction/Serum Reaction
15. Anoxic Brain Damage
16. Aspiration Pneumonia
17. Blood Incompatibility
18. Birth Trauma or Injury
19. C. Diff. Enteritis
20. Catheter Associated UTI
21. Cardiac Arrest
22. Cardiogenic Shock
23. Cellulitis/Skin Infection
24. Cerebral Infarction
25. Coma
26. Complication CNS
27. Complication of Nervous System Device
28. Complication of Other Unspecified Device
29. Complication of Surgical Wound or Wound Healing incl. Hematoma
30. Complication of Vascular Device
31. Complication or Infection of Colostomy/Enterostomy
32. Complications due to Orthopedic Prosthesis or Device
33. Complications due to Peritoneal Dialysis Catheter
34. Complications of Acute Myocardial Infarction (AMI)
35. Complications of Anesthesia
36. Complications of Cardiac Device/Graft
37. Complications of Cystostomy
38. Complications of OB Surgery
39. Complications of Transplanted Organ
40. DVT/PE with Total Knee or Hip Replacement
41. Deep Vein Thrombosis
42. Delivery with 3rd or 4th Degree Laceration
43. Dural Tear
44. Embolism/Thrombus (non-pulmonary)
45. Encephalopathy
46. Enteritis
47. Falls and Trauma
48. Foreign Object Retained After Surgery
49. Fat Embolism
50. Fetal-Maternal Hemorrhage
51. Fluid Overload
52. Gastrointestinal (GI) Ulceration & Hemorrhage

53. Hemorrhage/Hematoma Complicating a Procedure
54. Iatrogenic Pneumothorax with Venous Catheterization
55. Iatrogenic Cerebrovascular Infarction
56. Iatrogenic Hypotension
57. Iatrogenic Pituitary Disorder/Diabetes Insipidus
58. Iatrogenic Pneumothorax
59. Infection due to Device / Graft
60. Infection due to Infusion
61. Infection following GI Procedure
62. Injury to Nerve
63. Intestinal Perforation
64. Intracranial Hemorrhage
65. Manifestations of Poor Glycemic Control
66. Maternal Condition Affecting Newborn
67. Maternal Distress
68. Maternal Hypotension
69. Mechanical Complication of Genitourinary (GU) Device or Graft
70. Methicillin-Resistant Staphylococcus Aureus (MRSA)
71. Obstetric Shock
72. Obstetrical Air Embolism
73. Obstetrical Amniotic Fluid Embolism
74. Obstetrical Deep Vein Thrombosis
75. Obstetrical Thromboembolism
76. Other Complications of Delivery
77. Other Complications of Medical / Surgical Care
78. Other Hypoglycemia
79. Other Infections
80. Other Obstetrical Embolism
81. Other Respiratory Complications
82. Other Shock
83. Other Urinary Tract Infection
84. Performance of Inappropriate Operation
85. Perioperative Infection
86. Perioperative Shock
87. Pneumonia
88. Post-Surgical Respiratory Failure
89. Pulmonary Embolism
90. Pyelonephritis
91. Respiratory Complication of Newborn
92. Stage III or IV Pressure Ulcer
93. Surgical Site Infection – Bariatric Surgery
94. Surgical Site Infection – Certain Orthopedic Procedures of Spine, Shoulder, and Elbow
95. Surgical Site Infection – Mediastinitis After CABG
96. Surgical Site Infection Following Cardiac Implantable Electronic Device (CIED)
97. Sepsis
98. Sepsis with Septic Shock
99. Septic Arterial Embolism

100. Status Asthmaticus
101. Subdural / Extradural Hemorrhage
102. Surgical Complication-Digestive System
103. Surgical Complication-Heart
104. Surgical Complication-Peripheral Vascular System
105. Surgical Complication-Urinary Tract
106. Tracheostomy Complication
107. Transfusion Reaction (non-ABO)
108. Transient Cerebral Ischemia
109. Uterine Rupture
110. Vascular Catheter-Associated Infection
111. Vascular Complications
112. Ventilator Associated Pneumonia
113. Ventricular Fibrillation
114. Volume Depletion/Dehydration

References:

Rhee et al. CCM, 2019 (PMID: 30768498)

Korvink M, Gunn LH, Molina G, Hayes T, Selves E, Duan M, Martin J. Risk Adjustment of ICD-10-CM Coded Potential Inpatient Complications Using Administrative Data. Med Care. 2023 Aug 1;61(8):514-520. doi: 10.1097/MLR.0000000000001865. Epub 2023 May 19. PMID: 37219083.