Potential Predictors for HPV Vaccination Completion Rates

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Abstract

Background: Human papillomavirus (HPV) is the most common sexually transmitted pathogen; its ease in transmission significantly contributes to its prevalence within the population. While most HPV infections are asymptomatic, a subset of infections cause genital warts, cervical cancer and various anogenital cancers. Accordingly, the vaccine Gardasil has been designed to prevent HPV infection and its associated sequelae. While Gardasil is effective against over 75% of cervical cancers, recent studies have demonstrated its limited adoption. In 2010, only 49% of females between the ages of 13-17 had received at least one dose. Moreover, Gardasil is a three-dose vaccine, and consequently, female patients that initiate the vaccination series often do not complete it in its entirety.

Methods: Data obtained from researchers at the Johns Hopkins Medical Institutions (JHMI) was used to determine which socioeconomic factors influence a female's likelihood of vaccination completion. The dataset consisted of female patients between the ages of 11-26 that had received at least one of the Gardasil vaccine doses from a JHMI clinic in Baltimore, USA, between the years 2006 and 2008. First, three logistic regression models were run with vaccination regimen completion, one shot completed and two shots completed as the dependent variables. Then, three LASSO logistic regression models were run to find relationships that were not influenced by model overfitting. The two regression methods were compared to determine if different results could be achieved.

Results: For the logistic regression, findings revealed that black females ($P = 0.006881$), females between the ages of 18-26 ($P = 0.000483$), and females that visited urban clinics ($P = 0.004582$) are at an increased risk of incomplete vaccinations. In contrast, females that were treated by obstetrician-gynecologists ($P = 0.006269$) had increased compliance with the Gardasil vaccination regimen compared to women that visited other healthcare professionals. For the LASSO logistic regression, the model that

penalized the most for overfitting showed that black females have a higher likelihood of only receiving one shot.

Conclusion: Due to the retrospective nature of the data, no causation can be established. However, these correlations shed light on what female populations should be studied further and potentially targeted to improve Gardasil vaccination completion

rates. Moreover, the differences in vaccination completion rates can, in turn, aggravate the existing disparities in cervical cancer risk among females.

Key Words

Human Papillomavirus, Gardasil, Logistic Regression, LASSO Regression

Introduction

Human papillomavirus (HPV) is a virus that has over 100 strains, of which approximately 40 are sexually transmitted.¹ While the majority of infections are asymptomatic or self-limiting, there is the risk of the infection progressing to cervical cancer, anogenital cancer, and/or genital warts.² Due to such comorbidities, the rapid dissemination of the virus is concerning. Epidemiological studies have estimated that 6.2 million individuals between the ages of 14-44 become infected with HPV every year.¹ Furthermore, by using these incidence rates, computational models have predicted that 80% of sexually active 50-year-old women are infected with genital HPV.³ Given HPV's prevalence, many women are at risk of developing infection-related morbidities, and as a result, it is no surprise that cervical cancer is ranked the second leading cause of death by cancer among women.⁴

In the interest of limiting HPV infection, in 2006, the vaccine Gardasil (Merck Labs) was approved and licensed by the United States Food and Drug Administration (FDA). The vaccine is quadrivalent, effective against HPV strains 6, 11, 16, and 18. To maximize effectiveness, the vaccination regimen requires three shots in total, with the second and third vaccinations occurring at the

second and sixth month, respectively.⁵ Upon completion, Gardasil is protective against approximately 75-80 % of all cervical cancers.⁶

Despite being the first vaccine that prevents cancer, Gardasil has not been widely received by the young female population. For instance, from a 2010 U.S. national survey, the Centers for Disease Control and Prevention (CDC) determined that only 49% of females between the ages of 13-17 had received at least one dose.⁷ Of those females, only 32% had received all three doses.⁷ The vaccination completion rates for Gardasil are low, and public health strategies must be implemented to address this problem.

Accordingly, the objective of this study was to analyze several socioeconomic variables that influence a female's likelihood of completing the Gardasil regimen. The statistical method selected needed to account for the fact that socioeconomic variables tend to be highly correlated. The reason being that when two or more variables are collinear, it is difficult to distinguish their respective predictive power on the response variable.⁸⁻¹⁰ When statistical models are vulnerable to multicollinearity, they run the risk of having unstable and/or inflated parameter and standard error estimates.⁹

Consequently, this study implemented a stepwise logistic regression in addition to a Least Absolute Shrinkage and Selection Operator (LASSO) logistic regression. The latter model penalizes independent variables that are highly correlated by reducing the parameter estimate towards an absolute value of zero.¹¹ This study is interested in seeing if the two models yield different results regarding the likelihood of completing the Gardasil regimen. We predict that the LASSO logistic regression will have a more conservative output compared to the basic stepwise logistic regression, as it will detect the highly correlated socioeconomic variables. As a result, less independent variables will be considered significant.

Materials and Methodology

Obtaining Data and Cleaning Data

The dataset used in this study was obtained from Professor Seth Spielman's educational website. It is an abridged version of the raw data produced by the researchers at Johns Hopkins Medical Institutions (JHMI).¹² The information in the dataset was acquired from young female patients (11-26 year olds) that received at least one of the Gardasil vaccine doses from a JHMI clinic in Baltimore, USA between the years 2006 and 2008.¹² In total, there were 1,413 female patients. The dataset included the following variables: Age, Age Group (11-17 year olds or 18-26 year olds) Race (White, Black, Hispanic, Other), Number of Shots

Completed (1, 2 or 3), Completion of Gardasil Vaccine Regimen, Type of Insurance (Privately Paid, Hospital-Based Insurance, Military or Governmental Medical Assistance), Location of Clinic (Odenton, White Marsh, Johns Hopkins Outpatient Center, Bayview Medical Center), Clinic Location Type (Suburban or Urban), and finally, Type of Practice Female Patient Visited (Pediatric, Family Practice, OB-GYN).

First, using Microsoft Excel, the categorical variables in the dataset were converted to dummy variables to facilitate analysis and the formation of interaction terms. The variables OneShot, TwoShot and Completed were not included in interaction terms because they would each serve as dependent variables in their respective analyses. Interactions between the measured socioeconomic variables are possible, and accordingly, the relationships were further investigated by creating interaction terms. For instance, the race of a patient and their type of health insurance can have a synergistic effect. Similarly, the race of a patient and whether they visited a suburban or urban clinic may be correlated. Lastly, the patient's age group was included in a number of interaction terms. If interested in an exhaustive list of the variables analyzed in this study, please refer to the Appendix.

Descriptive Statistics

The R package ggplot2 was used to visualize the basic features of the dataset such as spread, variability and percentages. Since visualizing the data does not account for confounding variables, multivariable logistic regression was performed thereafter.

Backwards Stepwise Akaike Information Criterion Logistic Regression

A logistic regression was performed for statistical analysis because the dependent variables OneShot, TwoShot and Completed are all binary. Since the dataset had over 30 variables, there was a risk that the resulting logistic regression model would contain insignificant variables. Accordingly, to avoid overfitting and multicollinearity, the Backwards Stepwise Akaike Information Criterion (AIC) Selection method was used. The procedure involves first creating a model with all the predictor variables and calculating the respective AIC value. Then, in a sequential manner, one predictor variable is removed and the AIC value is recalculated. The logistic regression model with the lowest AIC value is used for analysis.

This process occurred three separate times, each with a different dependent variable –OneShot, TwoShot and Completed. For the

logistic regression, variables with a p-value less than 0.05 were considered significant. If interested in the R output for this method, please refer to the Appendix.

LASSO Logistic Regression

As the dataset had thirty-four variables, the logistic regressions executed were susceptible to overloading predictor variables. Therefore, there was a risk of the three models demonstrating relationships that were not genuine due to overfitting. To circumvent this problem, a LASSO regression was performed to penalize the model whenever independent variables were highly correlated and did not contribute to the model. The magnitude of the penalty depends on the lambda value chosen, where lower values are more liberal and higher values are more conservative. Like before, a LASSO logistic regression was run for the three separate dependent variables. If interested in the R output for this method, please refer to the Appendix.

Results

Descriptive Statistics

The 1,413 female participants were grouped into two age groups – 11-17 year olds and 18-26 year olds. The division was almost equal, with 49.6 % of the participants being categorized in the younger group and the remaining 50.4% being categorized in the older group. The median age for the 11-17 year olds group was 15, and the median age for the 18-26 year olds group was approximately 21. The wider spread of the older group was simply a reflection of the group’s greater age range. Lastly, the unequal whiskers for the younger group show that their participants are skewed towards older ages. Refer to Figure 1 for the respective boxplot.

Figure 1: Age Distribution of Female Participants

The 1,413 female participants were not distributed equally in terms of race. The participants were predominantly White

(51.8%), followed by Black (31.4%) and then Hispanic (3.7%). The remaining participants were categorized as “Other” (13.1%). This racial distribution is observable in Figure 2.

Figure 2: Race Distribution of Female Participants

As mentioned earlier, to complete the Gardasil regimen correctly, females must receive three shots within twelve months. The 1,413 female participants were categorized by how many Gardasil shots they received. To avoid redundancy, those that received three shots were not considered for the two-shot and one-shot categories, and similarly, those that received two shots were not considered for the one-shot category. Sixty-two percent of female participants ended their Gardasil regimen prematurely at the one-shot and two-shot stage. The remaining 38% received three shots; however, this finding does not necessarily equate to the completing the vaccine regimen correctly. In fact, 13% of the females that received three shots received their third shot beyond the twelve-month period, thereby making the vaccination regimen less effective. These distributions are all observable in Figure 3.

Figure 3: Not all females who receive three shots complete the Gardasil vaccination regimen correctly.

Backwards Stepwise Akaike Information Criterion (AIC) Logistic Regression

Three separate logistic regressions were performed to

determine if there were potential predictor variables for: 1) the likelihood of completing the Gardasil regimen; 2) the likelihood of only receiving one shot, and; 3) the likelihood of only receiving two shots. Each logistic regression started with 34 variables, and after the backwards stepwise method, a number of variables were removed. The remaining predictor variables and their respective statistical significances are outlined in Table 1.

The multivariate analysis revealed several trends with regards to Gardasil vaccination completion. For example, the older the female participant (Age) is, the less likely they are to complete the regimen ($P = 0.042795$) and were more likely to stop at the two shots stage ($P = 0.00649$). This observation was further supported by the older age group (X18.26) being strongly correlated to only receiving one shot of the vaccine ($P = 0.000483$).

Another trend was that Black female participants were less likely to complete the Gardasil regimen ($P = 0.006881$), especially if they visited urban clinics in Baltimore (BlackUrban, $P = 0.002511$). However, there are two subsets of the Black population that are more likely to complete the Gardasil regimen: older Black females (X18.26Black, $P = 0.034092$) and Black females that receive governmental medical assistance (BlackMedAssist, $P = 0.025268$). Interestingly, White females under governmental medical assistance (WhiteMedAssist) were also more likely to complete the Gardasil regimen ($P = 0.022921$). However, in general, females with this aid are less likely to complete the Gardasil regimen (MedicalAssistance, $P = 0.000581$). This suggests that insurance affects females differently. Another manifestation of this is that Black female participants that privately pay for the Gardasil vaccine are more likely to end the regimen at the two-shot stage (Black Private, $P = 0.02087$).

Furthermore, regardless of race, female participants were less likely to complete their vaccination regimen if they visited an urban clinic (Urban, $P = 0.004582$). For instance, Black female participants were less likely to reach completion (BlackUrban, $P = 0.002511$), Hispanic female participants were more likely to end at the second shot stage (HispanicUrban, $P = 0.01170$), and White female participants were less likely to complete the regimen (WhiteUrban, $P = 0.012499$).

Lastly, the type of physician practice visited by the patient for the Gardasil vaccine had an impact on vaccination completion. Obstetrician-gynecologists had higher retention with their patients (OB.GYN, $P = 0.006269$). Therefore, the female participants were less likely to end at the second shot stage ($P = 0.00052$). A physician's influence was also observed in older patients that visit

pediatric doctors (X18.26Pediatric). They tended to only receive one vaccination dose ($P = 0.049453$).

Table 1: Influence of Predictor Variables on Gardasil Regimen Progress

	OneShot Logistic Regression Estimate Values	TwoShot Logistic Regression Estimate Values	Completed Logistic Regression Estimate Values
X18.26	0.4834		
Urban	0.7429		
Age		0.00248	-0.06651
White	-0.2378		
Hispanic			
Black			-0.61859
MedicalAssistance	0.4605	0.30478	-1.70935
HospitalBasedInsurance			0.44822
OB.GYN		-0.81889	0.48838
Odontom	0.6078		
JohnHopkins	0.4478		
BlackUrban			-0.95882
BlackPrivate		0.48248	
BlackMedAssist			1.29520
WhiteUrban			-0.648
WhiteMedAssist		-0.51815	1.28958
HispanicUrban		1.87936	
X18.26Black		-0.86687	0.73070
X18.26Pediatric	0.7634		

P-Value Significance Legend
0.1
0.05
0.01
0.001

LASSO Logistic Regression

Three separate LASSO logistic regressions were run with completion of the Gardasil regimen as the dependent variable. The LASSO logistic regression with the minimum lambda value (0.007850481) penalized the model the least for additional variables, and consequently, a number of variables were deemed significant. However, when the LASSO logistic regression was run with the maximum lambda value (0.06670973), no variables were deemed significant. As a result, the LASSO logistic regression with the average lambda value (0.03728011) was run. It demonstrated that Black females who visited urban clinics in Baltimore and females with governmental medical assistance were less likely to complete the Gardasil regimen. In contrast, females that visited the White Marsh clinic were more likely to complete their Gardasil regimen. The R output does not provide p-values, therefore, further analysis is required to determine how significant these results are. These relationships are observable in Table 2.

Three separate LASSO logistic regressions were run with receiving only one shot of the Gardasil regimen as the dependent variable. The LASSO logistic regression with the minimum lambda value (0.002292268) penalized the model the least for additional variables, and consequently, a number of variables were deemed significant. When the LASSO logistic regression

was run under the most conservative conditions (maximum $\lambda = 0.05420043$), only the X18.26Black variable remained. This suggests that the relationship between older Black females and their increased likelihood of only receiving one shot may be important. As mentioned earlier, no p-value is linked to this predictor variable. As a result, it is difficult to determine how important the X18.26Black interaction term is.

Table 2: LASSO Regression with Completed as Dependent Variable

Age	-0.040917829	
X18.26	-0.166649056	
Urban	-0.078616478	
Black	-0.307881820	-0.1363584
White		
Hispanic		
MedicalAssistance	-0.487052708	-0.2080779
PrivateInsurance		
HospitalBasedInsurance	0.307686767	
Odonton		
WhiteMarsh	0.327652806	0.1629270
JohnHopkins	-0.020537804	
Pediatric		
OB.GYN	0.237699919	
BlackUrban	-0.379188154	-0.1759369
BlackMedAssist		
BlackPrivate		
BlackHospital		
WhiteUrban		
WhiteMedAssist		
WhitePrivate	0.003634982	
WhiteHospital		
HispanicUrban		
HispanicMedAssist	-0.162072245	
HispanicPrivate		
HispanicHospital	1.569762580	
X18.26Pediatric	-0.372290587	
X18.26OB.GYN	0.074103728	
X18.26Black		
X18.26White		
X18.26Hispanic		

A LASSO logistic regression with the average λ value (0.02824635) was also run and shared some of the relationships observed the LASSO logistic regression run with the Completed dependent variable. For instance, it was previously observed that female participants who visited the White Marsh clinic were more likely to complete the Gardasil regimen. Here, it is shown that female participants that visited the White Marsh clinic were less likely to only receive one shot. Another example of shared observations was that female participants who receive governmental medical assistance were less likely to complete the Gardasil regimen and were more likely to only receive one shot. Once again, the R output does not provide p-values, therefore, further analysis is required to determine how significant these

results are. Other relationships are observable in Table 3.

Table 3: LASSO Regression with OneShot as Dependent Variable

	$\lambda = 0.002292258$	$\lambda = 0.02824635$	$\lambda = 0.06420043$
Age	0.003881171		
X18.26	0.392500147	0.10914557	
Urban			
Black	0.030204286		
White	-0.196116467		
Hispanic			
MedicalAssistance	0.454718114	0.16008246	
PrivateInsurance	0.087284153		
HospitalBasedInsurance	-0.175653242		
Odonton			
WhiteMarsh	-0.540197352	-0.14550846	
JohnHopkins	0.382516787	0.17192759	
Pediatric	-0.062279159		
OB.GYN			
BlackUrban	0.157963744	0.08966726	
BlackMedAssist			
BlackPrivate			
BlackHospital			
WhiteUrban	0.127007901		
WhiteMedAssist	0.139419590		
WhitePrivate			
WhiteHospital	0.277320189		
HispanicUrban	-1.919418331		
HispanicMedAssist	1.332114480		
HispanicPrivate	-0.644943294		
HispanicHospital	-2.196236015		
X18.26Pediatric	0.693807779	0.20349806	
X18.26OB.GYN	-0.061578547		
X18.26Black	0.114343715	0.18557947	3.829585e-08
X18.26White			
X18.26Hispanic	1.270748705		

Three separate LASSO regressions were run with receiving only two shots of the Gardasil regimen as the dependent variable. The LASSO logistic regression with the minimum λ value (0.001047045) penalized the model the least for additional variables, and consequently, a number of variables were deemed significant. However, when the LASSO logistic regression was run with the maximum λ value (0.03591857), no variables were deemed significant. As a result, the LASSO logistic regression with the average λ value (0.01848281) was run. Interestingly, the relationships observed were not previously observed with the Completed and OneShot LASSO logistic regressions. Female participants that had hospital-based insurance and female participants that were treated by obstetrician-gynecologists were less likely to only receive two shots of the Gardasil regimen. In contrast, Hispanic females that visited urban clinics in Baltimore were more likely to only receive two shots of the Gardasil regimen. As mentioned earlier, due to the lack of p-values, further analysis is required to determine the significance of these predictor values. These relationships are outlined in Table 4.

Discussion

This study’s analysis revealed that approximately a third of the female participants completed the Gardasil vaccination

regimen within the recommended twelve months. The logistic regression and LASSO logistic regression helped determine potential predictor variables that could influence a female's likelihood in vaccination completion. We purposely used and compared two separate regression methods in this study in order to identify weaknesses with each approach and more confidently assess predictor variables. For example, the model for the logistic regression was determined by a backwards stepwise AIC method.

analysis will be analyzed.

The data analysis suggests that the older the female patient, the more likely they will not complete the vaccination regimen. This may be because majority of young females have their parents or guardians book their medical appointments, and therefore, do not hold as much personal and financial responsibility in terms of their health. An older female has personal and financial obligations that may impede them from completing the vaccination regimen.

Another trend was that people who visited urban clinics were less likely to complete their vaccination regimen. To determine the underlying reasons for this trend, future studies should examine the ease of access and clinic wait times of both urban clinics and suburban clinics. In terms of physician practice, female participants that visited obstetrician-gynecologists tended to have higher compliance to the Gardasil regimen compared to those that visited family doctors or pediatricians. Future studies should determine if doctors of different specialties have different vaccination strategies or vary in how strongly they recommend getting vaccinated against HPV.

In terms of race, it was noted that, in general, Black female participants are at risk of an incomplete vaccination regimen. To interpret this relationship better, more socioeconomic variables should be included in the dataset such as household income, educational status or distance from clinic. That being said, the stepwise logistic regression model revealed two Black subpopulations that were more likely to complete their vaccination regimen: females between the ages of 18-26 and females that received government medical assistance. Yet, this phenomenon was not shared with the more conservative LASSO logistic regression. The model deemed that Black females between the ages of 18-26 are more likely to only complete one out of the three vaccinations. In fact, this was the only observation that was supported under the most penalized model after accounting for overfitting and multicollinearity. For future studies, adjustments to the dataset are recommended. As mentioned earlier, more socioeconomic variables would be beneficial. In addition, since each patient's personal identifiers have not been included in the dataset, it is difficult to determine if there are any duplicate entries. As a result, each patient should have a unique number associated with their entry for cross-referencing purposes. The reason why this would be beneficial is because there could be cross-over cases between the four clinics in Baltimore, USA. For example, the female patient may have visited the Bayview Medical Center for her first two shots and then Odenton for her last shot in the

	lambda = 0.001047045	lambda = 0.01848281
Age	0.05465661	
X18.26	0.04524844	
Urban		
Black	0.20918602	
White		
Hispanic	-0.86340396	
MedicalAssistance	0.18542950	
PrivateInsurance	-0.04653889	
HospitalBasedInsurance	-1.37802579	-0.01605313
Odenton	-0.27345241	
WhiteMarsh	0.01565802	
JohnHopkins	-0.26991062	
Pediatric	-0.22800962	
OB.GYN	-0.54363684	-0.09776230
BlackUrban		
BlackMedAssist		
BlackPrivate	0.29362642	
BlackHospital	1.48058502	
WhiteUrban	0.05878695	
WhiteMedAssist	-0.34801687	
WhitePrivate		
WhiteHospital	0.87527484	
HispanicUrban	1.81947849	0.49185211
HispanicMedAssist		
HispanicPrivate		
HispanicHospital	-1.82488381	
X18.26Pediatric	-0.29290566	
X18.26OB.GYN		
X18.26Black	-0.61563100	
X18.26White	-0.05450602	
X18.26Hispanic		

Table 4: LASSO Regression with TwoShot as Dependent Variable

A different model could have been achieved if done forwards or if another criteria besides AIC was used. As for the LASSO logistic regression, it is difficult to determine how conservative the lambda should be. Furthermore, the LASSO logistic regression is not accompanied by p-values, which makes it difficult to determine how significant a predictor variable is for the dependent variable being analyzed. Accordingly, these results should encourage future studies to investigate the causality underlying these trends. In the subsequent paragraphs, the suggested relationships from our data

vaccination regimen. Is this patient inputted in the dataset twice? Or is the patient's information combined? If so, which variables would be used in these cross-over cases (e.g. suburban vs. urban, OB-GYN vs. pediatric vs. family)? Another source of error is that the data accumulated by JHMI assumes that the female patient revisits the same clinic for each subsequent Gardasil vaccination dose. For example, if a female visited the Odenton clinic for her first shot and then visited an out-of-city clinic for her subsequent two shots, the dataset would have reported her as an incomplete vaccination regimen.

Conclusion

While the merits of Gardasil are evident, the opportunity to limit HPV infection and cervical cancer is limited on two fronts: first, the low vaccination rates and second, the low rates of completion for females that do commence the Gardasil vaccination regimen. Through the use of data science, this study revealed certain female subpopulations that are more and less likely to complete the vaccination series, and in turn, these results can be used to direct more robust analyses. We are hopeful that future research will identify the vaccination behaviours within distinct female cohorts, and what effective strategies should be implemented to target these cohorts to increase overall vaccination completion rates.

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Appendix

```
[1] "TwoShots"          "OneShot"          "Completed"
[4] "Age"               "X18.26"           "Urban"
[7] "Black"             "White"            "Hispanic"
[10] "MedicalAssistance" "PrivateInsurance" "HospitalBasedInsurance"
[13] "Odonton"           "WhiteMarsh"       "JohnHopkins"
[16] "Pediatric"         "OB.GYN"           "BlackUrban"
[19] "BlackMedAssist"    "BlackPrivate"      "BlackHospital"
[22] "WhiteUrban"        "WhiteMedAssist"    "WhitePrivate"
[25] "WhiteHospital"     "HispanicUrban"     "HispanicMedAssist"
[28] "HispanicPrivate"   "HispanicHospital"  "X18.26Pediatric"
[31] "X18.26OB.GYN"     "X18.26Black"      "X18.26White"
[34] "X18.26Hispanic"
```

1. Variables in Dataset

2. R OUTPUT: Backwards Stepwise AIC Logistic Regression

This is the R output for the Completed dependent variable, which helped determine what variables should be included in the logistic regression model.

```
> fullmod = glm(Completed ~ . - OneShot - TwoShots, family="binomial", data=data)
> nullmod = glm(Completed ~ 1, family="binomial", data=data)
> backwards = step(fullmod)

Start: AIC=1751.29
Completed ~ (TwoShots + OneShot + Age + X18.26 + Urban + Black +
  White + Hispanic + MedicalAssistance + PrivateInsurance +
  HospitalBasedInsurance + Odonton + WhiteMarsh + JohnHopkins +
  Pediatric + OB.GYN + BlackUrban + BlackMedAssist + BlackPrivate +
  BlackHospital + WhiteUrban + WhiteMedAssist + WhitePrivate +
  WhiteHospital + HispanicUrban + HispanicMedAssist + HispanicPrivate +
  HispanicHospital + X18.26Pediatric + X18.26OB.GYN + X18.26Black +
  X18.26White + X18.26Hispanic) - OneShot - TwoShots

# model at the beginning of backwards stepwise AIC.

Step: AIC=1728.72
Completed ~ Age + X18.26 + Black + MedicalAssistance + HospitalBasedInsurance +
  Odonton + Pediatric + OB.GYN + BlackUrban + BlackMedAssist +
  WhiteUrban + WhiteMedAssist + HispanicHospital + X18.26Pediatric +
  X18.26Black + X18.26White

Df Deviance AIC
<none> 1694.7 1728.7
- Pediatric 1 1696.8 1728.8
- Odonton 1 1697.0 1729.0
- X18.26 1 1697.2 1729.2
- X18.26Pediatric 1 1697.3 1729.3
- X18.26White 1 1697.5 1729.5
- HispanicHospital 1 1697.8 1729.8
- HospitalBasedInsurance 1 1697.8 1729.8
- Age 1 1698.8 1730.8
- X18.26Black 1 1699.3 1731.3
- BlackMedAssist 1 1700.2 1732.2
- WhiteMedAssist 1 1700.4 1732.4
- WhiteUrban 1 1701.1 1733.1
- Black 1 1702.2 1734.2
- OB.GYN 1 1702.2 1734.2
- BlackUrban 1 1704.1 1736.1
- MedicalAssistance 1 1709.3 1741.3

# model at the end of backwards stepwise AIC.
```

Variable

```
> Completed = glm(Completed ~ Age + X18.26 + Black + MedicalAssistance + HospitalBasedInsurance +
  Odonton + Pediatric + OB.GYN + BlackUrban + BlackMedAssist + WhiteUrban + WhiteMedAssist +
  HispanicHospital + X18.26Pediatric + X18.26Black + X18.26White, family="binomial", data=data)
> summary(Completed)

Call:
glm(formula = Completed ~ Age + X18.26 + Black + MedicalAssistance +
  HospitalBasedInsurance + Odonton + Pediatric + OB.GYN + BlackUrban +
  BlackMedAssist + WhiteUrban + WhiteMedAssist + HispanicHospital +
  X18.26Pediatric + X18.26Black + X18.26White, family = "binomial",
  data = data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5084  -0.9315  -0.7047   1.2567   2.3272

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.70269    0.48208   1.458  0.14947
Age         -0.05551    0.02740  -2.026  0.04795 *
X18.26      -0.50560    0.32054  -1.577  0.114724
Black       -0.61859    0.22889  -2.703  0.006881 **
MedicalAssistance -1.70936    0.49684  -3.441  0.000581 ***
HospitalBasedInsurance  0.44822    0.25256   1.775  0.075944 .
Odonton      -0.29777    0.19551  -1.523  0.127738
Pediatric    0.29236    0.20359   1.436  0.150991
OB.GYN       0.48838    0.17867   2.733  0.006269 **
BlackUrban   -0.95662    0.31655  -3.022  0.002511 **
BlackMedAssist 1.29520    0.57892   2.237  0.025268 *
WhiteUrban   -0.64826    0.25954  -2.498  0.012499 *
WhiteMedAssist 1.28508    0.56493   2.275  0.022921 *
HispanicHospital 13.79246   378.54648   0.036  0.970935
X18.26Pediatric -0.87049    0.57913  -1.503  0.132812
X18.26Black   0.73078    0.34484   2.119  0.034892 *
X18.26White   0.40679    0.24996   1.627  0.103646

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 1796.0 on 1412 degrees of freedom
Residual deviance: 1694.7 on 1396 degrees of freedom
AIC: 1728.7

Number of Fisher Scoring iterations: 12
```

4. R OUTPUT: Logistic Regression with OneShot as Dependent Variable

6. R OUTPUT: LASSO Regression with Completed as Dependent Variable

```
> OneShot = glm(OneShot ~ X18.26 + Urban + White + Hispanic + MedicalAssistance + Odonton +
  JohnHopkins + HispanicUrban + HispanicMedAssist + X18.26Pediatric + X18.26Hispanic,
  family="binomial", data=data)
> summary(OneShot)

Call:
glm(formula = OneShot ~ X18.26 + Urban + White + Hispanic + MedicalAssistance +
  Odonton + JohnHopkins + HispanicUrban + HispanicMedAssist +
  X18.26Pediatric + X18.26Hispanic, family = "binomial", data = data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5309  -0.8630  -0.7366   1.3716   2.0140

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.6492    0.2475  -6.663 2.69e-11 ***
X18.26       0.4834    0.1385   3.490 0.000483 ***
Urban       0.7429    0.2620   2.835 0.004582 ***
White       -0.2378    0.1239  -1.919 0.055014 .
Hispanic    -14.4474   626.2070  -0.023 0.981593
MedicalAssistance 0.4605    0.1841   2.502 0.012351 *
Odonton     0.6078    0.2183   2.784 0.005376 **
JohnHopkins 0.4478    0.2706   1.655 0.097994 .
HispanicUrban -16.5521   624.5637  -0.027 0.978857
HispanicMedAssist 30.2821   884.4293   0.034 0.972686
X18.26Pediatric 0.7634    0.3886   1.965 0.049453 *
X18.26Hispanic 15.4890   626.2072   0.025 0.980267

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 1752.7 on 1412 degrees of freedom
Residual deviance: 1674.3 on 1401 degrees of freedom
AIC: 1698.3

Number of Fisher Scoring iterations: 15
```

Variable

The following R output is for when lambda is at its minimum.

3. R OUTPUT: Logistic Regression with Completed as Dependent

Variable

The following R output is for when lambda is at its average value.

7. R OUTPUT: LASSO Regression with OneShot as Dependent

```
> xtrain <- as.matrix(data[,c(4:34)])
> ytrain <- as.matrix(data[,c(3)])

> library(glmnet)
> CV = cv.glmnet(x=xtrain, y=ytrain, family="binomial", type.measure = "class", alpha = 1, nlambda = 100)
> CV

$lambda.min
[1] 0.007850481

$lambda.1se
[1] 0.06670973

attr(,"class")
[1] "cv.glmnet"

> fit = glmnet(x=xtrain, y=ytrain, family="binomial", alpha=1, lambda=0.007850481)
> x <- as.matrix(fit$beta[,1])
> x
```

		[,1]
Age		-0.040917829
X18.26		-0.166649056
Urban		-0.078616478
Black		-0.307881820
White		0.000000000
Hispanic		0.000000000
MedicalAssistance		-0.487852708
PrivateInsurance		0.000000000
HospitalBasedInsurance		0.307686767
Odonton		0.000000000
WhiteMarsh		0.327652806
JohnHopkins		-0.020537604
Pediatric		0.000000000
OB.GYN		0.237699919
BlackUrban		-0.379188154
BlackMedAssist		0.000000000
BlackPrivate		0.000000000
BlackHospital		0.000000000
WhiteUrban		0.000000000
WhiteMedAssist		0.000000000
WhitePrivate		0.003634982
WhiteHospital		0.000000000
HispanicUrban		0.000000000
HispanicMedAssist		-0.162872245
HispanicPrivate		0.000000000
HispanicHospital		1.569762580
X18.26Pediatric		-0.372290587
X18.26OB.GYN		0.074103728
X18.26BLack		0.000000000
X18.26White		0.000000000
X18.26Hispanic		0.000000000

```
2 > CV = cv.glmnet(x=xtrain, y=ytrain, family="binomial", type.measure = "class", alpha = 1, nlambda = 100)
3 > CV
4
5 $lambda.min
6 [1] 0.001047045
7
8 $lambda.1se
9 [1] 0.03591857
10
11 attr(,"class")
12 [1] "cv.glmnet"
13
14 > l = (0.001047045 + 0.03591857)/2
15 > l
16 [1] 0.01848281
17
18
19 > fit = glmnet(x=xtrain, y=ytrain, family="binomial", alpha=1, lambda=l)
20 > x <- as.matrix(fit$beta[,1])
21 > x
```

		[,1]
Age		0.000000000
18-26		0.000000000
Urban		0.000000000
Black		0.000000000
White		0.000000000
Hispanic		0.000000000
MedicalAssistance		0.000000000
PrivateInsurance		0.000000000
HospitalBasedInsurance		-0.01605313
Odonton		0.000000000
WhiteMarsh		0.000000000
JohnHopkins		0.000000000
Pediatric		0.000000000
OB-GYN		-0.09776230
BlackUrban		0.000000000
BlackMedAssist		0.000000000
BlackPrivate		0.000000000
BlackHospital		0.000000000
WhiteUrban		0.000000000
WhiteMedAssist		0.000000000
WhitePrivate		0.000000000
WhiteHospital		0.000000000
HispanicUrban		0.49185211
HispanicMedAssist		0.000000000
HispanicPrivate		0.000000000
HispanicHospital		0.000000000
18-26Pediatric		0.000000000
18-26OB-GYN		0.000000000
18-26BLack		0.000000000
18-26White		0.000000000
18-26Hispanic		0.000000000

Variable

The following R output is for when lambda is at its maximum.

8. R OUTPUT: LASSO Regression with TwoShot as Dependent

```
> ytrain <- as.matrix(data[,c(2)])
> CV = cv.glmnet(x=xtrain, y=ytrain, family="binomial", type.measure = "class", alpha = 1, nlambda = 100)
> CV

$lambda.min
[1] 0.002292268

$lambda.1se
[1] 0.05420043

attr(,"class")
[1] "cv.glmnet"

> fit = glmnet(x=xtrain, y=ytrain, family="binomial", alpha=1, lambda=0.05420043)
> x <- as.matrix(fit$beta[,1])
> x
```

		[,1]
Age		0.000000e+00
X18.26		0.000000e+00
Urban		0.000000e+00
Black		0.000000e+00
White		0.000000e+00
Hispanic		0.000000e+00
MedicalAssistance		0.000000e+00
PrivateInsurance		0.000000e+00
HospitalBasedInsurance		0.000000e+00
Odonton		0.000000e+00
WhiteMarsh		0.000000e+00
JohnHopkins		0.000000e+00
Pediatric		0.000000e+00
OB.GYN		0.000000e+00
BlackUrban		0.000000e+00
BlackMedAssist		0.000000e+00
BlackPrivate		0.000000e+00
BlackHospital		0.000000e+00
WhiteUrban		0.000000e+00
WhiteMedAssist		0.000000e+00
WhitePrivate		0.000000e+00
WhiteHospital		0.000000e+00
HispanicUrban		0.000000e+00
HispanicMedAssist		0.000000e+00
HispanicPrivate		0.000000e+00
HispanicHospital		0.000000e+00
X18.26Pediatric		0.000000e+00
X18.26OB.GYN		0.000000e+00
X18.26BLack		3.829585e-08
X18.26White		0.000000e+00
X18.26Hispanic		0.000000e+00