GYNECOLOGY

A model to predict risk of blood transfusion after gynecologic surgery

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BACKGROUND: A model that predicts a patient's risk of receiving a blood transfusion may facilitate selective preoperative testing and more efficient perioperative blood management utilization.

OBJECTIVE: We sought to construct and validate a model that predicts a patient's risk of receiving a blood transfusion after gynecologic surgery.

STUDY DESIGN: In all, 18,319 women who underwent gynecologic surgery at 10 institutions in a single health system by 116 surgeons from January 2010 through June 2014 were analyzed. The data set was split into a model training cohort of 12,219 surgeries performed from January 2010 through December 2012 and a separate validation cohort of 6100 surgeries performed from January 2013 through June 2014. In all, 47 candidate risk factors for transfusion were collected. Multiple logistic models were fit onto the training cohort to predict transfusion within 30 days of surgery. Variables were removed using stepwise backward reduction to find the best parsimonious model. Model discrimination was measured using the concordance index. The model was internally validated using 1000 bootstrapped samples and temporally validated by testing the model's performance in the validation cohort. Calibration and decision curves were plotted to inform clinicians about the accuracy of

predicted probabilities and whether the model adds clinical benefit when making decisions.

RESULTS: The transfusion rate in the training cohort was 2% (95% confidence interval, 1.72–2.22). The model had excellent discrimination and calibration during internal validation (bias-corrected concordance index, 0.906; 95% confidence interval, 0.890–0.928) and maintained accuracy during temporal validation using the separate validation cohort (concordance index, 0.915; 95% confidence interval, 0.872–0.954). Calibration curves demonstrated the model was accurate up to 40% then it began to overpredict risk. The model provides superior net benefit when clinical decision thresholds are between 0–50% predicted risk.

CONCLUSION: This model accurately predicts a patient's risk of transfusion after gynecologic surgery facilitating selective preoperative testing and more efficient perioperative blood management utilization.

Key words: blood management, blood transfusion, blood transfusion risk, gynecologic surgery, perioperative, predict, predictive model, preoperative testing

Introduction

In 2012, the American Congress of Obstetrics and Gynecology and 70 specialty societies joined the American Board of Internal Medicine Foundation Choosing Wisely program with the goal of advancing national dialogue on avoiding wasteful or unnecessary medical tests, treatments, and procedures.¹ The group recommended against routinely ordering complete blood cell counts, basic or comprehensive metabolic panels, and coagulation tests in low-risk patients for 3 reasons: (1) these studies are typically normal before low-risk surgery, (2) abnormal results lead to a change in management in as few as 3% of patients, and (3) randomized trials

demonstrated no difference in intraoperative or postoperative patient outcomes when preoperative testing is performed.^{2–7}

Despite these efforts, gynecologists heuristically order routine preoperative laboratory testing in low- and high-risk patients before surgery even when many of these laboratory results are already present in the medical record. One major reason for this testing is to identify medically high-risk patients, optimize them before surgery, and lower their risk. Specifically, providers are concerned about risk of anemia and surgical blood loss along with the need for a possible transfusion. Transfusion carries significant uncommon risks including allergic reaction, fever, and—even more rare—acute immune hemolytic reaction, delayed hemolytic reaction, transfusion-associated circulatory overload, transfusion-related acute lung injury, and bloodborne infections.⁸ Blood transfusions are also correlated with adverse postoperative outcomes and their associated costs, including

septic, wound, thromboembolic, and pulmonary complications; longer hospital stays; higher hospital charges; and patient death.^{9–11}

The average risk of transfusion is variable in gynecology and ranges from 0.01% for operative hysteroscopy, 2–5% for operative laparoscopy, 0.3–11% for hysterectomy, 21% for myomectomy, and up to 78% for cytoreductive surgery.^{12–18} However, the overall average risk of a woman requiring a blood transfusion after gynecologic surgery is low making routine testing a high-cost, low-value decision. Improving the accuracy of predicting a patient's specific risk requires the surgeon to incorporate known risk factors and crudely estimate whether the patient is lower, similar, or higher than these averages.

Prediction models can be useful when estimating a patient's risk is challenging. This can be due to the need to account for multiple risk factors or when clinical practice is highly variable, and may result in unnecessary testing or variability in treatment. For this reason, prediction

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models are being incorporated into care paths and clinical practice guidelines. An accurate model that could predict the probability of transfusion may facilitate efforts to reduce unnecessary testing in low-risk patients since low-value, frequently employed interventions such as preoperative testing represent significant unreimbursed cost to health systems and expose patients to harm. Such a model could also aid in identifying high-risk patients and facilitate more efficient use of blood management services potentially decreasing associated patient risks and costs of transfusion.¹⁹

The objectives of this study were to build and validate a model that accurately predicts the probability of transfusion given a set of baseline patient characteristics and risk factors of women undergoing gynecologic surgery in a multiinstitutional health system.

Materials and Methods

This was an institutional review board–approved, retrospective cohort analysis of women who underwent gynecologic surgery at 10 institutions in a single health system by 116 surgeons from Jan. 1, 2010, through June 30, 2014. Guidelines for the transparent reporting of a multivariable prediction model for individual prognosis or diagnosis statement were used in this study.²⁰ Eligible patients were identified if they had gynecologic surgery through review of their *Current Procedural Terminology* codes during the study period. Patients who underwent obstetric surgical procedures were excluded. Data were extracted from the institution-wide electronic medical record and using an electronic blood utilization tool, Haemonetics IMPACT.²¹ The outcome of the model was defined as any patient identified as receiving ≥ 1 U of packed red blood cells, cryoprecipitate, platelets, or plasma on the day of or within 30 days of their surgery date. Candidate predictors of blood transfusion were compiled from a literature review, expert opinion, and clinical judgment and collected from the electronic record.^{22–25}

Once the data set was complete it was divided into a model training and test set. When an external validation data set

TABLE 1
Variability in rates of transfusion using common gynecologic surgery categories

Common gynecologic surgery categories ^a	Rate of transfusion, %	95% Confidence interval
Procedure		
Colpopexy	1	0.57–2.13
Ectopic	2	0.56–6.62
Hysterectomy	4	3.13–4.20
Myomectomy	7	4.44–10.3
Approach		
Hysteroscopy	0	0.14–0.40
Vaginal	1	0.54–1.62
Laparoscopy	1	0.68–1.73
Laparotomy	9	7.80–10.33
Procedure for malignancy	16	13.1–20.1
Overall average transfusion rate	2	1.72–2.22

^a Not mutually exclusive.

Stanhiser et al. Transfusion prediction model. Am J Obstet Gynecol 2017.

is unavailable to test a new model but an existing modeling data set is sufficiently large, as in this case, it is recommended to split by time and develop the model using data from one period and evaluate its performance from data from a future period. This method is stronger methodologically than randomly splitting a data set.²⁰ However, there are no guidelines on how to choose the time cut points, so we arbitrarily chose to divide the total cohort into thirds by using two-thirds to build and internally validate the model using patients who underwent surgery in a time period after the development cohort. The total cohort was split into a model training cohort of 12,219 surgeries performed from January 2010 through December 2012 and a separate validation cohort of 6100 surgeries performed from January 2013 through June 2014.

In all, 47 candidate risk factors were considered for fitting on the training data set (Supplemental Table). Missing values in risk factors were assessed for missing at random using methods described by Harrell²⁶ and multiple imputation using chained equations were used to calculate missing values.²⁷

Imputed values were used for predictors in each model while the outcomes for all models were based only on actual and not imputed events.

A multiple logistic model was fit on the training cohort. Continuous variables were modeled by fitting 3, 4, and 5 knot-restricted cubic splines to avoid the assumption of a linear association between the continuous variable and the outcome.²⁸ Categorical variables were not considered for model fitting when expected events were <5 , when the SE was >0.4 , or when collinearity was detected using a variable inflation factor that was >10 .²⁸ The variable selection process was done using Harrell et al's²⁹ model approximation process of backward elimination to rank the variables in order of importance starting from the full model using a bootstrap bias-corrected concordance index as the stopping criteria. This process started with the full model and removed each variable one at a time, while calculating the model's accuracy at the point of each variable removal. Each variable's removal was determined by the variable that produced the smallest reduction in the adjusted R^2 . This was repeated until the accuracy's change was <0.01

resulting in the best parsimonious model.

Model performance was measured using the concordance index, calibration plots, and Brier score. The concordance index is a measurement of discrimination and measures the model's ability to assign a higher predicted probability to a patient who is at high risk and a lower predicted probability to a patient who is at low risk. The concordance index ranges from 0.5-1, where 0.5 indicates that the model is no better than chance at making a prediction and 1 indicates that the model perfectly identifies those who experienced the event and those who did not. The calibration plot measures the relationship between the model's predicted probability and the actual probability. A perfect relationship will follow a straight 45-degree line. The Brier score measures the overall accuracy of a model's predictions.³⁰ The model was internally validated using 1000 bootstrap samples to produce bias-corrected estimates of the model's performance. This was followed by testing the model's performance on the separate test cohort. The final prediction model's relationship among the predictors was visualized using a nomogram and an online calculator was built for easy clinical use located at: <http://riskcalc.org:3838/>.

A decision curve analysis is a form of decision analysis. A decision curve was plotted to inform clinicians about the range of threshold probabilities for which the prediction model would be of clinical value.³¹ Decision curve analysis offers insight into clinical consequences of using the model by determining the relationship between a chosen predicted probability threshold and the relative value of false-positive and false-negative results to obtain a value of net benefit of using the model at that threshold.³² All analyses were performed using R version 3.2.3 (R Foundation for Statistical Computing, Vienna, Austria).

Results

A total of 18,319 gynecologic surgeries occurred during the study period. The overall average rate of transfusion in the training cohort was 239 of 12,219

TABLE 2

Variables in model to predict risk of transfusion after gynecologic surgery

	Adjusted odds ratio	Lower 95% CI	Upper 95% CI
Intercept	4.166	−2.808	11.140
BMI	−0.158	−0.454	0.138
BMI ^a	3.867	−7.852	15.586
BMI ^b	−4.988	−17.089	7.114
Fibroids	−0.770	−1.742	0.202
Heavy menstrual bleeding	−2.141	−3.179	−1.103
Hemoglobin, g/dL	−0.996	−1.184	−0.809
History of laparotomy	−2.435	−3.766	−1.103
Hypertension	1.634	0.816	2.451
Hysteroscopy	−3.933	−5.522	−2.345
Laparotomy	4.824	3.815	5.832
Malignancy	1.651	0.554	2.747
Myomectomy	2.572	1.042	4.102
Ovarian cancer	2.375	1.261	3.490
Parity	2.118	0.438	3.798
Parity ^a	−14.428	−24.179	−4.677
Parity ^b	39.671	10.766	68.577
Parity ^c	−37.782	−72.677	−2.888

Equation is available upon request for further research purposes by contacting authors.

BMI, body mass index; CI, confidence interval.

^a Nonlinear component A of the function describing the variable and the probability of transfusion; ^b Nonlinear component B of the function describing the variable and the probability of transfusion; ^c Nonlinear component C of the function describing parity and the probability of transfusion.

Stanhisser et al. Transfusion prediction model. Am J Obstet Gynecol 2017.

(2%; 95% confidence interval [CI], 1.72–2.22%) surgeries. Rates of transfusion grouped by common gynecologic procedures, common approaches used by gynecologic surgeons, or for malignancy only are compared to the overall average rate of transfusion in Table 1. As expected, hysterectomy and myomectomy had higher than average rates of transfusion (4% and 7%, respectively) and when procedures were performed for malignancy, this rate rose to an average of 16%.

The unadjusted comparisons of the 47 candidate predictors in the training cohort are presented in the Supplemental Table. Among the candidate predictors, expected events were <5 in 3 categorical variables, the SE was >0.4 in 21 variables, and collinearity was detected in 1 variable leaving 22 candidate predictors

considered. Body mass index (BMI) and parity had significant nonlinear associations with risk of transfusion (Supplemental Figures 1 and 2).

Twelve variables were included within the final model. Low hemoglobin, history of hypertension, history of ovarian cancer, and performing a laparotomy, myomectomy, or a procedure for malignancy increased the risk of blood transfusion. In contrast, history of fibroids, heavy menstrual bleeding, previous laparotomy, or performing a hysteroscopy were associated with a decreased risk of blood transfusion (Table 2). The nomogram illustrates the strength of association of the predictors to the outcome as well as the nonlinear associations between BMI and parity and risk of transfusion (Figure 1).

FIGURE 1
Nomogram for predicting probability of transfusion after gynecologic surgery

First row (points) is point assigned to each variable's measurement from rows 2-13, which are variables included in predictive model. Assigned points for all variables are then summed and total can be located on line 14 (total points). Once total points are located, draw vertical line down to bottom line to obtain predicted probability of transfusion. For parity predictor, following values should be read from left to right: (2 or 3), 4, 5, 6, 0, 7, 8, 9, 10, and 1.

Stanisier et al. Transfusion prediction model. Am J Obstet Gynecol 2017.

On internal validation, the final parsimonious model had excellent discrimination as demonstrated by a bias-corrected concordance index of 0.906 (95% CI, 0.890–0.928) and a Brier score of 0.017. On temporal validation, the model continued to have excellent discriminatory ability (concordance index, 0.915; 95% CI, 0.872–0.954). [Figure 2](#) demonstrates the calibration curve of the model's performance on the

validation cohort. The model provided excellent predictions throughout the range of predicted risks and was accurate through a range of predicted probabilities of 0% to approximately 40% risk of transfusion.

The decision curve demonstrated that the transfusion model has additional clinical value since it has the highest net benefit across a broad range of predicted probabilities ranging from 0-50% risk

([Figure 3](#)). This suggests that basing decisions on the model will result in an overall net benefit compared to not using the model.

Comment

We have successfully built and temporally validated a model that accurately predicts a patient's risk of receiving blood transfusion after gynecologic surgery. The initial tests of the model's generalizability are promising as it was developed from a large cohort and tested in a subsequent cohort from multiple different institutions in a single health system by >100 different surgeons. The model had excellent discrimination (>90% accurate) between women at lower and higher risk and was able to maintain this accuracy across a large range of useful predicted probabilities (up to 40-50% risk). The model was accurate up to approximately 40-50% risk of transfusion, and then it began to slightly overpredict risk. We believe this slight overprediction, however, is unlikely to change a clinician's decision on management. Beyond accuracy, the model appears to be clinically valuable and likely to do more good than harm when used to make decisions when the predicted probability is between 0-50% as displayed by the decision curve.³³

This study also has important secondary findings. We have determined overall average rates of blood transfusion in gynecologic surgery and rates of transfusion depending on different groupings of gynecologic surgery ([Table 1](#)). These average estimates are useful for policy makers, those responsible for allocating institutional resources, and those communicating with patients. This study also contributed to the existing body of literature investigating risk factors for transfusion in women undergoing surgery. Although many of these findings were expected to increase the risk of blood transfusion (eg, low hemoglobin, history of ovarian cancer, laparotomy, myomectomy, or a procedure for malignancy), we were also able to demonstrate interesting unadjusted nonlinear associations with BMI and parity that may need further investigation. At first glance, a history of

FIGURE 2**Calibration curve demonstrating transfusion model's performance when tested on validation cohort**

Calibration curve demonstrating transfusion model's performance when tested on validation cohort of women undergoing gynecologic surgery from January 2013 through June 2014.

CI, confidence interval.

Stanhisser et al. Transfusion prediction model. *Am J Obstet Gynecol* 2017.

fibroids, heavy menstrual bleeding, or a previous laparotomy were surprisingly associated with a decreased risk of blood transfusion. However, it is possible that

these factors are routinely recognized during clinical care allowing surgeons to intervene prior to or during surgery and potentially reduce risk when all other

risk factors are considered in the model. It is for this reason we suggest using caution in generalizing the identified variables in the model to cause-effect relationships rather than factors that predict transfusion.

Our findings are comparable to previous studies. Prediction models for blood transfusion in other specialties have found predictors to include older age, lower BMI, and lower preoperative hemoglobin, as well as specialty-specific factors.²²⁻²⁶ The gynecologic literature supports increased risk of transfusion with lower hemoglobin, malignancy, and performing laparotomy or myomectomy, as our study reports. However, it is difficult to determine an overall rate of transfusion from existing literature. Although the risks of procedure-specific transfusion have been reported, these studies are limited by comparatively low sample size reducing the ability to identify important risk factors particularly in low-risk surgical procedures.

The strengths of this study are use of a large cohort of women undergoing a variety of gynecologic surgeries by different gynecologic surgeons across multiple institutions within a health care system to build and temporally validate a highly accurate model and the use of advanced predictive analytic techniques that follow recent reporting guidelines. A further strength is that the predictors included within the model are well-defined clinical factors that are routinely known preoperatively and easily collected in practice, as well as the availability of an easy-to-use online calculator. This increases the model's potential ease of use.

This study has several significant limitations. Just as clinical trials or cohorts followed from a single institution need to be further tested in other centers, our model's ability to accurately perform using data from different health care systems across wide geographic areas is unknown. Although we believe the relatively large number and variety of procedures, institutions, and surgeons included within this study likely supports the model's early use, it should be further tested in diverse populations

FIGURE 3**Decision curve for transfusion after gynecologic surgery decision model**

Stanhisser et al. Transfusion prediction model. *Am J Obstet Gynecol* 2017.

with a variety of care practices. Additionally, the model is not perfect and the predictions are slightly overestimated when >40%. This likely results from the relatively few patients whose risk is actually greater than this threshold reducing the model fit at this extreme.

There are several opportunities to innovatively use this type of model. By integrating the model into the electronic record it affords a chance to automate electronic decision support around preoperative planning and blood management. The model is especially useful in patients who have any preexisting hemoglobin value in their medical record. If the model identifies patients at low risk of transfusion this may automatically question the need to order a type and screen, type and cross, or potentially unnecessary repeat testing such as a complete blood cell count or further preoperative laboratory testing overall. This model may therefore be a valuable tool within our specialty to further the Choosing Wisely program's campaign to avoid wasteful and unnecessary medical tests. In our institution, reducing unnecessary testing in patients at low risk for blood transfusion is estimated to save the institution approximately \$77,000 per 1000 gynecologic surgeries. Alternatively, identifying patients at high risk for transfusion may improve efficiency of perioperative blood management and reduce transfusions. The costs associated with transfusing a single unit of blood are significant and do not include the cost of treating any adverse associations of transfusion or the associated increased length of hospital stay. These costs far outweigh the lower cost of oral treatments of anemia, intravenous iron therapy, and cell salvage utilization. We suspect that for each transfusion avoided, the patient and financial benefit may be significant due to the large number of patients undergoing gynecologic surgery. Future investigations should include measuring the model's impact on patient and cost outcomes.

Overall, our new model accurately predicts risk of transfusion after

gynecologic surgery in early testing of a multiinstitutional health system. Identification of patients at low risk for transfusion may eliminate further unnecessary preoperative testing in patients with existing preoperative hemoglobin levels. Identification of patients at high risk for transfusion may allow improved perioperative blood management utilization potentially reducing transfusions and their associated risks and costs. ■

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SUPPLEMENTAL TABLE

Descriptive analysis and univariate analysis of all variables considered in training set along with their association to transfusion outcome

Variables	Model training cohort = 12,219 N (%) or mean (SD)	Any transfusion = 239 (2%) N (%) or mean (SD)	No transfusion = 11,980 (98%) N (%) or mean (SD)	Pvalue
Age, y	49.8 (12.7)	53.8 (14.4)	49.6 (12.7)	<.001
Missing	10 (0%)	0	10	
Race				
Caucasian	9108 (75%)	160 (2%)	8948 (98%)	.005
Other	3075 (25%)	79 (3%)	2996 (97%)	
Missing	36 (0%)	0	36	
Parity	1.9 (1.4)	1.8 (1.5)	1.9 (1.4)	.159
Missing	1999 (16%)	51	1948	
BMI	30.7 (8.1)	30.3 (9.4)	30.7 (8.1)	.580
Missing	26 (0%)	4	22	
Planned hysterectomy				<.001
Yes	4905 (40%)	178 (4%)	4727 (96%)	
No	7314 (60%)	61 (1%)	7253 (99%)	
Missing	0 (0%)			
Planned robotic approach				.204
Yes	750 (6%)	10 (1%)	740 (99%)	
No	11,469 (94%)	229 (2%)	11,240 (98%)	
Missing	0 (0%)			
Planned laparoscopic approach				.005
Yes	1742 (14%)	19 (1%)	1723 (99%)	
No	10,477 (86%)	220 (2%)	10,257 (98%)	
Missing	0 (0%)			
Planned vaginal approach				.003
Yes	1481 (12%)	14 (1%)	1467 (99%)	
No	10,513 (98%)	225 (2%)	7913 (98%)	
Missing	0 (0%)			
Planned laparotomy				<.001
Yes	2025 (17%)	182 (9%)	1843 (91%)	
No	10,194 (83%)	57 (1%)	10,137 (99%)	
Missing	0 (0%)			
Planned myomectomy				<.001
Yes	321 (3)	22 (7%)	299 (93%)	
No	11,898 (97%)	217 (2%)	11,681 (98%)	
Missing	0 (0%)			

Stanhiser et al. Transfusion prediction model. Am J Obstet Gynecol 2017.

(continued)

SUPPLEMENTAL TABLE

Descriptive analysis and univariate analysis of all variables considered in training set along with their association to transfusion outcome (continued)

Variables	Model training cohort = 12,219 N (%) or mean (SD)	Any transfusion = 239 (2%) N (%) or mean (SD)	No transfusion = 11,980 (98%) N (%) or mean (SD)	Pvalue
Planned colpopexy				.063
Yes	890 (7%)	10 (1%)	880 (99%)	
No	11,329 (93%)	229 (2%)	11,100 (98%)	
Missing	0 (0%)			
Gynecology oncology procedure, ie, nodes, radical, omentectomy				<.001
Yes	454 (4%)	3 (3%)	137 (98%)	
No	11,765 (96%)	236 (2%)	11,843 (98%)	
Missing	0 (0%)			
Planned surgery for ectopic				.755
Yes	140 (1%)	3 (3%)	108 (97%)	
No	12,079 (99%)	183 (2%)	8878 (98%)	
Missing	0 (0%)			
Planned hysteroscopy				<.001
Yes	6263 (51%)	15 (0%)	6248 (100%)	
No	5956 (49%)	224 (4%)	5732 (96%)	
Missing	0 (0%)			
Preoperative hemoglobin, g/dL	12.6 (1.7)	11.1 (1.9)	12.6 (1.7)	<.001
Missing	6620 (54%)	131	6489	
Preoperative platelets, $\times 10^9/L$	284 (80)	326 (141)	283 (78)	.003
Missing	6642 (54%)	133	6509	
Any radiation history				.548
Yes	154 (1%)	4 (2%)	235 (98%)	
No	12,065 (99%)	150 (1%)	11,830 (99%)	
Missing	0 (0%)			
Abortion history				.269
Yes	175 (1%)	1 (1%)	174 (99%)	
No	12,044 (99%)	238 (2%)	11,806 (98%)	
Missing	0 (0%)			
Anemia history				<.001
Yes	2157 (18%)	70 (3%)	2087 (97%)	
No	10,062 (82%)	169 (2%)	9893 (98%)	
Missing	0 (0%)			
Carcinomatosis history				<.001
Yes	53 (0%)	12 (23%)	41 (77%)	
No	12,166 (100%)	227 (2%)	11,939 (98%)	
Missing	0 (0%)			

Stanhiser et al. Transfusion prediction model. Am J Obstet Gynecol 2017.

(continued)

SUPPLEMENTAL TABLE

Descriptive analysis and univariate analysis of all variables considered in training set along with their association to transfusion outcome (continued)

Variables	Model training cohort = 12,219 N (%) or mean (SD)	Any transfusion = 239 (2%) N (%) or mean (SD)	No transfusion = 11,980 (98%) N (%) or mean (SD)	Pvalue
Cervical cancer history				>.001
Yes	78 (1%)	7 (9%)	71 (91%)	
No	12,141 (99%)	232 (2%)	11,909 (98%)	
Missing	0 (0%)			
Diabetes mellitus type 2 history				.271
Yes	451 (4%)	12 (3%)	439 (97%)	
No	11,768 (96%)	227 (2%)	11,541 (98%)	
Missing	0 (0%)			
Drug abuse history				.001
Yes	3 (0%)	2 (67%)	1 (33%)	
No	12,216 (100%)	237 (2%)	11,979 (98%)	
Missing	0 (0%)			
Ectopic pregnancy history				1
Yes	6 (0%)	0 (0%)	6 (100%)	
No	12,213 (100%)	239 (2%)	11,974 (98%)	
Missing	0 (0%)			
Uterine fibroids history				.463
Yes	4521 (37%)	83 (2%)	4438 (98%)	
No	7698 (63%)	156 (2%)	7542 (98%)	
Missing	0 (0%)			
Previous cesarean delivery				.772
Yes	152 (1%)	2 (1%)	150 (99%)	
No	12,067 (99%)	237 (2%)	11,830 (98%)	
Missing	0 (0%)			
Hypertension history				<.001
Yes	4507 (37%)	130 (3%)	4377 (97%)	
No	7712 (63%)	109 (1%)	7603 (99%)	
Missing	0 (0%)			
Heavy menstrual bleeding history				<.001
Yes	5281 (43%)	50 (1%)	5231 (99%)	
No	6938 (57%)	189 (3%)	6749 (97%)	
Missing	0 (0%)			
Previous myomectomy				.299
Yes	18 (0%)	1 (0%)	17 (100%)	
No	12,201 (100%)	238 (2%)	11,963 (98%)	
Missing	0 (0%)			

Stanhiser et al. Transfusion prediction model. Am J Obstet Gynecol 2017.

(continued)

SUPPLEMENTAL TABLE

Descriptive analysis and univariate analysis of all variables considered in training set along with their association to transfusion outcome (continued)

Variables	Model training cohort = 12,219 N (%) or mean (SD)	Any transfusion = 239 (2%) N (%) or mean (SD)	No transfusion = 11,980 (98%) N (%) or mean (SD)	Pvalue
Ovarian cancer				<.001
Yes	449 (4%)	74 (17%)	375 (83%)	
No	11,770 (96%)	165 (1%)	11,605 (99%)	
Missing	0 (0%)			
Systemic lupus erythematosus				.283
Yes	111 (1%)	0 (0%)	111 (100%)	
No	12,108 (99%)	239 (2%)	11,869 (98%)	
Missing	0 (0%)			
Smoking history				.110
Yes	29 (0%)	2 (7%)	27 (93%)	
No	12,190 (100%)	237 (2%)	11,953 (98%)	
Missing	0 (0%)			
Uterine cancer history				<.001
Yes	381 (3%)	32 (8%)	349 (92%)	
No	11,838 (97%)	207 (2%)	11,631 (98%)	
Missing	0 (0%)			
Vulvar cancer history				.257
Yes	15 (0%)	1 (7%)	14 (93%)	
No	12,204 (100%)	238 (2%)	11,966 (98%)	
Missing	0 (0%)			
Previous dilation and curettage				<.001
Yes	976 (8%)	4 (0%)	972 (100%)	
No	11,243 (92%)	235 (2%)	11,008 (98%)	
Missing	0 (0%)			
Previous dilation and evacuation				1
Yes	2 (0%)	0 (0%)	2 (100%)	
No	12,217 (100%)	239 (2%)	11,978 (98%)	
Missing	0 (0%)			
Previous laparoscopy for ectopic pregnancy				.761
Yes	144 (1%)	3 (2%)	141 (98%)	
No	12,075 (99%)	236 (2%)	11,839 (98%)	
Missing				
Previous exploratory laparotomy				<.001
Yes	525 (4%)	24 (5%)	501 (95%)	
No	11,694 (96%)	215 (2%)	11,479 (98%)	
Missing	0 (0%)			

Stanhiser et al. Transfusion prediction model. Am J Obstet Gynecol 2017.

(continued)

SUPPLEMENTAL TABLE

Descriptive analysis and univariate analysis of all variables considered in training set along with their association to transfusion outcome (continued)

Variables	Model training cohort = 12,219 N (%) or mean (SD)	Any transfusion = 239 (2%) N (%) or mean (SD)	No transfusion = 11,980 (98%) N (%) or mean (SD)	Pvalue
Previous total abdominal hysterectomy				<.001
Yes	1426 (12%)	80 (6%)	1346 (94%)	
No	10,793 (88%)	159 (2%)	10,634 (98%)	
Missing	0 (0%)			
Previous total laparoscopy hysterectomy				.002
Yes	465 (4%)	1 (0%)	464 (100%)	
No	11,754 (96%)	238 (2%)	11,516 (98%)	
Missing	0 (0%)			
Previous total vaginal hysterectomy				.005
Yes	1283 (11%)	12 (1%)	1271 (99%)	
No	10,936 (89%)	227 (2%)	10,709 (98%)	
Missing	0 (0%)			
Previous debulking surgery				<.001
Yes	39 (0%)	11 (28%)	28 (72%)	
No	12,180 (100%)	228 (2%)	11,952 (98%)	
Missing	0 (0%)			
Previous radical hysterectomy				<.001
Yes	294 (2%)	27 (9%)	267 (91%)	
No	11,925 (98%)	212 (2%)	11,713 (98%)	
Missing	0 (0%)			
Previous sacral colpopexy				.532
Yes	308 (3%)	4 (1%)	304 (99%)	
No	11,911 (97%)	235 (2%)	11,676 (98%)	
Missing	0 (0%)			
Previous uterine colpopexy				.030
Yes	701 (6%)	6 (1%)	695 (99%)	
No	11,518 (94%)	233 (2%)	11,285 (98%)	
Missing	0 (0%)			
Anticoagulant use within ± 72 h of surgery				<.001
Yes	20 (0%)	4 (20%)	16 (80%)	
No	12,199 (100%)	235 (2%)	11,964 (98%)	
Missing	0 (%)			

BMI, body mass index.

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SUPPLEMENTAL FIGURE 1**Estimated spline transformation of body mass index and transfusion risk**

Predictions with group size of 1000 patients (triangles) and location of knot (arrows).

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SUPPLEMENTAL FIGURE 2

Estimated spline transformation of parity and transfusion risk

Predictions with group size of 1000 patients (triangles) and location of knot (arrows).

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