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Using JMP® to Examine Predictors of Childbirth Satisfaction in United States Army Hospitals

Dr Melissa Gliner, Senior Health Policy Analyst, US Army MEDCOM **Kenneth Kovats,** Senior Nurse Analyst, US Army MEDCOM, **Dawn Garcia,** Nurse Analyst, US Army MEDCOM, **Richard Thorp,** Deputy Chief of Analysis and Evaluation, US Army MEDCOM

Background and purpose

One of the major inpatient product lines for the US Army's medical system is childbirth. However patient satisfaction scores tend to be significantly lower than other Inpatient product lines at Army hospitals, as well other hospitals in the civilian sector. Understanding what factors lead to satisfaction or dissatisfaction is of critical importance to determine managerial intervention. In the civilian sector, Nurse Communication and Care Transition HCAHPS composites have been shown to have the greatest impact on the Overall Hospital Rating among childbirth respondents. However, factors relating to how a person rates her care may in fact be different between the military and civilian sectors, which is evaluated in this study. We applied 3 modeling techniques using JMP Pro 13 (Logistic Regression, Classification Trees, and Bootstrap Forest) to identify the key indicators of patient satisfaction for childbirth admissions at U.S. Army Hospitals, and then selected a model which could be used by Hospital Leaders to focus their performance improvement efforts.

Data Sources and Processing

Patient Satisfaction data are from the TRICARE Inpatient Satisfaction Survey (TRISS). TRISS questions are modeled after the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) The dependent variable was question 21 from the survey:
Using any number from 0 to 10, where 0 is the worst hospital possible and 10 is the best hospital possible, what number would you use to rate this hospital during your stay?

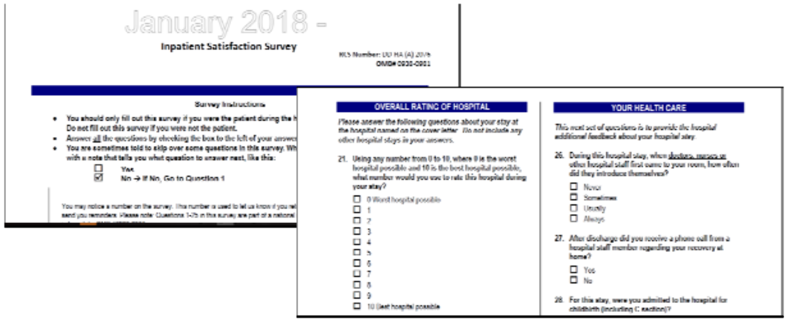
- Patients were considered "satisfied" if they indicated "9" or "10" on an 11-point scale. The scores are represented as "percent satisfied."
- The scores were recoded as "0" (dissatisfied) or "1" (satisfied).

Variables examined in the model were from the following composites: Communication with Nurses, Communication with Doctors, Responsiveness of Hospital Staff, Communication about Medicine, Cleanliness of Hospital, Quietness of Hospital, Discharge Information, and Care Transition

Methodology:

For all model builds, completed TRISS survey results from patients discharged from Army Hospitals during the period April 2017 – March 2018 with principle reason for admission = "Maternity care" (based on MS-DRG codes in the patient record). 5,086 completed. For purposes of model comparison, data was split into training (70%) and validation (30%) data sets, divided equally between "Satisfied" and "Dissatisfied" responses to Q21. Although this analysis was fundamentally exploratory and not predictive, using a cross-validation technique ensured more parsimonious models and prevented overfitting.

Example of TRICARE Inpatient Satisfaction Survey (TRISS)



January 2018 -
Inpatient Satisfaction Survey

OMB# 0930-0981

Survey Instructions

- You should only fill out this survey if you were the patient during the h
  Do not fill out this survey if you were not the patient.
- Answer all the questions by checking the box to the left of your answer
- You are sometimes told to skip over some questions in this survey. Wh
  with a note that tells you what question to answer next, like this:
  ☐ Yes
  ☑ No → If No, Go to Question 1

OVERALL RATING OF HOSPITAL

Please answer the following questions about your stay at the hospital named on the cover letter. Do not include any other hospital stays in your answers.

21. Using any number from 0 to 10, where 0 is the worst hospital possible and 10 is the best hospital possible, what number would you use to rate this hospital during your stay?
☐ 0 Worst hospital possible
☐ 1
☐ 2
☐ 3
☐ 4
☐ 5
☐ 6
☐ 7
☐ 8
☐ 9
☐ 10 Best hospital possible

YOUR HEALTH CARE

This next set of questions is to provide the hospital additional feedback about your hospital stay.

26. During this hospital stay, when doctors, nurses or other hospital staff first came to your room, how often did they introduce themselves?
☐ Never
☐ Sometimes
☐ Usually
☐ Always

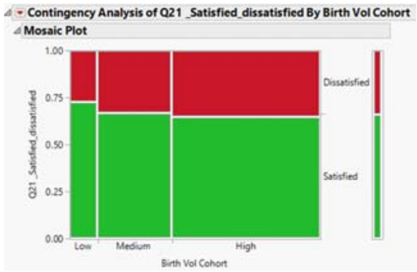
27. After discharge did you receive a phone call from a hospital staff member regarding your recovery at home?
☐ Yes
☐ No

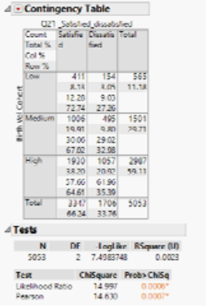
28. For this stay, were you admitted to the hospital for childbirth (including C section)?

Contingency table Satisfied vs. Satisfied for Army Birth Hospitals, broken out by Birth volume

Based on Question 21: "What number would you use to rate this hospital during your stay?" (0 = worst, 10 = best)
- Satisfied: Score 9-10, Dissatisfied: Score 0-8

Cohorts based on Annual births for period July 2017-June 2018
- Low: < 600 births, Medium: 1450-601 births, High: >1450 births





Contingency Table

Q21 _Satisfied_dissatisfied

Birth Vol Cohort	Count Total % Col % Row %	Satisfied	Dissatisfied	Total
	Low	411 8.13 12.28 72.74	154 3.05 9.03 27.26	565 11.18
	Medium	1006 19.91 30.06 67.02	495 9.80 29.02 32.98	1501 29.71
	High	1930 38.20 57.66 64.61	1057 20.92 61.96 35.39	2987 59.11
	Total	3347 66.24	1706 33.76	5053

Tests

N	DF	-LogLike	RSquare (U)
5053	2	7.4983748	0.0023

Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	14.997	0.0006*
Pearson	14.630	0.0007*

Survey Questions

Q1_nurse_courtesy_respect	How often did nurses treat you with courtesy and respect?	Never	Sometimes	Usually	Always
		9	162	453	4458
		0.18%	3.19%	8.91%	87.72%

Q2_nurse_listen	How often did nurses listen carefully to you?	Never	Sometimes	Usually	Always
		21	268	757	4032
		0.41%	5.28%	14.91%	79.40%

Q3_nurse_explain	How often did nurses explain things in a way you could understand?	Never	Sometimes	Usually	Always
		19	183	655	4223
		0.37%	3.60%	12.89%	83.13%

Q4_call_button	After you pressed the call button, how often did you get help as soon as you wanted it?	Never	Sometimes	Usually	Always	N/A
		22	263	808	3430	554
		0.43%	5.18%	15.91%	67.56%	10.91%

Q5_dr_courtesy_respect	How often did doctors treat you with courtesy and respect?	Never	Sometimes	Usually	Always
		25	150	376	4510
		0.49%	2.96%	7.43%	89.11%

Q6_dr_listen	How often did doctors listen carefully to you?	Never	Sometimes	Usually	Always
		46	218	524	4276
		0.91%	4.30%	10.35%	84.44%

Q7_dr_explain	How often did doctors explain things in a way you could understand?	Never	Sometimes	Usually	Always
		28	153	559	4320
		0.55%	3.02%	11.05%	85.38%

Q8_cleanliness	How often were your room and bathroom kept clean?	Never	Sometimes	Usually	Always
		70	288	609	4098
		1.38%	5.69%	12.02%	80.91%

Q9_quiet	How often was the area around your room quiet at night?	Never	Sometimes	Usually	Always
		40	214	766	4055
		0.79%	4.22%	15.09%	79.90%

Q13_pain_control	Did you need medicine for pain?	Never	Sometimes	Usually	Always	N/A
		45	313	900	3176	436
		0.92%	6.43%	18.48%	65.22%	8.95%

Q14_help_pain	How often did the hospital staff do everything they could to help you with your pain?	Never	Sometimes	Usually	Always	N/A
		24	210	474	3732	436
		0.49%	4.31%	9.72%	76.54%	8.94%

Q16_med_for	Before giving you any new medicine, how often did hospital staff tell you what the medicine was for?	Never	Sometimes	Usually	Always	N/A
		21	76	171	2107	2631
		0.42%	1.52%	3.42%	42.09%	52.56%

Q17_side_effects	Before giving you any new medicine, how often did hospital staff describe possible side effects in a way you could understand?	Never	Sometimes	Usually	Always	N/A
		231	229	322	1582	2631
		4.62%	4.58%	6.45%	31.67%	52.67%

Q19_help_after_discharge	Did doctors, nurses or other hospital staff talk with you about whether you would have the help you needed when you left the hospital?	No	Yes	N/A
		700	4215	51
		14.10%	84.88%	1.03%

Q20_symptoms	Did you get information in writing about what symptoms or health problems to look out for after you left the hospital?	No	Yes	N/A
		153	4801	51
		3.06%	95.92%	1.02%

Q23_ct_preference	Staff took my preferences and those of my family or caregiver into account in deciding what my health care needs would be when I left.	Strongly disagree	Disagree	Agree	Strongly agree
		54	138	2134	2683
		1.08%	2.76%	42.60%	53.56%

Q24_ct_understanding	When I left the hospital, I had a good understanding of the things I was responsible for in managing my health.	Strongly disagree	Disagree	Agree	Strongly agree
		29	64	1512	3425
		0.58%	1.27%	30.06%	68.09%

Q25_ct_purpose_med	When I left the hospital, I clearly understood the purpose for taking each of my medications.	Strongly disagree	Disagree	Agree	Strongly agree	N/A
		37	54	1147	3636	152
		0.74%	1.07%	22.82%	72.34%	3.02%

Q30_supported_your_breastfeeding	Were you offered education or support about breastfeeding while in the hospital?	No	Yes	N/A
		229	4547	207
		4.60%	91.25%	4.15%

Q31_wash_hands	How often did your staff wash or sanitize their hands before touching you?	Never	Sometimes	Usually	Always	N/A
		26	138	399	4136	16
		0.55%	2.93%	8.46%	87.72%	0.34%

Main Page | Nominal Logistic Model | Classification Tree Model | Bootstrap Forest Model | MTF Cohort Trees | Results/Conclusion

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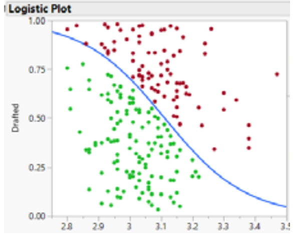
Logistic Regression Model

- Used for categorical responses (Binary, Discrete, Ordinal)
- Models the probability that Y = specific target, based on the independent variable (X_i)
- Uses the logistic response function



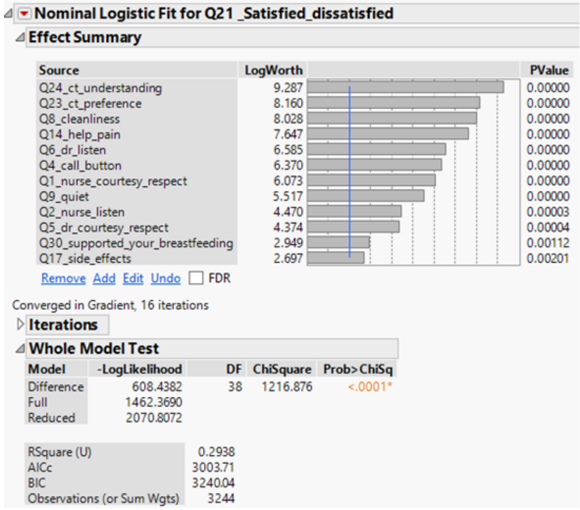
$$\pi = P(Y = target) = \frac{e^{(b_0+b_1X_i)}}{1+e^{(b_0+b_1X_i)}}$$

$$logit\ (\pi) = log_e\left[\frac{\pi}{1-\ \pi}\right] = \ b_0 + b_1X_i$$

After performing a backward stepwise variable selection, the model was reduced to 10 significant variables which impact overall patient satisfaction.

Model performance based on the validation data set:

- Rsquare = 0.26
- Misclassification rate = 0.21
- AUC = 0.82



Nominal Logistic Fit for Q21 _Satisfied_dissatisfied

Effect Summary

Source	LogWorth	PValue
Q24_ct_understanding	9.287	0.00000
Q23_ct_preference	8.160	0.00000
Q8_cleanliness	8.028	0.00000
Q14_help_pain	7.647	0.00000
Q6_dr_listen	6.585	0.00000
Q4_call_button	6.370	0.00000
Q1_nurse_courtesy_respect	6.073	0.00000
Q9_quiet	5.517	0.00000
Q2_nurse_listen	4.470	0.00003
Q5_dr_courtesy_respect	4.374	0.00004
Q30_supported_your_breastfeeding	2.949	0.00112
Q17_side_effects	2.697	0.00201

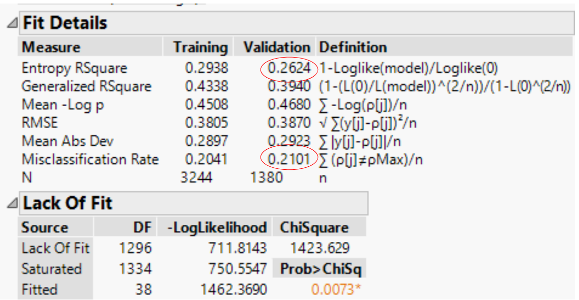
Converged in Gradient, 16 iterations

Iterations

Whole Model Test

Model	-LogLikelihood	DF	ChiSquare	Prob>ChiSq
Difference	608.4382	38	1216.876	<.0001*
Full	1462.3690			
Reduced	2070.8072			

RSquare (U)	0.2938
AICc	3003.71
BIC	3240.04
Observations (or Sum Wgts)	3244

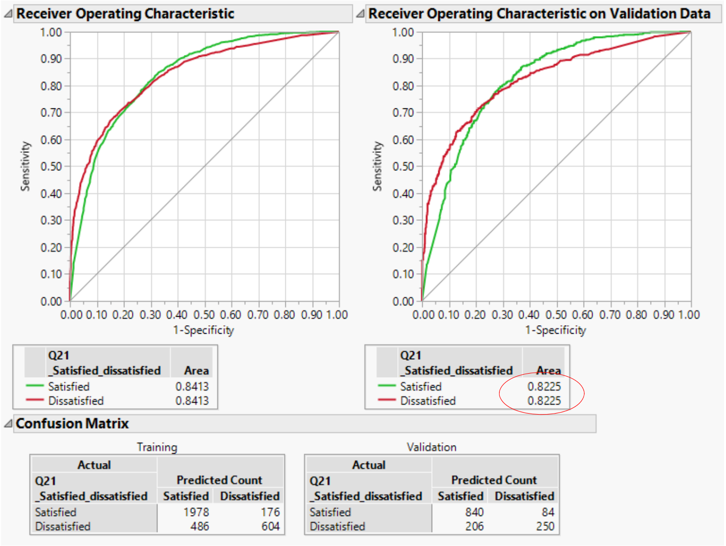


Fit Details

Measure	Training	Validation	Definition
Entropy RSquare	0.2938	0.2624	1-Loglike(model)/Loglike(0)
Generalized RSquare	0.4338	0.3940	(1-(L(0)/L(model))^(2/n))/(1-L(0)^(2/n))
Mean -Log p	0.4508	0.4680	∑ -Log(ρ[j])/n
RMSE	0.3805	0.3870	√ ∑(y[j]-ρ[j])²/n
Mean Abs Dev	0.2897	0.2923	∑ |y[j]-ρ[j]|/n
Misclassification Rate	0.2041	0.2101	∑ (ρ[j]≠ρMax)/n
N	3244	1380	n

Lack Of Fit

Source	DF	-LogLikelihood	ChiSquare
Lack Of Fit	1296	711.8143	1423.629
Saturated	1334	750.5547	Prob>ChiSq
Fitted	38	1462.3690	0.0073*



Q21 _Satisfied_dissatisfied	Area
🟩 Satisfied	0.8413
🟥 Dissatisfied	0.8413

Q21 _Satisfied_dissatisfied	Area
🟩 Satisfied	0.8225
🟥 Dissatisfied	0.8225

Confusion Matrix

Training

Actual	Predicted Count	
Q21 _Satisfied_dissatisfied	Satisfied	Dissatisfied
Satisfied	1978	176
Dissatisfied	486	604

Validation

Actual	Predicted Count	
Q21 _Satisfied_dissatisfied	Satisfied	Dissatisfied
Satisfied	840	84
Dissatisfied	206	250

Key significant questions (drivers)- in order of LogWorth:

Q 24. When I left the hospital, I had a good understanding of the things I was responsible for in managing my health.
Q 23. Staff took my preferences and those of my family or caregiver into account in deciding what my health care needs would be when I left.
Q 8. How often were your room and bathroom kept clean?
Q 14. How often did the hospital staff do everything they could to help you with your pain?
Q 6. How often did doctors listen carefully to you?

Q 4. After you pressed the call button, how often did you get help as soon as you wanted it?
Q 1. How often did nurses treat you with courtesy and respect?
Q 9. How often was the area around your room quiet at night?
Q 2. How often did nurses listen carefully to you?
Q 5. How often did doctors treat you with courtesy and respect?

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Classification Tree Model

Classification trees models predict the probability of the outcome variable through a series of consecutive splits among the predictor variables.

- Segments data into homogenous groups (based on y), while maximizing the difference in the response of groups.
- Splits based on maximizing the difference in the average response rates b/t paired branches
- Adding more branches so more of the variability in the response is explained by the model
- Splitting stops when Validation R^2 fails to improve

Advantages of classification trees

- Easily understood and explainable to a non-technical audience– more useful in managerial processes.
- Non-linear and non-parametric –allows for a wide range of predictor-response variable relationships.

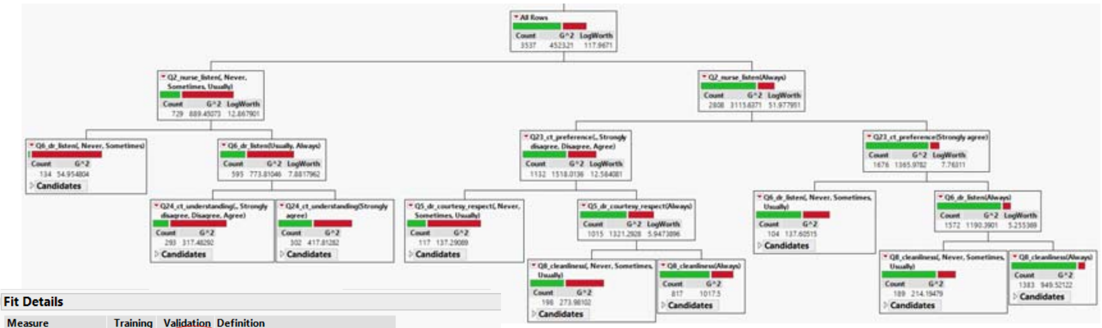
Disadvantage of classification trees:

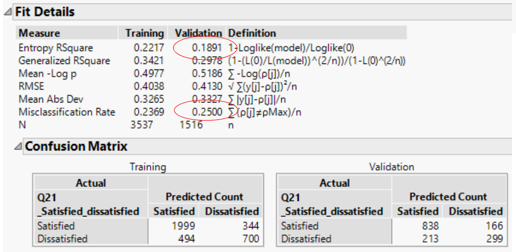
- Often miss relationships between predictors, as they split on a single variable.
- Lower performance than more complex modeling (i.e. discriminant analysis)

In this case, the Classification Tree Model (slightly) underperforms compared to the other models:

- Rsquare = 0.19
- Misclassification rate = 0.25
- AUC = 0.77

However, the reduced number of significant variables (6) provides the client with fewer actionable drivers to concentrate their performance improvement efforts to improve overall patient satisfaction.





Fit Details

Measure	Training	Validation	Definition
Entropy RSquare	0.2217	0.1891	1-Loglike(model)/Loglike(0)
Generalized RSquare	0.3421	0.2978	(1-(L(0)/L(model))^(2/n))/(1-L(0)^(2/n))
Mean -Log p	0.4977	0.5186	∑ -Log(ρ[j])/n
RMSE	0.4038	0.4130	√ ∑(y[j]-ρ[j])²/n
Mean Abs Dev	0.3265	0.3327	∑ |y[j]-ρ[j]|/n
Misclassification Rate	0.2369	0.2500	∑ (ρ[j]≠ρMax)/n
N	3537	1516	n

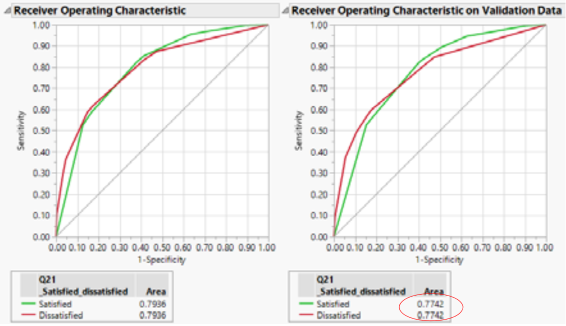
Confusion Matrix

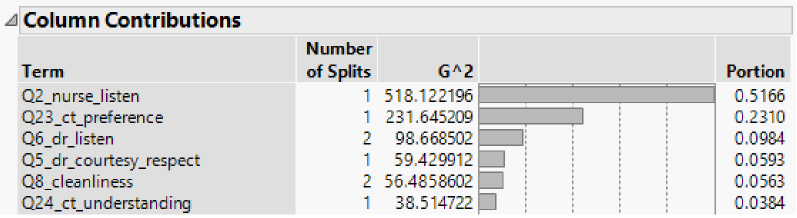
Training

Actual Q21 _Satisfied_dissatisfied	Predicted Count Satisfied	 Dissatisfied
Satisfied	1999	344
Dissatisfied	494	700

Validation

Actual Q21 _Satisfied_dissatisfied	Predicted Count Satisfied	 Dissatisfied
Satisfied	838	166
Dissatisfied	213	299





Column Contributions

Term	Number of Splits	G^2	Portion
Q2_nurse_listen	1	518.122196	0.5166
Q23_ct_preference	1	231.645209	0.2310
Q6_dr_listen	2	98.668502	0.0984
Q5_dr_courtesy_respect	1	59.429912	0.0593
Q8_cleanliness	2	56.4858602	0.0563
Q24_ct_understanding	1	38.514722	0.0384

Key significant questions (drivers)- in order of LogWorth:

Q 2. How often did nurses listen carefully to you?
Q 23. Staff took my preferences and those of my family or caregiver into account in deciding what my health care needs would be when I left.
Q 6. How often did doctors listen carefully to you?
Q 5. How often did doctors treat you with courtesy and respect?
Q 8. How often were your room and bathroom kept clean?
Q 24. When I left the hospital, I had a good understanding of the things I was responsible for in managing my health.

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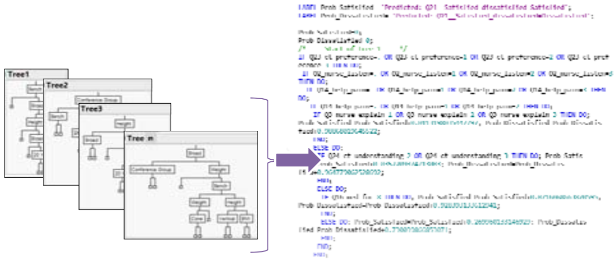
Bootstrap Forest Model

The Bootstrap Forest technique uses multiple decision trees, with each tree using random sampling of the factors to build an aggregated predictive model.

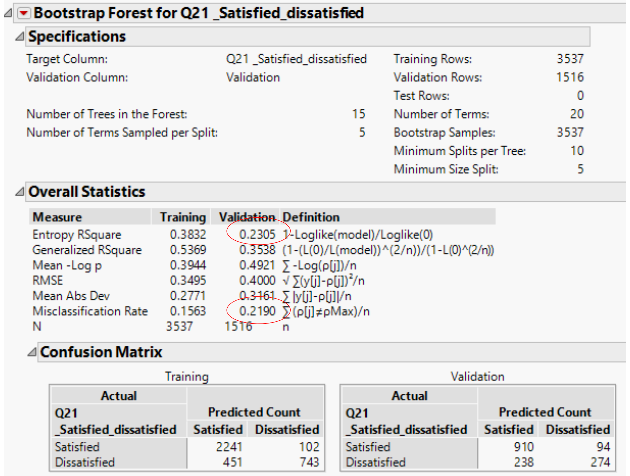
- Creates multiple decision trees (via sampling with replacement)
- Limited splitting to a randomly selected sample of columns
- Averages the multiple models to obtain a predicted model
- "Early stopping" process if adding trees does not improve validation test statistic



Due to the nature of the bagging and random sampling of the Bootstrap Forest model, even more variables (20) are contained in the final model. However, the "Column Contributions" table provides the relative contribution for each predictor in the model.

It performs similar to the Logistic Regression model

- Rsquare = 0.23
- Misclassification rate = 0.22
- AUC = 0.81



Bootstrap Forest for Q21 _Satisfied_dissatisfied

Specifications

Target Column:	Q21 _Satisfied_dissatisfied	Training Rows:	3537
Validation Column:	Validation	Validation Rows:	1516
		Test Rows:	0
Number of Trees in the Forest:	15	Number of Terms:	20
Number of Terms Sampled per Split:	5	Bootstrap Samples:	3537
		Minimum Splits per Tree:	10
		Minimum Size Split:	5

Overall Statistics

Measure	Training	Validation	Definition
Entropy RSquare	0.3832	0.2305	1-Loglike(model)/Loglike(0)
Generalized RSquare	0.5369	0.3538	(1-(L(0)/L(model))^(2/n))/(1-L(0)^(2/n))
Mean -Log p	0.3944	0.4921	∑ -Log(ρ[j])/n
RMSE	0.3495	0.4000	$\sqrt{\sum(y[j]-\rho[j])^2/n}$
Mean Abs Dev	0.2771	0.3161	∑ |y[j]-ρ[j]|/n
Misclassification Rate	0.1563	0.2190	∑ (ρ[j]≠ρMax)/n
N	3537	1516	n

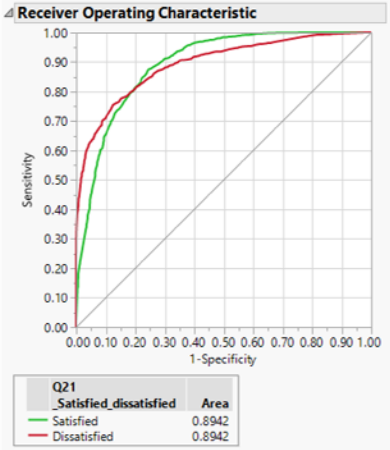
Confusion Matrix

Training

Actual Q21 _Satisfied_dissatisfied	Predicted Count Satisfied	Dissatisfied
Satisfied	2241	102
Dissatisfied	451	743

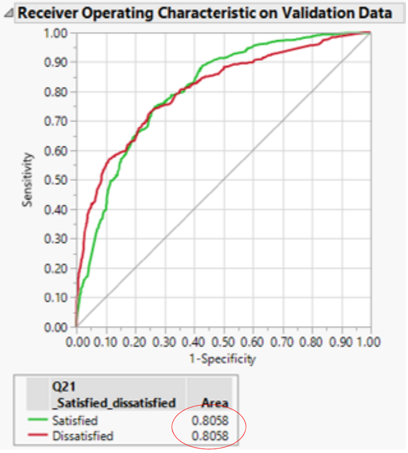
Validation

Actual Q21 _Satisfied_dissatisfied	Predicted Count Satisfied	Dissatisfied
Satisfied	910	94
Dissatisfied	238	274



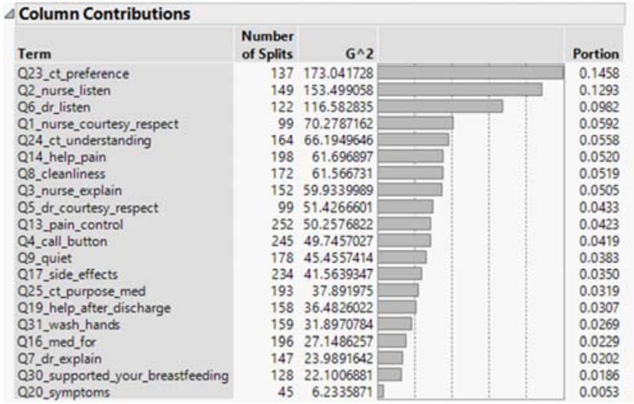
Receiver Operating Characteristic

Q21 _Satisfied_dissatisfied	Area
🟩 Satisfied	0.8942
🟥 Dissatisfied	0.8942



Receiver Operating Characteristic on Validation Data

Q21 _Satisfied_dissatisfied	Area
🟩 Satisfied	0.8058
🟥 Dissatisfied	0.8058



Column Contributions

Term	Number of Splits	G^2	Portion
Q23_ct_preference	137	173.041728	0.1458
Q2_nurse_listen	149	153.499058	0.1293
Q6_dr_listen	122	116.582835	0.0982
Q1_nurse_courtesy_respect	99	70.2787162	0.0592
Q24_ct_understanding	164	66.1949646	0.0558
Q14_help_pain	198	61.696897	0.0520
Q8_cleanliness	172	61.566731	0.0519
Q3_nurse_explain	152	59.9339989	0.0505
Q5_dr_courtesy_respect	99	51.4266601	0.0433
Q13_pain_control	252	50.2576822	0.0423
Q4_call_button	245	49.7457027	0.0419
Q9_quiet	178	45.4557414	0.0383
Q17_side_effects	234	41.5639347	0.0350
Q25_ct_purpose_med	193	37.891975	0.0319
Q19_help_after_discharge	158	36.4826022	0.0307
Q31_wash_hands	159	31.8970784	0.0269
Q16_med_for	196	27.1486257	0.0229
Q7_dr_explain	147	23.9891642	0.0202
Q30_supported_your_breastfeeding	128	22.1006881	0.0186
Q20_symptoms	45	6.2335871	0.0053

Key significant questions (drivers)- in order of LogWorth:

Q 23. Staff took my preferences and those of my family or caregiver into account in deciding what my health care needs would be when I left.
Q 2. How often did nurses listen carefully to you?
Q 6. How often did doctors listen carefully to you?
Q 1. How often did nurses treat you with courtesy and respect?
Q 24. When I left the hospital, I had a good understanding of the things I was responsible for in managing my health.

Q 14. How often did the hospital staff do everything they could to help you with your pain?
Q 8. How often were your room and bathroom kept clean?
Q 3. How often did nurses explain things in a way you could understand?
Q 5. How often did doctors treat you with courtesy and respect?
Q 13. Did you need medicine for pain?

Q 4. After you pressed the call button, how often did you get help as soon as you wanted it?
Q 9. How often was the area around your room quiet at night?
Q 17. Before giving you any new medicine, how often did hospital staff describe possible side effects in a way you could understand?
Q 25. When I left the hospital, I clearly understood the purpose for taking each of my medications.
Q 19. Did doctors, nurses or other hospital staff talk with you about whether you would have the help you needed when you left the hospital?

Main Page | Nominal Logistic Model | Classification Tree Model | Bootstrap Forest Model | MTF Cohort Trees | Results/Conclusion

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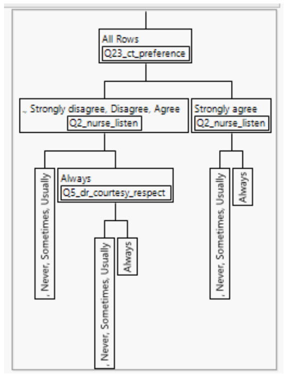
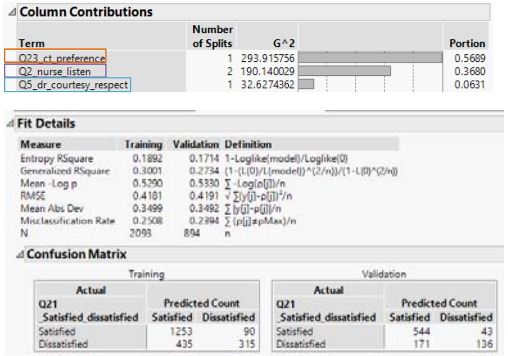
Classification Trees based on Hospital Cohorts (by Birth Volume)

High Birth Volume Hospitals (> 1450 births)





Column Contributions

Term	Number of Splits	G^2	Portion
Q23_ct_preference	1	293.915756	0.5689
Q2_nurse_listen	2	190.140029	0.3680
Q5_dr_courtesy_respect	1	32.6274362	0.0631

Fit Details

Measure	Training	Validation	Definition
Entropy RSquare	0.1892	0.1714	1-Loglike(model)/Loglike(0)
Generalized RSquare	0.3001	0.2734	(1-(L(0)/L(model))^(2/n))/(1-L(0)^(2/n))
Mean -Log p	0.5290	0.5330	∑ -Log(ρ[j])/n
RMSE	0.4181	0.4191	√ ∑(y[j]-ρ[j])²/n
Mean Abs Dev	0.3499	0.3492	∑ |y[j]-ρ[j]|/n
Misclassification Rate	0.2508	0.2394	∑ (ρ[j]≠ρMax)/n
N	2093	894	n

Confusion Matrix

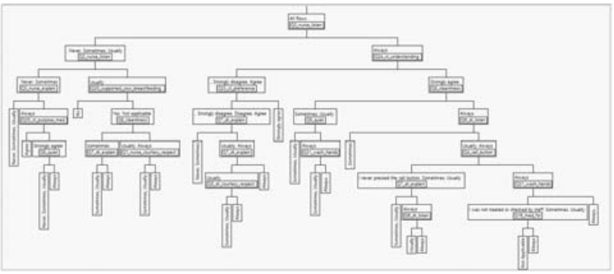
Training

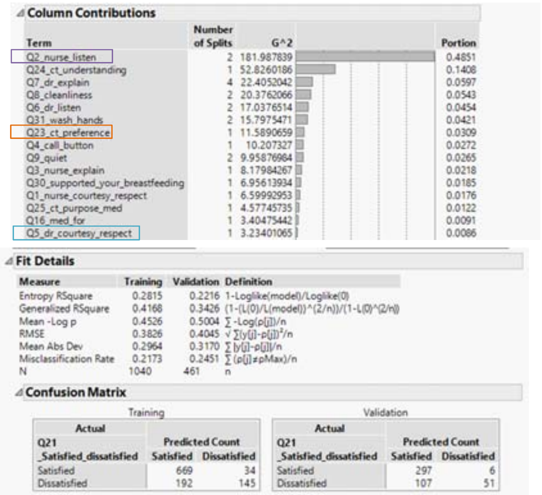
Actual Q21 _Satisfied_dissatisfied	Predicted Count Satisfied	Predicted Count Dissatisfied
Satisfied	1253	90
Dissatisfied	435	315

Validation

Actual Q21 _Satisfied_dissatisfied	Predicted Count Satisfied	Predicted Count Dissatisfied
Satisfied	544	43
Dissatisfied	171	136

Medium Birth Volume Hospitals





Column Contributions

Term	Number of Splits	G^2	Portion
Q2_nurse_listen	2	181.987839	0.4851
Q24_ct_understanding	1	52.8260186	0.1408
Q7_dr_explain	4	22.4052042	0.0597
Q8_cleanliness	2	20.3762066	0.0543
Q6_dr_listen	2	17.0376514	0.0454
Q31_wash_hands	2	15.7975471	0.0421
Q23_ct_preference	1	11.5890659	0.0309
Q4_call_button	1	10.207327	0.0272
Q9_quiet	2	9.95876984	0.0265
Q3_nurse_explain	1	8.17984267	0.0218
Q30_supported_your_breastfeeding	1	6.95613934	0.0185
Q1_nurse_courtesy_respect	1	6.59992953	0.0176
Q25_ct_purpose_med	1	4.57745735	0.0122
Q16_med_for	1	3.40475442	0.0091
Q5_dr_courtesy_respect	1	3.23401065	0.0086

Fit Details

Measure	Training	Validation	Definition
Entropy RSquare	0.2815	0.2216	1-Loglike(model)/Loglike(0)
Generalized RSquare	0.4168	0.3426	(1-(L(0)/L(model))^(2/n))/(1-L(0)^(2/n))
Mean -Log p	0.4526	0.5004	∑ -Log(ρ[j])/n
RMSE	0.3826	0.4045	√ ∑(y[j]-ρ[j])²/n
Mean Abs Dev	0.2964	0.3170	∑ |y[j]-ρ[j]|/n
Misclassification Rate	0.2173	0.2451	∑ (ρ[j]≠ρMax)/n
N	1040	461	n

Confusion Matrix

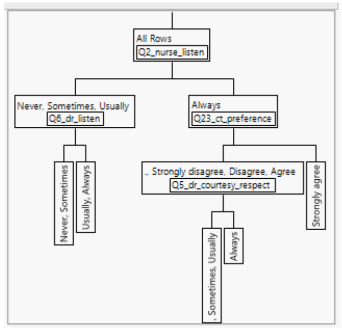
Training

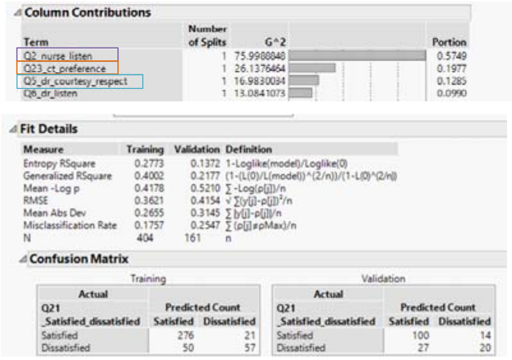
Actual Q21 _Satisfied_dissatisfied	Predicted Count Satisfied	Predicted Count Dissatisfied
Satisfied	669	34
Dissatisfied	192	145

Validation

Actual Q21 _Satisfied_dissatisfied	Predicted Count Satisfied	Predicted Count Dissatisfied
Satisfied	297	6
Dissatisfied	107	51

Small Birth Volume Hospitals





Column Contributions

Term	Number of Splits	G^2	Portion
Q2_nurse_listen	1	75.9988848	0.5749
Q23_ct_preference	1	26.1376464	0.1977
Q5_dr_courtesy_respect	1	16.9830034	0.1285
Q6_dr_listen	1	13.0841073	0.0990

Fit Details

Measure	Training	Validation	Definition
Entropy RSquare	0.2773	0.1372	1-Loglike(model)/Loglike(0)
Generalized RSquare	0.4002	0.2177	(1-(L(0)/L(model))^(2/n))/(1-L(0)^(2/n))
Mean -Log p	0.4178	0.5210	∑ -Log(ρ[j])/n
RMSE	0.3621	0.4154	√ ∑(y[j]-ρ[j])²/n
Mean Abs Dev	0.2655	0.3145	∑ |y[j]-ρ[j]|/n
Misclassification Rate	0.1757	0.2547	∑ (ρ[j]≠ρMax)/n
N	404	161	n

Confusion Matrix

Training

Actual Q21 _Satisfied_dissatisfied	Predicted Count Satisfied	Predicted Count Dissatisfied
Satisfied	276	21
Dissatisfied	50	57

Validation

Actual Q21 _Satisfied_dissatisfied	Predicted Count Satisfied	Predicted Count Dissatisfied
Satisfied	100	14
Dissatisfied	27	20

Cohorts based on Annual births for period July 2017-June 2018-- Low: < 600 births, Medium: 1450-601 births, High: >1450 births

All 3 cohort models contain “Q23: ct_preference”, “Q2 Nurse_listen”, & “Q5 dr_courtesy_respect”. “Q6_Dr_listen” only appeared in the Small hospital cohort. There is significance in “Q6_Dr_Listen” between cohorts (p<.0001)

Main Page | Nominal Logistic Model | Classification Tree Model | Bootstrap Forest Model | MTF Cohort Trees | Results/Conclusion

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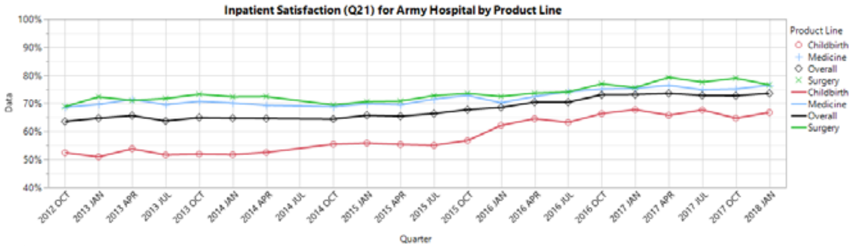

Q21: "Using any number from 0 to 10, where 0 is the worst hospital possible and 10 is the best hospital possible, what number would you use to rate this hospital during your stay?" (0-8: Dissatisfied, 9-10: Satisfied)
Note: The HCAHPS benchmark (50th percentile) is 73%

Analysis

Although improving, Army Hospital Inpatient satisfaction for Childbirth continues to be below those of Medical & Surgical inpatients.

Three modeling techniques in JMP were used to determine predictors of childbirth satisfaction in Army hospitals. In the logistic regression model, items from the Care Transition composite were the strongest determinants of overall satisfaction (Overall Hospital Rating). The Decision Tree (classification – categorical target variable) revealed "nurses listen" to be the top predictor of overall satisfaction, with items from Care Transition included in the model which maximized R^2. The Bootstrap Forest model indicated questions from both Nurse Communication and Care Transition were significant drivers of overall satisfaction. Finally, birth volume was examined to explore whether drivers of satisfaction were different based on size of hospital. Of note, there was a significant difference in "Dr. Listens" between hospital cohorts, in that it was only a predictor of satisfaction in small hospitals.

Although the Nominal Logistic model performed higher than the other 2 models (R2, misclassification rate, AUC, and RMSE), all 3 modeling types shared similar variables. When we reviewed the results with hospital and clinical leaders, they appreciated the classification tree model more, as it had fewer significant variables– which helped leaders identify where they should focus their performance improvement efforts.

Model Comparison (Validation data set)

	Rsquare	Misclass Rate	AUC	RMSE
Nominal Logistic	0.26	0.21	0.82	0.38
Classification Tree	0.19	0.25	0.77	0.41
Bootstrap Forest	0.23	0.22	0.81	0.40

Impact of Results

The Army Medical Department's Childbirth Satisfaction scores have historically been lower (significantly) than those in the Civilian Sector. Our analysis found, for the most part, similar drivers of overall satisfaction: all models revealed questions from the Nurse Communication and Care Transition Composites to be significant predictors of overall satisfaction. Therefore, focused should be placed on following leading practices in these areas: nurse hourly rounding; post-discharge phone calls.

Conclusions / Next Steps

This study only looked at certain predictors of satisfaction (survey data and number of births). The next steps will be to add other factors to the model. It may be that variables such as birth preferences, size of hospital, and birth order add in our understanding of the experience. Further studies into Nursing Satisfaction by unit type may also provide insight as how it may impact patient satisfaction.

References:

Kemp, K., Chan, N., McCormack, B. and Douglas-England, K. (2015). Drivers of Inpatient Hospital Experience Using the HCAHPS Survey. Health Services Research, Aug; 50(4); 982-997.

Grayson, Gardner, Stephens (2015). Building Better Models with JMP Pro. SAS Institute, Cary, NC.

Goodman, R., Campbell, K., Cook, J., et al (1998). The Economic Efficiency Factor and its use in service line evaluation. Army Medical Department Journal. July: 2-8.

Goodman, P., Mackey, M. Tavakoli, A. (2004). Factors Related to Childbirth Satisfaction. Journal of Advanced Nursing Practice, 46(2); 212-219.
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Main Page
Nominal Logistic Model
Classification Tree Model
Bootstrap Forest Model
MTF Cohort Trees
Results/Conclusion

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