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ORIGINAL RESEARCH

PARCCS

A Machine Learning Risk-Prediction Model for Acute Peripartum Cardiovascular Complications During Delivery Admissions

Salman Zahid, MD,[a] Shikha Jha, MD,[b] Gurleen Kaur, MD,[c] Youn-Hoa Jung, MD,[d] Anum S. Minhas, MD, MHS,[e] Allison G. Hays, MD,[e] Erin D. Michos, MD, MHS[e]

ABSTRACT

BACKGROUND Maternal mortality in the United States remains high, with cardiovascular (CV) complications being a leading cause.

OBJECTIVES The purpose of this paper was to develop the PARCCS (Prediction of Acute Risk for Cardiovascular Complications in the Peripartum Period Score) for acute CV complications during delivery.

METHODS Data from the National Inpatient Sample (2016-2020) and International Classification of Diseases, Tenth Revision codes to identify delivery admissions were used. Acute CV/renal complications were defined as a composite of pre-eclampsia/eclampsia, peripartum cardiomyopathy, renal complications, venous thromboembolism, arrhythmias, and pulmonary edema. A risk prediction model, PARCCS, was developed using machine learning consisting of 14 variables and scored out of 100 points.

RESULTS Of the 2,371,661 pregnant patients analyzed, 7.0% had acute CV complications during delivery hospitalization. Patients with CV complications had a higher prevalence of comorbidities and were more likely to be of Black race and lower income. The PARCCS variables included electrolyte imbalances (13 points [p]), age (3p for age <20 years), cesarean delivery (4p), obesity (5p), pre-existing heart failure (28p), multiple gestations (4p), Black race (2p), gestational hypertension (3p), low income (1p), gestational diabetes (2p), chronic diabetes (6p), prior stroke (22p), coagulopathy (5p), and nonelective admission (2p). Using the validation set, the performance of the model was evaluated with an area under the receiver-operating characteristic curve of 0.68 and a 95% CI of 0.67 to 0.68.

CONCLUSIONS PARCCS has the potential to be an important tool for identifying pregnant individuals at risk of acute peripartum CV complications at the time of delivery. Future studies should further validate this score and determine whether it can improve patient outcomes. (JACC Adv 2024;3:101095) © 2024 The Authors. Published by Elsevier on behalf of the American College of Cardiology Foundation. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

From the [a]Division of Cardiovascular Medicine, Knight Cardiovascular Institute, Oregon Health and Science University, Portland, Oregon, USA; [b]Division of Cardiovascular Medicine, University of Wisconsin, Madison, Wisconsin, USA; [c]Department of Medicine, Brigham, and Women's Hospital, Boston, USA; [d]Division of Cardiac Anesthesiology and Critical Care Medicine, Department of Anesthesiology, Johns Hopkins University School of Medicine, Baltimore, Maryland, USA; and the [e]Division of Cardiology, Department of Medicine, Johns Hopkins University School of Medicine, Baltimore, Maryland, USA.

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ABBREVIATIONS AND ACRONYMS

AUC = area under the curve

CV = cardiovascular

HCUP = Healthcare Cost and Utilization Project

HF = heart failure

ICD-10-CM = International Classification of Diseases-10th Revision-Clinical Modification

NIS = Nationwide Inpatient Sample

NPV = negative predictive value

PARCCS = Prediction of Acute Risk for Cardiovascular Complications in the Peripartum Period Score

PPV = positive predictive value

PRC = precision-recall curve

Maternal mortality continues to rise in the United States, with a rate higher than that of other developed nations.[1-3] Over the period of 1987 to 2019, there has been a gradual increase in maternal mortality rates in the United States, with cardiovascular (CV) disease being a leading cause of pregnancy-related mortality, particularly among Black women.[2,4-8] Furthermore, the Centers for Disease Control estimate that 4 out of 5 pregnancy-related deaths in the United States are preventable.[6] The rise in maternal mortality is believed to be a consequence of several factors, including an increase in individuals of advanced maternal age undergoing pregnancy, pre-existing medical conditions like diabetes mellitus and hypertension, and more individuals with congenital heart disease surviving to childbearing age.[1] To address this issue, developing accurate risk prediction models is crucial to identifying individuals at high risk for adverse peripartum CV events. These models have the potential to enable health care professionals to implement appropriate preventive measures and interventions to reduce maternal mortality due to CV complications.

Therefore, the aim of this study is to develop a machine learning risk prediction model using a nationally representative U.S. dataset, the Nationwide Inpatient Sample (NIS), to predict CV complications during delivery admissions. We called this model the PARCCS (Prediction of Acute Risk for Cardiovascular Complications in the Peripartum Period Score).

METHODS

STUDY DATA. The study used data from the NIS database between 2016 and 2020. The NIS is part of the Healthcare Cost and Utilization Project (HCUP), managed by the Agency for Healthcare Research and Quality in partnership with the federal and state governments and the health care industry.[9] The NIS contains administrative claims data from over 7 million inpatient hospitalizations annually in 47 states and the District of Columbia, representing more than 97% of the U.S. population. The NIS data are publicly available and de-identified, so institutional review board approval and informed consent were not necessary. The study adhered to the guidelines provided by the HCUP, and observations with a cell count of less than 11 were reported as "<11."

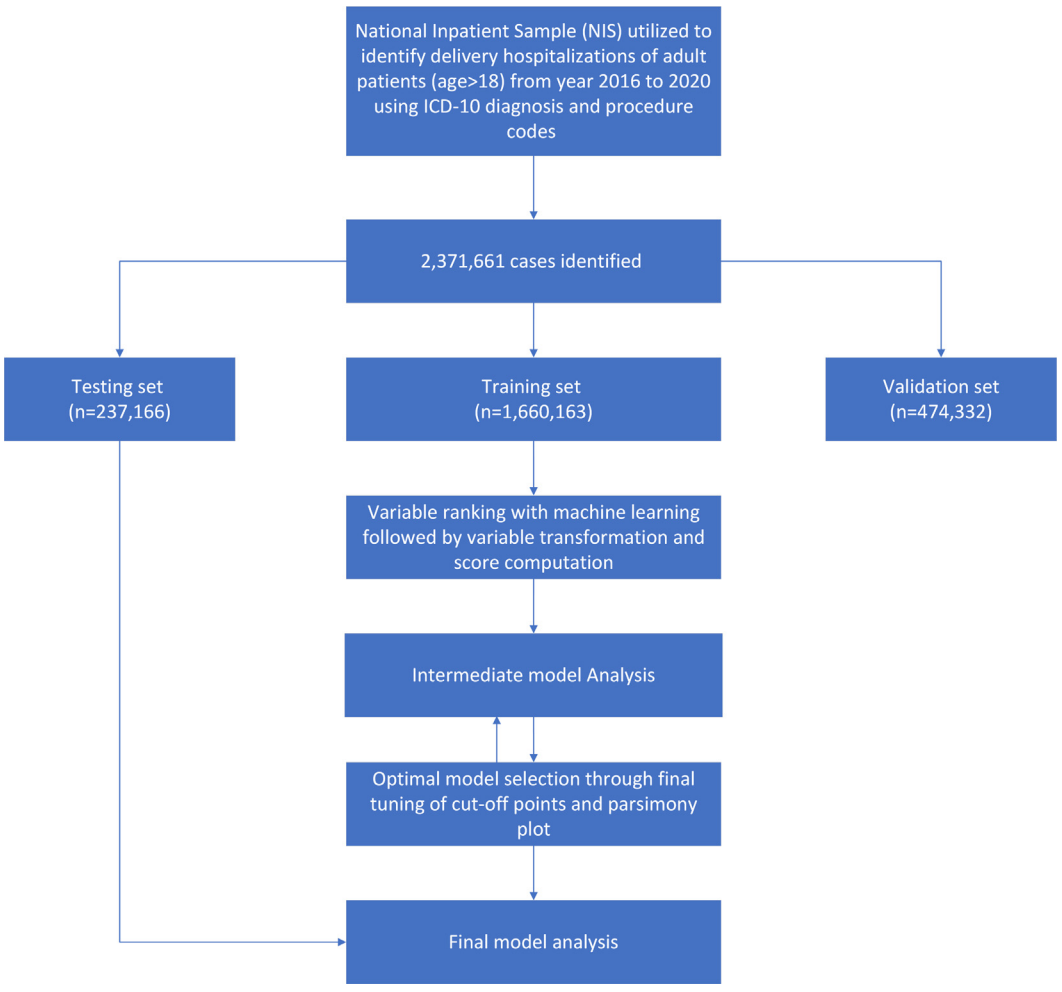
STUDY DESIGN AND DATA SELECTION. This study employed the International Classification of Diseases-10th Revision-Clinical Modification (ICD-10-CM) claims codes to conduct an analysis of NIS data. The initial step involved the identification of hospitalizations associated with delivery through the utilization of ICD-10-CM codes (Supplemental Table 1). The Supplemental Table 2 and **Figure 1** present a comprehensive overview of the critical study design and findings and the methods employed (**Central Illustration**).

STUDY DEFINITIONS. In this study, CV complications were defined as a composite outcome consisting of several conditions, including pre-eclampsia/eclampsia, peripartum cardiomyopathy, acute heart failure (HF), acute coronary syndrome, cardiac arrhythmias, renal complications (acute kidney injury), pulmonary edema, and venous thromboembolism at the time of delivery. Due to the similarity in patterns of risk factors associated with each of these complications and small numbers for several of the individual outcomes, a decision was made to employ a composite end point.[10,11] Pre-existing comorbidities were identified using the comorbidity software provided by the HCUP. Information on race/ethnicity was obtained from the HCUP participating organizations. Median household income was determined annually, and low income in 2020 was defined as an annual income less than $50,000 to $64,999. Electrolyte abnormalities were defined per the clinical classification's software provided by HCUP, which considers secondary comorbidity diagnoses and includes pre-existing hyponatremia, hypernatremia, and acid-base disorders. The study variables were defined using ICD-10 codes and are listed in the supplementary material (Supplemental Table 1).

PRIMARY OUTCOME. The primary outcome of the study was acute peripartum CV complications during delivery admission among pregnant individuals.

STATISTICAL ANALYSIS. In this study, the authors utilized the R package called "AutoScore" to automatically develop clinical scoring models for specific outcomes.[12] First, we split data randomly into three subsets: training, validation, and testing subsets, with a ratio of 0.7, 0.2, and 0.1, respectively. The training set, validation set, and test set were all obtained from the same dataset (the NIS). The training set was used to create the scores, the validation set was used for interim evaluation, and the test set was used to determine the final model's performance metrics. **Figure 1** provides an illustration of the framework. All variables included in the model were selected based on clinical preference, expert

FIGURE 1 Study Flow Diagram

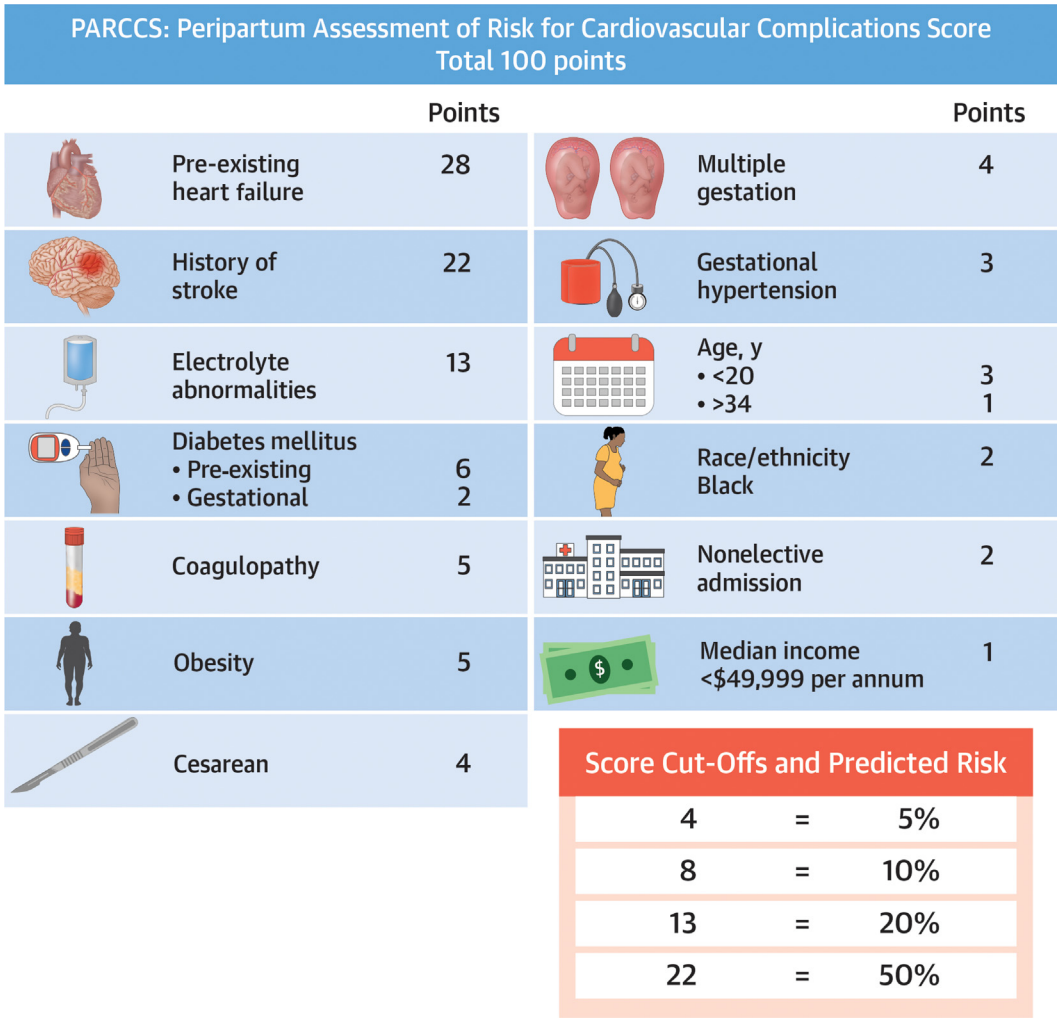


Variable ranking and transformation: The described machine learning method employs a random forest algorithm to generate decision trees, utilizing bootstrapping to reduce overfitting. Variable ranking based on mean decrease impurity measurement aids in selecting important variables that undergo a transformation, such as stratifying continuous variables like age into categories. Intermediate model analysis: The scoring model's performance was evaluated by varying the number of variables, and the optimal trade-off between model complexity and prediction accuracy was determined through a parsimony plot. Final model analysis: The performance of the chosen model was subsequently assessed using the testing dataset. ICD-10 = International Classification of Diseases-10th Revision.

knowledge, or real-world applications.[10,13-15] The initial step in the AutoScore framework involves variable ranking, which is performed using the random forest algorithm. In the AutoScore framework, after variable selection, all chosen variables undergo variable transformation. This involves converting continuous variables into categorical variables, which enables the modeling of nonlinear effects. After selecting and transforming the variables, a risk score was generated to predict the outcome of interest. The score assigned an integer point to each category of an individual variable, and logistic regression was used to weigh the points. The total score was computed by summing up all points (a total of 100).

EVALUATION OF THE PREDICTIVE MODEL. The scoring model's performance was evaluated using receiver operating characteristic analysis, with intermediate evaluation based on the validation set. The area under the curve (AUC) was used as the primary metric for final model evaluation based on an unseen test set. The precision-recall curve (PRC) was

CENTRAL ILLUSTRATION **PARCCS: A Machine Learning Risk-Prediction Model**



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A total of 14 variables were selected based on predictive ability as well as clinical relevance. On performance evaluation using the same testing dataset, an area under the curve of 0.68 (95% CI: 0.67-0.68) was achieved. The PARCCS has a total score range of 0 to 100.

constructed because it is particularly useful when dealing with imbalanced datasets, where the number of negative instances significantly outweighs the positive instances. In such cases, accuracy alone can be misleading, and the precision-recall curve provides a more comprehensive evaluation of the model's ability to correctly identify positive instances while minimizing false positives. Performance metrics such as sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) were calculated under optimal cutoffs, which were defined as the points closest to the upper-left corner of the receiver operating characteristic curves. The model's predictive performance was evaluated by comparing performance metrics under different cutoffs. The demonstration included cutoffs that allowed sensitivity or specificity to reach around 95% to meet certain requirements in clinical settings. The model's

TABLE 1 Baseline Hospitalization Characteristics for Training Set, Testing Set, and Validation Set

	Training Set (N = 1,660,163)			Testing Set (N = 237,166)			Validation Set (N = 474,332)		
	Without CV Complications (n = 1,542,925)	With CV Complications (n = 117,238)	*P* Value	Without CV Complications (n = 220,387)	With CV Complications (n = 16,779)	*P* Value	Without CV Complications (n = 441,157)	With CV Complications (n = 33,175)	*P Value*
Age, y	29.09 ± 5.64	29.35 ± 6.12	<0.001	29.08 ± 5.64	29.46 ± 6.13	<0.001	29.09 ± 5.64	29.38 ± 6.12	<0.001
Mode of admission									
Elective admission	777,596 (50.5)	51,400 (43.9)	<0.001	111,256 (50.6)	7,311 (43.7)	<0.001	222,695 (50.6)	14,682 (44.4)	<0.001
Comorbidities									
Prior MI	239 (0.0)	177 (0.2)	<0.001	36 (0.0)	21 (0.1)	<0.001	68 (0.0)	38 (0.1)	<0.001
Alcohol use	<11 (<0.01)[a]	<11 (<0.01)[a]	0.001	<11 (<0.01)[a]	<11 (<0.06)[a]	1.000	<11 (<0.01)[a]	<11 (<0.01)[a]	0.511
Blood loss anemia	4,110 (0.3)	522 (0.4)	<0.001	592 (0.3)	88 (0.5)	<0.001	1,176 (0.3)	147 (0.4)	<0.001
Pre-existing HF	63 (0.0)	773 (0.7)	<0.001	9 (0.0)	106 (0.6)	<0.001	<11 (<0.01)	220 (0.7)	<0.001
Coagulopathy	27,786 (1.8)	5,085 (4.3)	<0.001	3,970 (1.8)	712 (4.2)	<0.001	7,846 (1.8)	1,432 (4.3)	<0.001
COPD	79,934 (5.2)	9,352 (8.0)	<0.001	11,344 (5.1)	1,354 (8.1)	<0.001	22,712 (5.1)	2,677 (8.1)	<0.001
Deficiency anemia	22,133 (1.4)	2,774 (2.4)	<0.001	3,093 (1.4)	439 (2.6)	<0.001	6,334 (1.4)	764 (2.3)	<0.001
Depression	52,988 (3.4)	6,364 (5.4)	<0.001	7,676 (3.5)	934 (5.6)	<0.001	15,185 (3.4)	1780 (5.4)	<0.001
Pre-existing diabetes	9,609 (0.6)	2,715 (2.3)	<0.001	1,306 (0.6)	379 (2.3)	<0.001	2,711 (0.6)	791 (2.4)	<0.001
Drug use	38,825 (2.5)	4,139 (3.5)	<0.001	5,669 (2.6)	613 (3.7)	<0.001	11,144 (2.5)	1,135 (3.4)	<0.001
Electrolyte abnormalities	5,139 (0.3)	4,444 (3.8)	<0.001	738 (0.3)	663 (4.0)	<0.001	1,540 (0.3)	1,239 (3.7)	<0.001
HIV	257 (0.0)	46 (0.0)	<0.001	36 (0.0)	<11 (<0.06)[a]	0.01	63 (0.0)	13 (0.0)	0.001
Pre-existing hypertension	1,558 (0.1)	919 (0.8)	<0.001	213 (0.1)	142 (0.8)	<0.001	421 (0.1)	248 (0.7)	<0.001
Hypothyroidism	56,572 (3.7)	5,835 (5.0)	<0.001	7,953 (3.6)	881 (5.3)	<0.001	16,053 (3.6)	1,672 (5.0)	<0.001
Liver disease	5,163 (0.3)	831 (0.7)	<0.001	743 (0.3)	114 (0.7)	<0.001	1,483 (0.3)	246 (0.7)	<0.001
Lymphoma	141 (0.0)	21 (0.0)	0.005	15 (0.0)	<11 (<0.06)[a]	1.000	31 (0.0)	<11 (<0.01)[a]	<0.001
Metastatic cancer	77 (0.0)	18 (0.0)	<0.001	10 (0.0)	<11 (<0.06)[a]	0.009	24 (0.0)	<11 (<0.01)[a]	<0.001
Neurological disorders	8,827 (0.6)	1,508 (1.3)	<0.001	1,329 (0.6)	204 (1.2)	<0.001	2,530 (0.6)	416 (1.3)	<0.001
Paralysis	201 (0.0)	83 (0.1)	<0.001	24 (0.0)	<11 (<0.06)[a]	0.658	60 (0.0)	17 (0.1)	<0.001
Peptic ulcer disease	150 (0.0)	33 (0.0)	<0.001	21 (0.0)	<11 (<0.06)[a]	1.000	54 (0.0)	<11 (<0.01)[a]	0.115
Peripheral vascular disease	140 (0.0)	54 (0.0)	<0.001	29 (0.0)	<11 (<0.06)	0.871	37 (0.0)	11 (0.0)	<0.001
Psychosis	1834 (0.1)	261 (0.2)	<0.001	243 (0.1)	42 (0.3)	<0.001	529 (0.1)	74 (0.2)	<0.001
Pulmonary hypertension	301 (0.0)	317 (0.3)	<0.001	37 (0.0)	44 (0.3)	<0.001	78 (0.0)	91 (0.3)	<0.001
Kidney failure	1112 (0.1)	648 (0.6)	<0.001	167 (0.1)	103 (0.6)	<0.001	327 (0.1)	175 (0.5)	<0.001
Connective tissue disease	5131 (0.3)	824 (0.7)	<0.001	758 (0.3)	108 (0.6)	<0.001	1,403 (0.3)	225 (0.7)	<0.001
Solid organ tumor	460 (0.0)	64 (0.1)	<0.001	85 (0.0)	<11 (<0.06)[a]	0.457	134 (0.0)	19 (0.1)	0.013
Valvular disease	511 (0.0)	147 (0.1)	<0.001	83 (0.0)	17 (0.1)	<0.001	160 (0.0)	37 (0.1)	<0.001
Weight loss	172 (0.0)	80 (0.1)	<0.001	21 (0.0)	12 (0.1)	<0.001	54 (0.0)	19 (0.1)	<0.001
Anemia	162,744 (10.5)	17,589 (15.0)	<0.001	22,958 (10.4)	2,548 (15.2)	<0.001	46,493 (10.5)	4,869 (14.7)	<0.001
History of CVA	141 (0.0)	539 (0.5)	<0.001	27 (0.0)	64 (0.4)	<0.001	48 (0.0)	129 (0.4)	<0.001
Coronary artery disease	212 (0.0)	145 (0.1)	<0.001	31 (0.0)	22 (0.1)	<0.001	61 (0.0)	45 (0.1)	<0.001
Smoking	68,691 (4.5)	5,640 (4.8)	<0.001	9,813 (4.5)	793 (4.7)	0.102	19,590 (4.4)	1,611 (4.9)	<0.001
End-stage kidney disease	61 (0.0)	51 (0.0)	<0.001	<11 (<0.01)[a]	<11 (<0.06)[a]	<0.001	13 (0.0)	18 (0.1)	<0.001
Chronic kidney disease	158 (0.0)	205 (0.2)	<0.001	19 (0.0)	39 (0.2)	<0.001	50 (0.0)	65 (0.2)	<0.001
Hyperlipidemia	4,069 (0.3)	859 (0.7)	<0.001	558 (0.3)	117 (0.7)	<0.001	1,182 (0.3)	242 (0.7)	<0.001

Continued on the next page

predicted probability was compared to the actual outcomes in the testing dataset by constructing a calibration plot using the "givitiR" package.[16]

The dataset was inspected for missing data. Overall, the rate of missing data were small (<1%) and recoded as a predominant category. Categorical variables were presented as frequencies and percentages, and continuous variables were reported as mean ± SD. Baseline characteristics were compared using Pearson's chi-square and Fisher's exact tests for categorical variables and the Mann-Whitney U test for continuous variables. For all analyses, a 2-tailed

TABLE 1 Continued

	Training Set (N = 1,660,163)			Testing Set (N = 237,166)			Validation Set (N = 474,332)		
	Without CV Complications (n = 1,542,925)	With CV Complications (n = 117,238)	*P* Value	Without CV Complications (n = 220,387)	With CV Complications (n = 16,779)	*P* Value	Without CV Complications (n = 441,157)	With CV Complications (n = 33,175)	*P Value*
Obstetric characteristics									
Multiple gestation	25,018 (1.6)	5,386 (4.6)	<0.001	3,581 (1.6)	778 (4.6)	<0.001	7,204 (1.6)	1,598 (4.8)	<0.001
Cesarean	469,377 (30.4)	58,284 (49.7)	<0.001	67,283 (30.5)	8,395 (50.0)	<0.001	134,547 (30.5)	16,704 (50.4)	<0.001
Preterm birth	79,664 (5.2)	11,822 (10.1)	<0.001	11,241 (5.1)	1,673 (10.0)	<0.001	22,717 (5.1)	3,359 (10.1)	<0.001
Assisted reproductive technology	3354 (0.2)	518 (0.4)	<0.001	439 (0.2)	72 (0.4)	<0.001	946 (0.2)	155 (0.5)	<0.001
Polycystic ovary syndrome	9,542 (0.6)	1,449 (1.2)	<0.001	1,347 (0.6)	223 (1.3)	<0.001	2,691 (0.6)	392 (1.2)	<0.001
Gestational diabetes	118,775 (7.7)	14,305 12.2)	<0.001	16,920 (7.7)	2013 (12.0)	<0.001	33,811 (7.7)	4,014 (12.1)	<0.001
Obesity	130,313 (8.4)	22,828 (19.5)	<0.001	18,467 (8.4)	3,302 (19.7)	<0.001	37,302 (8.5)	6,471 (19.5)	<0.001
Gestational hypertension	79,664 (5.2)	11,822 (10.1)	<0.001	11,241 (5.1)	1,673 (10.0)	<0.001	22,717 (5.1)	3,359 (10.1)	<0.001
Systemic lupus erythematosus	2084 (0.1)	405 (0.3)	<0.001	276 (0.1)	57 (0.3)	<0.001	541 (0.1)	111 (0.3)	<0.001
Rheumatoid arthritis	2,114 (0.1)	266 (0.2)	<0.001	330 (0.1)	27 (0.2)	0.797	617 (0.1)	67 (0.2)	0.005
Racial/ethnic and socioeconomic characteristics									
Black	214,654 (13.9)	24,448 (20.9)	<0.001	30,489 (13.8)	3,438 (20.5)	<0.001	61,158 (13.9)	6,898 (20.8)	<0.001
Hispanic	297,876 (19.3)	22,654 (19.3)	0.889	42,298 (19.2)	3,202 (19.1)	0.737	85,086 (19.3)	6,403 (19.3)	0.957
Asian or Pacific Islander	94,088 (6.1)	5,315 (4.5)	<0.001	13,431 (6.1)	849 (5.1)	<0.001	26,697 (6.1)	1,526 (4.6)	<0.001
Medicaid	646,686 (41.9)	52,009 (44.4)	<0.001	92,292 (41.9)	7,461 (44.5)	<0.001	184,176 (41.7)	14,656 (44.2)	<0.001
Low income	417,662 (27.1)	36,736 (31.3)	<0.001	59,662 (27.1)	5,247 (31.3)	<0.001	119,090 (27.0)	10,413 (31.4)	<0.001

Values are mean ± SD or n (%). [a]Observations <11 are not reported as per HCUP guidelines.
COPD = chronic obstructive pulmonary disease; CV = cardiovascular; CVA = cerebral vascular accident; HCUP = Healthcare Cost and Utilization Project; HF = heart failure; MI = myocardial infarction.

$P = 0.05$ was considered statistically significant. Analyses were performed using R software for statistical computing version 4.3.

RESULTS

BASELINE CHARACTERISTICS OF THE STUDY SAMPLE. The analysis included a total of 2,371,661 pregnant patients at delivery hospitalization, of whom 2,204,469 (93%) had no CV complications and 167,192 (7%) had CV complications. Supplemental Table 3 details the hospitalization characteristics of delivery admissions, categorized by the presence or absence of CV complications in the overall sample. The mean age of individuals with CV complications was 29 years. The percentage of elective admissions was higher among patients without CV complications (50.5%) than those with CV complications (44.0%) ($P < 0.01$). In the study, it was observed that individuals with peripartum CV complications were more commonly Black patients and belonged to the lowest zip code quartile of income. These individuals also had a higher prevalence of comorbidities such as HF, history of stroke, electrolyte abnormalities, cesarean delivery, obesity, diabetes, coagulopathy, gestational hypertension, and multiple gestation.

Table 1 compares the baseline characteristics of the three different sets of patient data: the training set, the validation set, and the testing set. The total number of patients in the datasets was as follows: the training set contained 1,660,163 patients, the validation set contained 474,332 patients, and the testing set contained 237,166 patients (Table 1).

PARCCS. The scoring model includes 14 variables that are used to predict the risk of CV complications during delivery admission. For each variable, there are specific intervals and point values assigned to them based on their impact on CV complications, with a score ranging from 0 to 100. The PARCCS variables included measures such as electrolyte imbalances (13 points [p]), age (3p for age <20 years), a cesarean delivery (4p), obesity (5p), pre-existing HF diagnosis (28p), multiple gestations (4p), Black race (2p), gestational hypertension (3p), low income (1p), gestational diabetes (2p), chronic diabetes (6p), prior stroke (22p), coagulopathy (5p), and nonelective admission (2p).

Using the validation set, the performance of the model was evaluated with an AUC of 0.68 and a 95% CI of 0.67 to 0.68. The best score threshold was determined to be a value of 6 or higher, and

performance indicators such as sensitivity, specificity, positive predictive value, and negative predictive value were calculated based on this threshold. These indicators give an idea of how well the model is able to correctly identify cases of peripartum CV complications.

PERFORMANCE METRICS OF THE PARCCS. Table 2 shows the performance of the predictive model for different predicted risk cutoffs. For example, at a predicted risk cutoff of 5%, a score cutoff of 4, and identification of 52% of patients as high-risk, the model has an accuracy of 51.2% (95% CI: 51.1%-51.3%). The sensitivity was 73.3% (95% CI: 72.8%-73.8%), which means that 73.3% of high-risk patients were correctly identified. The specificity was 49.5% (95% CI: 49.4%-49.7%), which means that only 49.5% of low-risk patients were correctly identified. The PPV was 9.8% (95% CI: 9.8%-9.9%), which means that among all patients identified as high-risk, only 9.8% were truly high-risk. The NPV was 96.1% (95% CI: 96.0%-96.2%), which means that among all patients identified as low-risk, 96.1% were truly low-risk. However, the model's accuracy and specificity improve as the score cutoff is raised. For example, at a cutoff of 13, the accuracy increased to 91.8%, and the specificity rose to 97.7%.

Overall, **Table 2** shows that as the predicted risk cutoff increases, the proportion of patients identified as high-risk decreases, but the specificity and PPV increase. At the same time, the sensitivity and NPV decrease. Therefore, choosing the appropriate cutoff depends on the balance between the risks of false positives (unnecessary interventions for low-risk patients) and false negatives (missed opportunities to intervene for high-risk patients).

The parsimony plot shows ranking of variables performed on the validation set. A higher AUC value implies better performance, with a perfect classifier having an AUC value of 1.0. The value of 0.68 suggests that the model has a moderate ability to distinguish between the positive and negative classes (**Figures 2 and 3**). The PRC exhibits a steep decline at the beginning, indicating a high recall with minimal false positives. As the recall increases, precision decreases significantly, reflecting the model's difficulty in maintaining high accuracy while capturing more positive instances (Supplemental Figure 1). The AUC value for the PRC curve was 0.18. The range of predicted probability of acute CV complications and score cutoff are given in Supplemental Figure 2. The calibration belt is a region of the calibration plot that shows the range of predicted probabilities for a given range of actual probabilities (Supplemental Figure 3).

DISCUSSION

In this work, we newly describe a risk score generated by machine learning, which we called the PARCCS. PARCCS has the potential to be an important tool for identifying pregnant individuals at risk of acute peripartum CV and renal complications at the delivery hospitalization.

The Centers for Disease Control's Pregnancy Mortality Surveillance System data spanning from 2017 to 2019 underscores a diverse array of causes contributing to pregnancy-related deaths.[8] Noteworthy findings reveal a significant prevalence of CV factors, with 14.5% attributed to CV conditions and a closely following 12.1% each for cardiomyopathy and hemorrhage. Infections or sepsis accounted for 14.3%, while thrombotic pulmonary or other embolism constituted 10.5%. Despite various factors playing a role, a compelling argument emerges for the prominence of CV causes in pregnancy-related mortality. This assertion is further supported by the cumulative impact of hypertensive disorders of pregnancy at 6.3% and cerebrovascular accidents at 5.8% on maternal mortality. Even in cases of unknown causes, where 7.0% of pregnancy-related deaths were recorded, the possibility of CV involvement cannot be discounted.[8] Consequently, the data signal a critical need for heightened attention to CV health in pregnant individuals, especially given the increasing prevalence of chronic conditions like hypertension and diabetes, which further amplify the risk of complications during pregnancy and the postpartum period.

Our study has developed a novel predictive model for peripartum CV complications during delivery, which incorporates both established and emerging risk factors.[17] While previous studies have examined predictive models for adverse pregnancy outcomes, our model is the first to specifically target CV complications during delivery.[18] Machine learning models are particularly useful in handling large amounts of complex data and identifying patterns that may not be easily recognizable by human analysis.[19] Unfortunately, it is well known that machine learning algorithms can produce biased predictions if the underlying data used to train the model does not include minority ethnic groups or account for socioeconomic disparities.[20] However, our risk prediction model has the advantage of being built on a diverse,

TABLE 2 Performance of the Predictive Model for Different Predicted Risk Cutoffs

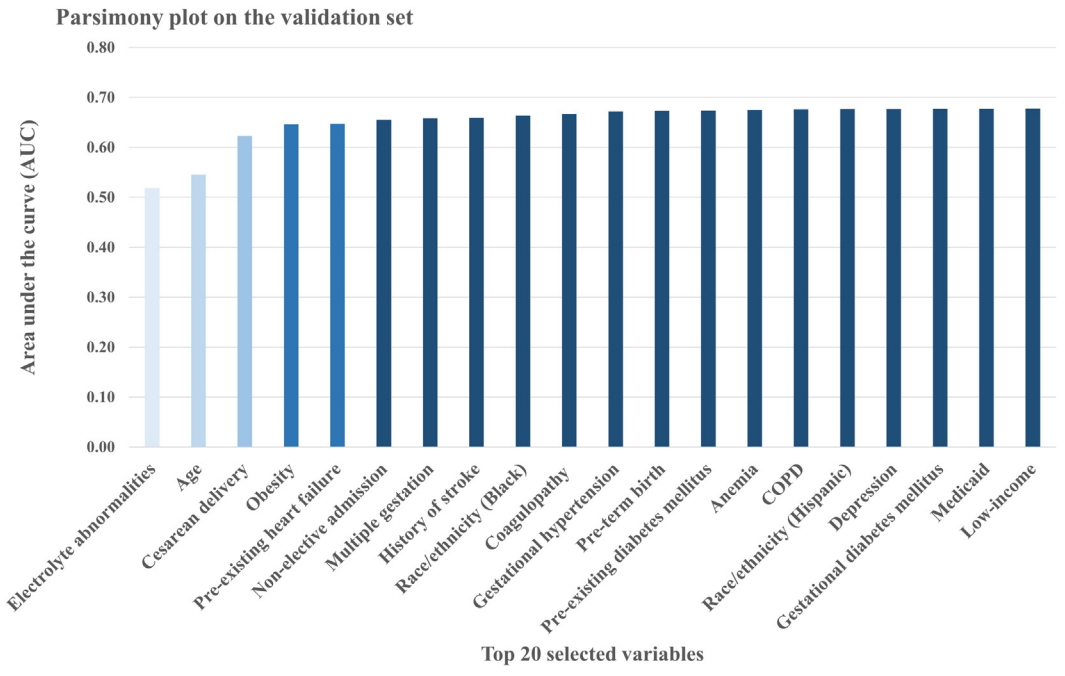
Predicted Risk, ≥	Score Cutoff, ≥	Percentage of Patients	Accuracy (95% CI)	Sensitivity (95% CI)	Specificity (95% CI)	PPV (95% CI)	NPV (95% CI)
5%	4	52	51.2% (51.1%-51.3%)	73.3% (72.8%-73.8%)	49.5% (49.4%-49.7%)	9.8% (9.8%-9.9%)	96.1% (96%-96.2%)
10%	8	16	82.2% (82.1%-82.3%)	38.1% (37.6%-38.6%)	85.5% (85.4%-85.7%)	16.6% (16.3%-16.8%)	94.8% (94.8%-94.9%)
20%	13	3	91.8% (91.7%-91.8%)	12.8% (12.5%-13.2%)	97.7% (97.7%-97.7%)	29.5% (28.8%-30.2%)	93.7% (93.7%-93.7%)
50%	22	0	93.1% (93.1%-93.1%)	2.6% (2.5%-2.8%)	99.9% (99.9%-99.9%)	63.3% (60.8%-65.9%)	93.2% (93.2%-93.2%)

NPV = negative predictive value; PPV = positive predictive value.

nationally representative U.S. dataset. Incorporating socioeconomic and racial/ethnic variables into acute peripartum CV complication risk prediction models can improve risk prediction accuracy and address health disparities in maternal health outcomes.[21] Race is largely a social construct, and disparities in maternal health outcomes experienced by Black patients likely reflect biases related to access to care and structural racism, rather than biological/genetic differences.[13,22] Indeed, our machine learning algorithm identified both Black race and low income as predictive variables in the PARCCS model. By utilizing a large dataset of patients that includes socioeconomic and racial/ethnic data, our machine learning model can identify risk factors that may have been overlooked in previous studies, with the goal of improving patient outcomes and decreasing health disparities in the United States. This approach has the potential to enhance the accuracy and fairness of risk prediction models and ultimately contribute to the goal of achieving equitable health care for all.

In our model, beyond accounting for race/ethnicity and socioeconomic characteristics, we have incorporated cardiometabolic risk factors

FIGURE 2 Parsimony Plot



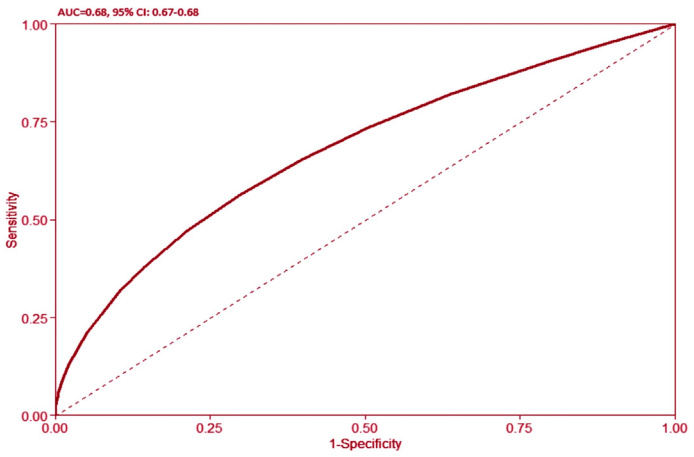
In the initial stage, 20 variables were ranked. This was subsequently narrowed down to 14 variables, which led to the creation of a parsimonious model. Additional variables beyond the chosen 14 did not contribute significantly to improving the model's performance. Detailed information regarding this selection process can be found in the methods section. COPD = chronic obstructive pulmonary disease.

specific to pregnancy. These factors encompass gestational hypertension, gestational diabetes, preexisting diabetes, a history of stroke, and obesity. Extensive literature has previously established the association of these risk factors with adverse pregnancy outcomes, particularly concerning CV complications.[11,17,23,24] Specifically, gestational hypertension and gestational diabetes have been shown to be associated with a 2-fold higher risk of acute peripartum CV complication at the time of delivery admission.[10,25] This inclusion serves to enhance the comprehensiveness of our predictive framework, acknowledging the multifaceted nature of influences on pregnancy-related health outcomes. The consideration of these factors not only aligns with existing research but also reinforces the relevance of our model in capturing a more nuanced understanding of the interplay between maternal health and CV risks during pregnancy.

We also used contemporary U.S. data to build this model, from the years 2016 to 2020. Furthermore, our model was developed using an inpatient dataset that is representative of the diverse population of the United States. This diversity in the dataset ensures that our model can be applied in various health care settings, potentially making it a valuable tool for clinicians in predicting and managing peripartum CV complications. Overall, our study could be an important contribution to the field of cardio-obstetrics and highlights the need for targeted predictive models for specific adverse outcomes.

The development of risk prediction models for acute peripartum CV complications can be easily incorporated into electronic health records (EHRs) and used in clinical practice, with the hope that earlier identification of risk could lead to the implementation of strategies that improve patient outcomes.[26] The integration of these models allows for a more comprehensive understanding of patient risk factors, facilitating personalized care and communication and coordination of care between health care professionals.[27-29] EHR integration also aids in tracking and monitoring patient outcomes, allowing for continuous quality improvement initiatives.[30] Moreover, the utilization of a composite outcome seeks to enhance the model's clinical applicability by facilitating the recognition of a diverse array of acute CV complications, thereby affording clinicians a comprehensive and clinically pertinent viewpoint. Nevertheless, it is imperative to recognize that this decision may exert an influence on the performance of the model. Overall, the development and integration of these risk prediction models in EHRs have the potential to significantly impact maternal health outcomes and improve the quality of care provided to pregnant individuals.

FIGURE 3 Receiver Operating Characteristics Curve



AUC = area under the curve.

STUDY LIMITATIONS. Risk prediction models based on administrative datasets may have lower accuracy compared to those that incorporate clinical and socioeconomic variables, but they are still valuable in clinical practice due to their broad applicability and accessibility.[31] The strength of the model is an NPV of 96% demonstrating its ability to correctly identify individuals who do not have acute peripartum CV complications at delivery. Our model exhibited elevated positive rates. However, when assessing the performance of a classification model, the choice of the evaluation metric is contingent upon the specific objectives and requirements of the task at hand. In certain instances, prioritizing the identification of true positives, even at the expense of some false positives, may constitute a valid strategy. The detection of an increased number of true positives facilitates improved explication and intervention in high-risk scenarios. By capturing a greater number of true positives, the model affords an opportunity for workup or intervention by the cardio-obstetrics team. Nevertheless, the absence of granular data does impact the model's performance within extensive datasets. Despite this limitation, the model harbors

potential for integration into real-world EHR due to its reliance on ICD-10 coding. Consequently, there is potential for ongoing refinement of the model, allowing it to evolve dynamically within the EHR environment. Founded on an extensive dataset that includes diverse samples, races/ethnicities, and socioeconomic variables, our model represents an initial stride in a promising trajectory.

The limitations of our model are intrinsically tied to the constraints of the dataset. One notable constraint stems from the absence of granular data pertaining to the timing of outcomes. Unfortunately, the dataset lacks detailed information on the temporal aspect of adverse CV events during pregnancy. Consequently, we were compelled to adopt a binary model, distinguishing only whether a peripartum CV complication occurred or not. This limitation restricts our ability to analyze the nuanced temporal dynamics of these outcomes. Individual outcome data were not presented due to a limited sample size (<11) in compliance with HCUP guidelines, necessitating the reporting of a composite outcome instead. Consequently, future research endeavors are warranted to formulate predictive models specifically tailored to individual complications, thereby evaluating the potential for enhanced model performance in such instances. Additionally, while income was a variable included in our model, the scope of socioeconomic characteristics could be broadened. For instance, incorporating educational level attainment and other socio-economic indicators, such as occupation or neighborhood characteristics, may offer a more comprehensive understanding of the multifaceted factors influencing CV outcomes during pregnancy. Our model has identified electrolyte imbalances as a significant predictor of acute CV complications. However, it is noteworthy that electrolyte imbalances are prevalent even among normal pregnancies, raising questions regarding their role as markers of disease severity or indicative of a predictive association. To elucidate this, further longitudinal studies are imperative. Unfortunately, due to inherent limitations in the NIS database, data on other socioeconomic variables were unavailable. Recognizing these limitations underscores the need for future research endeavors to encompass a more extensive array of socioeconomic variables to enhance the precision and applicability of predictive models in maternal CV health. Finally, we did not include COVID-19 infection as a variable (available only in the 2020 NIS dataset), although it has been associated with CV complications during pregnancy,[32] as this is a rapidly changing field with the development of COVID vaccines and changes in COVID viral variants that influence CV outcomes.

CONCLUSIONS

PARCCS: A Machine Learning Risk-Prediction Model for Acute Peripartum Cardiovascular Complications during Delivery Admissions Score has the potential to be a valuable tool in the fight against rising maternal morbidity and mortality rates in the United States due to CV causes. This easy-to-use risk prediction model can be employed in diverse health care systems, and its accuracy and specificity make it a useful tool for identifying patients at risk for acute peripartum CV and renal complications at the time of delivery. However, future studies using longitudinal data are required to further validate the PARCCS score and determine whether its use does improve patient outcomes and reduce maternal mortality rates in the United States by providing an opportunity for earlier intervention and targeted monitoring. Overall, the development and implementation of risk prediction models like PARCCS are crucial in addressing the maternal health crisis and improving the quality of care provided to pregnant women of diverse racial, ethnic, and socioeconomic backgrounds in the United States.

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ADDRESS FOR CORRESPONDENCE: Dr Erin D. Michos, Division of Cardiology, Johns Hopkins Hospital, 600 N. Wolfe Street, Blalock 524-B, Baltimore, Maryland 21287, USA. E-mail: edonnell@jhmi.edu. X handle: @ErinMichos.

PERSPECTIVES

COMPETENCY IN PRACTICE-BASED LEARNING AND IMPROVEMENT: The study employed a nationwide dataset to construct a predictive model based on machine learning techniques, aiming to identify acute CV complications occurring during the peripartum period. This user-friendly risk prediction model (PARCCS score) is adaptable for implementation in various health care settings, rendering it a valuable tool for the early identification of individuals susceptible to acute peripartum CV complications.

TRANSLATIONAL OUTLOOK: To establish the validity of the risk prediction score and assess its potential impact on enhancing patient outcomes and decreasing maternal mortality rates in the United States, it is imperative for forthcoming research endeavors to utilize longitudinal data. These studies can ascertain whether the implementation of the PARCCS score leads to improved results by enabling earlier intervention and precise monitoring strategies.

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KEY WORDS cardiovascular disease, CVD, machine learning, preeclampsia, risk prediction

APPENDIX For supplemental tables and figures, please see the online version of this paper.