Supplementary Materials

Supplementary Table 1: Percent breakdown of stage amongst HAPI cases reviewed from nursing records via an event reporting system (data from Miller et. al., 2019); 2015-2018

Year	*2015*				*2016*			
	1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
HAPI Stage								
Unstageable	6	8	2	5	5	1	0	1
Suspected Deep Tissue Injury	17	26	26	18	30	14	12	16
Stage 3	6	1	1	0	0	0	0	0
Stage 2	8	12	9	6	12	6	10	2
Stage 1	3	9	6	7	6	4	3	5

Year	*2017*				*2018*	*2015-2018*	
	1Q	2Q	3Q	4Q	1Q	Total	Proportion
HAPI Stage							
Unstageable	6	8	2	5	5	31	7.2%
Suspected Deep Tissue Injury	17	26	26	18	30	233	54.1%
Stage 3	6	1	1	0	0	8	1.9%
Stage 2	8	12	9	6	12	96	22.3%
Stage 1	3	9	6	7	6	63	14.6%

Supplementary Table 2: Percent breakdown of whether HAPI was medical device related via an event reporting system (data from Miller et. al., 2019); 2nd Quarter 2017-2nd Quarter 2018

Medical Device Related?	*Total*	*Proportion*
Yes	34	36.2%
No	55	58.5%
Unknown	5	5.3%

Supplementary Table 3: Dictionary of utilized predictors and variable names in models

Predictor	Variable Name	Description
Age	Ageatarrival	Patient age when they arrived at the hospital
Sex	male	Indicator variable equal to 1 if the patient is male and 0 if the patient is female
Race	white	Indicator variable equal to 1 if the patient has declared their race as white/Caucasian and 0 if they have not declared a race of white/Caucasian

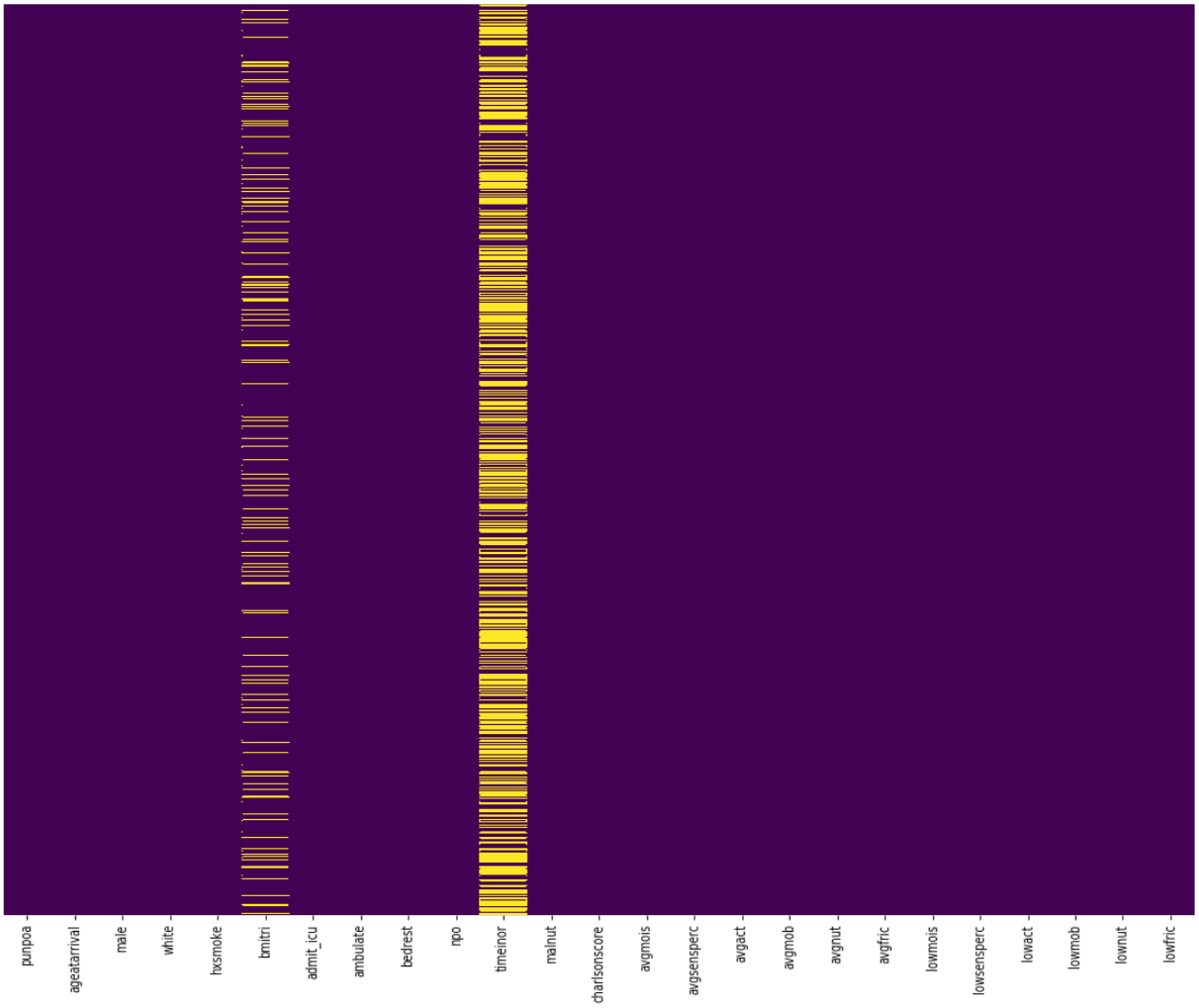
Smoking history	hxsmoke	Indicator variable equal to 1 if the patient has a history of smoking cigarettes and 0 if the patient has no history of smoking cigarettes.
Body Mass Index	bmitri	Ordinal variable indicating if the patient was “normal” (18.5 <= x < 34.9, “underweight” (< 18.5) or “overweight” (>= 35) according to the study cut-points.
Admitted to ICU	admit_icu	Indicator variable equal to 1 if the patient has spent any time in the ICU and 0 otherwise
Ambulation status	ambulate	Indicator variable whether the patient had mobility orders indicating that the patient should ambulate at any point during the admission
Bed rest orders	bedrest	A variable indicating whether the patient had mobility orders indicating that the patient should be restricted to bed rest at any point during the admission
Nothing by mouth	npo	A variable indicating whether the patient had diet orders indicating that the patient should take nothing by mouth at any point during the admission
Time in OR	timeinor	The amount of time (in days) the patient spent in the OR this admission
Malnutrition	malnut	A variable indicating whether the patient had a diagnosis of malnutrition on this admission
Charlson Score	charlsonscore	Total score based on Charlson comorbidity index
Mean Braden Score	avgbraden	Average total Braden score for this admission
Minimum Braden Score	lowbraden	Lowest total Braden score for this admission
Mean moisture	avgmois	Average score (1-4) for the degree to which the skin is exposed to moisture on the Braden Scale
Mean sensory perception	avgsensperc	Average score (1-4) for the patient’s ability to respond meaningfully to pressure related discomfort on the Braden Scale

Mean activity	avgact	Average score (1-4) for the degree of physical activity on the Braden Scale
Mean mobility	avgmob	Average score (1-4) for the patient's ability to change and control body position on the Braden Scale
Mean nutrition	avgnut	Average score (1-4) for the patient's usual food intake patterns on the Braden Scale
Mean friction	avgfric	Average score (1-3) for the level of friction and shear when moving patient on the Braden Scale
Mean moisture	avgmois	Average score (1-4) for the degree to which the skin is exposed to moisture on the Braden Scale
Minimum moisture	lowmois	Lowest score (1-4) for the degree to which the skin is exposed to moisture on the Braden Scale
Minimum sensory perception	lowsensperc	Lowest score (1-4) for the patient's ability to respond meaningfully to pressure related discomfort on the Braden Scale
Minimum activity	lowact	Lowest score (1-4) for the degree of physical activity on the Braden Scale
Minimum mobility	lowmob	Lowest score (1-4) for the patient's ability to change and control body position on the Braden Scale
Minimum nutrition	lownut	Lowest score (1-4) for the patient's usual food intake patterns on the Braden Scale
Minimum friction	lowfric	Lowest score (1-3) for the level of friction and shear when moving patient on the Braden Scale

Supplementary Table 4: Patient Demographics and Braden Scores stratified by HAPI. Two sample t-tests were used for continuous variables and chi-squared tests for categorical variables.

Variable	Missing Values	HAPI Absent	HAPI Present	P value
N		56986	241	
Ageatarrival, mean (SD)	0	60.1 (18.4)	65.5 (15.0)	<0.001
Male, n (%)	0	29536 (51.8)	94 (39.0)	<0.001
Yes		27450 (48.2)	147 (61.0)	
No	0	29536 (51.8)	94 (39.0)	
White, n (%)				0.905
Yes		55618 (97.6)	236 (97.9)	
No	0	1368 (2.4)	5 (2.1)	

Hxsmoke, n (%)				0.271
Yes		28360 (49.8)	129 (53.5)	
No	0	28626 (50.2)	112 (46.5)	
Bmitri, n (%)				0.007
normal	10057	36265 (77.2)	139 (76.4)	
overweight		9233 (19.6)	30 (16.5)	
underweight		1490 (3.2)	13 (7.1)	
Npo, n (%)				<0.001
Yes		37723 (66.2)	224 (92.9)	
No	0	19263 (33.8)	17 (7.1)	
Timeinor, mean (SD)	33443	0.1 (0.1)	0.2 (0.2)	<0.001
Admlt_icu, n (%)				<0.001
Yes		9508 (16.7)	90 (37.3)	
No	0	47478 (83.3)	151 (62.7)	
Ambulate, n (%)				0.974
Yes		11893 (20.9)	50 (20.7)	
No	0	45093 (79.1)	191 (79.3)	
Bedrest, n (%)				<0.001
Yes		16632 (29.2)	121 (50.2)	
No	0	40354 (70.8)	120 (49.8)	
Malnut, n (%)				<0.001
Yes		4482 (7.9)	98 (40.7)	
No	0	52504 (92.1)	143 (59.3)	
Avgmois, mean (SD)	0	3.7 (0.4)	3.3 (0.3)	<0.001
Lowmois, mean (SD)	0	3.2 (0.7)	2.3 (0.8)	<0.001
Avgsensperc, mean (SD)	0	3.6 (0.5)	2.9 (0.7)	<0.001
Lowsensperc, mean (SD)	0	3.1 (0.9)	1.9 (0.9)	<0.001
Avgact, mean (SD)	0	2.7 (0.8)	1.9 (0.7)	<0.001
Lowact, mean (SD)	0	2.0 (1.0)	1.2 (0.5)	<0.001
Avgmob, mean (SD)	0	3.2 (0.6)	2.5 (0.6)	<0.001
Lowmob, mean (SD)	0	2.7 (0.8)	1.7 (0.7)	<0.001
Avgnut, mean (SD)	0	2.8 (0.5)	2.4 (0.4)	<0.001
Lownut, mean (SD)	0	2.2 (0.8)	1.3 (0.6)	<0.001
Avgfric, mean (SD)	0	2.6 (0.4)	2.0 (0.4)	<0.001
Lowfric, mean (SD)	0	2.2 (0.7)	1.2 (0.4)	<0.001
Lowbraden, mean (SD)	0	16.2 (3.5)	11.2 (2.8)	<0.001
Avgbraden, mean (SD)	0	18.5 (2.7)	14.9 (2.4)	<0.001
Charlsonscore, mean (SD)	0	0.5 (1.6)	0.4 (1.5)	0.13



Supplementary Figure 1: Summary of missing values across cohort (BMI and Time in OR)

Further Description of Analytical Approaches

Naive Bayes

Naive Bayes is a simple modeling approach that utilizes Bayes' Theorem to calculate and maximize posterior class probabilities; *maximum a posteriori* (MAP) hypothesis is based on the probability of observing each of the predictors d_i (assumed to be independent), $P(d_i|c)$, given the selection of that class or outcome c:

$$\mathrm{MAP} = \max_{c \in C} \left(\Pi_i \frac{P(d_i|c) * P(c)}{P(d_i)} \right)$$

$P(c)$ represents the probability of finding the class in the dataset; observing the outcome more often means it should be predicted as the outcome more often. When $P(d_i|c)$ is high, this means that the observed data is highly probable given the observed outcome and as such, the outcome should be predicted.

Decision Trees

Decision trees are computational heuristics that generate a series of binary splitting rules over the predictors that serve to divide the samples into subgroups. Each subsequent split should more meaningfully inform the prediction of an outcome given the previous split. This criterion is actualized through the measure of information gain, where the entropy, a measure of disorder of labels within bins denoted by the splits (S_1/S_2), should maximally decrease in subsequent splits as compared to the previous splits (S). This is formulated as such:

$$G(S) = H(S) - \left(\frac{n_{S_1}}{n_S} * H(S_1) + \frac{n_{S_2}}{n_S} * H(S_2) \right)$$

Another commonly used criterion is Gini Impurity, which measures how often a randomly chosen element would be incorrectly identified (p_i is the probability of extracting the *ith* label from a split S). The maximal decrease in impurity is used to form decision splits; here, the formula for Gini Impurity is given by:

$$G(S) = 1 - \left(\sum_i p_i^2 \right)$$

Random Forest

The random forest approach extends the decision tree method to make predictions based on consensus votes from multiple constructed decision trees. The algorithm operates by first picking a subset of “n” out of a total of “N” variables available. Then it constructs a decision tree using the same methodology as mentioned above (one tree/learner is a collection of decision splits), but alternatively at each split within each tree picking a new n subset of features and bootstrapping the training samples. Each resultant tree/learner makes a HAPI classification and the predictions from each of the trees are tallied to derive the final prediction of the “forest”. This algorithm is considered to be an ensemble approach, where improvements are derived by the incorporation of several weaker models.

Predictor importance is typically assessed using the mean decrease in Gini coefficient (node impurity), where the reduction of Gini impurity is calculated for each variable and averaged across all decision trees where the variable had appeared. However, evaluating the importance of predictors using this criterion may assign lower importance to higher cardinal and/or collinear predictors by spreading importance between predictors that have similar likelihood of being selected at a higher decision node (while the other predictor may be selected at a node with lower impurity decrease, and vice versa across different decision trees). Permutation-based methods (eg. evaluating changes in model performance by removing a predictor and/or in combinations with other predictors) are therefore recommended.

XGBoost

XGBoost is another ensemble method that incorporates decision trees as its base algorithm. Random Forests employ bagging techniques, which reduces the estimate variance by bootstrap aggregation, i.e. averaging multiple model estimates. In contrast, boosting, as utilized by XGBoost, reduces the bias introduced by individual weak learners by sequentially constructing learners in a way that assigns higher weights to misclassified samples from the previous learner. Learners are also weighted based on their ability to classify data when it comes time to aggregate the predictions of the individual learners.

In summary, Random Forest parallelizes the construction and voting of decision trees to arrive at a conclusion, while XGBoost sequentially and greedily updates learners and weights assigned to samples based on mistakes from previous learners.

Logistic Regression

Binary logistic regression, a member of the generalized linear model (GLM) family, is a classic statistical method used to model binary outcomes. GLMs can model response variables with non-normally distributed errors, and can also utilize nonlinear link functions such as the logit function to depict the direct relationship between the expected value of the dependent variable and the independent variables:

$$\mathrm{Logit}(p) = \log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \cdots + \beta_n * x_n$$

Which can be expressed as:

$$P(Y = 1 | x_1, x_2, \ldots, x_n) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 * x_1 + \beta_2 * x_2 + \cdots + \beta_n * x_n)}}$$

Compared to the aforementioned machine learning methods, these models have highly interpretable model coefficients. The exponentiation of summed coefficients corresponds to the odds ratio of the outcome across a unit change in the value of the predictor - a clinically interpretable quantity.

In situations where many potential predictors are available, these models can be regularized using LASSO, Ridge and Elastic Net to home in on important predictors. The coefficients of the LASSO, Ridge and Elastic Net models do not represent valid odds ratios, thus a traditional Logistic Regression model, unregularized (without the use of LASSO, Ridge and Elastic Net) must be utilized to derive valid odds ratios. In this paper, we elected to not penalize the logistic regression model as the number of predictors was relatively small.

Supplementary Table 5: Spearman's Rank Correlation Coefficients Between Important Features of Top Performing Models (pearson r; p-value)

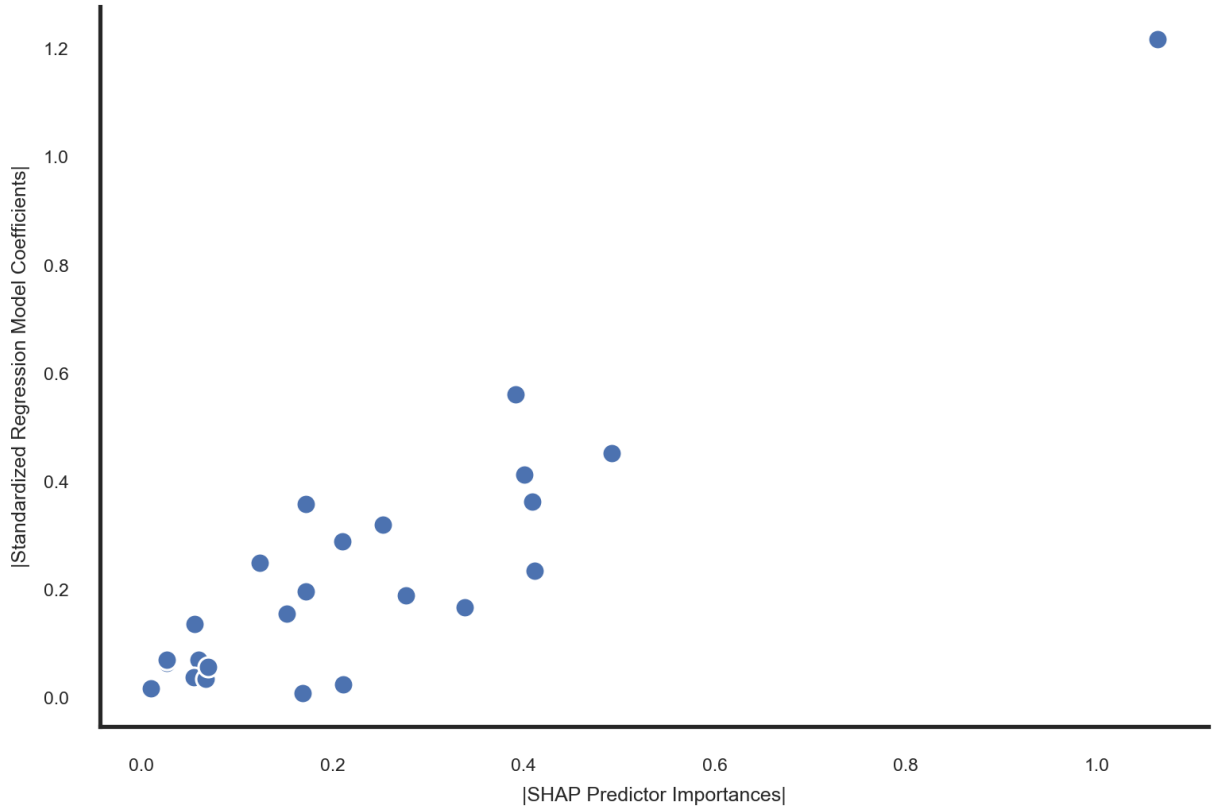
	Logistic Regression	Random Forest	XG-Boost
Logistic Regression	1.0,0.0	0.667,0.0004	0.653,0.0005
Random Forest	0.667,0.0004	1.0,0.0	0.690,0.0002
XG-Boost	0.653,0.0005	0.690,0.0002	1.0,0.0

Supplementary Table 6: Ranking of overall important features for each modeling approach. Lower ranks constitute important features.

	Logistic Regression	Random Forest	XG-Boost
lowfric	1	1	3
avgmob	2	3	2
avgfric	3	8	1
lownut	4	19	10
npo	5	4	6
avgact	6	7	12
avgmois	7	16	19
lowsensperc	8	2	16
lowmois	9	9	7
avgnut	10	11	5
lowmob	11	10	22
charlsonscore	12	22	8
malnut	13	6	13
hxsmoke	14	5	4
lowact	15	15	9
timeinor	16	13	20
white	17	14	11
admit_icu	18	20	21
avgsensperc	19	12	15
bmitri	20	23	17
male	21	24	14
ageatarrival	22	21	23
ambulate	23	18	18
bedrest	24	17	24

Supplementary Table 7: Global Feature Importance; Random Forest Values are significantly lower because SHAP values are to be interpreted as an increase or decrease in HAPI probability, while SHAP values for Logistic Regression and XG-Boost are to be interpreted as a Log-Odds

	SHAP Logistic Regression	Random Forest	XG-Boost	Logistic Regression Standardized Coefficients
lowfric	1.07	0.06	0.44	1.22
avgmob	0.43	0.02	0.51	0.45
avgfric	0.39	0.04	0.58	0.41
lownut	0.39	0.03	0.08	0.56
npo	0.38	0.01	0.13	0.23
avgact	0.36	0.01	0.20	0.36
avgmois	0.28	0.02	0.14	0.17
lowsensperc	0.27	0.03	0.09	0.29
lowmois	0.26	0.01	0.03	0.19
avgnut	0.26	0.01	0.37	0.32
lowmob	0.20	0.01	0.01	0.03
charlsonscore	0.19	0.00	0.19	0.36
malnut	0.16	0.01	0.09	0.20
hxsmoke	0.16	0.00	0.00	0.01
lowact	0.14	0.01	0.00	0.25
timeinor	0.12	0.02	0.17	0.16
white	0.05	0.00	0.00	0.04
admit_icu	0.05	0.00	0.00	0.06
avgsensperc	0.03	0.03	0.19	0.14
bmitri	0.03	0.00	0.02	0.04
male	0.02	0.00	0.00	0.07
ageatarrival	0.02	0.01	0.11	0.06
ambulate	0.01	0.00	0.00	0.07
bedrest	0.01	0.00	0.00	0.02



Supplementary Figure 2: Agreement between SHAP and standardized regression coefficients (r=0.914, p=4.5e-10)

Supplementary Table 8: Standardized Regression Coefficients of Logistic Regression Model

	coef	std err	z	P>|z|	[0.025	0.975]
const	-1.7	1.0	-1.7	0.1	-3.7	0.3
ageatarrival	0.0	0.0	0.7	0.5	-0.0	0.0
male	0.1	0.2	0.9	0.4	-0.2	0.4
white	-0.3	0.5	-0.5	0.6	-1.2	0.7
hxsmoke	0.0	0.2	0.1	0.9	-0.3	0.3
bmitri	-0.1	0.2	-0.5	0.6	-0.4	0.2
admit_icu	-0.2	0.2	-0.9	0.4	-0.5	0.2
ambulate	0.2	0.2	0.9	0.4	-0.2	0.6
bedrest	-0.0	0.2	-0.2	0.8	-0.4	0.3
npo	0.5	0.3	1.7	0.1	-0.1	1.1
timeinor	1.4	0.4	3.5	0.0	0.6	2.2
malnut	0.7	0.2	4.3	0.0	0.4	1.1
charlsonscore	-0.2	0.1	-3.4	0.0	-0.4	-0.1
avgmois	0.4	0.3	1.5	0.1	-0.1	1.0
avgsensperc	0.3	0.2	1.1	0.3	-0.2	0.7

avgact	0.5	0.2	2.0	0.0	0.0	0.9
avgmob	-0.8	0.3	-2.4	0.0	-1.4	-0.1
avgnut	0.6	0.2	2.8	0.0	0.2	1.1
avgfric	-0.9	0.3	-3.2	0.0	-1.5	-0.4
lowmois	-0.3	0.1	-2.0	0.0	-0.5	-0.0
lowsensperc	-0.3	0.2	-2.0	0.0	-0.6	-0.0
lowact	0.2	0.2	1.3	0.2	-0.1	0.6
lowmob	0.0	0.2	0.2	0.9	-0.3	0.4
lownut	-0.7	0.2	-3.8	0.0	-1.1	-0.4
lowfric	-1.8	0.2	-7.8	0.0	-2.3	-1.4

Supplementary Table 9: Regression Coefficients of Logistic Regression Model

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-7.4	0.2	-35.7	0.0	-7.8	-7.0
ageatarrival	0.1	0.1	0.7	0.5	-0.1	0.2
male	0.1	0.1	0.9	0.4	-0.1	0.2
white	-0.0	0.1	-0.5	0.6	-0.2	0.1
hxsmoke	0.0	0.1	0.1	0.9	-0.1	0.2
bmitri	-0.0	0.1	-0.5	0.6	-0.2	0.1
admit_icu	-0.1	0.1	-0.9	0.4	-0.2	0.1
ambulate	0.1	0.1	0.9	0.4	-0.1	0.2
bedrest	-0.0	0.1	-0.2	0.8	-0.2	0.1
npo	0.2	0.1	1.7	0.1	-0.0	0.5
timeinor	0.2	0.0	3.5	0.0	0.1	0.2
malnut	0.2	0.0	4.3	0.0	0.1	0.3
charlsonscore	-0.4	0.1	-3.4	0.0	-0.6	-0.2
avgmois	0.2	0.1	1.5	0.1	-0.1	0.4
avgsensperc	0.1	0.1	1.1	0.3	-0.1	0.4
avgact	0.4	0.2	2.0	0.0	0.0	0.7
avgmob	-0.5	0.2	-2.4	0.0	-0.8	-0.1
avgnut	0.3	0.1	2.8	0.0	0.1	0.5
avgfric	-0.4	0.1	-3.2	0.0	-0.7	-0.2
lowmois	-0.2	0.1	-2.0	0.0	-0.4	-0.0
lowsensperc	-0.3	0.1	-2.0	0.0	-0.6	-0.0
lowact	0.2	0.2	1.3	0.2	-0.1	0.6
lowmob	0.0	0.2	0.2	0.9	-0.3	0.3
lownut	-0.6	0.1	-3.8	0.0	-0.8	-0.3
lowfric	-1.2	0.2	-7.8	0.0	-1.5	-0.9