

WGU D208

January 10, 2024

```
[1]: %%html
<style>
.toc-item > li {
    list-style-type: upper-alpha;
}
</style>
```

<IPython.core.display.HTML object>

0.1 Kamal Shaham

0.2 D209: Predictive Modeling

0.3 Instructor: Dr. Eric Straw

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```

0.4 A. Research Question

According to a study by Baek et al. (2018), shorter hospital stays have been linked to lower risks of opportunistic infections and side effects from medications. They also reduce the financial burden of hospital fees and aid in increasing bed turnover rates, thereby enhancing hospital profits. Hospitals continuously grapple with the issue of readmissions, and any factors contributing to their reduction are of significant value. As defined in the medical data dictionary (D208 Datasets), a patient readmitted to the hospital within a month of discharge is categorized as a readmission. This leads to an important research question: Is there a correlation between patient observations and the initial length of their hospital stay? Utilizing patient medical data, we aim to determine if certain variables might impact the duration of a patient's initial hospital stay.

0.4.1 A2. Goals of data analysis

The goal of this data analysis is to determine if any variables influence a patient's hospital readmission rate. Through the application of analytical models like multiple linear regression, we aim to identify the best fit. As emphasized in Dr. Middleton's webinars, the dependent variable in this context will be continuous. By examining factors that affect the duration of a patient's initial hospital stay, we can provide hospitals with valuable data that can be instrumental to enhancing treatments and potentially reducing readmission rates.

0.5 B. Method Justification

Assumptions are made when using a multiple linear regression model to determine if there is a good fit. According to (Zach, 2021) these include: - Linear relationships - there needs to be a linear relationship between the independent variable x , and the dependent variable, y . Linear relationships can be found by using visualizations (scatterplots) or statistical tests. - Error distribution - errors need to be normally distributed. To check if the residuals of a model follow a normal distribution a histogram or Q-Q plot can be used to verify normality. - No multicollinearity - two or more of the predictors do not correlate strongly with each other. This can be checked via generating a matrix of the tolerances and variance inflation factor of each independent variable. - Homoscedasticity - the variance of the residuals needs to be the same for all values of x , this case being the independent variable. Can be checked with a scatterplot of residuals vs predicted values.

0.5.1 B2. Two benefits of using Python

Python will be used to perform this data analysis. Python has several statistical packages such as Matplotlib, SciPy, and Statsmodels. Tools in Python allow for intuitive visualizations of statistical observations. For example, multiple linear regression can be utilized by importing the sklearn and statsmodels packages. The Seaborn package is used for visualizations throughout this analysis.

0.5.2 B3. Justification for using multiple linear regression

Multiple linear regression, in the context of our research question, will involve analyzing each factor in the dataset to determine if any variables correlate with the 'Initial_days' variable. Several factors within the dataset are continuous variables, which may potentially influence 'Initial_days'. By utilizing this data, hospitals can offer improved treatment options and potentially reduce readmissions.

C. Data Preparation The data will need to be prepared prior to running the data analysis model. Dealing with missing or null values will need to be addressed. Missing values can potentially be filled with zeros or populated with the average of the respective column. Duplicated data will also need to be removed from the dataset. Outliers will need to be identified and potentially addressed. In order to run linear regression on categorical variables, they will need to be converted to numerical values. When dealing with categorical variables that have more than two levels and can't be sorted ordinally, one-hot encoding will need to be utilized. In addition to one-hot encoding the variables, we'll need to drop one variable when adding them to our regression model to mitigate multicollinearity. Patient location/job demographics (state, city, job, area, etc.) will not provide any benefit to our analysis and thus can be removed.

```
[12]: %matplotlib inline
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from scipy import stats
data=pd.read_csv('medical_clean.csv')
print(data.head())
print(data.columns)
```

```

#check for missing/null values
print(data.isnull().sum())

#check for duplicate values of any rows
print(data.duplicated().any())

# Check for duplicate values based on customer_id unique key
print(data.duplicated('Customer_id').any())

# remove unused columns
data.drop(['CaseOrder', 'Customer_id', 'Interaction', 'UID', 'City', 'Marital', 'State', 'County', 'Zip', 'Lat', 'Lng', 'Population', 'Area', 'TimeZone', 'Job', 'Gender'], axis=1, inplace=True)
print(data.head())
print(data.columns)
print(data.info())

# rename unclear survey response columns
survey_col_names = {
    'Item1': 'Timely_admis',
    'Item2': 'Timely_treat',
    'Item3': 'Timely_visits',
    'Item4': 'Reliability',
    'Item5': 'Options',
    'Item6': 'Hours_treat',
    'Item7': 'Courteous_staff',
    'Item8': 'Active_listening'
}

data = data.rename(columns=survey_col_names)

categorical_cols = ['ReAdmis', 'Complication_risk', 'Initial_admin', 'Services', 'Overweight', 'Anxiety', 'Arthritis', 'Asthma', 'Soft_drink', 'Diabetes', 'Allergic_rhinitis', 'BackPain', 'Stroke', 'HighBlood', 'Hyperlipidemia', 'Reflux_esophagitis']

# Generate dummy variables
data = pd.get_dummies(data, columns=categorical_cols, drop_first=True)

print(data.info())

print(data.head())

# Set the option to display all the columns
pd.set_option('display.max_columns', None)

```

```
# Set the option to display all the rows
pd.set_option('display.max_rows', None)
print(data.describe(include='all'))
print(data.columns)
```

	CaseOrder	Customer_id	Interaction	\
0	1	C412403	8cd49b13-f45a-4b47-a2bd-173ffa932c2f	
1	2	Z919181	d2450b70-0337-4406-bdbb-bc1037f1734c	
2	3	F995323	a2057123-abf5-4a2c-abad-8ffe33512562	
3	4	A879973	1dec528d-eb34-4079-adce-0d7a40e82205	
4	5	C544523	5885f56b-d6da-43a3-8760-83583af94266	

	UID	City	State	County	Zip	\
0	3a83ddb66e2ae73798bdf1d705dc0932	Eva	AL	Morgan	35621	
1	176354c5eef714957d486009feabf195	Marianna	FL	Jackson	32446	
2	e19a0fa00aeda885b8a436757e889bc9	Sioux Falls	SD	Minnehaha	57110	
3	cd17d7b6d152cb6f23957346d11c3f07	New Richland	MN	Waseca	56072	
4	d2f0425877b10ed6bb381f3e2579424a	West Point	VA	King William	23181	

	Lat	Lng	Population	Area	TimeZone	\
0	34.34960	-86.72508	2951	Suburban	America/Chicago	
1	30.84513	-85.22907	11303	Urban	America/Chicago	
2	43.54321	-96.63772	17125	Suburban	America/Chicago	
3	43.89744	-93.51479	2162	Suburban	America/Chicago	
4	37.59894	-76.88958	5287	Rural	America/New_York	

	Job	Children	Age	Income	Marital	\
0	Psychologist, sport and exercise	1	53	86575.93	Divorced	
1	Community development worker	3	51	46805.99	Married	
2	Chief Executive Officer	3	53	14370.14	Widowed	
3	Early years teacher	0	78	39741.49	Married	
4	Health promotion specialist	1	22	1209.56	Widowed	

	Gender	ReAdmis	VitD_levels	Doc_visits	Full_meals_eaten	vitD_supp	\
0	Male	No	19.141466	6	0	0	
1	Female	No	18.940352	4	2	1	
2	Female	No	18.057507	4	1	0	
3	Male	No	16.576858	4	1	0	
4	Female	No	17.439069	5	0	2	

	Soft_drink	Initial_admin	HighBlood	Stroke	Complication_risk	\
0	No	Emergency Admission	Yes	No	Medium	
1	No	Emergency Admission	Yes	No	High	
2	No	Elective Admission	Yes	No	Medium	
3	No	Elective Admission	No	Yes	Medium	
4	Yes	Elective Admission	No	No	Low	

	Overweight	Arthritis	Diabetes	Hyperlipidemia	BackPain	Anxiety	\
0	No	Yes	Yes	No	Yes	Yes	
1	Yes	No	No	No	No	No	
2	Yes	No	Yes	No	No	No	
3	No	Yes	No	No	No	No	
4	No	No	No	Yes	No	No	

	Allergic_rhinitis	Reflux_esophagitis	Asthma	Services	Initial_days	\
0	Yes		No	Yes	Blood Work	10.585770
1	No		Yes	No	Intravenous	15.129562
2	No		No	No	Blood Work	4.772177
3	No		Yes	Yes	Blood Work	1.714879
4	Yes		No	No	CT Scan	1.254807

	TotalCharge	Additional_charges	Item1	Item2	Item3	Item4	Item5	Item6	\
0	3726.702860	17939.403420	3	3	2	2	4	3	
1	4193.190458	17612.998120	3	4	3	4	4	4	
2	2434.234222	17505.192460	2	4	4	4	3	4	
3	2127.830423	12993.437350	3	5	5	3	4	5	
4	2113.073274	3716.525786	2	1	3	3	5	3	

	Item7	Item8
0	3	4
1	3	3
2	3	3
3	5	5
4	4	3

```
Index(['CaseOrder', 'Customer_id', 'Interaction', 'UID', 'City', 'State',
      'County', 'Zip', 'Lat', 'Lng', 'Population', 'Area', 'TimeZone', 'Job',
      'Children', 'Age', 'Income', 'Marital', 'Gender', 'ReAdmis',
      'VitD_levels', 'Doc_visits', 'Full_meals_eaten', 'vitD_supp',
      'Soft_drink', 'Initial_admin', 'HighBlood', 'Stroke',
      'Complication_risk', 'Overweight', 'Arthritis', 'Diabetes',
      'Hyperlipidemia', 'BackPain', 'Anxiety', 'Allergic_rhinitis',
      'Reflux_esophagitis', 'Asthma', 'Services', 'Initial_days',
      'TotalCharge', 'Additional_charges', 'Item1', 'Item2', 'Item3', 'Item4',
      'Item5', 'Item6', 'Item7', 'Item8'],
      dtype='object')
```

CaseOrder	0
Customer_id	0
Interaction	0
UID	0
City	0
State	0
County	0
Zip	0
Lat	0
Lng	0

Population 0
 Area 0
 TimeZone 0
 Job 0
 Children 0
 Age 0
 Income 0
 Marital 0
 Gender 0
 ReAdmis 0
 VitD_levels 0
 Doc_visits 0
 Full_meals_eaten 0
 vitD_supp 0
 Soft_drink 0
 Initial_admin 0
 HighBlood 0
 Stroke 0
 Complication_risk 0
 Overweight 0
 Arthritis 0
 Diabetes 0
 Hyperlipidemia 0
 BackPain 0
 Anxiety 0
 Allergic_rhinitis 0
 Reflux_esophagitis 0
 Asthma 0
 Services 0
 Initial_days 0
 TotalCharge 0
 Additional_charges 0
 Item1 0
 Item2 0
 Item3 0
 Item4 0
 Item5 0
 Item6 0
 Item7 0
 Item8 0

dtype: int64

False

False

	Children	Age	Income	ReAdmis	VitD_levels	Doc_visits	Full_meals_eaten	\
0	1	53	86575.93	No	19.141466	6	0	
1	3	51	46805.99	No	18.940352	4	2	
2	3	53	14370.14	No	18.057507	4	1	
3	0	78	39741.49	No	16.576858	4	1	

4	1	22	1209.56	No	17.439069	5	0
---	---	----	---------	----	-----------	---	---

	vitD_supp	Soft_drink	Initial_admin	HighBlood	Stroke	\
0	0	No	Emergency Admission	Yes	No	
1	1	No	Emergency Admission	Yes	No	
2	0	No	Elective Admission	Yes	No	
3	0	No	Elective Admission	No	Yes	
4	2	Yes	Elective Admission	No	No	

	Complication_risk	Overweight	Arthritis	Diabetes	Hyperlipidemia	BackPain	\
0	Medium	No	Yes	Yes	No	Yes	
1	High	Yes	No	No	No	No	
2	Medium	Yes	No	Yes	No	No	
3	Medium	No	Yes	No	No	No	
4	Low	No	No	No	Yes	No	

	Anxiety	Allergic_rhinitis	Reflux_esophagitis	Asthma	Services	\
0	Yes	Yes	No	Yes	Blood Work	
1	No	No	Yes	No	Intravenous	
2	No	No	No	No	Blood Work	
3	No	No	Yes	Yes	Blood Work	
4	No	Yes	No	No	CT Scan	

	Initial_days	TotalCharge	Additional_charges	Item1	Item2	Item3	Item4	\
0	10.585770	3726.702860	17939.403420	3	3	2	2	
1	15.129562	4193.190458	17612.998120	3	4	3	4	
2	4.772177	2434.234222	17505.192460	2	4	4	4	
3	1.714879	2127.830423	12993.437350	3	5	5	3	
4	1.254807	2113.073274	3716.525786	2	1	3	3	

	Item5	Item6	Item7	Item8
0	4	3	3	4
1	4	4	3	3
2	3	4	3	3
3	4	5	5	5
4	5	3	4	3

```
Index(['Children', 'Age', 'Income', 'ReAdmis', 'VitD_levels', 'Doc_visits',
      'Full_meals_eaten', 'vitD_supp', 'Soft_drink', 'Initial_admin',
      'HighBlood', 'Stroke', 'Complication_risk', 'Overweight', 'Arthritis',
      'Diabetes', 'Hyperlipidemia', 'BackPain', 'Anxiety',
      'Allergic_rhinitis', 'Reflux_esophagitis', 'Asthma', 'Services',
      'Initial_days', 'TotalCharge', 'Additional_charges', 'Item1', 'Item2',
      'Item3', 'Item4', 'Item5', 'Item6', 'Item7', 'Item8'],
      dtype='object')
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 10000 entries, 0 to 9999
```

```
Data columns (total 34 columns):
```

#	Column	Non-Null Count	Dtype
---	--------	----------------	-------


```

---  -----  -----  -----
0  Children      10000 non-null  int64
1  Age           10000 non-null  int64
2  Income        10000 non-null  float64
3  ReAdmis       10000 non-null  object
4  VitD_levels   10000 non-null  float64
5  Doc_visits    10000 non-null  int64
6  Full_meals_eaten 10000 non-null  int64
7  vitD_supp     10000 non-null  int64
8  Soft_drink    10000 non-null  object
9  Initial_admin 10000 non-null  object
10 HighBlood     10000 non-null  object
11 Stroke        10000 non-null  object
12 Complication_risk 10000 non-null  object
13 Overweight    10000 non-null  object
14 Arthritis     10000 non-null  object
15 Diabetes      10000 non-null  object
16 Hyperlipidemia 10000 non-null  object
17 BackPain      10000 non-null  object
18 Anxiety       10000 non-null  object
19 Allergic_rhinitis 10000 non-null  object
20 Reflux_esophagitis 10000 non-null  object
21 Asthma        10000 non-null  object
22 Services      10000 non-null  object
23 Initial_days  10000 non-null  float64
24 TotalCharge   10000 non-null  float64
25 Additional_charges 10000 non-null  float64
26 Item1         10000 non-null  int64
27 Item2         10000 non-null  int64
28 Item3         10000 non-null  int64
29 Item4         10000 non-null  int64
30 Item5         10000 non-null  int64
31 Item6         10000 non-null  int64
32 Item7         10000 non-null  int64
33 Item8         10000 non-null  int64
dtypes: float64(5), int64(13), object(16)
memory usage: 2.6+ MB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 38 columns):
#   Column                                     Non-Null Count  Dtype
---  -----  ---
0   Children                                  10000 non-null  int64
1   Age                                       10000 non-null  int64
2   Income                                   10000 non-null  float64
3   VitD_levels                             10000 non-null  float64
4   Doc_visits                              10000 non-null  int64

```

5	Full_meals_eaten	10000	non-null	int64
6	vitD_supp	10000	non-null	int64
7	Initial_days	10000	non-null	float64
8	TotalCharge	10000	non-null	float64
9	Additional_charges	10000	non-null	float64
10	Timely_admis	10000	non-null	int64
11	Timely_treat	10000	non-null	int64
12	Timely_visits	10000	non-null	int64
13	Reliability	10000	non-null	int64
14	Options	10000	non-null	int64
15	Hours_treat	10000	non-null	int64
16	Courteous_staff	10000	non-null	int64
17	Active_listening	10000	non-null	int64
18	ReAdmis_Yes	10000	non-null	uint8
19	Complication_risk_Low	10000	non-null	uint8
20	Complication_risk_Medium	10000	non-null	uint8
21	Initial_admin_Emergency Admission	10000	non-null	uint8
22	Initial_admin_Observation Admission	10000	non-null	uint8
23	Services_CT Scan	10000	non-null	uint8
24	Services_Intravenous	10000	non-null	uint8
25	Services_MRI	10000	non-null	uint8
26	Overweight_Yes	10000	non-null	uint8
27	Anxiety_Yes	10000	non-null	uint8
28	Arthritis_Yes	10000	non-null	uint8
29	Asthma_Yes	10000	non-null	uint8
30	Soft_drink_Yes	10000	non-null	uint8
31	Diabetes_Yes	10000	non-null	uint8
32	Allergic_rhinitis_Yes	10000	non-null	uint8
33	BackPain_Yes	10000	non-null	uint8
34	Stroke_Yes	10000	non-null	uint8
35	HighBlood_Yes	10000	non-null	uint8
36	Hyperlipidemia_Yes	10000	non-null	uint8
37	Reflux_esophagitis_Yes	10000	non-null	uint8

dtypes: float64(5), int64(13), uint8(20)

memory usage: 1.6 MB

None

	Children	Age	Income	VitD_levels	Doc_visits	Full_meals_eaten	\
0	1	53	86575.93	19.141466	6	0	
1	3	51	46805.99	18.940352	4	2	
2	3	53	14370.14	18.057507	4	1	
3	0	78	39741.49	16.576858	4	1	
4	1	22	1209.56	17.439069	5	0	

	vitD_supp	Initial_days	TotalCharge	Additional_charges	Timely_admis	\
0	0	10.585770	3726.702860	17939.403420	3	
1	1	15.129562	4193.190458	17612.998120	3	
2	0	4.772177	2434.234222	17505.192460	2	
3	0	1.714879	2127.830423	12993.437350	3	

4 2 1.254807 2113.073274 3716.525786 2

	Timely_treat	Timely_visits	Reliability	Options	Hours_treat	\
0	3	2	2	4	3	
1	4	3	4	4	4	
2	4	4	4	3	4	
3	5	5	3	4	5	
4	1	3	3	5	3	

	Courteous_staff	Active_listening	ReAdmis_Yes	Complication_risk_Low	\
0	3	4	0	0	
1	3	3	0	0	
2	3	3	0	0	
3	5	5	0	0	
4	4	3	0	1	

	Complication_risk_Medium	Initial_admin_Emergency	Admission	\
0	1		1	
1	0		1	
2	1		0	
3	1		0	
4	0		0	

	Initial_admin_Observation	Admission	Services_CT	Scan	\
0		0		0	
1		0		0	
2		0		0	
3		0		0	
4		0		1	

	Services_Intravenous	Services_MRI	Overweight_Yes	Anxiety_Yes	\
0	0	0	0	1	
1	1	0	1	0	
2	0	0	1	0	
3	0	0	0	0	
4	0	0	0	0	

	Arthritis_Yes	Asthma_Yes	Soft_drink_Yes	Diabetes_Yes	\
0	1	1	0	1	
1	0	0	0	0	
2	0	0	0	1	
3	1	1	0	0	
4	0	0	1	0	

	Allergic_rhinitis_Yes	BackPain_Yes	Stroke_Yes	HighBlood_Yes	\
0	1	1	0	1	
1	0	0	0	1	
2	0	0	0	1	

3	0	0	1	0
4	1	0	0	0

	Hyperlipidemia_Yes	Reflux_esophagitis_Yes
0	0	0
1	0	1
2	0	0
3	0	1
4	1	0

	Children	Age	Income	VitD_levels	Doc_visits \
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	2.097200	53.511700	40490.495160	17.964262	5.012200
std	2.163659	20.638538	28521.153293	2.017231	1.045734
min	0.000000	18.000000	154.080000	9.806483	1.000000
25%	0.000000	36.000000	19598.775000	16.626439	4.000000
50%	1.000000	53.000000	33768.420000	17.951122	5.000000
75%	3.000000	71.000000	54296.402500	19.347963	6.000000
max	10.000000	89.000000	207249.100000	26.394449	9.000000

	Full_meals_eaten	vitD_supp	Initial_days	TotalCharge \
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	1.001400	0.398900	34.455299	5312.172769
std	1.008117	0.628505	26.309341	2180.393838
min	0.000000	0.000000	1.001981	1938.312067
25%	0.000000	0.000000	7.896215	3179.374015
50%	1.000000	0.000000	35.836244	5213.952000
75%	2.000000	1.000000	61.161020	7459.699750
max	7.000000	5.000000	71.981490	9180.728000

	Additional_charges	Timely_admis	Timely_treat	Timely_visits \
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	12934.528587	3.518800	3.506700	3.511100
std	6542.601544	1.031966	1.034825	1.032755
min	3125.703000	1.000000	1.000000	1.000000
25%	7986.487755	3.000000	3.000000	3.000000
50%	11573.977735	4.000000	3.000000	4.000000
75%	15626.490000	4.000000	4.000000	4.000000
max	30566.070000	8.000000	7.000000	8.000000

	Reliability	Options	Hours_treat	Courteous_staff \
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	3.515100	3.496900	3.522500	3.494000
std	1.036282	1.030192	1.032376	1.021405
min	1.000000	1.000000	1.000000	1.000000
25%	3.000000	3.000000	3.000000	3.000000
50%	4.000000	3.000000	4.000000	3.000000
75%	4.000000	4.000000	4.000000	4.000000
max	7.000000	7.000000	7.000000	7.000000

	Active_listening	ReAdmis_Yes	Complication_risk_Low \
count	10000.000000	10000.000000	10000.000000
mean	3.509700	0.366900	0.212500
std	1.042312	0.481983	0.409097
min	1.000000	0.000000	0.000000
25%	3.000000	0.000000	0.000000
50%	3.000000	0.000000	0.000000
75%	4.000000	1.000000	0.000000
max	7.000000	1.000000	1.000000

	Complication_risk_Medium	Initial_admin_Emergency Admission \
count	10000.000000	10000.000000
mean	0.451700	0.506000
std	0.497687	0.499989
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	1.000000
75%	1.000000	1.000000
max	1.000000	1.000000

	Initial_admin_Observation Admission	Services_CT Scan \
count	10000.000000	10000.000000
mean	0.243600	0.122500
std	0.429276	0.327879
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	0.000000
max	1.000000	1.000000

	Services_Intravenous	Services_MRI	Overweight_Yes	Anxiety_Yes \
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	0.313000	0.038000	0.709400	0.321500
std	0.463738	0.191206	0.454062	0.467076
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	1.000000	0.000000
75%	1.000000	0.000000	1.000000	1.000000
max	1.000000	1.000000	1.000000	1.000000

	Arthritis_Yes	Asthma_Yes	Soft_drink_Yes	Diabetes_Yes \
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	0.357400	0.28930	0.257500	0.27380
std	0.479258	0.45346	0.437279	0.44593
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000

75%	1.000000	1.000000	1.000000	1.000000
max	1.000000	1.000000	1.000000	1.000000

	Allergic_rhinitis_Yes	BackPain_Yes	Stroke_Yes	HighBlood_Yes	\
count	10000.000000	10000.000000	10000.000000	10000.000000	
mean	0.394100	0.411400	0.199300	0.409000	
std	0.488681	0.492112	0.399494	0.491674	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	
50%	0.000000	0.000000	0.000000	0.000000	
75%	1.000000	1.000000	0.000000	1.000000	
max	1.000000	1.000000	1.000000	1.000000	

	Hyperlipidemia_Yes	Reflux_esophagitis_Yes
count	10000.000000	10000.000000
mean	0.337200	0.413500
std	0.472777	0.492486
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	1.000000	1.000000
max	1.000000	1.000000

```
Index(['Children', 'Age', 'Income', 'VitD_levels', 'Doc_visits',
      'Full_meals_eaten', 'vitD_supp', 'Initial_days', 'TotalCharge',
      'Additional_charges', 'Timely_admis', 'Timely_treat', 'Timely_visits',
      'Reliability', 'Options', 'Hours_treat', 'Courteous_staff',
      'Active_listening', 'ReAdmis_Yes', 'Complication_risk_Low',
      'Complication_risk_Medium', 'Initial_admin_Emergency Admission',
      'Initial_admin_Observation Admission', 'Services_CT Scan',
      'Services_Intravenous', 'Services_MRI', 'Overweight_Yes', 'Anxiety_Yes',
      'Arthritis_Yes', 'Asthma_Yes', 'Soft_drink_Yes', 'Diabetes_Yes',
      'Allergic_rhinitis_Yes', 'BackPain_Yes', 'Stroke_Yes', 'HighBlood_Yes',
      'Hyperlipidemia_Yes', 'Reflux_esophagitis_Yes'],
      dtype='object')
```

C2. Variable Statistical Summaries In order to use multiple linear regression to answer this research question, summary statistics will need to be generated for every variable used. Geographic variables of the patient, such as population, city, and state, will not provide benefit to our analysis, so they will not be included. There is potential for different modeling to be used on these columns for further analysis. The tables below contain the independent variables (with 'Initial_days' being our dependent variable), their data types, their categorical/continuous classification, and sample data from each column. A summary statistics table is generated, detailing each variable's standard deviation, interquartile ranges, mean, and median (noted as 50% value in the output).

The categorical variables in the data were converted to numerical types to perform regression analysis. Histograms and box plots were generated for each variable to check for distribution. Based on these histograms, it can be seen that 'Income', 'Children', 'vitD_supp', and 'Full_meals_eaten' are not normally distributed.

- Age: Integer, Example: 53
- ReAdmis: Character (binary categorical), Example: No
- VitD_levels: Numeric, Example: 19.141466
- Doc_visits: Integer, Example: 6
- Full_meals_eaten: Integer, Example: 0
- vitD_supp: Integer, Example: 0
- Soft_drink: Character (binary categorical), Example: No
- Initial_admin: Character (nominal categorical), Example: Emergency Admission
- HighBlood: Character (binary categorical), Example: Yes
- Stroke: Character (binary categorical), Example: No
- Complication_risk: Character (ordinal categorical), Example: Medium
- Overweight: Character (binary categorical), Example: No
- Arthritis: Character (binary categorical), Example: Yes
- Diabetes: Character (binary categorical), Example: Yes
- Hyperlipidemia: Character (binary categorical), Example: No
- BackPain: Character (binary categorical), Example: Yes
- Anxiety: Character (binary categorical), Example: Yes
- Allergic_rhinitis: Character (binary categorical), Example: Yes
- Reflux_esophagitis: Character (binary categorical), Example: No
- Asthma: Character (binary categorical), Example: Yes
- Services: Character (Nominal categorical), Example: Blood Work
- Initial_days: Numeric, Example: 10.585770
- TotalCharge: Numeric, Example: 3726.702860
- Additional_charges: Numeric, Example: 17939.403420
- Item1 (Timely_admis): Integer, Example: 3
- Item2 (Timely_treat): Integer, Example: 3
- Item3 (Timely_visits): Integer, Example: 2
- Item4 (Reliability): Integer, Example: 2
- Item5 (Options): Integer, Example: 4
- Item6 (Hours_treat): Integer, Example: 3
- Item7 (Courteous_staff): Integer, Example: 3
- Item8 (Active_listening): Integer, Example: 4

```
[108]: print(data.info())
print(data.head())
print(data.describe(include='all'))
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 10000 entries, 0 to 9999
```

```
Data columns (total 36 columns):
```

#	Column	Non-Null Count	Dtype
0	Age	10000 non-null	int64
1	VitD_levels	10000 non-null	float64
2	Doc_visits	10000 non-null	int64
3	Full_meals_eaten	10000 non-null	int64
4	vitD_supp	10000 non-null	int64
5	Initial_days	10000 non-null	float64

6	TotalCharge	10000	non-null	float64
7	Additional_charges	10000	non-null	float64
8	Timely_admis	10000	non-null	int64
9	Timely_treat	10000	non-null	int64
10	Timely_visits	10000	non-null	int64
11	Reliability	10000	non-null	int64
12	Options	10000	non-null	int64
13	Hours_treat	10000	non-null	int64
14	Courteous_staff	10000	non-null	int64
15	Active_listening	10000	non-null	int64
16	ReAdmis_Yes	10000	non-null	uint8
17	Complication_risk_Low	10000	non-null	uint8
18	Complication_risk_Medium	10000	non-null	uint8
19	Initial_admin_Emergency Admission	10000	non-null	uint8
20	Initial_admin_Observation Admission	10000	non-null	uint8
21	Services_CT Scan	10000	non-null	uint8
22	Services_Intravenous	10000	non-null	uint8
23	Services_MRI	10000	non-null	uint8
24	Overweight_Yes	10000	non-null	uint8
25	Anxiety_Yes	10000	non-null	uint8
26	Arthritis_Yes	10000	non-null	uint8
27	Asthma_Yes	10000	non-null	uint8
28	Soft_drink_Yes	10000	non-null	uint8
29	Diabetes_Yes	10000	non-null	uint8
30	Allergic_rhinitis_Yes	10000	non-null	uint8
31	BackPain_Yes	10000	non-null	uint8
32	Stroke_Yes	10000	non-null	uint8
33	HighBlood_Yes	10000	non-null	uint8
34	Hyperlipidemia_Yes	10000	non-null	uint8
35	Reflux_esophagitis_Yes	10000	non-null	uint8

dtypes: float64(4), int64(12), uint8(20)

memory usage: 1.4 MB

None

	Age	VitD_levels	Doc_visits	Full_meals_eaten	vitD_supp	Initial_days	\
0	53	19.141466	6	0	0	10.585770	
1	51	18.940352	4	2	1	15.129562	
2	53	18.057507	4	1	0	4.772177	
3	78	16.576858	4	1	0	1.714879	
4	22	17.439069	5	0	2	1.254807	

	TotalCharge	Additional_charges	Timely_admis	Timely_treat	Timely_visits	\
0	3726.702860	17939.403420	3	3	2	
1	4193.190458	17612.998120	3	4	3	
2	2434.234222	17505.192460	2	4	4	
3	2127.830423	12993.437350	3	5	5	
4	2113.073274	3716.525786	2	1	3	

	Reliability	Options	Hours_treat	Courteous_staff	Active_listening	\
--	-------------	---------	-------------	-----------------	------------------	---

0	2	4	3	3	4
1	4	4	4	3	3
2	4	3	4	3	3
3	3	4	5	5	5
4	3	5	3	4	3

	ReAdmis_Yes	Complication_risk_Low	Complication_risk_Medium	\
0	0	0	1	
1	0	0	0	
2	0	0	1	
3	0	0	1	
4	0	1	0	

	Initial_admin_Emergency Admission	Initial_admin_Observation Admission	\
0	1	0	
1	1	0	
2	0	0	
3	0	0	
4	0	0	

	Services_CT Scan	Services_Intravenous	Services_MRI	Overweight_Yes	\
0	0	0	0	0	
1	0	1	0	1	
2	0	0	0	1	
3	0	0	0	0	
4	1	0	0	0	

	Anxiety_Yes	Arthritis_Yes	Asthma_Yes	Soft_drink_Yes	Diabetes_Yes	\
0	1	1	1	0	1	
1	0	0	0	0	0	
2	0	0	0	0	1	
3	0	1	1	0	0	
4	0	0	0	1	0	

	Allergic_rhinitis_Yes	BackPain_Yes	Stroke_Yes	HighBlood_Yes	\
0	1	1	0	1	
1	0	0	0	1	
2	0	0	0	1	
3	0	0	1	0	
4	1	0	0	0	

	Hyperlipidemia_Yes	Reflux_esophagitis_Yes
0	0	0
1	0	1
2	0	0
3	0	1
4	1	0

	Age	VitD_levels	Doc_visits	Full_meals_eaten	\
--	-----	-------------	------------	------------------	---

count	10000.000000	10000.000000	10000.000000	10000.000000
mean	53.511700	17.964262	5.012200	1.001400
std	20.638538	2.017231	1.045734	1.008117
min	18.000000	9.806483	1.000000	0.000000
25%	36.000000	16.626439	4.000000	0.000000
50%	53.000000	17.951122	5.000000	1.000000
75%	71.000000	19.347963	6.000000	2.000000
max	89.000000	26.394449	9.000000	7.000000

	vitD_supp	Initial_days	TotalCharge	Additional_charges	\
count	10000.000000	10000.000000	10000.000000	10000.000000	
mean	0.398900	34.455299	5312.172769	12934.528587	
std	0.628505	26.309341	2180.393838	6542.601544	
min	0.000000	1.001981	1938.312067	3125.703000	
25%	0.000000	7.896215	3179.374015	7986.487755	
50%	0.000000	35.836244	5213.952000	11573.977735	
75%	1.000000	61.161020	7459.699750	15626.490000	
max	5.000000	71.981490	9180.728000	30566.070000	

	Timely_admis	Timely_treat	Timely_visits	Reliability	Options	\
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	
mean	3.518800	3.506700	3.511100	3.515100	3.496900	
std	1.031966	1.034825	1.032755	1.036282	1.030192	
min	1.000000	1.000000	1.000000	1.000000	1.000000	
25%	3.000000	3.000000	3.000000	3.000000	3.000000	
50%	4.000000	3.000000	4.000000	4.000000	3.000000	
75%	4.000000	4.000000	4.000000	4.000000	4.000000	
max	8.000000	7.000000	8.000000	7.000000	7.000000	

	Hours_treat	Courteous_staff	Active_listening	ReAdmis_Yes	\
count	10000.000000	10000.000000	10000.000000	10000.000000	
mean	3.522500	3.494000	3.509700	0.366900	
std	1.032376	1.021405	1.042312	0.481983	
min	1.000000	1.000000	1.000000	0.000000	
25%	3.000000	3.000000	3.000000	0.000000	
50%	4.000000	3.000000	3.000000	0.000000	
75%	4.000000	4.000000	4.000000	1.000000	
max	7.000000	7.000000	7.000000	1.000000	

	Complication_risk_Low	Complication_risk_Medium	\
count	10000.000000	10000.000000	
mean	0.212500	0.451700	
std	0.409097	0.497687	
min	0.000000	0.000000	
25%	0.000000	0.000000	
50%	0.000000	0.000000	
75%	0.000000	1.000000	
max	1.000000	1.000000	

	Initial_admin_Emergency Admission	Initial_admin_Observation Admission \
count	10000.000000	10000.000000
mean	0.506000	0.243600
std	0.499989	0.429276
min	0.000000	0.000000
25%	0.000000	0.000000
50%	1.000000	0.000000
75%	1.000000	0.000000
max	1.000000	1.000000

	Services_CT Scan	Services_Intravenous	Services_MRI	Overweight_Yes \
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	0.122500	0.313000	0.038000	0.709400
std	0.327879	0.463738	0.191206	0.454062
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	1.000000
75%	0.000000	1.000000	0.000000	1.000000
max	1.000000	1.000000	1.000000	1.000000

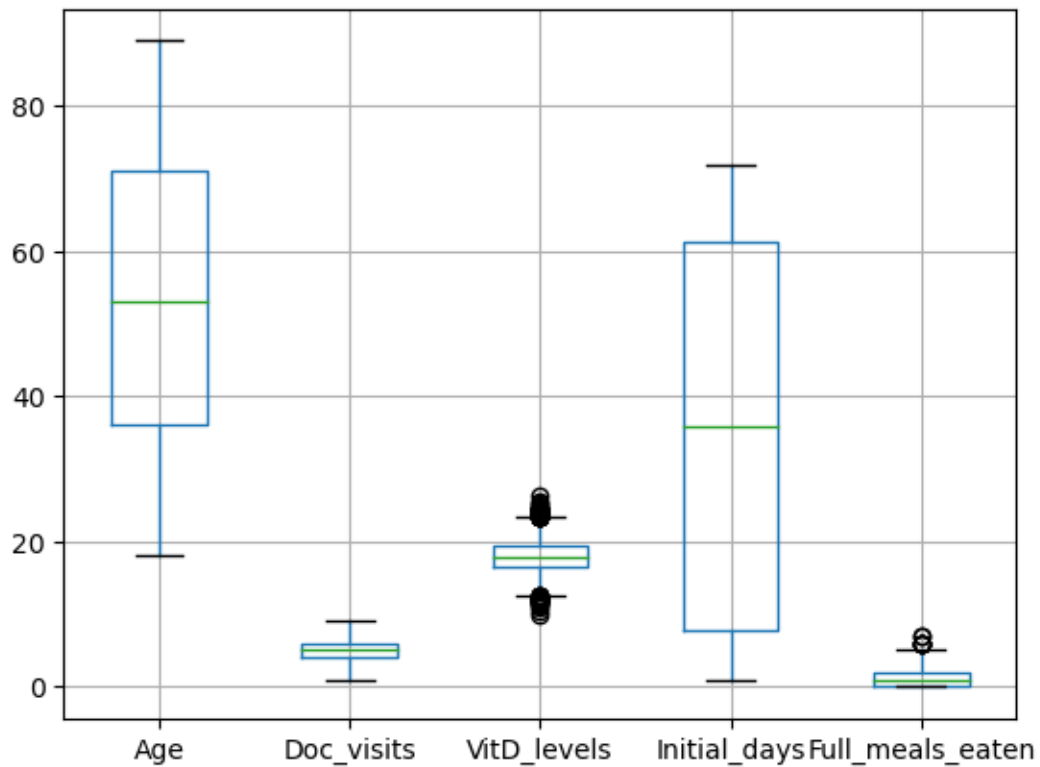
	Anxiety_Yes	Arthritis_Yes	Asthma_Yes	Soft_drink_Yes	Diabetes_Yes \
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	0.321500	0.357400	0.28930	0.257500	0.27380
std	0.467076	0.479258	0.45346	0.437279	0.44593
min	0.000000	0.000000	0.00000	0.000000	0.00000
25%	0.000000	0.000000	0.00000	0.000000	0.00000
50%	0.000000	0.000000	0.00000	0.000000	0.00000
75%	1.000000	1.000000	1.00000	1.000000	1.00000
max	1.000000	1.000000	1.00000	1.000000	1.00000

	Allergic_rhinitis_Yes	BackPain_Yes	Stroke_Yes	HighBlood_Yes \
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	0.394100	0.411400	0.199300	0.409000
std	0.488681	0.492112	0.399494	0.491674
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	1.000000	1.000000	0.000000	1.000000
max	1.000000	1.000000	1.000000	1.000000

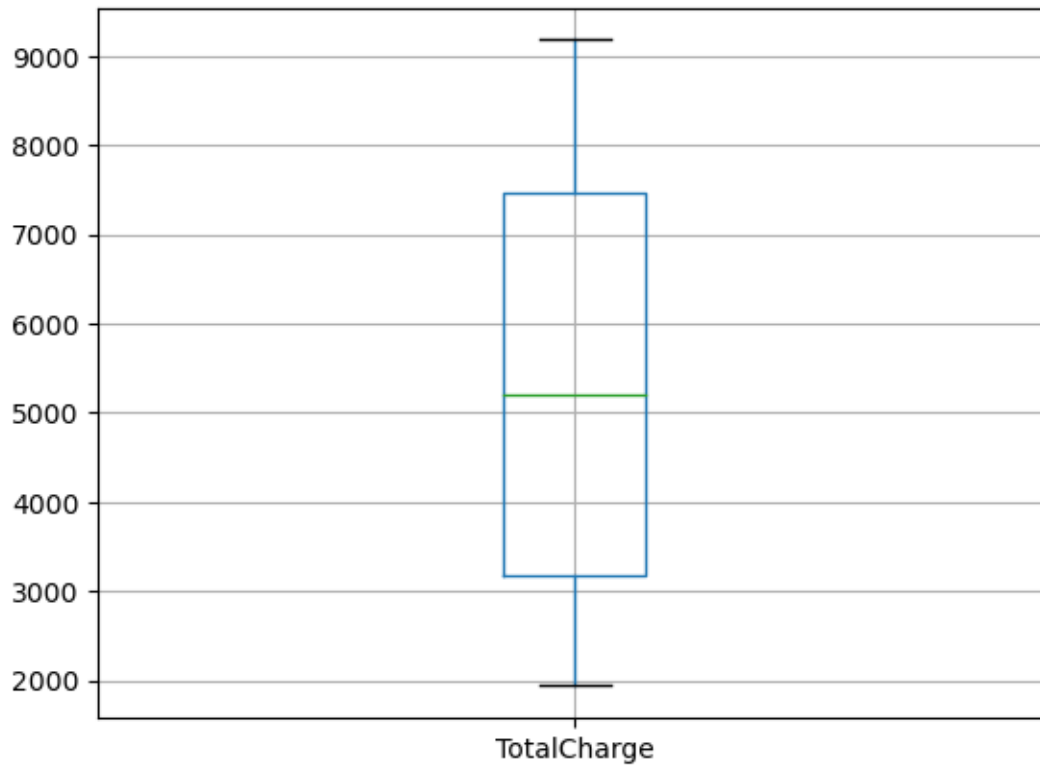
	Hyperlipidemia_Yes	Reflux_esophagitis_Yes
count	10000.000000	10000.000000
mean	0.337200	0.413500
std	0.472777	0.492486
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000

75%	1.000000	1.000000
max	1.000000	1.000000

```
[3]: # check for outliers with smaller group of variables
data.boxplot(column=['Age', 'Doc_visits', 'VitD_levels', 'Initial_days', 'Full_meals_eaten'])
plt.show()
```



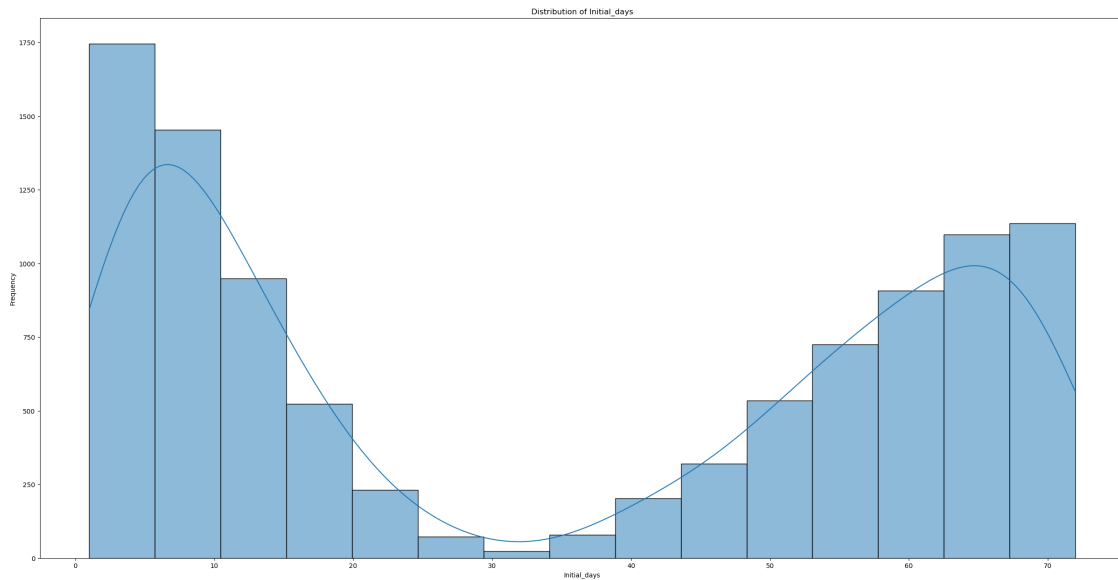
```
[4]: # check for outliers with smaller group of variables
data.boxplot(column=['TotalCharge'])
plt.show()
```



```
[5]: plt.subplots(figsize=(30,15))

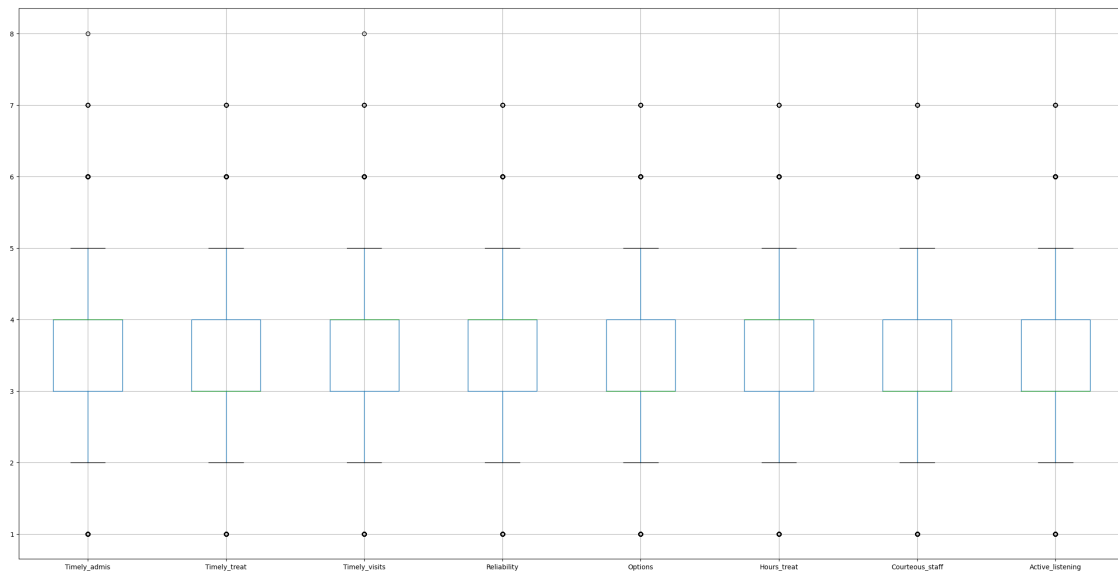
# Create a histogram of the frequency of initial_days
sns.histplot(data['Initial_days'], kde=True)

plt.title('Distribution of Initial_days')
plt.xlabel('Initial_days')
plt.ylabel('Frequency')
plt.show()
```



```
[6]: plt.subplots(figsize=(30,15))

data.boxplot(column=['Timely_admis', 'Timely_treat', 'Timely_visits', 'Reliability', 'Options', 'Hours_treat', 'Courteous_staff', 'Active_listening'])
plt.show()
```

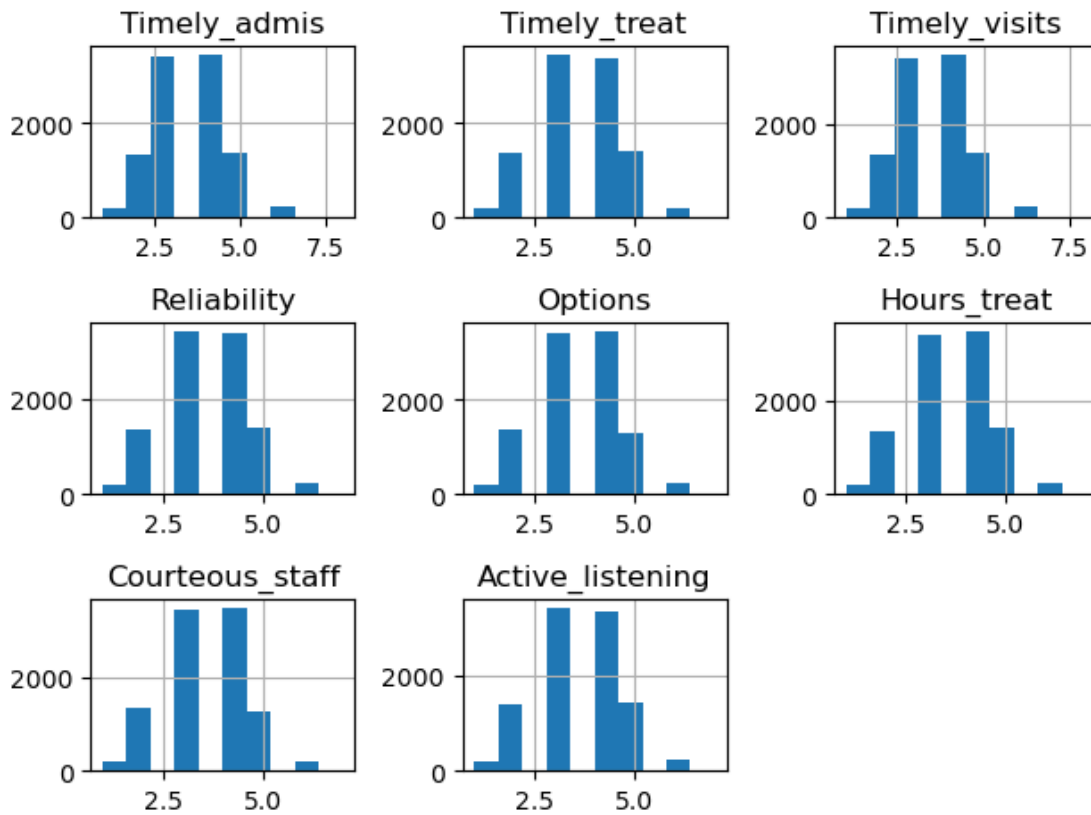


C3. Univariate/Bivariate Visualizations

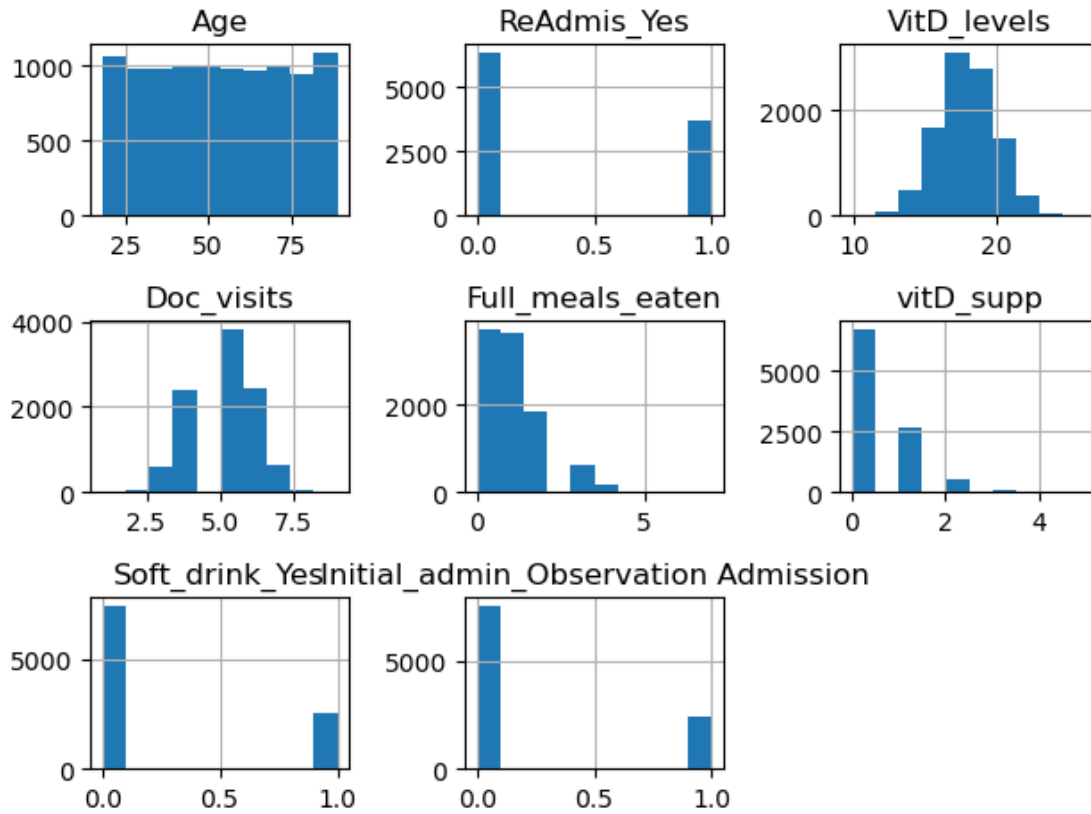
Below we generate both univariate and bivariate visualizations for the independent and dependent

variables.

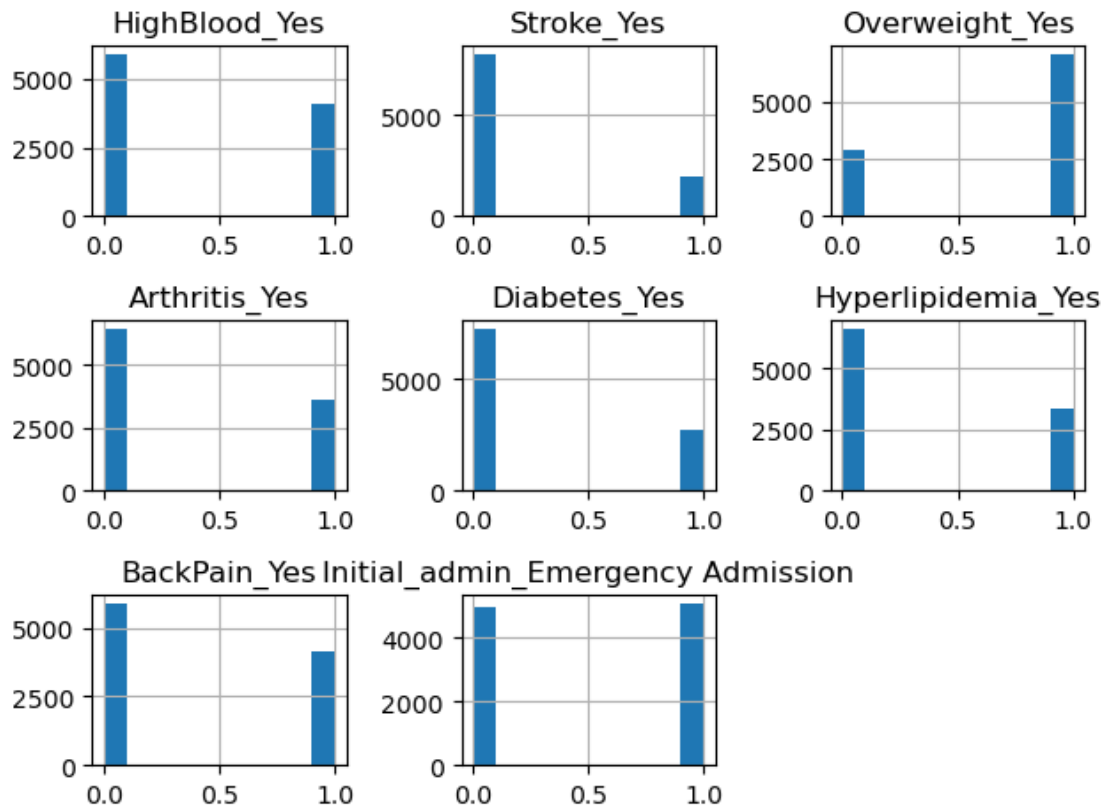
```
[7]: data[['Timely_admis', 'Timely_treat', 'Timely_visits', 'Reliability',  
        ↪ 'Options', 'Hours_treat', 'Courteous_staff', 'Active_listening']].hist()  
plt.tight_layout()  
plt.show()
```



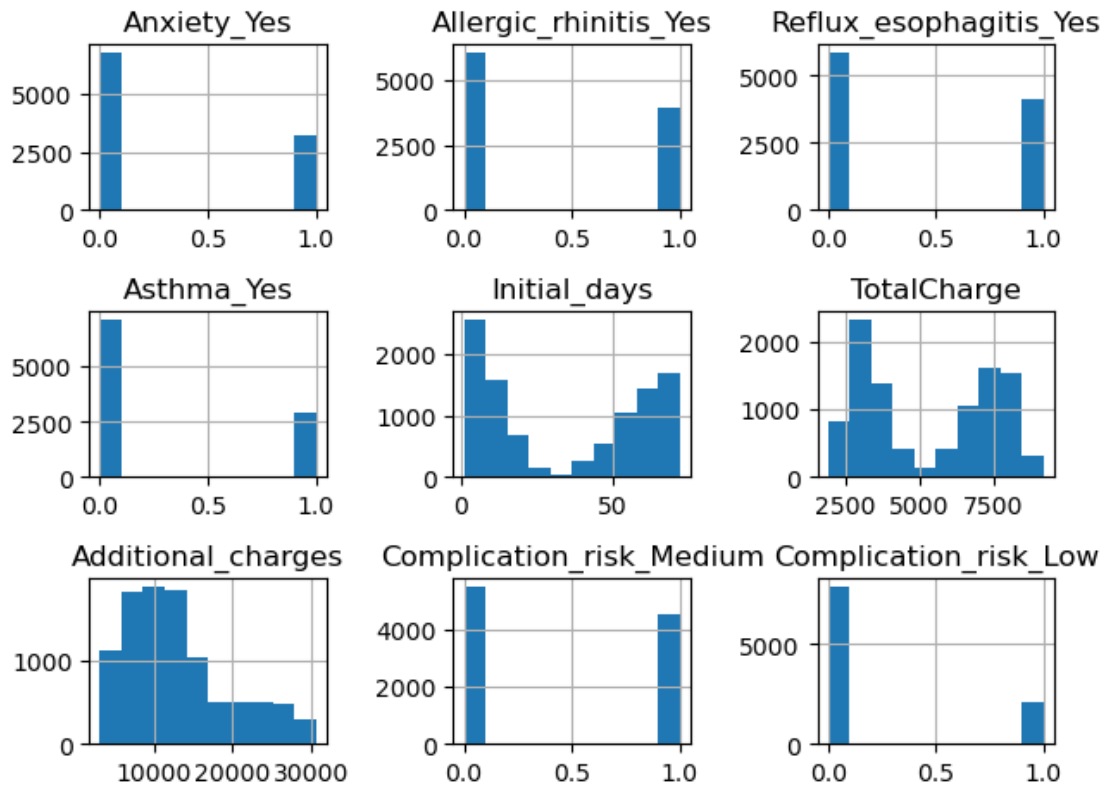
```
[52]: data[['Age', 'ReAdmis_Yes', 'VitD_levels',  
        'Doc_visits', 'Full_meals_eaten', 'vitD_supp', 'Soft_drink_Yes',  
        ↪ 'Initial_admin_Observation Admission']].hist()  
plt.tight_layout()  
plt.show()
```



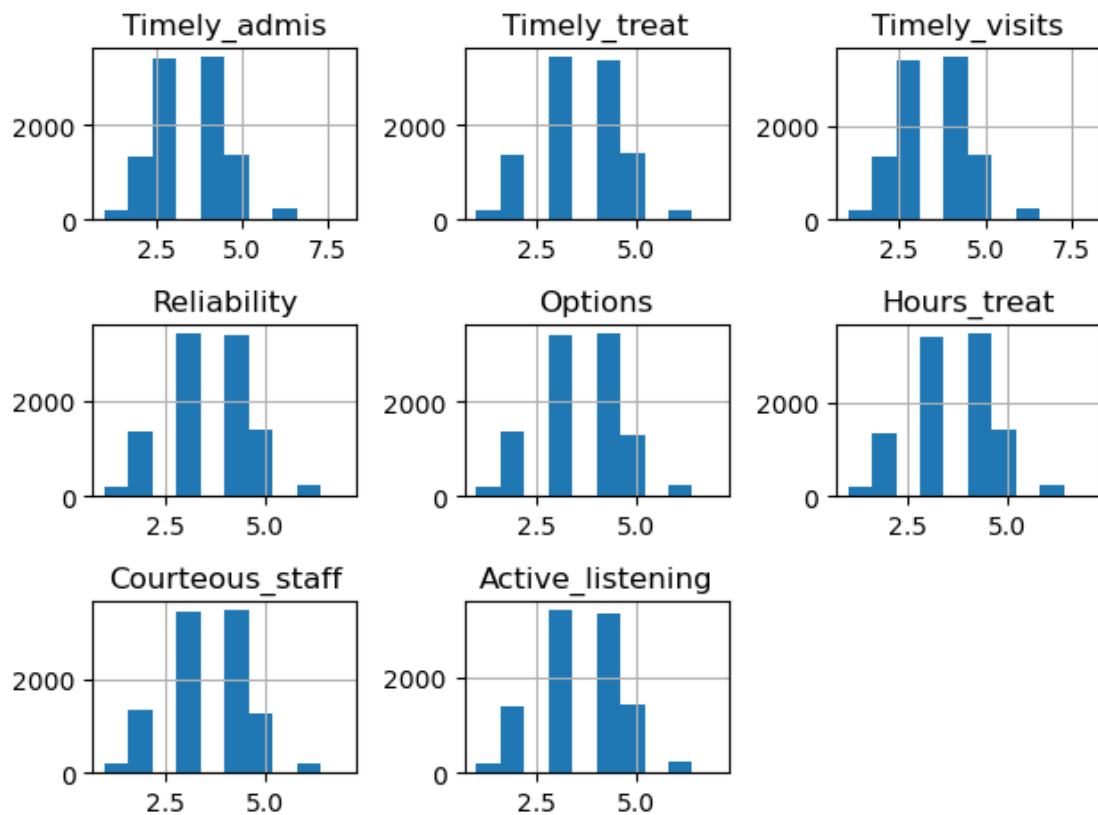
```
[8]: data[['HighBlood_Yes', 'Stroke_Yes', 'Overweight_Yes', 'Arthritis_Yes', '
        ↪Diabetes_Yes',
        'Hyperlipidemia_Yes', 'BackPain_Yes', 'Initial_admin_Emergency',
        ↪Admission']].hist()
plt.tight_layout()
plt.show()
```

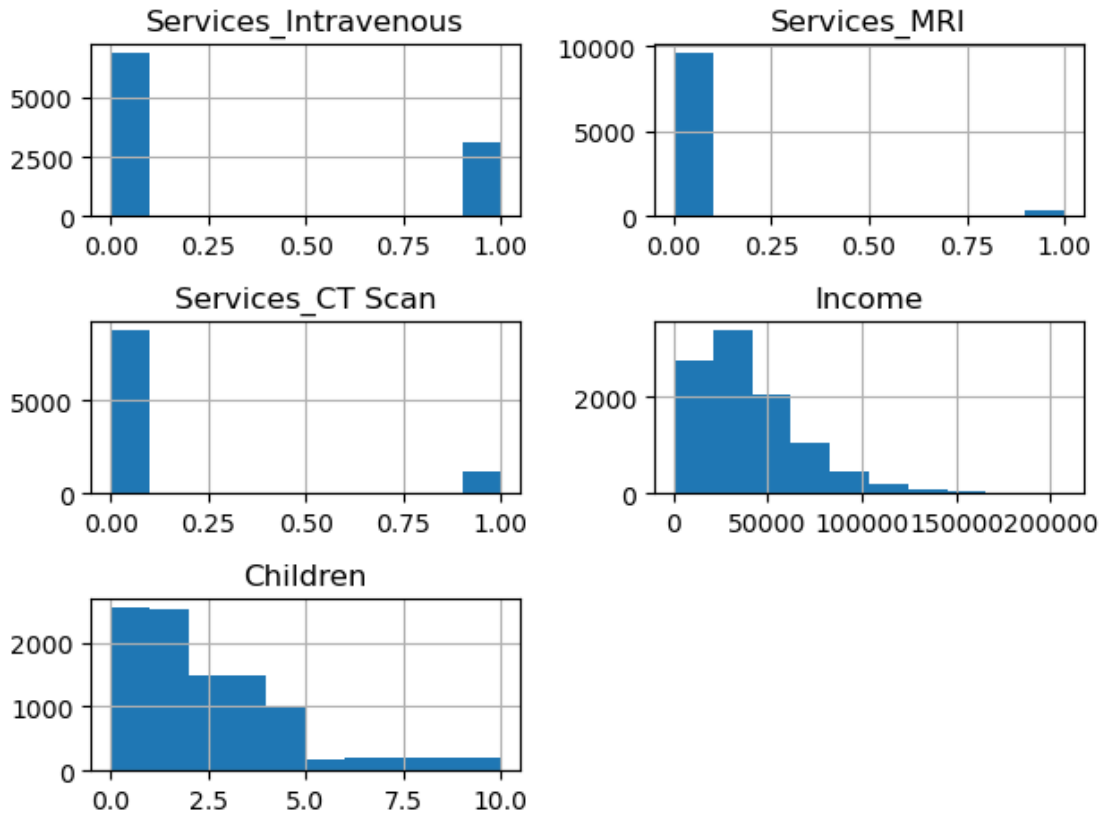
```
[45]: data[['Anxiety_Yes', 'Allergic_rhinitis_Yes',
           'Reflux_esophagitis_Yes', 'Asthma_Yes', 'Initial_days', 'TotalCharge',
           'Additional_charges', 'Complication_risk_Medium',
           ↪ 'Complication_risk_Low']].hist()
plt.tight_layout()
plt.show()
```



```
[9]: data[['Timely_admis', 'Timely_treat', 'Timely_visits',
          'Reliability', 'Options', 'Hours_treat', 'Courteous_staff',
          'Active_listening']].hist()
plt.tight_layout()
plt.show()
```

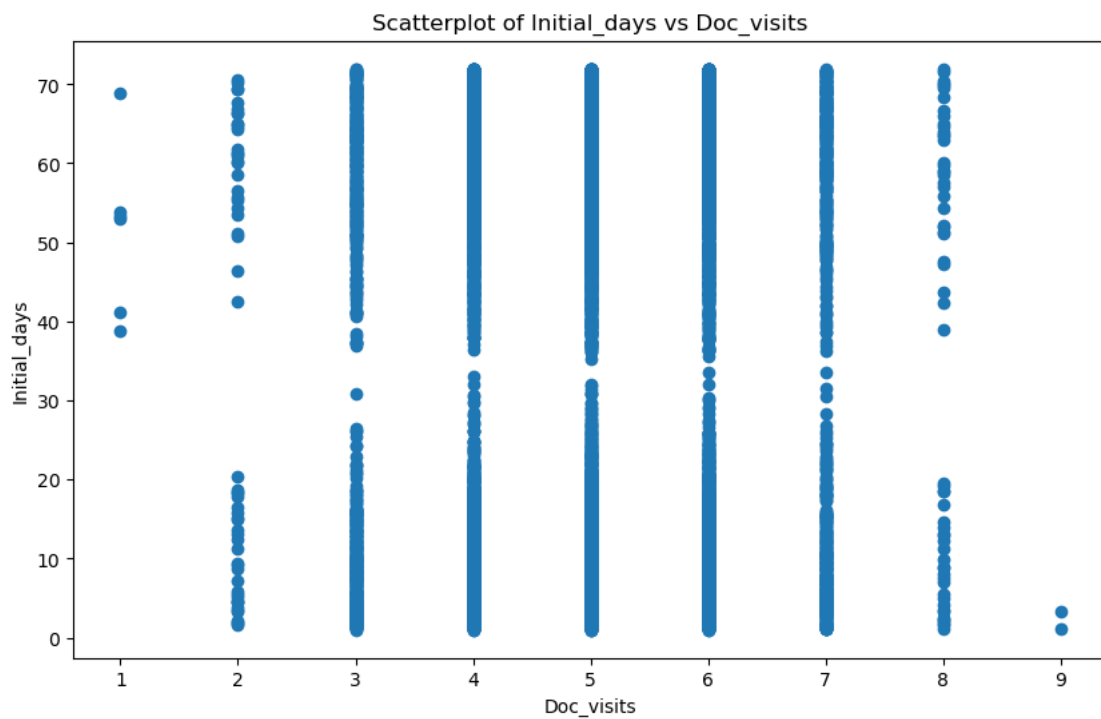
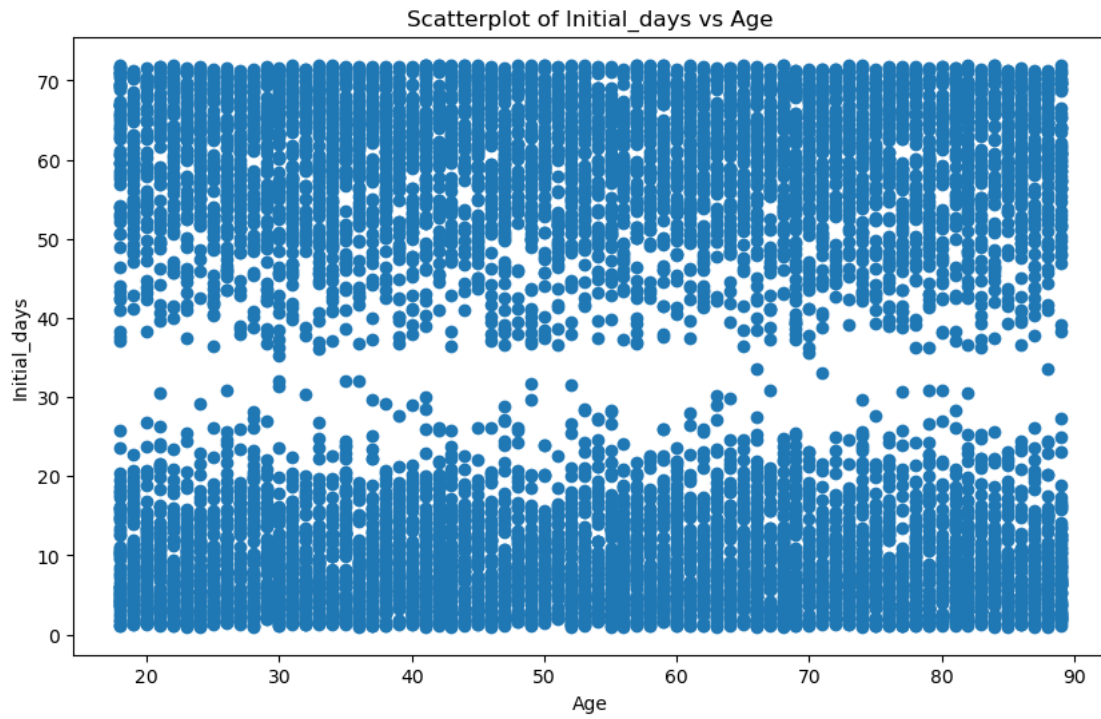


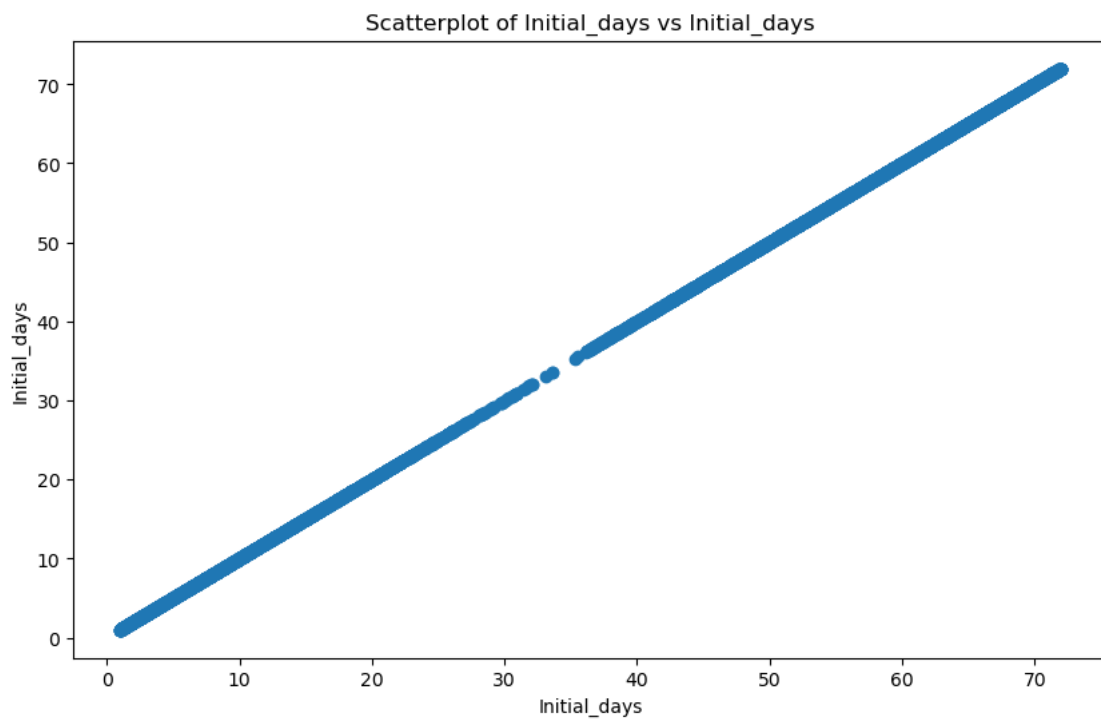
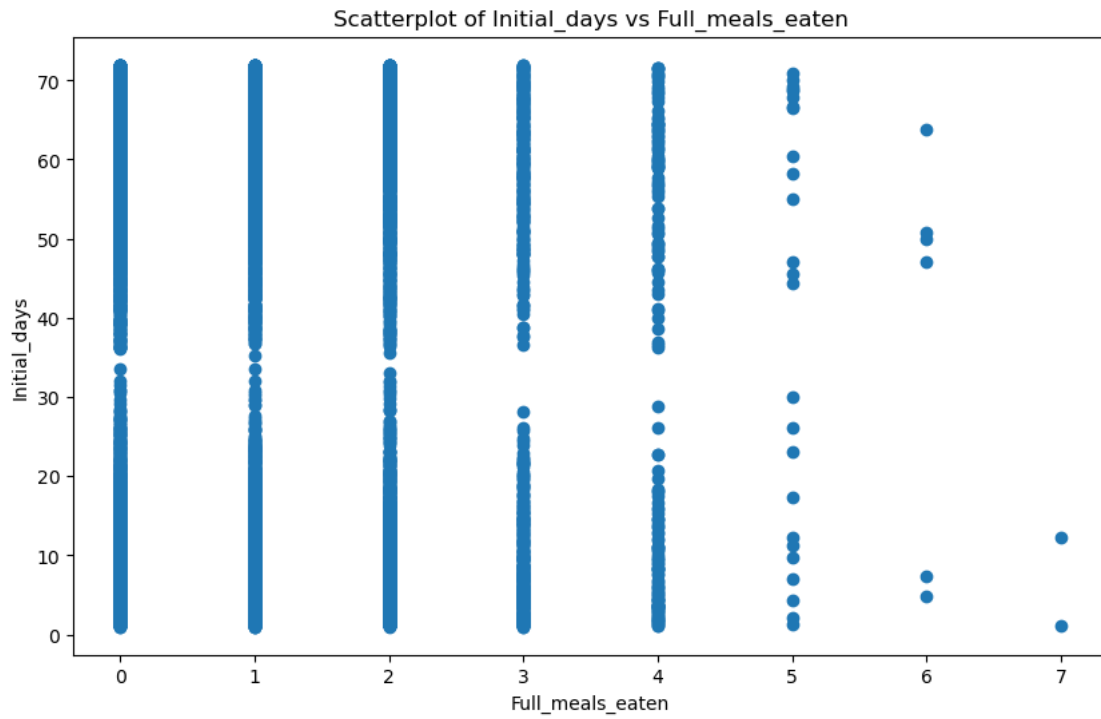
```
[10]: data[['Services_Intravenous', 'Services_MRI', 'Services_CT Scan', 'Income', 'Children']].hist()
plt.tight_layout()
plt.show()
```

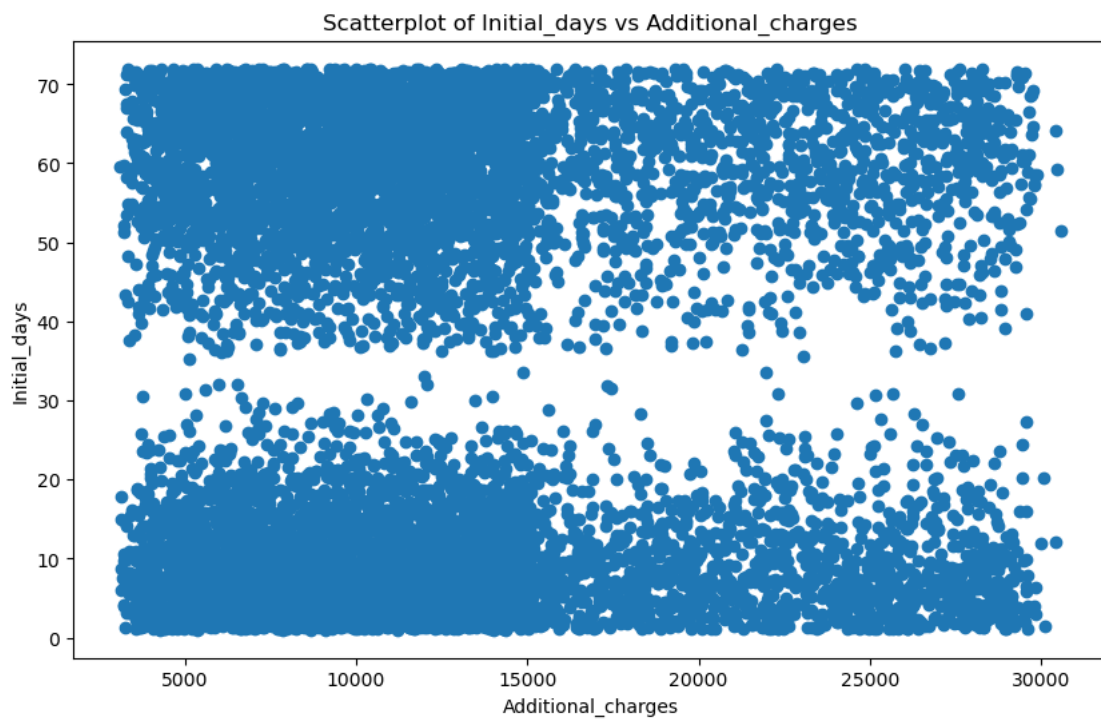
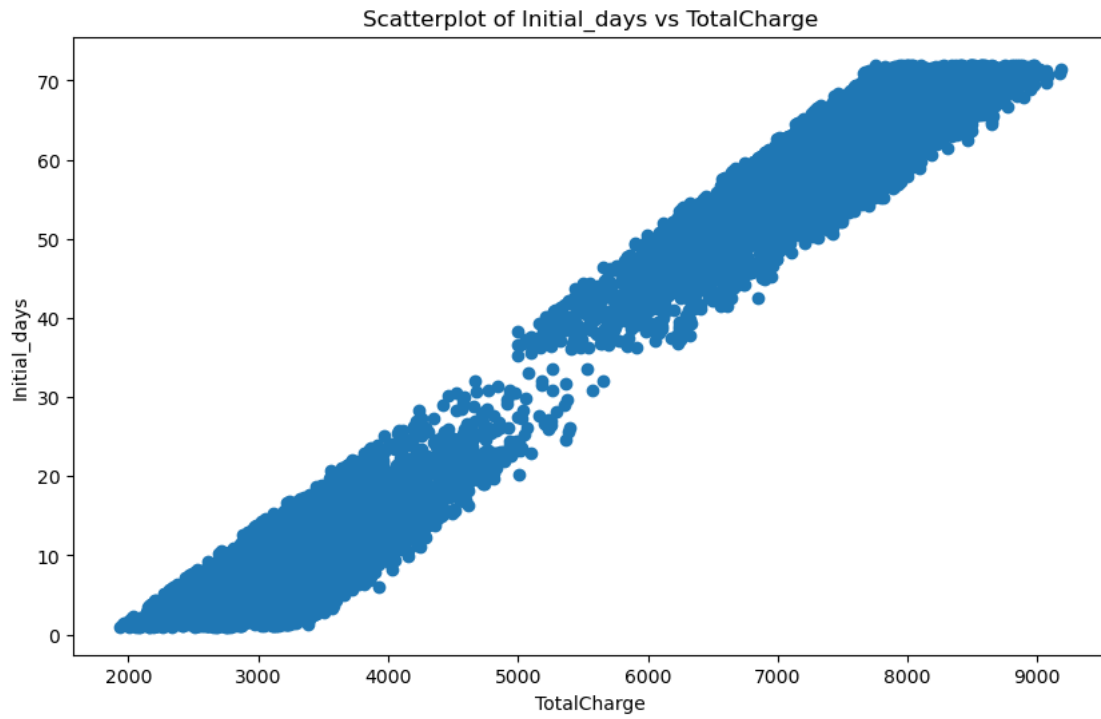


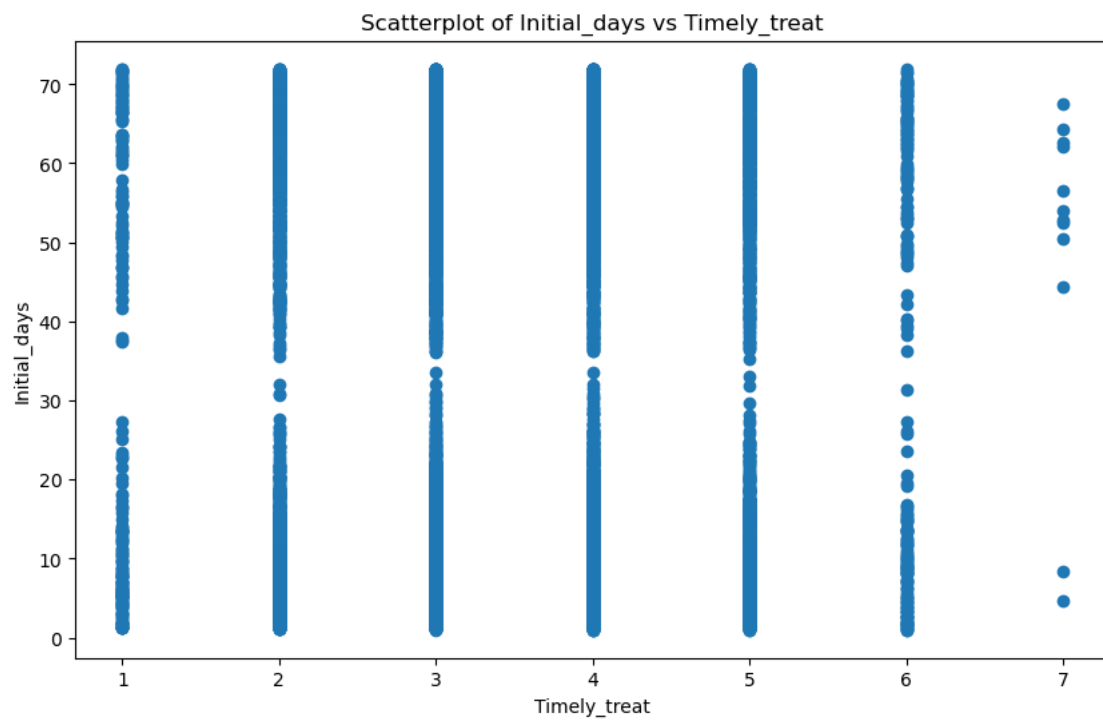
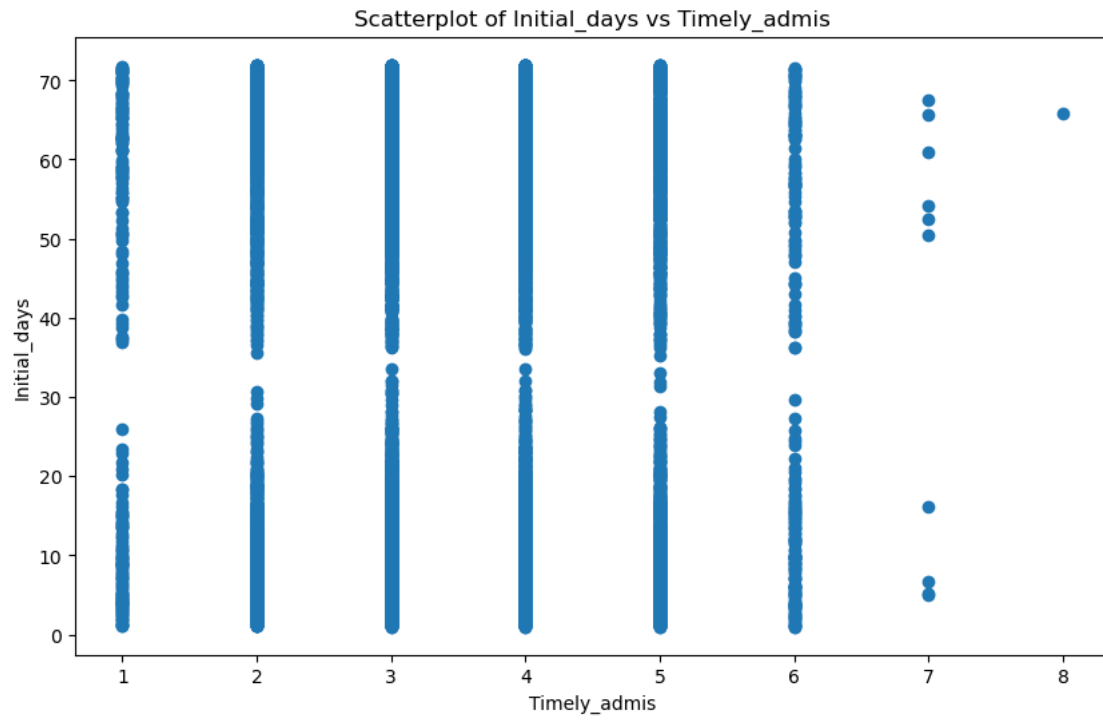
```
[11]: contData = ['Age', 'Doc_visits', 'Full_meals_eaten',
    'Initial_days', 'TotalCharge', 'Additional_charges', 'Timely_admis',
    'Timely_treat', 'Timely_visits', 'Reliability', 'Options',
    'Hours_treat', 'Courteous_staff', 'Active_listening', 'ReAdmis_Yes',
    'Complication_risk_Low', 'Complication_risk_Medium',
    'Initial_admin_Emergency Admission',
    'Initial_admin_Observation Admission', 'Services_CT Scan',
    'Services_Intravenous', 'Services_MRI', 'Overweight_Yes', 'Anxiety_Yes',
    'Arthritis_Yes', 'Asthma_Yes', 'Diabetes_Yes',
    'Allergic_rhinitis_Yes', 'BackPain_Yes', 'Stroke_Yes', 'HighBlood_Yes',
    'Hyperlipidemia_Yes', 'Reflux_esophagitis_Yes', 'Income', 'Children']

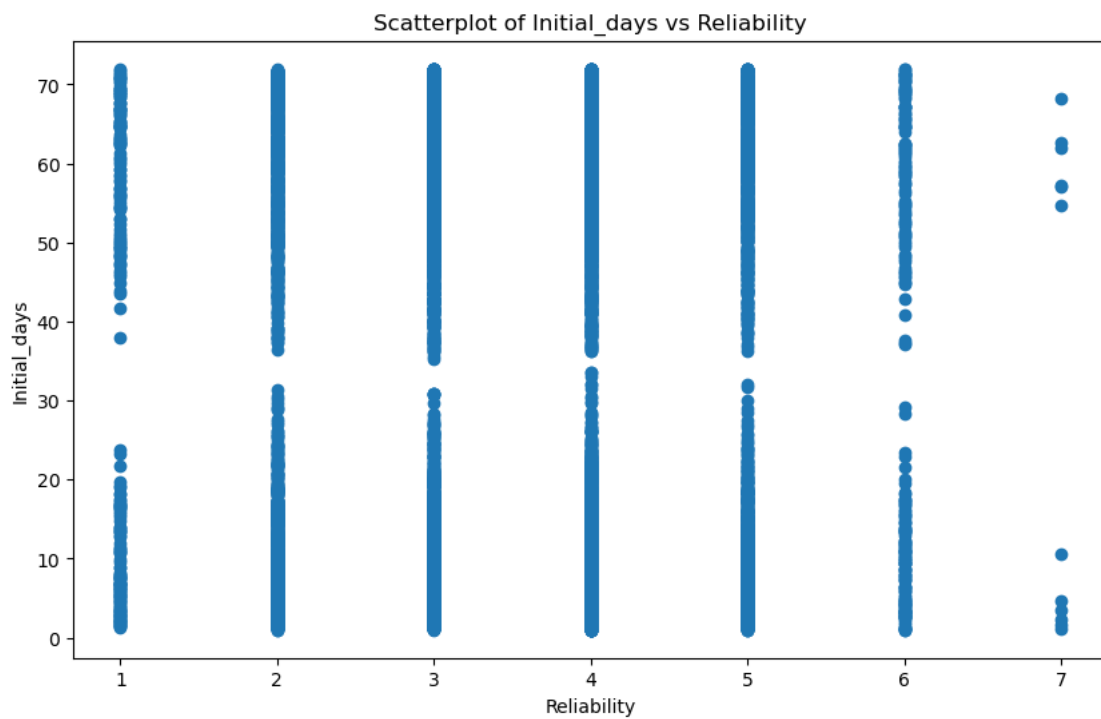
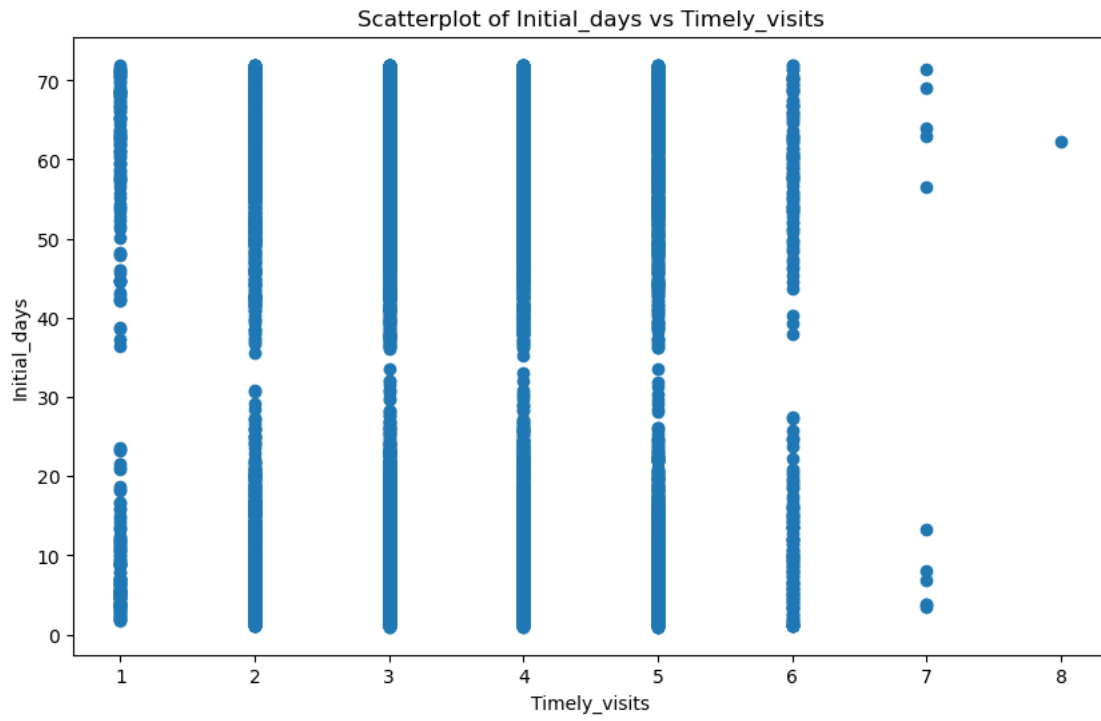
for column in contData:
    plt.figure(figsize=(10, 6))
    plt.scatter(data[column], data['Initial_days'])
    plt.title(f'Scatterplot of Initial_days vs {column}')
    plt.xlabel(column)
    plt.ylabel('Initial_days')
    plt.show()
```

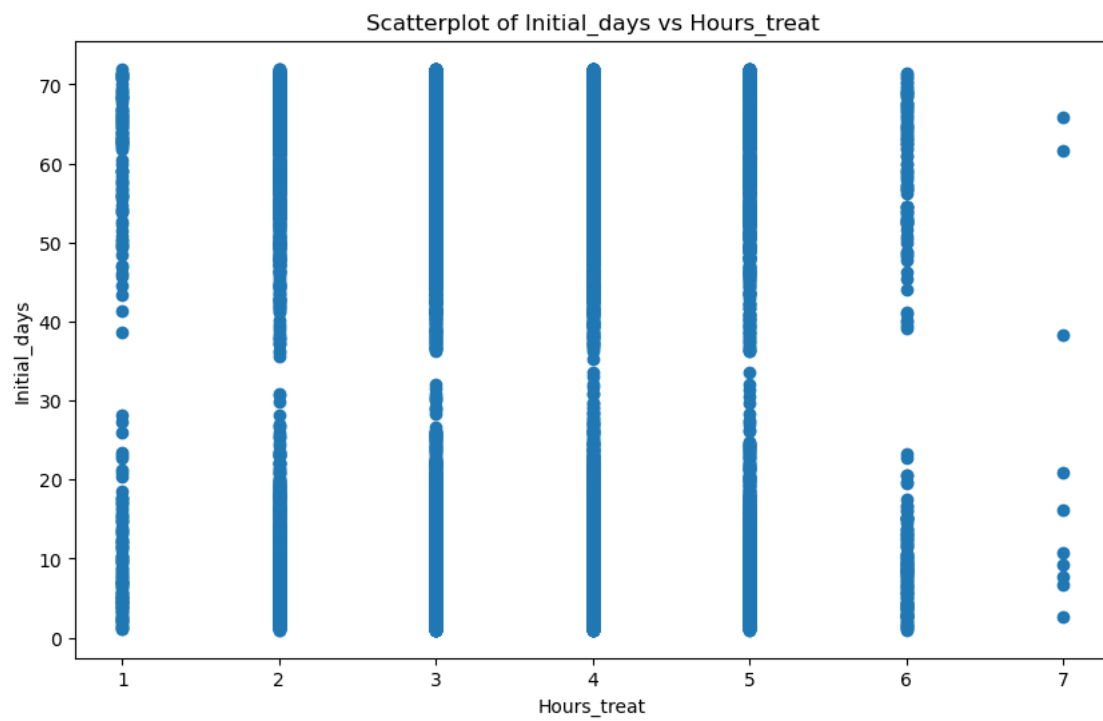
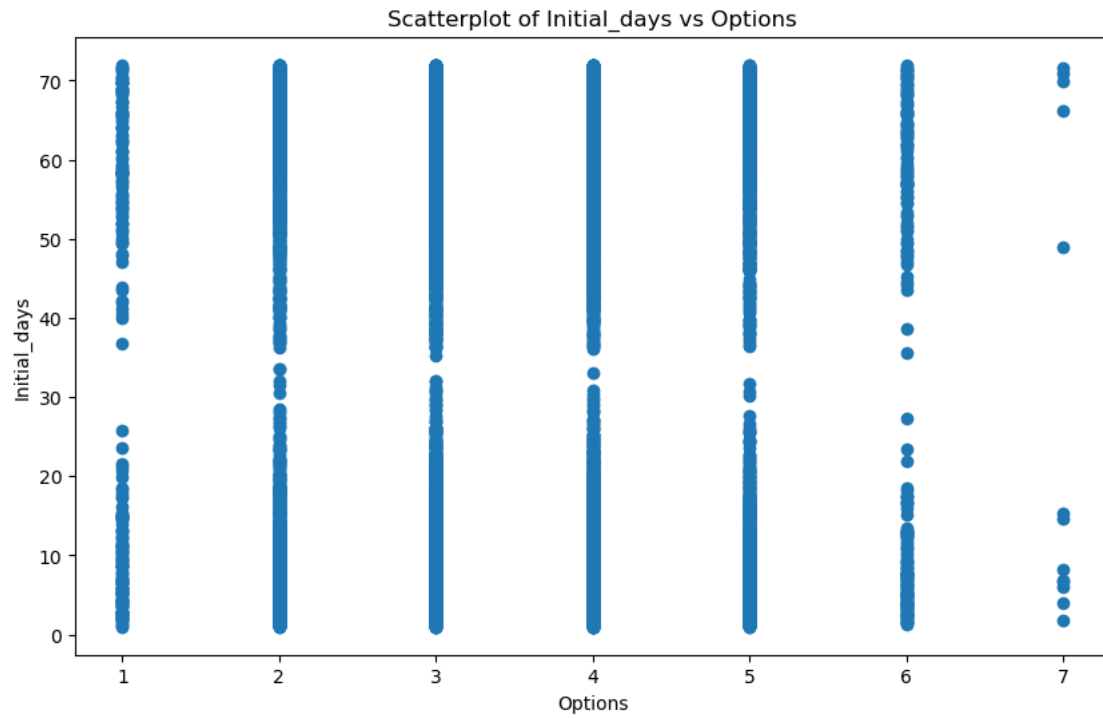


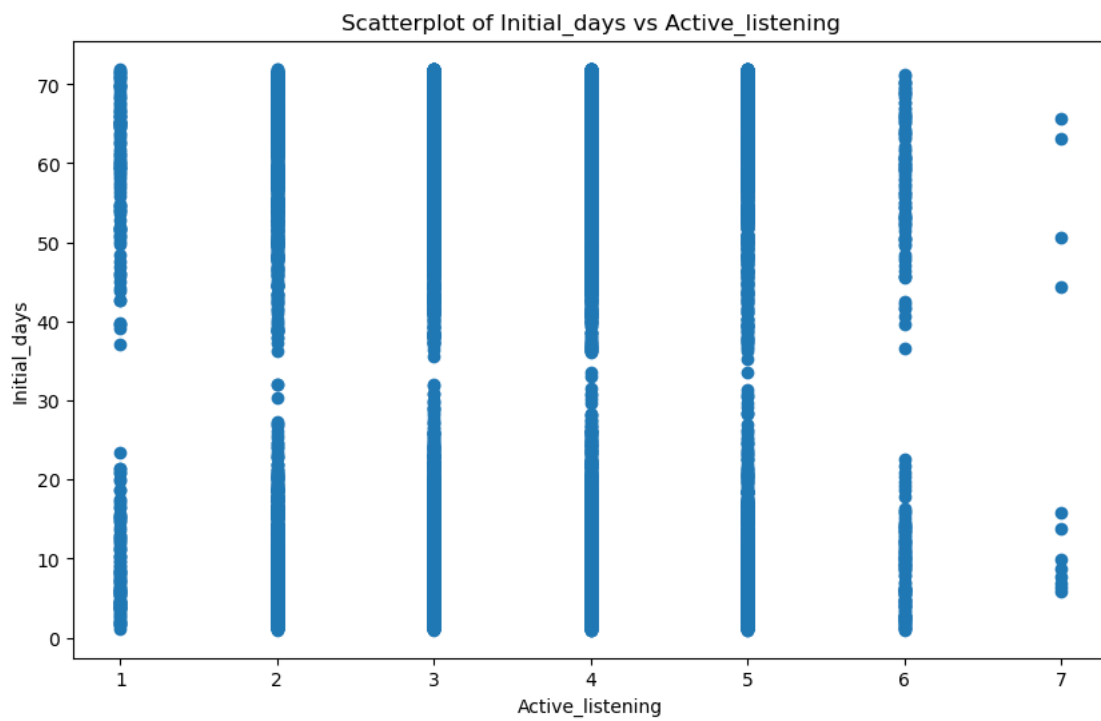
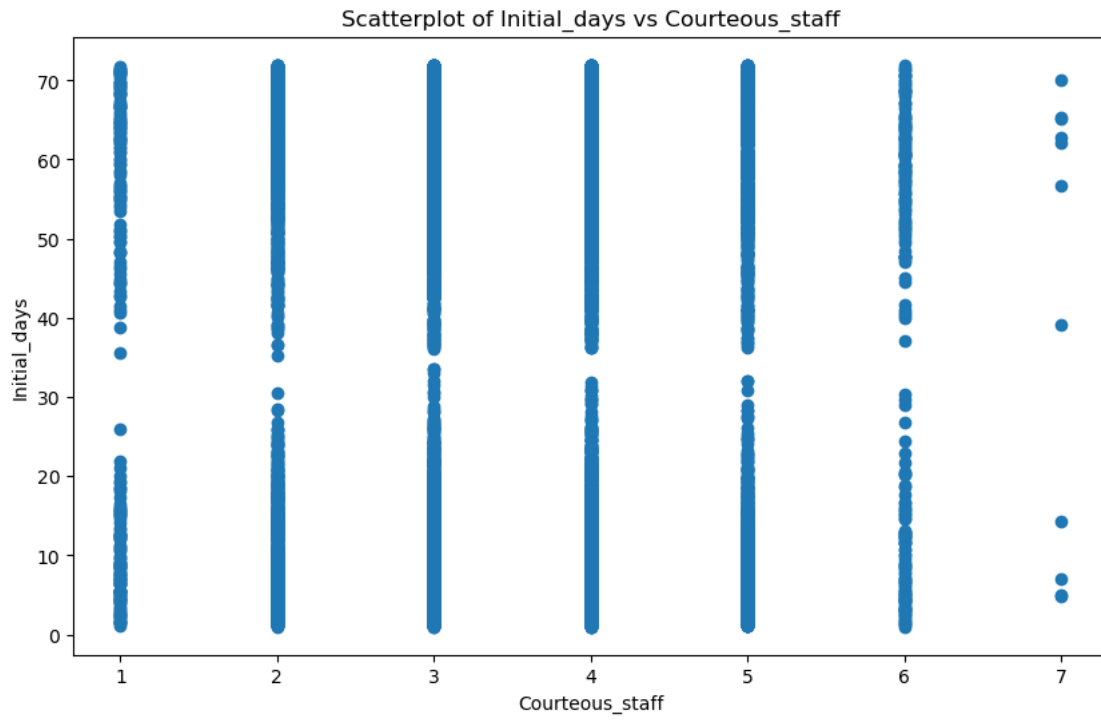


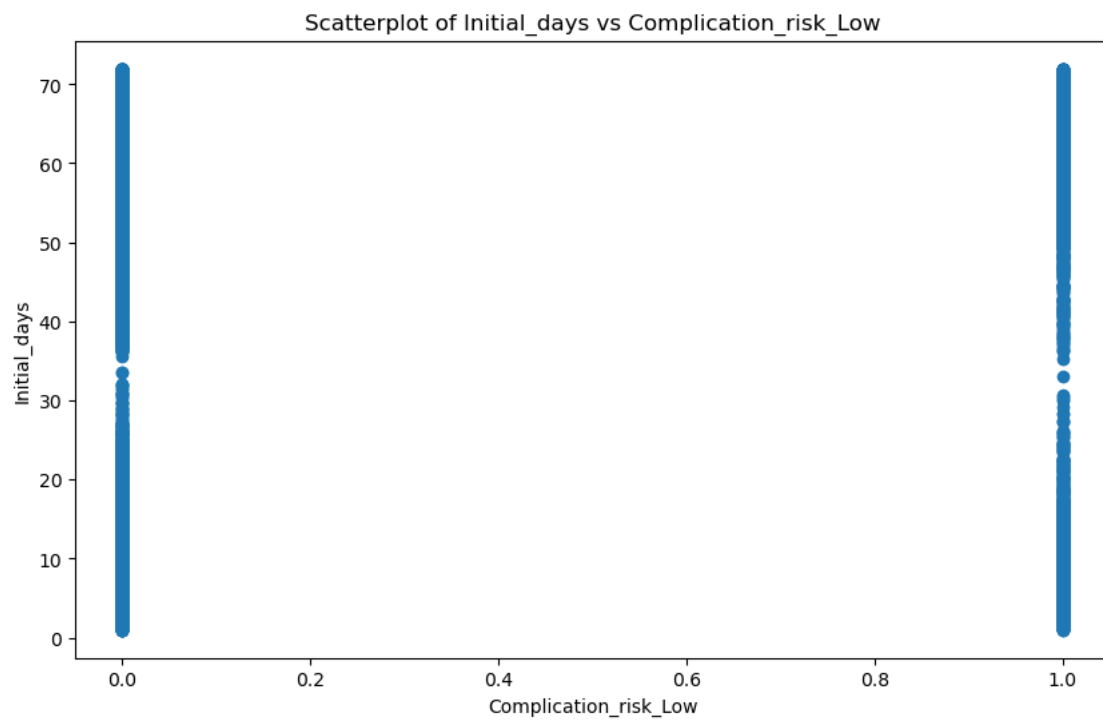
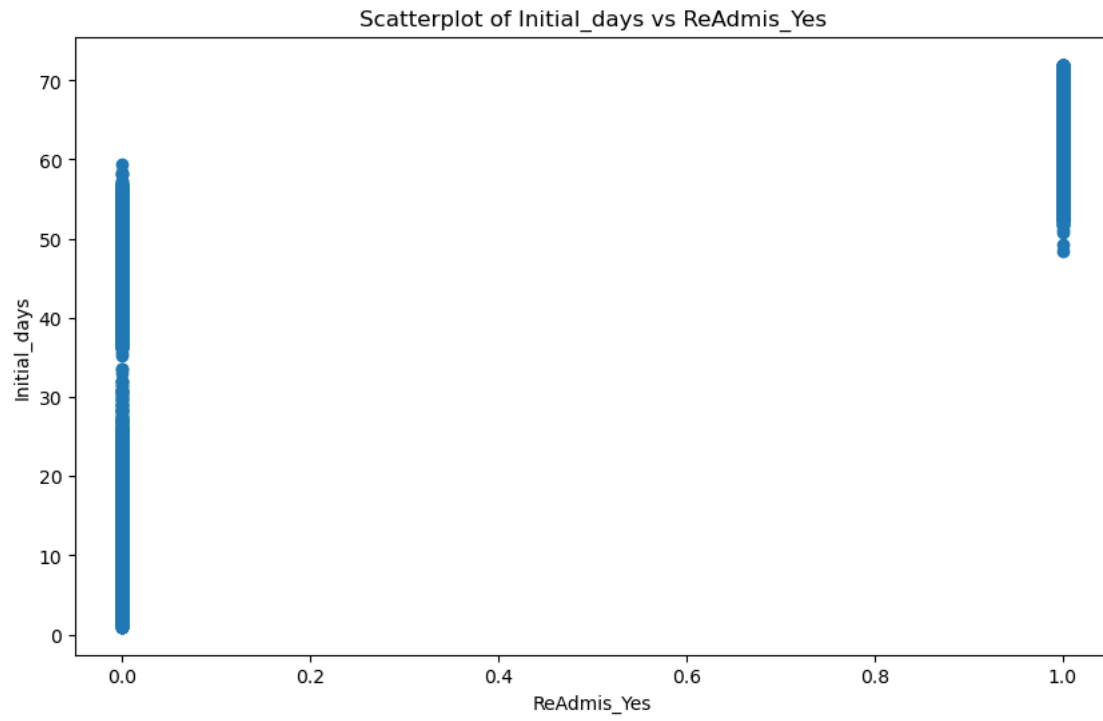


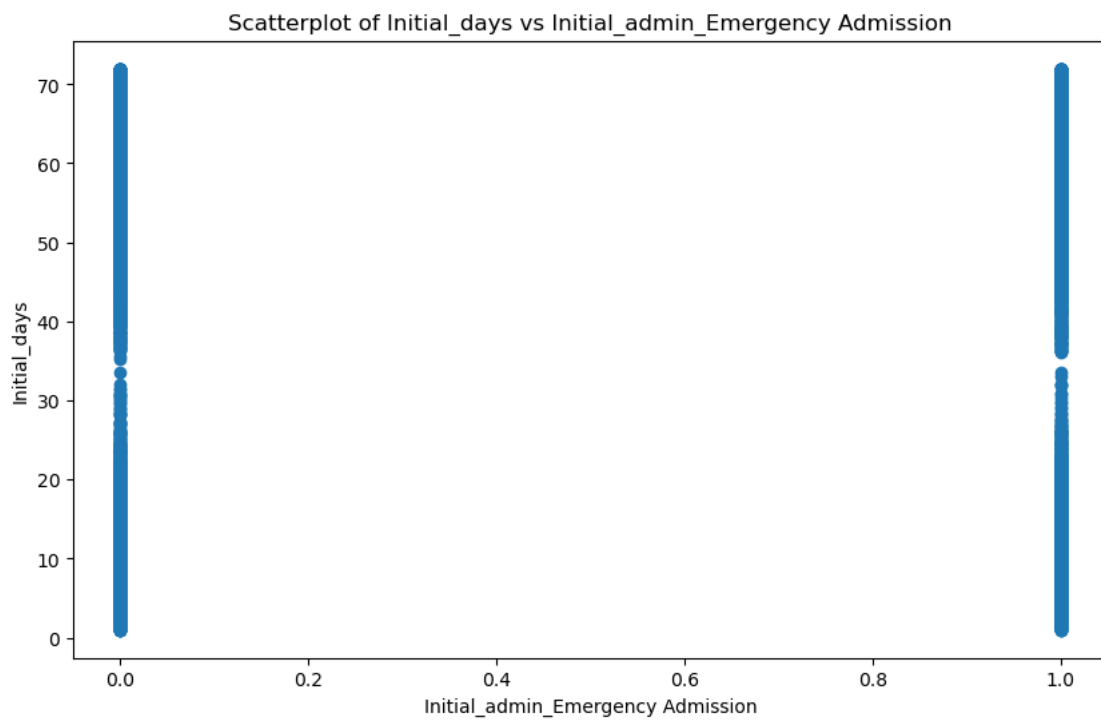
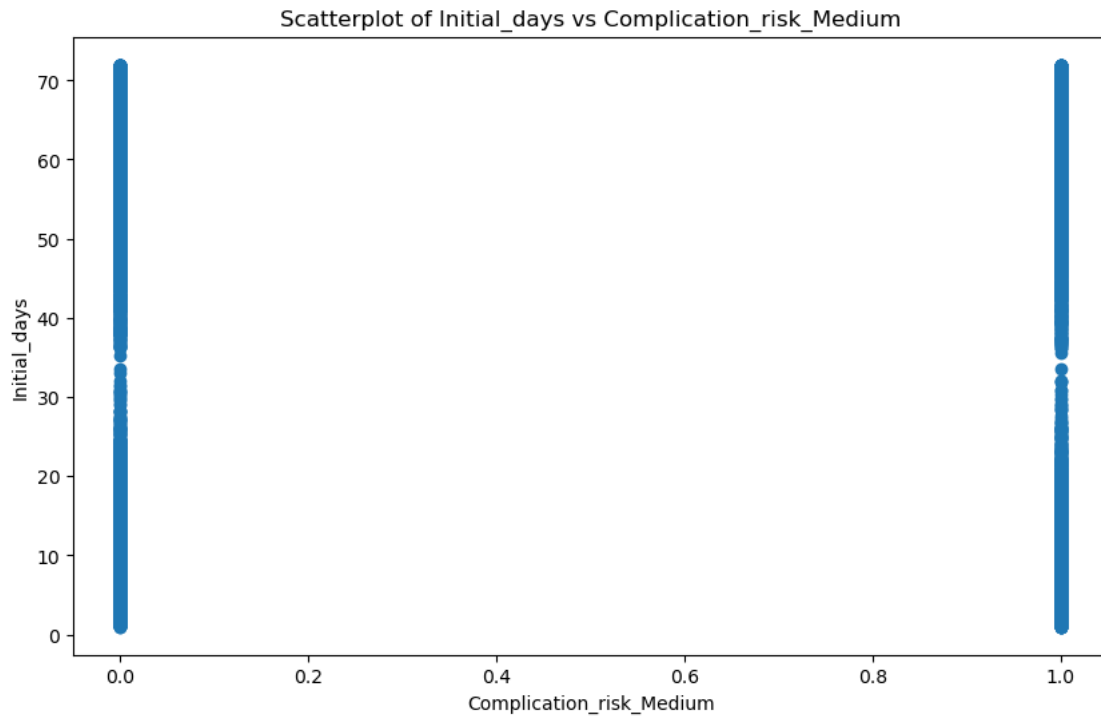


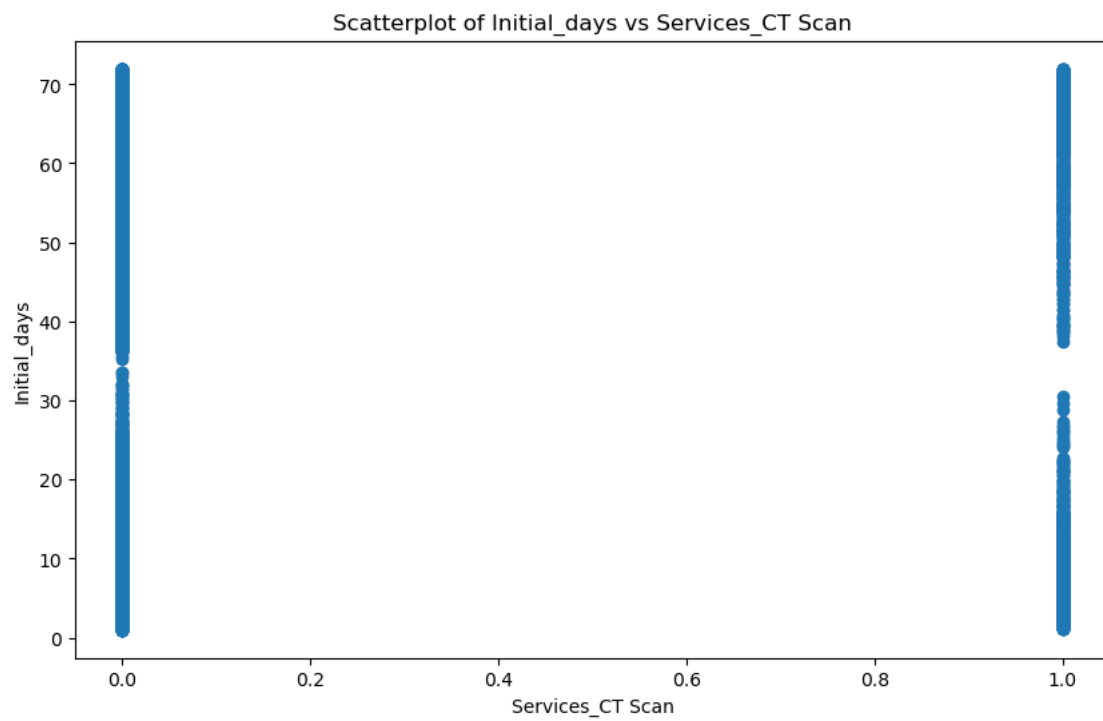
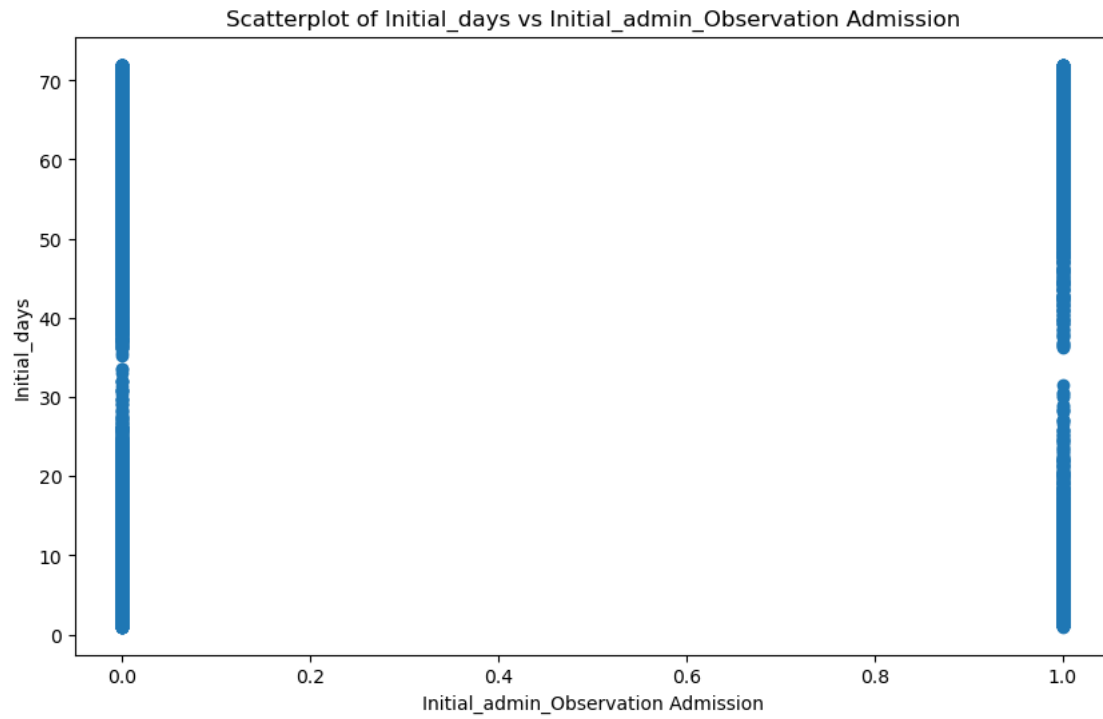


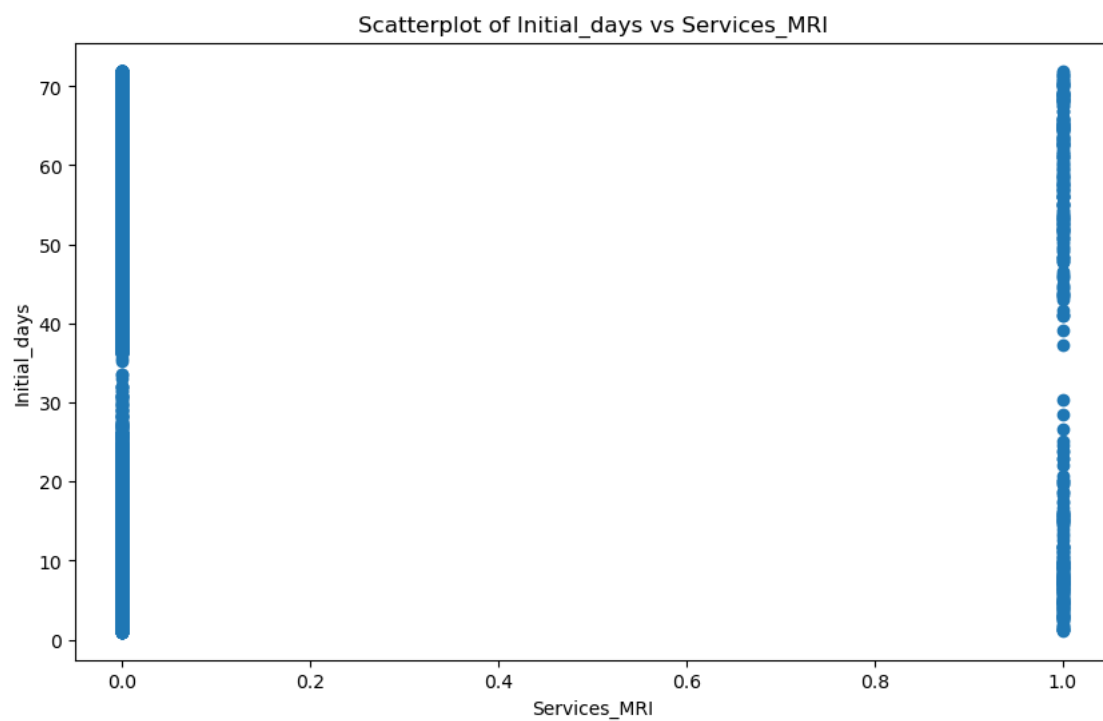
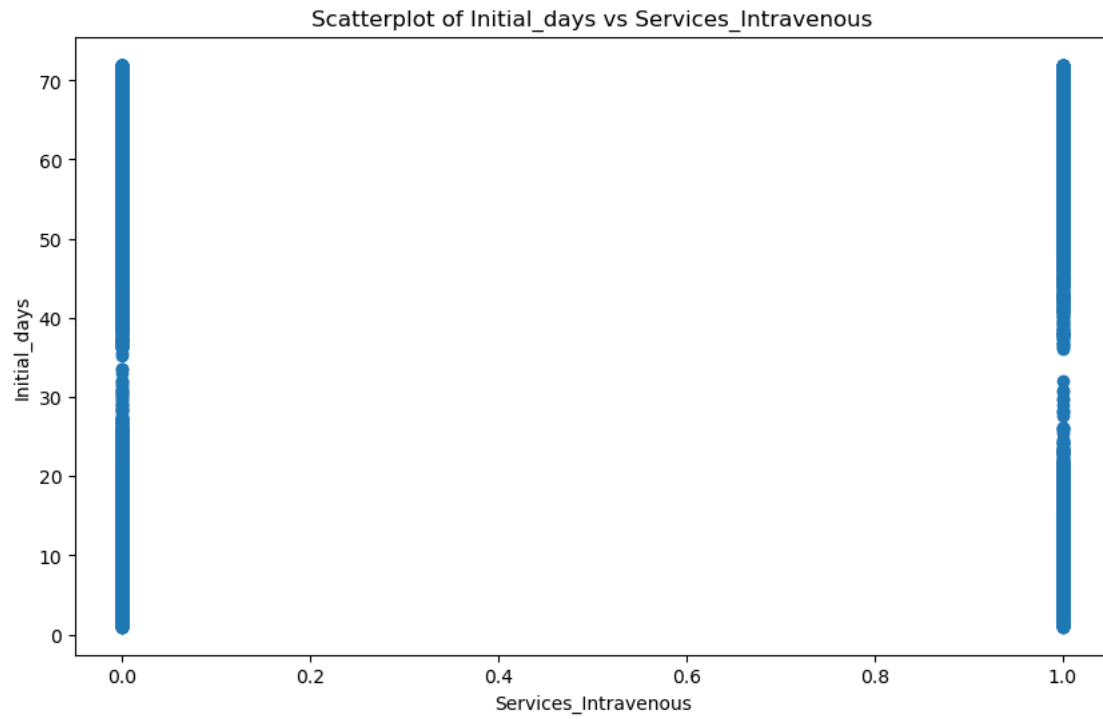


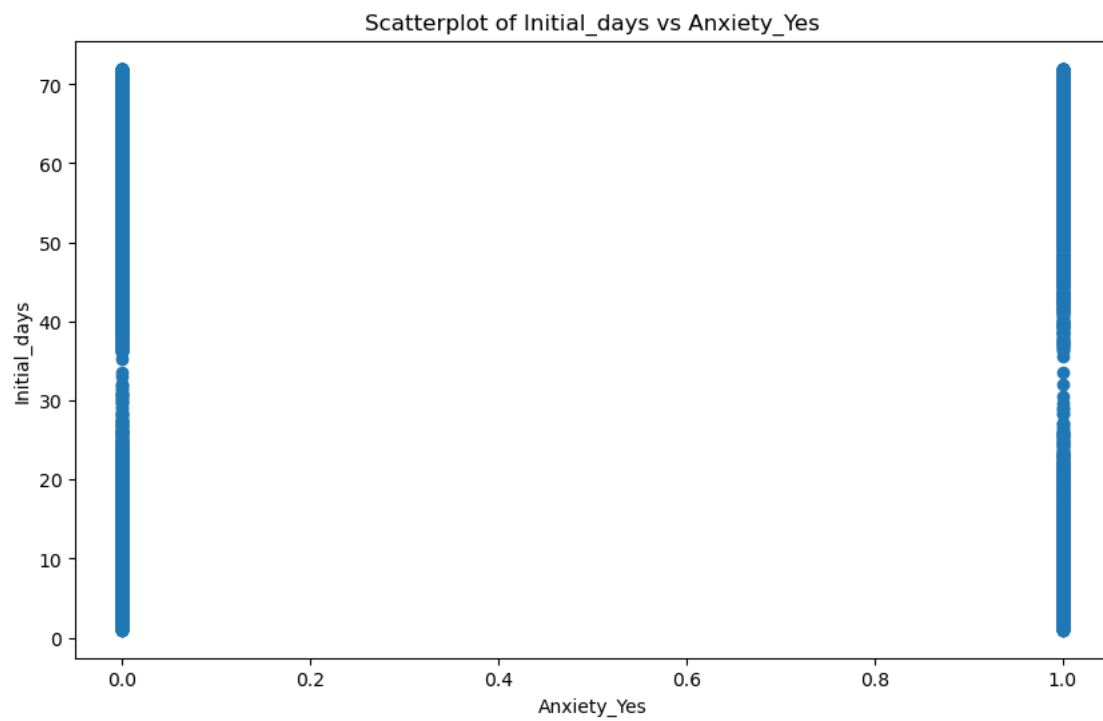
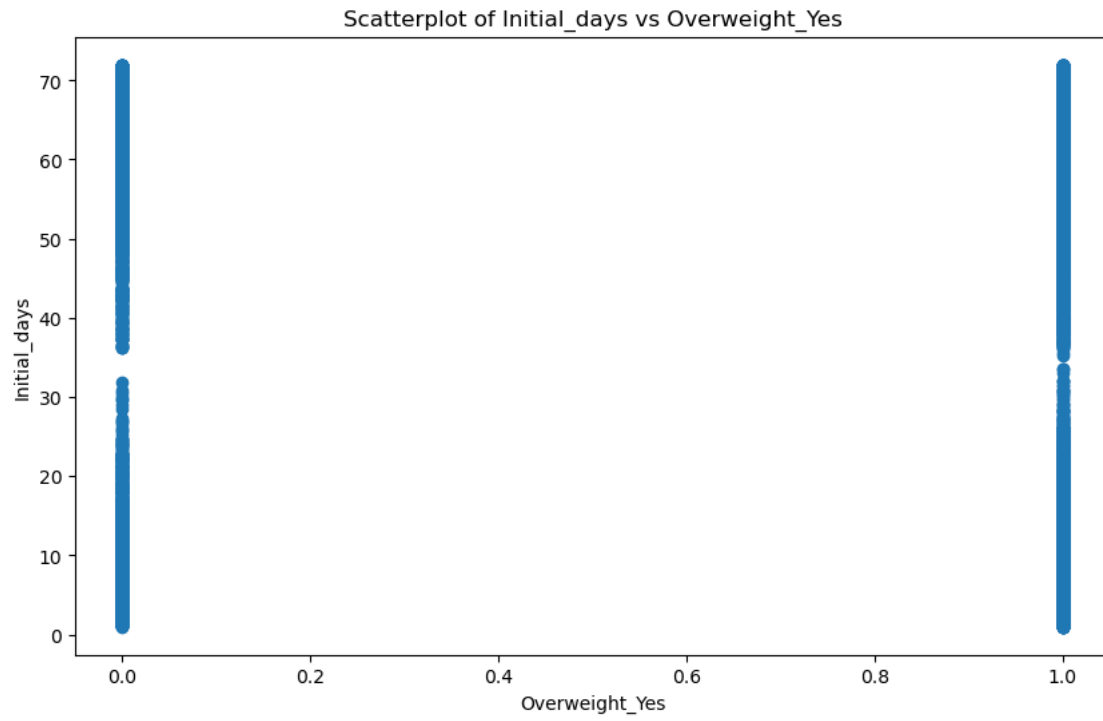


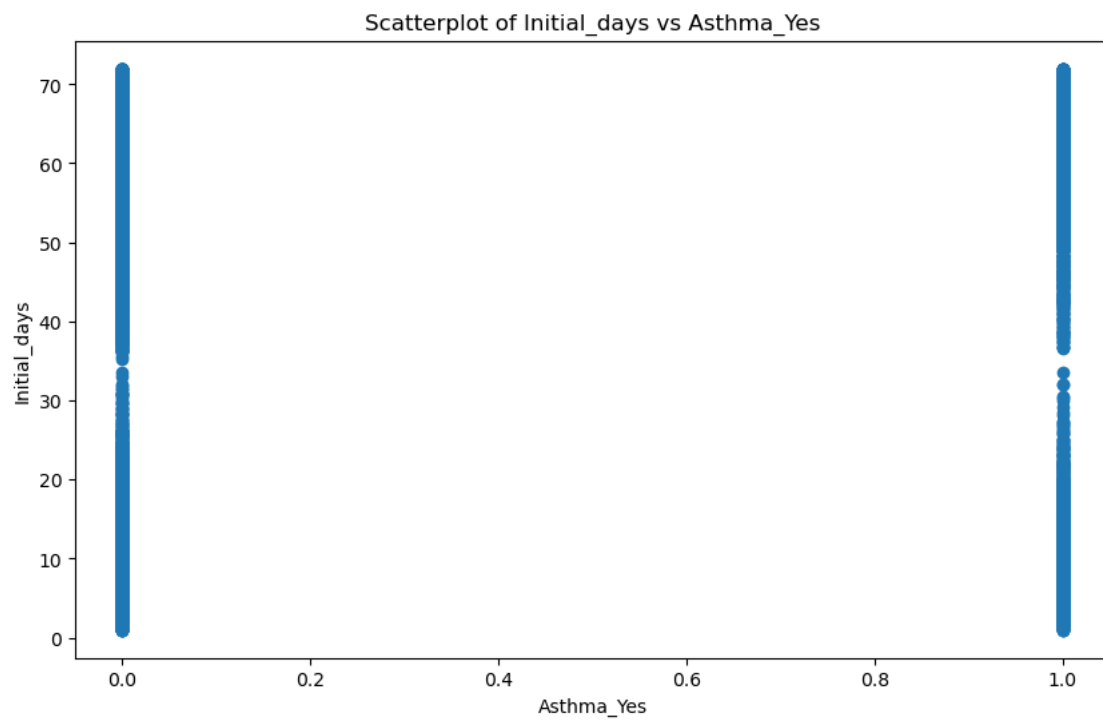
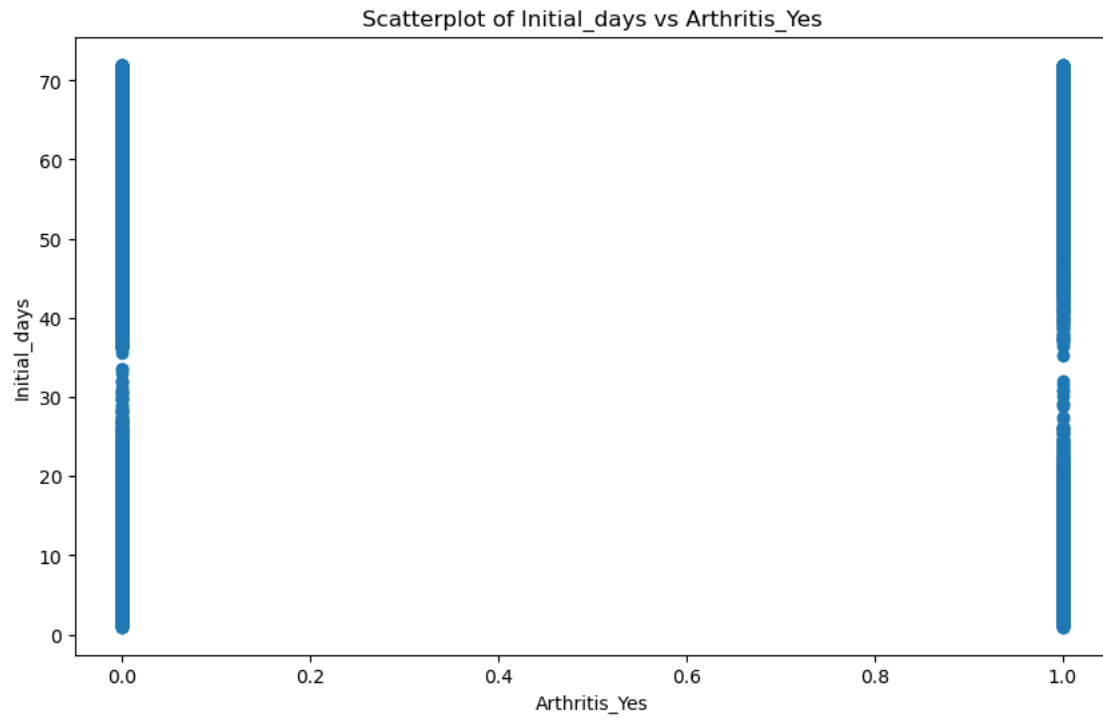


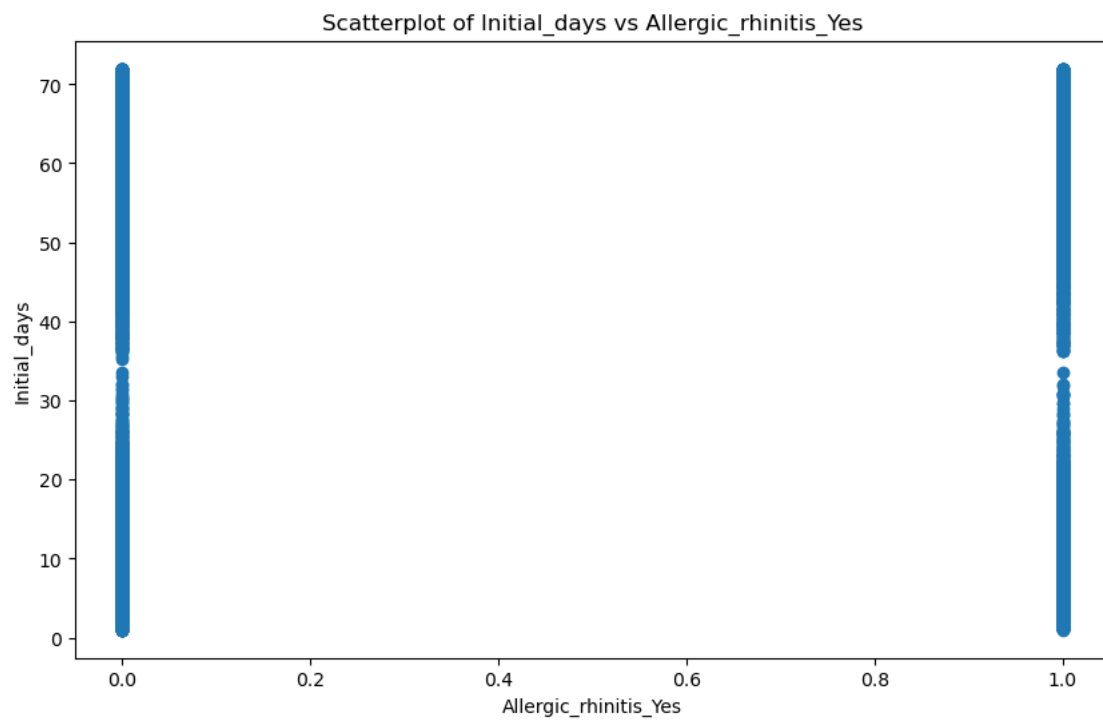
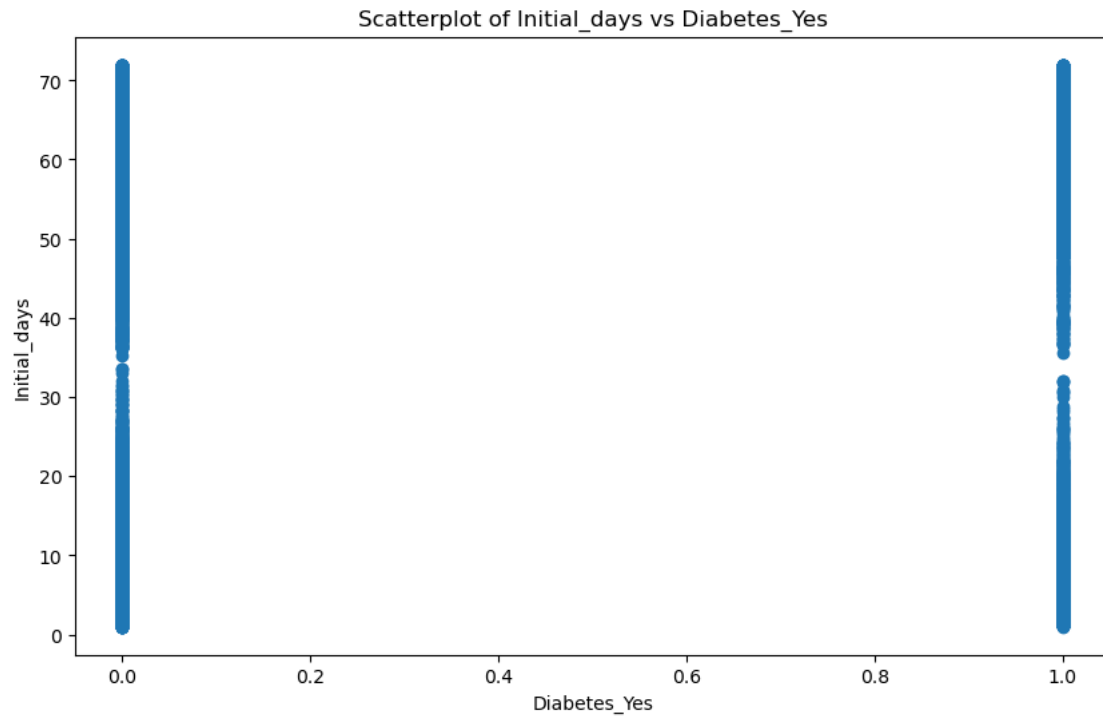


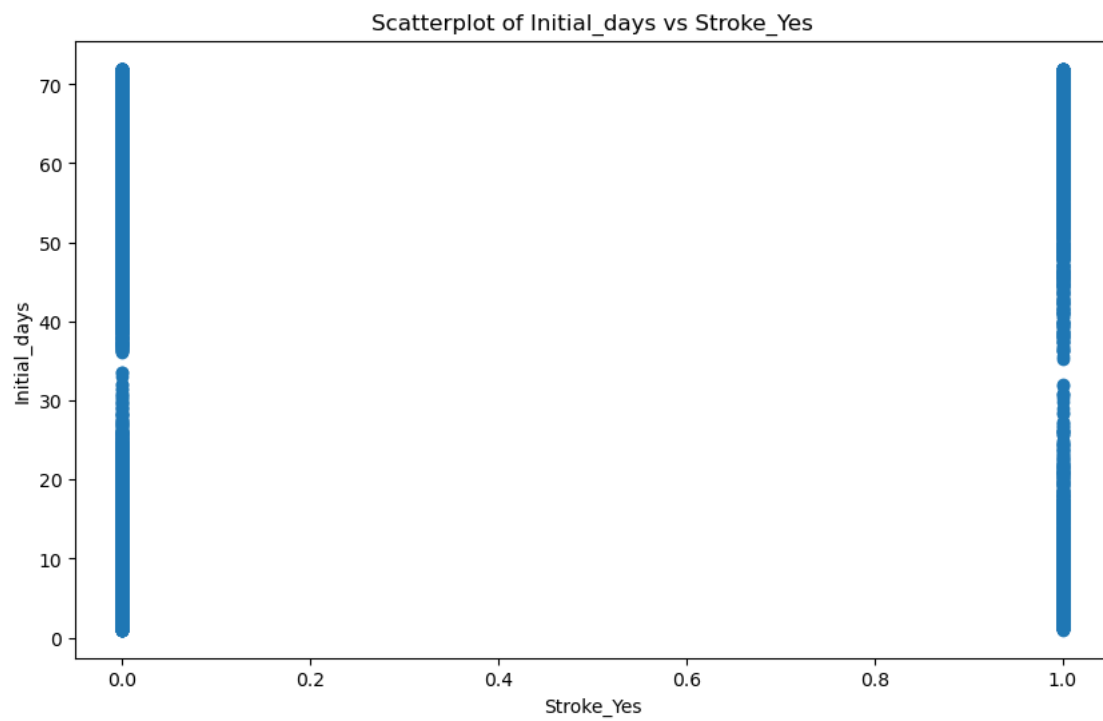
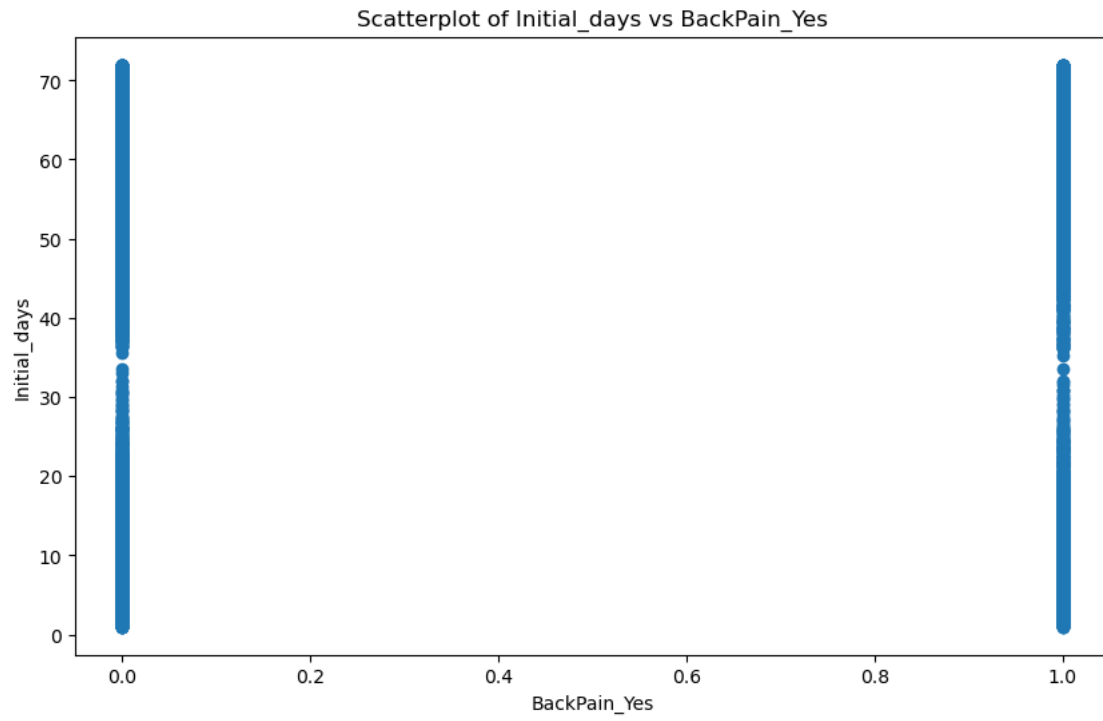


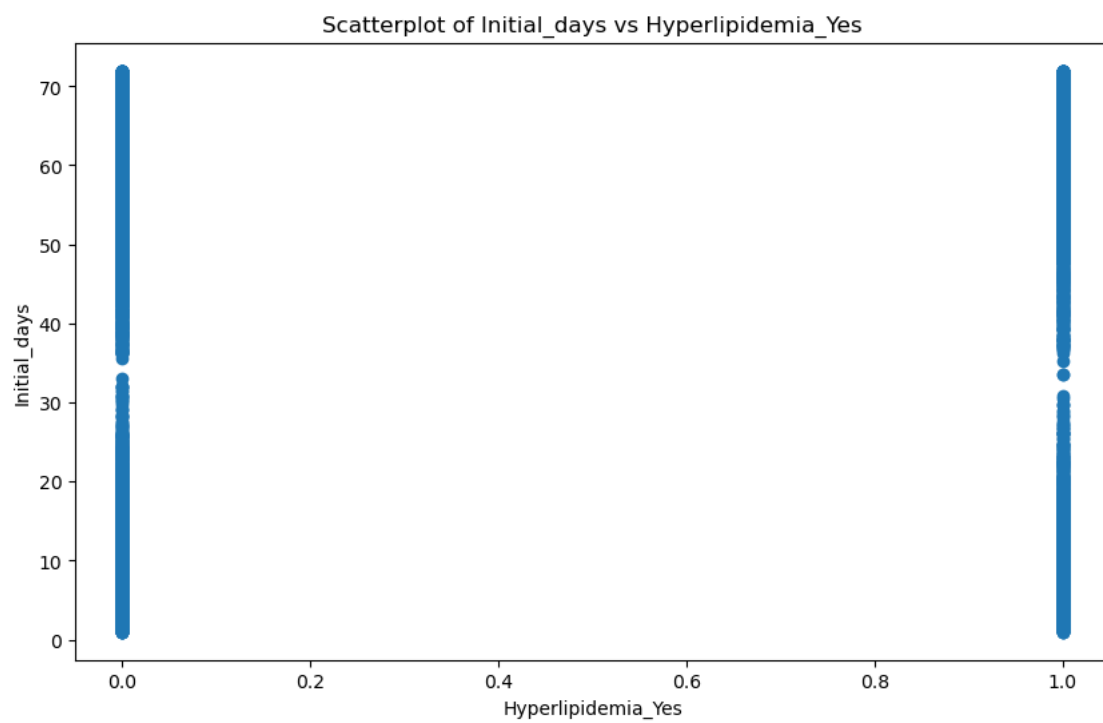
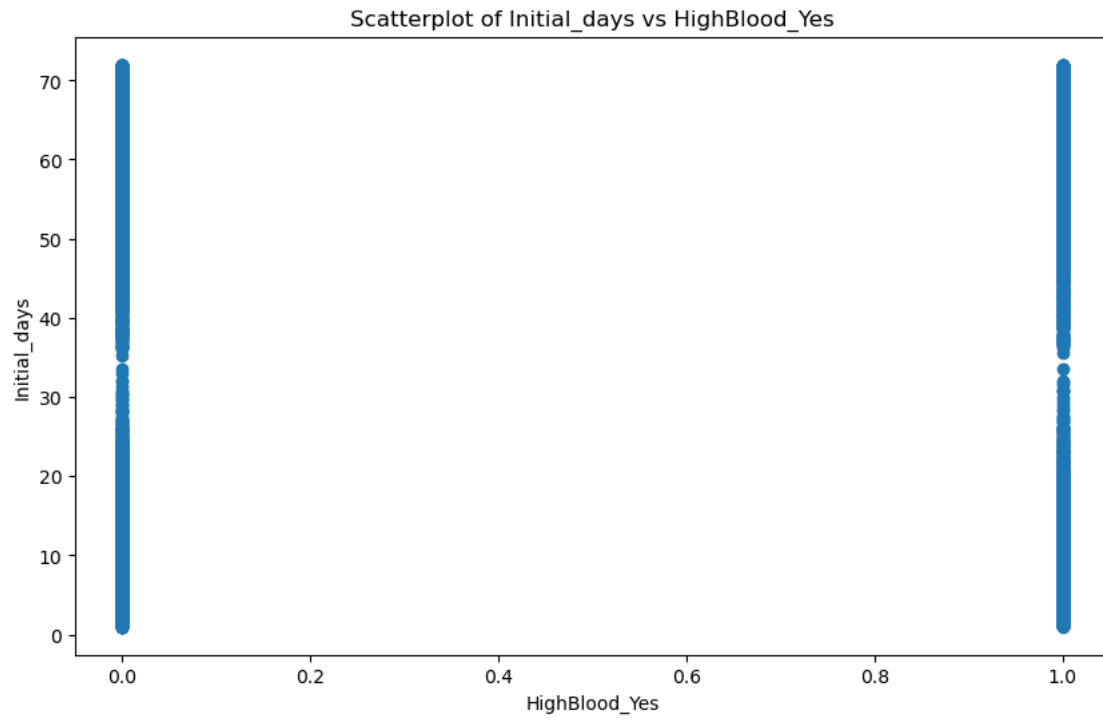


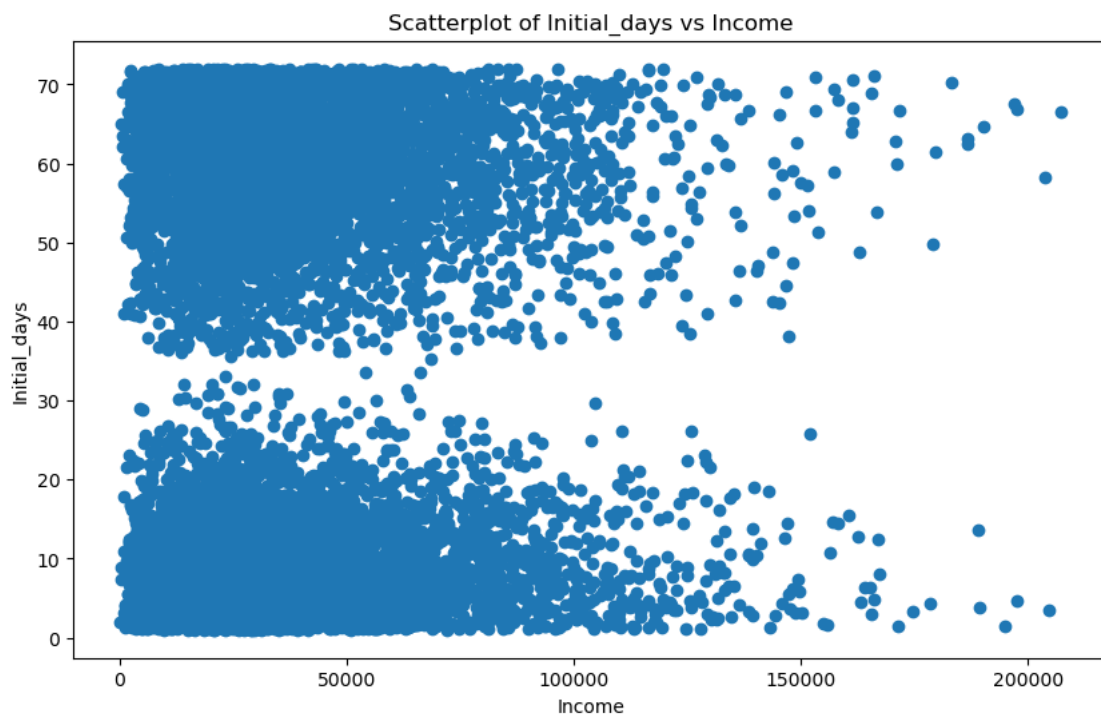
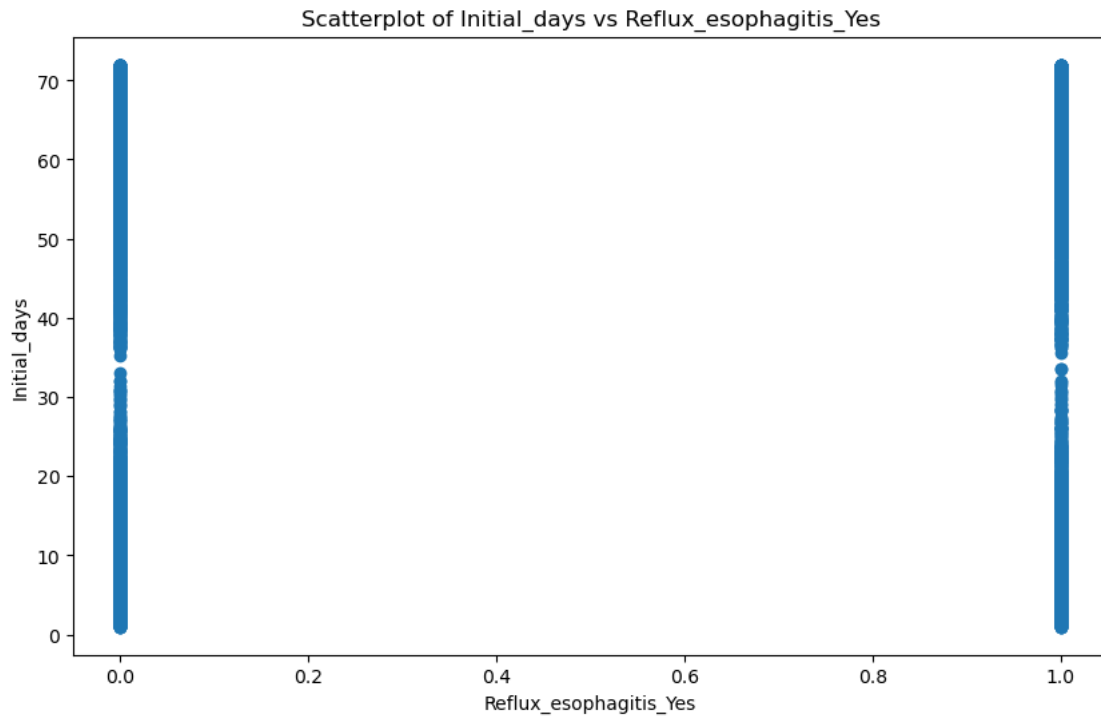


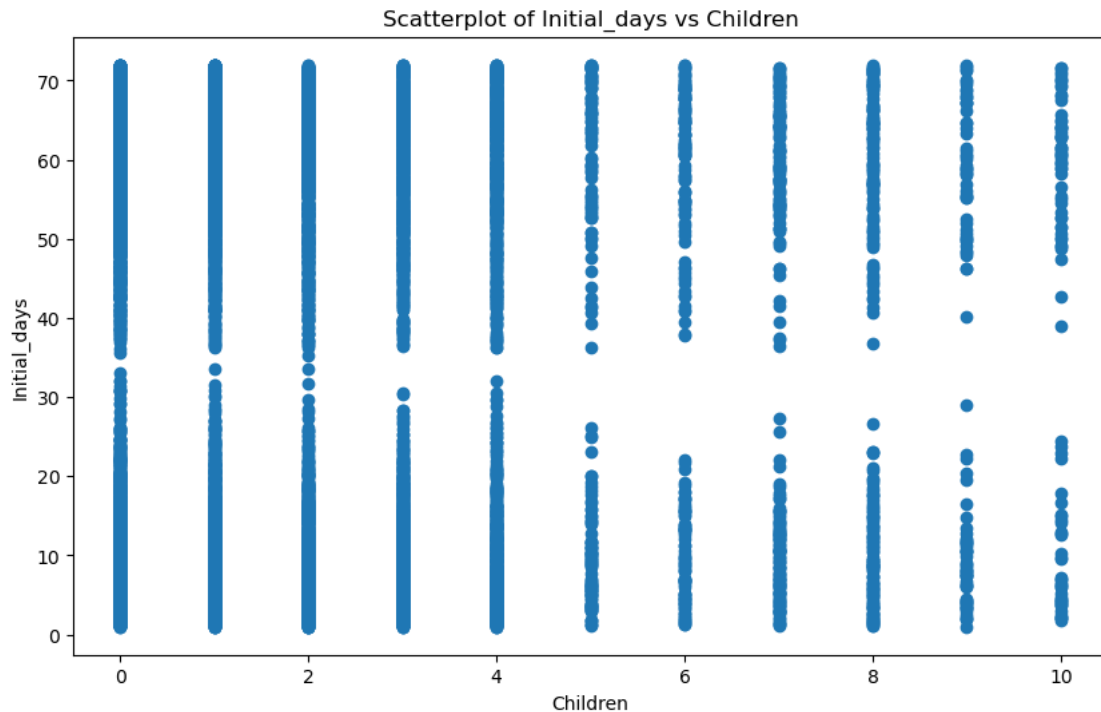












C4. Data Transformation Goals

Before statistical analysis can take place, the data will need a review. The first step is to check for missing/null values and verifying none exist. We also check if any duplicated data exists and handle it accordingly. The majority of the columns identified as not providing any benefit to this particular analysis were patient location based and thus needed to be dropped. Several column names such as Item1 through Item8 will be renamed to provide clarity during analysis. Lastly, we need to convert categorical variables to numerical types. Any columns with Yes/No values or Low, Medium, and High, will be converted to numerical along with using the drop-one method:

```
[71]: %matplotlib inline
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy import stats
data=pd.read_csv('medical_clean.csv')
print(data.head())
print(data.columns)

#check for missing/null values
print(data.isnull().sum())

#check for duplicate values of any rows
print(data.duplicated().any())
```

```

# Check for duplicate values based on customer_id unique key
print(data.duplicated('Customer_id').any())

# remove unused columns
data.drop(['CaseOrder', 'Customer_id', 'Interaction', 'UID', 'City', 'Children',
↪ 'Income', 'Marital', 'State', 'County', 'Zip', 'Lat', 'Lng', 'Population',
↪ 'Area', 'TimeZone', 'Job', 'Gender'], axis=1, inplace=True)
print(data.head())
print(data.columns)
print(data.info())

# rename unclear survey response columns
survey_col_names = {
    'Item1': 'Timely_admis',
    'Item2': 'Timely_treat',
    'Item3': 'Timely_visits',
    'Item4': 'Reliability',
    'Item5': 'Options',
    'Item6': 'Hours_treat',
    'Item7': 'Courteous_staff',
    'Item8': 'Active_listening'
}

data = data.rename(columns=survey_col_names)

categorical_cols = ['ReAdmis', 'Complication_risk', 'Initial_admin', 'Services',
↪ 'Overweight', 'Anxiety', 'Arthritis', 'Asthma',
↪ 'Soft_drink',
↪ 'Diabetes', 'Allergic_rhinitis', 'BackPain', 'Stroke',
↪ 'HighBlood',
↪ 'Hyperlipidemia', 'Reflux_esophagitis']

# dummy variables
data = pd.get_dummies(data, columns=categorical_cols, drop_first=True)

print(data.info())

print(data.head())

# display all columns
pd.set_option('display.max_columns', None)
# display all the rows
pd.set_option('display.max_rows', None)

print(data.describe(include='all'))
print(data.columns)

```

	CaseOrder	Customer_id	Interaction	\
0	1	C412403	8cd49b13-f45a-4b47-a2bd-173ffa932c2f	
1	2	Z919181	d2450b70-0337-4406-bdbb-bc1037f1734c	
2	3	F995323	a2057123-abf5-4a2c-abad-8ffe33512562	
3	4	A879973	1dec528d-eb34-4079-adce-0d7a40e82205	
4	5	C544523	5885f56b-d6da-43a3-8760-83583af94266	

	UID	City	State	County	Zip	\
0	3a83ddb66e2ae73798bdf1d705dc0932	Eva	AL	Morgan	35621	
1	176354c5eef714957d486009feabf195	Marianna	FL	Jackson	32446	
2	e19a0fa00aeda885b8a436757e889bc9	Sioux Falls	SD	Minnehaha	57110	
3	cd17d7b6d152cb6f23957346d11c3f07	New Richland	MN	Waseca	56072	
4	d2f0425877b10ed6bb381f3e2579424a	West Point	VA	King William	23181	

	Lat	Lng	Population	Area	TimeZone	\
0	34.34960	-86.72508	2951	Suburban	America/Chicago	
1	30.84513	-85.22907	11303	Urban	America/Chicago	
2	43.54321	-96.63772	17125	Suburban	America/Chicago	
3	43.89744	-93.51479	2162	Suburban	America/Chicago	
4	37.59894	-76.88958	5287	Rural	America/New_York	

	Job	Children	Age	Income	Marital	\
0	Psychologist, sport and exercise	1	53	86575.93	Divorced	
1	Community development worker	3	51	46805.99	Married	
2	Chief Executive Officer	3	53	14370.14	Widowed	
3	Early years teacher	0	78	39741.49	Married	
4	Health promotion specialist	1	22	1209.56	Widowed	

	Gender	ReAdmis	VitD_levels	Doc_visits	Full_meals_eaten	vitD_supp	\
0	Male	No	19.141466	6	0	0	
1	Female	No	18.940352	4	2	1	
2	Female	No	18.057507	4	1	0	
3	Male	No	16.576858	4	1	0	
4	Female	No	17.439069	5	0	2	

	Soft_drink	Initial_admin	HighBlood	Stroke	Complication_risk	\
0	No	Emergency Admission	Yes	No	Medium	
1	No	Emergency Admission	Yes	No	High	
2	No	Elective Admission	Yes	No	Medium	
3	No	Elective Admission	No	Yes	Medium	
4	Yes	Elective Admission	No	No	Low	

	Overweight	Arthritis	Diabetes	Hyperlipidemia	BackPain	Anxiety	\
0	No	Yes	Yes	No	Yes	Yes	
1	Yes	No	No	No	No	No	
2	Yes	No	Yes	No	No	No	
3	No	Yes	No	No	No	No	
4	No	No	No	Yes	No	No	

	Allergic_rhinitis	Reflux_esophagitis	Asthma	Services	Initial_days	\
0	Yes	No	Yes	Blood Work	10.585770	
1	No	Yes	No	Intravenous	15.129562	
2	No	No	No	Blood Work	4.772177	
3	No	Yes	Yes	Blood Work	1.714879	
4	Yes	No	No	CT Scan	1.254807	

	TotalCharge	Additional_charges	Item1	Item2	Item3	Item4	Item5	Item6	\
0	3726.702860	17939.403420	3	3	2	2	4	3	
1	4193.190458	17612.998120	3	4	3	4	4	4	
2	2434.234222	17505.192460	2	4	4	4	3	4	
3	2127.830423	12993.437350	3	5	5	3	4	5	
4	2113.073274	3716.525786	2	1	3	3	5	3	

	Item7	Item8
0	3	4
1	3	3
2	3	3
3	5	5
4	4	3

```
Index(['CaseOrder', 'Customer_id', 'Interaction', 'UID', 'City', 'State',
      'County', 'Zip', 'Lat', 'Lng', 'Population', 'Area', 'TimeZone', 'Job',
      'Children', 'Age', 'Income', 'Marital', 'Gender', 'ReAdmis',
      'VitD_levels', 'Doc_visits', 'Full_meals_eaten', 'vitD_supp',
      'Soft_drink', 'Initial_admin', 'HighBlood', 'Stroke',
      'Complication_risk', 'Overweight', 'Arthritis', 'Diabetes',
      'Hyperlipidemia', 'BackPain', 'Anxiety', 'Allergic_rhinitis',
      'Reflux_esophagitis', 'Asthma', 'Services', 'Initial_days',
      'TotalCharge', 'Additional_charges', 'Item1', 'Item2', 'Item3', 'Item4',
      'Item5', 'Item6', 'Item7', 'Item8'],
      dtype='object')
```

CaseOrder	0
Customer_id	0
Interaction	0
UID	0
City	0
State	0
County	0
Zip	0
Lat	0
Lng	0
Population	0
Area	0
TimeZone	0
Job	0
Children	0
Age	0

Income	0
Marital	0
Gender	0
ReAdmis	0
VitD_levels	0
Doc_visits	0
Full_meals_eaten	0
vitD_supp	0
Soft_drink	0
Initial_admin	0
HighBlood	0
Stroke	0
Complication_risk	0
Overweight	0
Arthritis	0
Diabetes	0
Hyperlipidemia	0
BackPain	0
Anxiety	0
Allergic_rhinitis	0
Reflux_esophagitis	0
Asthma	0
Services	0
Initial_days	0
TotalCharge	0
Additional_charges	0
Item1	0
Item2	0
Item3	0
Item4	0
Item5	0
Item6	0
Item7	0
Item8	0

dtype: int64

False

False

	Age	ReAdmis	VitD_levels	Doc_visits	Full_meals_eaten	vitD_supp	\
0	53	No	19.141466	6	0	0	
1	51	No	18.940352	4	2	1	
2	53	No	18.057507	4	1	0	
3	78	No	16.576858	4	1	0	
4	22	No	17.439069	5	0	2	

	Soft_drink	Initial_admin	HighBlood	Stroke	Complication_risk	\
0	No	Emergency Admission	Yes	No	Medium	
1	No	Emergency Admission	Yes	No	High	
2	No	Elective Admission	Yes	No	Medium	

3	No	Elective Admission	No	Yes	Medium
4	Yes	Elective Admission	No	No	Low

	Overweight	Arthritis	Diabetes	Hyperlipidemia	BackPain	Anxiety	\
0	No	Yes	Yes	No	Yes	Yes	
1	Yes	No	No	No	No	No	
2	Yes	No	Yes	No	No	No	
3	No	Yes	No	No	No	No	
4	No	No	No	Yes	No	No	

	Allergic_rhinitis	Reflux_esophagitis	Asthma	Services	Initial_days	\
0	Yes		No	Blood Work	10.585770	
1	No		Yes	Intravenous	15.129562	
2	No		No	Blood Work	4.772177	
3	No		Yes	Blood Work	1.714879	
4	Yes		No	CT Scan	1.254807	

	TotalCharge	Additional_charges	Item1	Item2	Item3	Item4	Item5	Item6	\
0	3726.702860	17939.403420	3	3	2	2	4	3	
1	4193.190458	17612.998120	3	4	3	4	4	4	
2	2434.234222	17505.192460	2	4	4	4	3	4	
3	2127.830423	12993.437350	3	5	5	3	4	5	
4	2113.073274	3716.525786	2	1	3	3	5	3	

	Item7	Item8
0	3	4
1	3	3
2	3	3
3	5	5
4	4	3

```
Index(['Age', 'ReAdmis', 'VitD_levels', 'Doc_visits', 'Full_meals_eaten',
      'vitD_supp', 'Soft_drink', 'Initial_admin', 'HighBlood', 'Stroke',
      'Complication_risk', 'Overweight', 'Arthritis', 'Diabetes',
      'Hyperlipidemia', 'BackPain', 'Anxiety', 'Allergic_rhinitis',
      'Reflux_esophagitis', 'Asthma', 'Services', 'Initial_days',
      'TotalCharge', 'Additional_charges', 'Item1', 'Item2', 'Item3', 'Item4',
      'Item5', 'Item6', 'Item7', 'Item8'],
      dtype='object')
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 10000 entries, 0 to 9999
```

```
Data columns (total 32 columns):
```

#	Column	Non-Null Count	Dtype
---	-----	-----	-----
0	Age	10000 non-null	int64
1	ReAdmis	10000 non-null	object
2	VitD_levels	10000 non-null	float64
3	Doc_visits	10000 non-null	int64
4	Full_meals_eaten	10000 non-null	int64

```

5   vitD_supp          10000 non-null int64
6   Soft_drink         10000 non-null object
7   Initial_admin      10000 non-null object
8   HighBlood          10000 non-null object
9   Stroke             10000 non-null object
10  Complication_risk  10000 non-null object
11  Overweight         10000 non-null object
12  Arthritis          10000 non-null object
13  Diabetes           10000 non-null object
14  Hyperlipidemia     10000 non-null object
15  BackPain           10000 non-null object
16  Anxiety            10000 non-null object
17  Allergic_rhinitis  10000 non-null object
18  Reflux_esophagitis 10000 non-null object
19  Asthma             10000 non-null object
20  Services           10000 non-null object
21  Initial_days       10000 non-null float64
22  TotalCharge        10000 non-null float64
23  Additional_charges 10000 non-null float64
24  Item1              10000 non-null int64
25  Item2              10000 non-null int64
26  Item3              10000 non-null int64
27  Item4              10000 non-null int64
28  Item5              10000 non-null int64
29  Item6              10000 non-null int64
30  Item7              10000 non-null int64
31  Item8              10000 non-null int64
dtypes: float64(4), int64(12), object(16)
memory usage: 2.4+ MB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 36 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Age                                   10000 non-null  int64
1   VitD_levels                          10000 non-null  float64
2   Doc_visits                           10000 non-null  int64
3   Full_meals_eaten                     10000 non-null  int64
4   vitD_supp                            10000 non-null  int64
5   Initial_days                         10000 non-null  float64
6   TotalCharge                          10000 non-null  float64
7   Additional_charges                   10000 non-null  float64
8   Timely_admis                         10000 non-null  int64
9   Timely_treat                         10000 non-null  int64
10  Timely_visits                        10000 non-null  int64
11  Reliability                          10000 non-null  int64
12  Options                             10000 non-null  int64

```

13	Hours_treat	10000	non-null	int64
14	Courteous_staff	10000	non-null	int64
15	Active_listening	10000	non-null	int64
16	ReAdmis_Yes	10000	non-null	uint8
17	Complication_risk_Low	10000	non-null	uint8
18	Complication_risk_Medium	10000	non-null	uint8
19	Initial_admin_Emergency Admission	10000	non-null	uint8
20	Initial_admin_Observation Admission	10000	non-null	uint8
21	Services_CT Scan	10000	non-null	uint8
22	Services_Intravenous	10000	non-null	uint8
23	Services_MRI	10000	non-null	uint8
24	Overweight_Yes	10000	non-null	uint8
25	Anxiety_Yes	10000	non-null	uint8
26	Arthritis_Yes	10000	non-null	uint8
27	Asthma_Yes	10000	non-null	uint8
28	Soft_drink_Yes	10000	non-null	uint8
29	Diabetes_Yes	10000	non-null	uint8
30	Allergic_rhinitis_Yes	10000	non-null	uint8
31	BackPain_Yes	10000	non-null	uint8
32	Stroke_Yes	10000	non-null	uint8
33	HighBlood_Yes	10000	non-null	uint8
34	Hyperlipidemia_Yes	10000	non-null	uint8
35	Reflux_esophagitis_Yes	10000	non-null	uint8

dtypes: float64(4), int64(12), uint8(20)

memory usage: 1.4 MB

None

	Age	VitD_levels	Doc_visits	Full_meals_eaten	vitD_supp	Initial_days	\
0	53	19.141466	6	0	0	10.585770	
1	51	18.940352	4	2	1	15.129562	
2	53	18.057507	4	1	0	4.772177	
3	78	16.576858	4	1	0	1.714879	
4	22	17.439069	5	0	2	1.254807	

	TotalCharge	Additional_charges	Timely_admis	Timely_treat	Timely_visits	\
0	3726.702860	17939.403420	3	3	2	
1	4193.190458	17612.998120	3	4	3	
2	2434.234222	17505.192460	2	4	4	
3	2127.830423	12993.437350	3	5	5	
4	2113.073274	3716.525786	2	1	3	

	Reliability	Options	Hours_treat	Courteous_staff	Active_listening	\
0	2	4	3	3	4	
1	4	4	4	3	3	
2	4	3	4	3	3	
3	3	4	5	5	5	
4	3	5	3	4	3	

	ReAdmis_Yes	Complication_risk_Low	Complication_risk_Medium	\
--	-------------	-----------------------	--------------------------	---

0	0	0	1
1	0	0	0
2	0	0	1
3	0	0	1
4	0	1	0

	Initial_admin_Emergency Admission	Initial_admin_Observation Admission	\
0	1		0
1	1		0
2	0		0
3	0		0
4	0		0

	Services_CT Scan	Services_Intravenous	Services_MRI	Overweight_Yes	\
0	0	0	0	0	
1	0	1	0	1	
2	0	0	0	1	
3	0	0	0	0	
4	1	0	0	0	

	Anxiety_Yes	Arthritis_Yes	Asthma_Yes	Soft_drink_Yes	Diabetes_Yes	\
0	1	1	1	0	1	
1	0	0	0	0	0	
2	0	0	0	0	1	
3	0	1	1	0	0	
4	0	0	0	1	0	

	Allergic_rhinitis_Yes	BackPain_Yes	Stroke_Yes	HighBlood_Yes	\
0		1	1	0	1
1		0	0	0	1
2		0	0	0	1
3		0	0	1	0
4		1	0	0	0

	Hyperlipidemia_Yes	Reflux_esophagitis_Yes
0	0	0
1	0	1
2	0	0
3	0	1
4	1	0

	Age	VitD_levels	Doc_visits	Full_meals_eaten	\
count	10000.000000	10000.000000	10000.000000	10000.000000	
mean	53.511700	17.964262	5.012200	1.001400	
std	20.638538	2.017231	1.045734	1.008117	
min	18.000000	9.806483	1.000000	0.000000	
25%	36.000000	16.626439	4.000000	0.000000	
50%	53.000000	17.951122	5.000000	1.000000	
75%	71.000000	19.347963	6.000000	2.000000	

max	89.000000	26.394449	9.000000	7.000000
-----	-----------	-----------	----------	----------

	vitD_supp	Initial_days	TotalCharge	Additional_charges \
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	0.398900	34.455299	5312.172769	12934.528587
std	0.628505	26.309341	2180.393838	6542.601544
min	0.000000	1.001981	1938.312067	3125.703000
25%	0.000000	7.896215	3179.374015	7986.487755
50%	0.000000	35.836244	5213.952000	11573.977735
75%	1.000000	61.161020	7459.699750	15626.490000
max	5.000000	71.981490	9180.728000	30566.070000

	Timely_admis	Timely_treat	Timely_visits	Reliability	Options \
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	3.518800	3.506700	3.511100	3.515100	3.496900
std	1.031966	1.034825	1.032755	1.036282	1.030192
min	1.000000	1.000000	1.000000	1.000000	1.000000
25%	3.000000	3.000000	3.000000	3.000000	3.000000
50%	4.000000	3.000000	4.000000	4.000000	3.000000
75%	4.000000	4.000000	4.000000	4.000000	4.000000
max	8.000000	7.000000	8.000000	7.000000	7.000000

	Hours_treat	Courteous_staff	Active_listening	ReAdmis_Yes \
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	3.522500	3.494000	3.509700	0.366900
std	1.032376	1.021405	1.042312	0.481983
min	1.000000	1.000000	1.000000	0.000000
25%	3.000000	3.000000	3.000000	0.000000
50%	4.000000	3.000000	3.000000	0.000000
75%	4.000000	4.000000	4.000000	1.000000
max	7.000000	7.000000	7.000000	1.000000

	Complication_risk_Low	Complication_risk_Medium \
count	10000.000000	10000.000000
mean	0.212500	0.451700
std	0.409097	0.497687
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	1.000000
max	1.000000	1.000000

	Initial_admin_Emergency Admission	Initial_admin_Observation Admission \
count	10000.000000	10000.000000
mean	0.506000	0.243600
std	0.499989	0.429276
min	0.000000	0.000000
25%	0.000000	0.000000

50%	1.000000	0.000000
75%	1.000000	0.000000
max	1.000000	1.000000

	Services_CT Scan	Services_Intravenous	Services_MRI	Overweight_Yes \
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	0.122500	0.313000	0.038000	0.709400
std	0.327879	0.463738	0.191206	0.454062
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	1.000000
75%	0.000000	1.000000	0.000000	1.000000
max	1.000000	1.000000	1.000000	1.000000

	Anxiety_Yes	Arthritis_Yes	Asthma_Yes	Soft_drink_Yes	Diabetes_Yes \
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	0.321500	0.357400	0.28930	0.257500	0.27380
std	0.467076	0.479258	0.45346	0.437279	0.44593
min	0.000000	0.000000	0.00000	0.000000	0.00000
25%	0.000000	0.000000	0.00000	0.000000	0.00000
50%	0.000000	0.000000	0.00000	0.000000	0.00000
75%	1.000000	1.000000	1.00000	1.000000	1.00000
max	1.000000	1.000000	1.00000	1.000000	1.00000

	Allergic_rhinitis_Yes	BackPain_Yes	Stroke_Yes	HighBlood_Yes \
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	0.394100	0.411400	0.199300	0.409000
std	0.488681	0.492112	0.399494	0.491674
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	1.000000	1.000000	0.000000	1.000000
max	1.000000	1.000000	1.000000	1.000000

	Hyperlipidemia_Yes	Reflux_esophagitis_Yes
count	10000.000000	10000.000000
mean	0.337200	0.413500
std	0.472777	0.492486
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	1.000000	1.000000
max	1.000000	1.000000

```
Index(['Age', 'VitD_levels', 'Doc_visits', 'Full_meals_eaten', 'vitD_supp',
      'Initial_days', 'TotalCharge', 'Additional_charges', 'Timely_admis',
      'Timely_treat', 'Timely_visits', 'Reliability', 'Options',
      'Hours_treat', 'Courteous_staff', 'Active_listening', 'ReAdmis_Yes',
      'Complication_risk_Low', 'Complication_risk_Medium',
```



```

'Initial_admin_Emergency Admission',
'Initial_admin_Observation Admission', 'Services_CT Scan',
'Services_Intravenous', 'Services_MRI', 'Overweight_Yes', 'Anxiety_Yes',
'Arthritis_Yes', 'Asthma_Yes', 'Soft_drink_Yes', 'Diabetes_Yes',
'Allergic_rhinitis_Yes', 'BackPain_Yes', 'Stroke_Yes', 'HighBlood_Yes',
'Hyperlipidemia_Yes', 'Reflux_esophagitis_Yes'],
dtype='object')

```

C5. Prepared Data CSV Attached prepared data csv as: prepared-data.csv

```
[4]: data.to_csv('prepared-data.csv')
```

D. Model Comparison and Analysis

The initial regression model will be run on the predictor variables mentioned above, and compared with the Initial_days variable as the target. Observations removed from the initial model were minor patient demographics (Marital, Gender) and some small medical observations such as VitD_levels and vitD_supp. The OLS Regression results can be found in the codeblock below with further analysis continued:

```
[5]: import statsmodels.api as sm

columns = ['Age', 'Doc_visits', 'Full_meals_eaten',
           'Initial_days', 'TotalCharge', 'Additional_charges', 'Timely_admis',
           'Timely_treat', 'Timely_visits', 'Reliability', 'Options',
           'Hours_treat', 'Courteous_staff', 'Active_listening', 'ReAdmis_Yes',
           'Complication_risk_Low', 'Complication_risk_Medium',
           'Initial_admin_Emergency Admission',
           'Initial_admin_Observation Admission', 'Services_CT Scan',
           'Services_Intravenous', 'Services_MRI', 'Overweight_Yes', 'Anxiety_Yes',
           'Arthritis_Yes', 'Asthma_Yes', 'Diabetes_Yes',
           'Allergic_rhinitis_Yes', 'BackPain_Yes', 'Stroke_Yes', 'HighBlood_Yes',
           'Hyperlipidemia_Yes', 'Reflux_esophagitis_Yes']

data = data[columns]

X = data.drop('Initial_days', axis=1)
X = sm.add_constant(X)

# our dependent variable
y = data['Initial_days']

# initial ols model
model = sm.OLS(y, X).fit()

# summary of the initial model
print(model.summary())

```

OLS Regression Results

=====

Dep. Variable:	Initial_days	R-squared:	1.000
Model:	OLS	Adj. R-squared:	1.000
Method:	Least Squares	F-statistic:	2.116e+16
Date:	Tue, 09 Jan 2024	Prob (F-statistic):	0.00
Time:	23:27:30	Log-Likelihood:	1.1236e+05
No. Observations:	10000	AIC:	-2.247e+05
Df Residuals:	9967	BIC:	-2.244e+05
Df Model:	32		
Covariance Type:	nonrobust		

		coef	std err	t	P> t
[0.025 0.975]					

const		-27.6939	3.74e-07	-7.41e+07	0.000
-27.694	-27.694				
Age		6.291e-09	4.71e-09	1.335	0.182
-2.94e-09	1.55e-08				
Doc_visits		1.232e-08	3.06e-08	0.402	0.688
-4.77e-08	7.24e-08				
Full_meals_eaten		-4.278e-08	3.18e-08	-1.347	0.178
-1.05e-07	1.95e-08				
TotalCharge		0.0122	2.84e-11	4.3e+08	0.000
0.012	0.012				
Additional_charges		-3.336e-11	1.97e-11	-1.692	0.091
-7.2e-11	5.28e-12				
Timely_admis		-3.225e-09	4.61e-08	-0.070	0.944
-9.36e-08	8.71e-08				
Timely_treat		-6.709e-08	4.25e-08	-1.578	0.115
-1.5e-07	1.63e-08				
Timely_visits		5.85e-08	3.93e-08	1.490	0.136
-1.84e-08	1.35e-07				
Reliability		-2.642e-09	3.5e-08	-0.076	0.940
-7.12e-08	6.59e-08				
Options		3.107e-08	3.68e-08	0.844	0.399
-4.11e-08	1.03e-07				
Hours_treat		1.482e-08	3.8e-08	0.390	0.697
-5.97e-08	8.93e-08				
Courteous_staff		-1.456e-08	3.58e-08	-0.407	0.684
-8.48e-08	5.56e-08				
Active_listening		5.151e-09	3.37e-08	0.153	0.879
-6.09e-08	7.12e-08				
ReAdmis_Yes		1.777e-07	1.27e-07	1.402	0.161
-7.08e-08	4.26e-07				
Complication_risk_Low		5.0464	8.99e-08	5.61e+07	0.000
5.046	5.046				
Complication_risk_Medium		5.0464	7.44e-08	6.78e+07	0.000

5.046	5.046				
Initial_admin_Emergency Admission	-6.2526	7.95e-08	-7.87e+07	0.000	
-6.253	-6.253				
Initial_admin_Observation Admission	1.235e-08	9.12e-08	0.135	0.892	
-1.66e-07	1.91e-07				
Services_CT Scan	2.916e-08	1.02e-07	0.287	0.774	
-1.7e-07	2.28e-07				
Services_Intravenous	5.913e-08	7.23e-08	0.818	0.413	
-8.25e-08	2.01e-07				
Services_MRI	1.424e-07	1.7e-07	0.838	0.402	
-1.91e-07	4.76e-07				
Overweight_Yes	4.336e-09	7.05e-08	0.061	0.951	
-1.34e-07	1.43e-07				
Anxiety_Yes	-1.0510	6.86e-08	-1.53e+07	0.000	
-1.051	-1.051				
Arthritis_Yes	-0.8781	6.69e-08	-1.31e+07	0.000	
-0.878	-0.878				
Asthma_Yes	-4.627e-08	7.06e-08	-0.655	0.512	
-1.85e-07	9.22e-08				
Diabetes_Yes	-0.9178	7.19e-08	-1.28e+07	0.000	
-0.918	-0.918				
Allergic_rhinitis_Yes	-0.7394	6.56e-08	-1.13e+07	0.000	
-0.739	-0.739				
BackPain_Yes	-1.0392	6.52e-08	-1.59e+07	0.000	
-1.039	-1.039				
Stroke_Yes	3.639e-08	8.04e-08	0.452	0.651	
-1.21e-07	1.94e-07				
HighBlood_Yes	-1.3708	1.82e-07	-7.52e+06	0.000	
-1.371	-1.371				
Hyperlipidemia_Yes	-1.1471	6.78e-08	-1.69e+07	0.000	
-1.147	-1.147				
Reflux_esophagitis_Yes	-0.7284	6.51e-08	-1.12e+07	0.000	
-0.728	-0.728				
=====					
Omnibus:	405.752	Durbin-Watson:	1.985		
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1309.867		
Skew:	0.013	Prob(JB):	3.68e-285		
Kurtosis:	4.773	Cond. No.	1.81e+05		
=====					

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.81e+05. This might indicate that there are strong multicollinearity or other numerical problems.

Based on the above OLS regression output we find the initial model equation:

$$\hat{Y} = -27.6939 + (6.291e-9 * \text{Age}) + (1.232e-8 * \text{Doc_visits}) - (4.278e-8 * \text{Full_meals_eaten})$$

+ 0.0122 * TotalCharge - (3.336e-11 * Additional_charges) - (3.225e-9 * Timely_admis) - (6.709e-8 * Timely_treat) + (5.85e-8 * Timely_visits) - (2.642e-9 * Reliability) + (3.107e-8 * Options) + (1.482e-8 * Hours_treat) - (1.456e-8 * Courteous_staff) + (5.151e-9 * Active_listening) + (1.777e-7 * ReAdmis_Yes) + 5.0464 * Complication_risk_Low + 5.0464 * Complication_risk_Medium - 6.2526 * Initial_admin_Emergency_Admission + (1.235e-8 * Initial_admin_Observation_Admission) + (2.916e-8 * Services_CT_Scan) + (5.913e-8 * Services_Intravenous) + (1.424e-7 * Services_MRI) + (4.336e-9 * Overweight_Yes) - 1.0510 * Anxiety_Yes - 0.8781 * Arthritis_Yes - (4.627e-8 * Asthma_Yes) - 0.9178 * Diabetes_Yes - 0.7394 * Allergic_rhinitis_Yes - 1.0392 * BackPain_Yes + (3.639e-8 * Stroke_Yes) - 1.3708 * HighBlood_Yes - 1.1471 * Hyperlipidemia_Yes - 0.7284 * Reflux_esophagitis_Yes

The initial model had an R-squared value of 1.00 which means 100% of the variation can be explained by this model. As mentioned in Dr.Middleton's Webinar, the Prob (F-statistic) value being 0.00 typically indicates that the regression model is statistically significant. The model above also tells us the condition number is large at 1.81e+05, this may indicate strong multicollinearity. To find where there may be multicollinearity, a correlation matrix and heatmap will be used. By using these tools, we can further narrow our model down.

D2. Model Evaluation Metric

We will first generate a correlation matrix of our independent variables. Then we will create a heatmap of these values along with our dependent variable. Lastly for each independent variable we will get there variance inflation factors and their p-values. These strategies will help with narrowing our model down further:

```
[9]: from statsmodels.stats.outliers_influence import variance_inflation_factor
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd
import statsmodels.api as sm

data1 = pd.read_csv('prepared-data.csv')
pd.set_option('display.max_columns', None)

columns = ['Age', 'Doc_visits', 'Full_meals_eaten', 'Initial_days',
           'TotalCharge', 'Additional_charges', 'Timely_admis', 'Timely_treat',
           'Timely_visits', 'Reliability', 'Options', 'Hours_treat',
           'Courteous_staff', 'Active_listening', 'ReAdmis_Yes',
           'Complication_risk_Low', 'Complication_risk_Medium',
           'Initial_admin_Emergency Admission', 'Initial_admin_Observation_
↪ Admission',
           'Services_CT Scan', 'Services_Intravenous', 'Services_MRI',
           'Overweight_Yes', 'Anxiety_Yes', 'Arthritis_Yes', 'Asthma_Yes',
           'Diabetes_Yes', 'Allergic_rhinitis_Yes', 'BackPain_Yes',
↪ 'Stroke_Yes',
           'HighBlood_Yes', 'Hyperlipidemia_Yes', 'Reflux_esophagitis_Yes']

data1 = data1[columns]
```

```
X = data1.drop('Initial_days', axis=1)
```

```
X_with_target = data1
```

```
correlation_matrix = X.corr()
```

```
print(correlation_matrix)
```

	Age	Doc_visits	Full_meals_eaten	\
Age	1.000000	0.006898	0.008555	
Doc_visits	0.006898	1.000000	-0.002767	
Full_meals_eaten	0.008555	-0.002767	1.000000	
TotalCharge	0.016876	-0.005043	-0.014306	
Additional_charges	0.716854	0.008072	0.018763	
Timely_admis	0.005552	0.003680	0.003724	
Timely_treat	0.003967	0.006024	-0.002022	
Timely_visits	0.004709	-0.002718	0.008246	
Reliability	0.003377	-0.006538	-0.009019	
Options	-0.008827	-0.009434	0.009538	
Hours_treat	-0.002087	0.012530	0.004294	
Courteous_staff	0.009423	0.008589	0.004087	
Active_listening	-0.003367	0.004571	-0.018382	
ReAdmis_Yes	0.015810	0.000246	-0.012172	
Complication_risk_Low	0.001085	-0.006061	-0.012119	
Complication_risk_Medium	-0.006021	-0.008091	-0.003254	
Initial_admin_Emergency Admission	-0.004538	0.003686	0.006333	
Initial_admin_Observation Admission	-0.008336	0.015658	0.004527	
Services_CT Scan	0.009506	0.014600	-0.002939	
Services_Intravenous	0.004142	-0.008700	0.016177	
Services_MRI	0.008529	-0.012822	-0.018954	
Overweight_Yes	-0.008292	0.011890	-0.008287	
Anxiety_Yes	0.006130	-0.001684	0.008602	
Arthritis_Yes	0.007110	-0.000719	0.011591	
Asthma_Yes	0.009229	-0.017989	0.012459	
Diabetes_Yes	0.003694	0.012781	0.009603	
Allergic_rhinitis_Yes	0.012092	0.002920	0.015120	
BackPain_Yes	0.021081	0.008514	-0.015676	
Stroke_Yes	0.012035	-0.002230	0.002784	
HighBlood_Yes	0.007147	0.008967	0.014784	
Hyperlipidemia_Yes	0.003736	-0.026730	0.000688	
Reflux_esophagitis_Yes	-0.019609	-0.005330	-0.000562	

	TotalCharge	Additional_charges	\
Age	0.016876	0.716854	
Doc_visits	-0.005043	0.008072	
Full_meals_eaten	-0.014306	0.018763	
TotalCharge	1.000000	0.029256	
Additional_charges	0.029256	1.000000	
Timely_admis	-0.019706	0.002423	

Timely_treat	-0.006055	0.002815
Timely_visits	-0.009051	-0.004422
Reliability	-0.010318	-0.000771
Options	0.003532	-0.014323
Hours_treat	-0.010480	-0.000448
Courteous_staff	0.004556	0.015209
Active_listening	-0.008250	-0.000467
ReAdmis_Yes	0.843726	0.013620
Complication_risk_Low	-0.013344	-0.035234
Complication_risk_Medium	-0.068781	-0.009418
Initial_admin_Emergency Admission	0.106985	0.034762
Initial_admin_Observation Admission	-0.066870	-0.029231
Services_CT Scan	0.010561	0.013137
Services_Intravenous	-0.016170	-0.001095
Services_MRI	0.007341	0.010134
Overweight_Yes	-0.012782	0.012771
Anxiety_Yes	0.031199	0.011666
Arthritis_Yes	0.032932	0.004788
Asthma_Yes	-0.014290	0.014083
Diabetes_Yes	0.011524	0.002450
Allergic_rhinitis_Yes	0.018919	0.016154
BackPain_Yes	0.035828	0.014245
Stroke_Yes	-0.003694	0.035140
HighBlood_Yes	0.019910	0.654316
Hyperlipidemia_Yes	0.017565	-0.002475
Reflux_esophagitis_Yes	0.026284	-0.011405

	Timely_admis	Timely_treat \
Age	0.005552	0.003967
Doc_visits	0.003680	0.006024
Full_meals_eaten	0.003724	-0.002022
TotalCharge	-0.019706	-0.006055
Additional_charges	0.002423	0.002815
Timely_admis	1.000000	0.655578
Timely_treat	0.655578	1.000000
Timely_visits	0.579585	0.521728
Reliability	-0.004614	0.003077
Options	-0.000368	-0.010018
Hours_treat	0.421233	0.366075
Courteous_staff	0.332855	0.291039
Active_listening	0.278067	0.242962
ReAdmis_Yes	-0.016785	-0.002423
Complication_risk_Low	-0.011477	-0.000883
Complication_risk_Medium	0.000697	0.001405
Initial_admin_Emergency Admission	0.011605	0.015289
Initial_admin_Observation Admission	-0.015080	-0.012455
Services_CT Scan	-0.012275	-0.005809
Services_Intravenous	-0.012715	-0.013123

Services_MRI	0.002968	0.006800
Overweight_Yes	0.002056	-0.001177
Anxiety_Yes	-0.007458	-0.009733
Arthritis_Yes	-0.008532	-0.012492
Asthma_Yes	-0.011303	-0.007648
Diabetes_Yes	0.013806	0.005994
Allergic_rhinitis_Yes	0.009402	0.014654
BackPain_Yes	-0.011687	-0.005413
Stroke_Yes	0.001948	-0.007706
HighBlood_Yes	-0.011017	-0.007745
Hyperlipidemia_Yes	0.019393	0.000697
Reflux_esophagitis_Yes	0.011367	0.017425

	Timely_visits	Reliability	Options \
Age	0.004709	0.003377	-0.008827
Doc_visits	-0.002718	-0.006538	-0.009434
Full_meals_eaten	0.008246	-0.009019	0.009538
TotalCharge	-0.009051	-0.010318	0.003532
Additional_charges	-0.004422	-0.000771	-0.014323
Timely_admis	0.579585	-0.004614	-0.000368
Timely_treat	0.521728	0.003077	-0.010018
Timely_visits	1.000000	-0.006324	-0.010496
Reliability	-0.006324	1.000000	-0.447372
Options	-0.010496	-0.447372	1.000000
Hours_treat	0.312874	0.235444	-0.310154
Courteous_staff	0.252302	0.192223	-0.268186
Active_listening	0.209498	0.161528	-0.229557
ReAdmis_Yes	-0.011699	-0.001983	0.005614
Complication_risk_Low	-0.023929	-0.010047	0.009038
Complication_risk_Medium	0.008826	-0.001688	0.011217
Initial_admin_Emergency Admission	0.012944	-0.002974	0.015472
Initial_admin_Observation Admission	-0.017605	0.002297	-0.024299
Services_CT Scan	-0.018045	-0.011773	0.017853
Services_Intravenous	-0.019993	0.002651	-0.012204
Services_MRI	0.012045	-0.004915	0.014307
Overweight_Yes	-0.002505	-0.003001	0.005771
Anxiety_Yes	-0.004807	0.005363	-0.016946
Arthritis_Yes	-0.020948	0.001416	0.002447
Asthma_Yes	0.000296	-0.004721	0.019796
Diabetes_Yes	-0.007469	-0.005052	0.017958
Allergic_rhinitis_Yes	0.001140	-0.007704	-0.004029
BackPain_Yes	-0.015480	0.012723	0.006659
Stroke_Yes	0.001304	-0.013430	0.005025
HighBlood_Yes	-0.015244	-0.004075	-0.013292
Hyperlipidemia_Yes	0.018551	0.020022	-0.009352
Reflux_esophagitis_Yes	-0.005584	0.016277	-0.011764

Hours_treat Courteous_staff \

Age	-0.002087	0.009423
Doc_visits	0.012530	0.008589
Full_meals_eaten	0.004294	0.004087
TotalCharge	-0.010480	0.004556
Additional_charges	-0.000448	0.015209
Timely_admis	0.421233	0.332855
Timely_treat	0.366075	0.291039
Timely_visits	0.312874	0.252302
Reliability	0.235444	0.192223
Options	-0.310154	-0.268186
Hours_treat	1.000000	0.377368
Courteous_staff	0.377368	1.000000
Active_listening	0.319886	0.274499
ReAdmis_Yes	-0.016894	-0.004974
Complication_risk_Low	-0.004100	0.002932
Complication_risk_Medium	0.008344	-0.020342
Initial_admin_Emergency Admission	0.017467	0.013583
Initial_admin_Observation Admission	-0.008758	-0.014229
Services_CT Scan	-0.025723	-0.018858
Services_Intravenous	0.008058	-0.009126
Services_MRI	-0.010412	-0.006002
Overweight_Yes	-0.003118	-0.009151
Anxiety_Yes	-0.002248	0.003520
Arthritis_Yes	-0.018074	-0.008286
Asthma_Yes	-0.009740	-0.013202
Diabetes_Yes	-0.004259	-0.004737
Allergic_rhinitis_Yes	-0.012721	0.008445
BackPain_Yes	-0.016056	-0.015781
Stroke_Yes	0.004282	-0.005280
HighBlood_Yes	-0.002369	0.007277
Hyperlipidemia_Yes	0.017648	0.016202
Reflux_esophagitis_Yes	0.009729	-0.013657

	Active_listening	ReAdmis_Yes \
Age	-0.003367	0.015810
Doc_visits	0.004571	0.000246
Full_meals_eaten	-0.018382	-0.012172
TotalCharge	-0.008250	0.843726
Additional_charges	-0.000467	0.013620
Timely_admis	0.278067	-0.016785
Timely_treat	0.242962	-0.002423
Timely_visits	0.209498	-0.011699
Reliability	0.161528	-0.001983
Options	-0.229557	0.005614
Hours_treat	0.319886	-0.016894
Courteous_staff	0.274499	-0.004974
Active_listening	1.000000	-0.016740
ReAdmis_Yes	-0.016740	1.000000

Complication_risk_Low	-0.007297	0.001186
Complication_risk_Medium	0.000518	0.002799
Initial_admin_Emergency Admission	-0.008268	0.019707
Initial_admin_Observation Admission	0.013270	-0.011972
Services_CT Scan	-0.011525	0.024395
Services_Intravenous	0.005305	-0.020313
Services_MRI	-0.006868	0.009309
Overweight_Yes	0.009549	-0.008586
Anxiety_Yes	0.014650	0.002406
Arthritis_Yes	0.002869	0.007663
Asthma_Yes	0.002209	-0.017133
Diabetes_Yes	-0.014752	-0.003058
Allergic_rhinitis_Yes	0.005355	-0.004651
BackPain_Yes	0.000213	0.013313
Stroke_Yes	0.000040	0.000918
HighBlood_Yes	0.002601	0.002270
Hyperlipidemia_Yes	-0.001970	0.004307
Reflux_esophagitis_Yes	-0.003236	0.005422

	Complication_risk_Low \
Age	0.001085
Doc_visits	-0.006061
Full_meals_eaten	-0.012119
TotalCharge	-0.013344
Additional_charges	-0.035234
Timely_admis	-0.011477
Timely_treat	-0.000883
Timely_visits	-0.023929
Reliability	-0.010047
Options	0.009038
Hours_treat	-0.004100
Courteous_staff	0.002932
Active_listening	-0.007297
ReAdmis_Yes	0.001186
Complication_risk_Low	1.000000
Complication_risk_Medium	-0.471487
Initial_admin_Emergency Admission	0.009168
Initial_admin_Observation Admission	-0.001509
Services_CT Scan	-0.015145
Services_Intravenous	0.002570
Services_MRI	0.004155
Overweight_Yes	-0.009947
Anxiety_Yes	-0.002192
Arthritis_Yes	0.002818
Asthma_Yes	0.003902
Diabetes_Yes	0.006675
Allergic_rhinitis_Yes	0.013276
BackPain_Yes	0.019759

Stroke_Yes	-0.001537
HighBlood_Yes	-0.027906
Hyperlipidemia_Yes	-0.005972
Reflux_esophagitis_Yes	0.000652

	Complication_risk_Medium \
Age	-0.006021
Doc_visits	-0.008091
Full_meals_eaten	-0.003254
TotalCharge	-0.068781
Additional_charges	-0.009418
Timely_admis	0.000697
Timely_treat	0.001405
Timely_visits	0.008826
Reliability	-0.001688
Options	0.011217
Hours_treat	0.008344
Courteous_staff	-0.020342
Active_listening	0.000518
ReAdmis_Yes	0.002799
Complication_risk_Low	-0.471487
Complication_risk_Medium	1.000000
Initial_admin_Emergency Admission	-0.010290
Initial_admin_Observation Admission	0.023246
Services_CT Scan	0.002861
Services_Intravenous	-0.005122
Services_MRI	0.011933
Overweight_Yes	0.018871
Anxiety_Yes	0.004640
Arthritis_Yes	0.017453
Asthma_Yes	0.006750
Diabetes_Yes	-0.001241
Allergic_rhinitis_Yes	-0.017744
BackPain_Yes	-0.009920
Stroke_Yes	0.000886
HighBlood_Yes	0.014528
Hyperlipidemia_Yes	0.010995
Reflux_esophagitis_Yes	-0.005622

	Initial_admin_Emergency Admission \
Age	-0.004538
Doc_visits	0.003686
Full_meals_eaten	0.006333
TotalCharge	0.106985
Additional_charges	0.034762
Timely_admis	0.011605
Timely_treat	0.015289
Timely_visits	0.012944

Reliability	-0.002974
Options	0.015472
Hours_treat	0.017467
Courteous_staff	0.013583
Active_listening	-0.008268
ReAdmis_Yes	0.019707
Complication_risk_Low	0.009168
Complication_risk_Medium	-0.010290
Initial_admin_Emergency Admission	1.000000
Initial_admin_Observation Admission	-0.574347
Services_CT Scan	0.007412
Services_Intravenous	-0.003787
Services_MRI	0.009122
Overweight_Yes	-0.009940
Anxiety_Yes	0.008655
Arthritis_Yes	-0.000603
Asthma_Yes	-0.005672
Diabetes_Yes	-0.008266
Allergic_rhinitis_Yes	0.006080
BackPain_Yes	0.000535
Stroke_Yes	-0.009743
HighBlood_Yes	-0.001440
Hyperlipidemia_Yes	0.018941
Reflux_esophagitis_Yes	-0.000126

	Initial_admin_Observation Admission \
Age	-0.008336
Doc_visits	0.015658
Full_meals_eaten	0.004527
TotalCharge	-0.066870
Additional_charges	-0.029231
Timely_admis	-0.015080
Timely_treat	-0.012455
Timely_visits	-0.017605
Reliability	0.002297
Options	-0.024299
Hours_treat	-0.008758
Courteous_staff	-0.014229
Active_listening	0.013270
ReAdmis_Yes	-0.011972
Complication_risk_Low	-0.001509
Complication_risk_Medium	0.023246
Initial_admin_Emergency Admission	-0.574347
Initial_admin_Observation Admission	1.000000
Services_CT Scan	-0.019476
Services_Intravenous	0.010817
Services_MRI	-0.010440
Overweight_Yes	0.009698

Anxiety_Yes	-0.004077
Arthritis_Yes	0.000182
Asthma_Yes	0.001678
Diabetes_Yes	0.000535
Allergic_rhinitis_Yes	-0.025280
BackPain_Yes	0.009861
Stroke_Yes	0.005543
HighBlood_Yes	0.006006
Hyperlipidemia_Yes	-0.009077
Reflux_esophagitis_Yes	-0.008650

	Services_CT Scan	Services_Intravenous \
Age	0.009506	0.004142
Doc_visits	0.014600	-0.008700
Full_meals_eaten	-0.002939	0.016177
TotalCharge	0.010561	-0.016170
Additional_charges	0.013137	-0.001095
Timely_admis	-0.012275	-0.012715
Timely_treat	-0.005809	-0.013123
Timely_visits	-0.018045	-0.019993
Reliability	-0.011773	0.002651
Options	0.017853	-0.012204
Hours_treat	-0.025723	0.008058
Courteous_staff	-0.018858	-0.009126
Active_listening	-0.011525	0.005305
ReAdmis_Yes	0.024395	-0.020313
Complication_risk_Low	-0.015145	0.002570
Complication_risk_Medium	0.002861	-0.005122
Initial_admin_Emergency Admission	0.007412	-0.003787
Initial_admin_Observation Admission	-0.019476	0.010817
Services_CT Scan	1.000000	-0.252196
Services_Intravenous	-0.252196	1.000000
Services_MRI	-0.074259	-0.134152
Overweight_Yes	0.002005	0.004074
Anxiety_Yes	-0.005771	0.007251
Arthritis_Yes	0.000754	-0.001198
Asthma_Yes	0.013862	-0.013559
Diabetes_Yes	0.014087	0.001937
Allergic_rhinitis_Yes	0.007008	-0.003766
BackPain_Yes	0.016757	-0.013446
Stroke_Yes	0.013635	-0.019871
HighBlood_Yes	0.011772	-0.008408
Hyperlipidemia_Yes	0.000600	-0.003848
Reflux_esophagitis_Yes	0.017628	-0.022007

	Services_MRI	Overweight_Yes \
Age	0.008529	-0.008292
Doc_visits	-0.012822	0.011890

Full_meals_eaten	-0.018954	-0.008287
TotalCharge	0.007341	-0.012782
Additional_charges	0.010134	0.012771
Timely_admis	0.002968	0.002056
Timely_treat	0.006800	-0.001177
Timely_visits	0.012045	-0.002505
Reliability	-0.004915	-0.003001
Options	0.014307	0.005771
Hours_treat	-0.010412	-0.003118
Courteous_staff	-0.006002	-0.009151
Active_listening	-0.006868	0.009549
ReAdmis_Yes	0.009309	-0.008586
Complication_risk_Low	0.004155	-0.009947
Complication_risk_Medium	0.011933	0.018871
Initial_admin_Emergency Admission	0.009122	-0.009940
Initial_admin_Observation Admission	-0.010440	0.009698
Services_CT Scan	-0.074259	0.002005
Services_Intravenous	-0.134152	0.004074
Services_MRI	1.000000	-0.002963
Overweight_Yes	-0.002963	1.000000
Anxiety_Yes	-0.006909	-0.011186
Arthritis_Yes	-0.004160	0.003954
Asthma_Yes	-0.001077	0.013943
Diabetes_Yes	0.018715	-0.007575
Allergic_rhinitis_Yes	0.000259	0.002819
BackPain_Yes	-0.000353	0.010083
Stroke_Yes	-0.003580	-0.001011
HighBlood_Yes	0.001681	0.026231
Hyperlipidemia_Yes	-0.002363	-0.006102
Reflux_esophagitis_Yes	0.001986	-0.012240

	Anxiety_Yes	Arthritis_Yes	Asthma_Yes	\
Age	0.006130	0.007110	0.009229	
Doc_visits	-0.001684	-0.000719	-0.017989	
Full_meals_eaten	0.008602	0.011591	0.012459	
TotalCharge	0.031199	0.032932	-0.014290	
Additional_charges	0.011666	0.004788	0.014083	
Timely_admis	-0.007458	-0.008532	-0.011303	
Timely_treat	-0.009733	-0.012492	-0.007648	
Timely_visits	-0.004807	-0.020948	0.000296	
Reliability	0.005363	0.001416	-0.004721	
Options	-0.016946	0.002447	0.019796	
Hours_treat	-0.002248	-0.018074	-0.009740	
Courteous_staff	0.003520	-0.008286	-0.013202	
Active_listening	0.014650	0.002869	0.002209	
ReAdmis_Yes	0.002406	0.007663	-0.017133	
Complication_risk_Low	-0.002192	0.002818	0.003902	
Complication_risk_Medium	0.004640	0.017453	0.006750	

Initial_admin_Emergency Admission	0.008655	-0.000603	-0.005672
Initial_admin_Observation Admission	-0.004077	0.000182	0.001678
Services_CT Scan	-0.005771	0.000754	0.013862
Services_Intravenous	0.007251	-0.001198	-0.013559
Services_MRI	-0.006909	-0.004160	-0.001077
Overweight_Yes	-0.011186	0.003954	0.013943
Anxiety_Yes	1.000000	0.012045	0.011758
Arthritis_Yes	0.012045	1.000000	-0.006423
Asthma_Yes	0.011758	-0.006423	1.000000
Diabetes_Yes	-0.002529	0.009097	0.016765
Allergic_rhinitis_Yes	0.004368	0.008748	0.004454
BackPain_Yes	0.009289	-0.018804	0.014261
Stroke_Yes	-0.013801	-0.018438	0.002443
HighBlood_Yes	0.008303	0.007314	0.006174
Hyperlipidemia_Yes	-0.013178	-0.007130	-0.009106
Reflux_esophagitis_Yes	-0.007566	0.014894	-0.001458

	Diabetes_Yes	Allergic_rhinitis_Yes \
Age	0.003694	0.012092
Doc_visits	0.012781	0.002920
Full_meals_eaten	0.009603	0.015120
TotalCharge	0.011524	0.018919
Additional_charges	0.002450	0.016154
Timely_admis	0.013806	0.009402
Timely_treat	0.005994	0.014654
Timely_visits	-0.007469	0.001140
Reliability	-0.005052	-0.007704
Options	0.017958	-0.004029
Hours_treat	-0.004259	-0.012721
Courteous_staff	-0.004737	0.008445
Active_listening	-0.014752	0.005355
ReAdmis_Yes	-0.003058	-0.004651
Complication_risk_Low	0.006675	0.013276
Complication_risk_Medium	-0.001241	-0.017744
Initial_admin_Emergency Admission	-0.008266	0.006080
Initial_admin_Observation Admission	0.000535	-0.025280
Services_CT Scan	0.014087	0.007008
Services_Intravenous	0.001937	-0.003766
Services_MRI	0.018715	0.000259
Overweight_Yes	-0.007575	0.002819
Anxiety_Yes	-0.002529	0.004368
Arthritis_Yes	0.009097	0.008748
Asthma_Yes	0.016765	0.004454
Diabetes_Yes	1.000000	0.005486
Allergic_rhinitis_Yes	0.005486	1.000000
BackPain_Yes	-0.013405	0.004023
Stroke_Yes	0.005792	-0.004837
HighBlood_Yes	-0.005858	0.011709

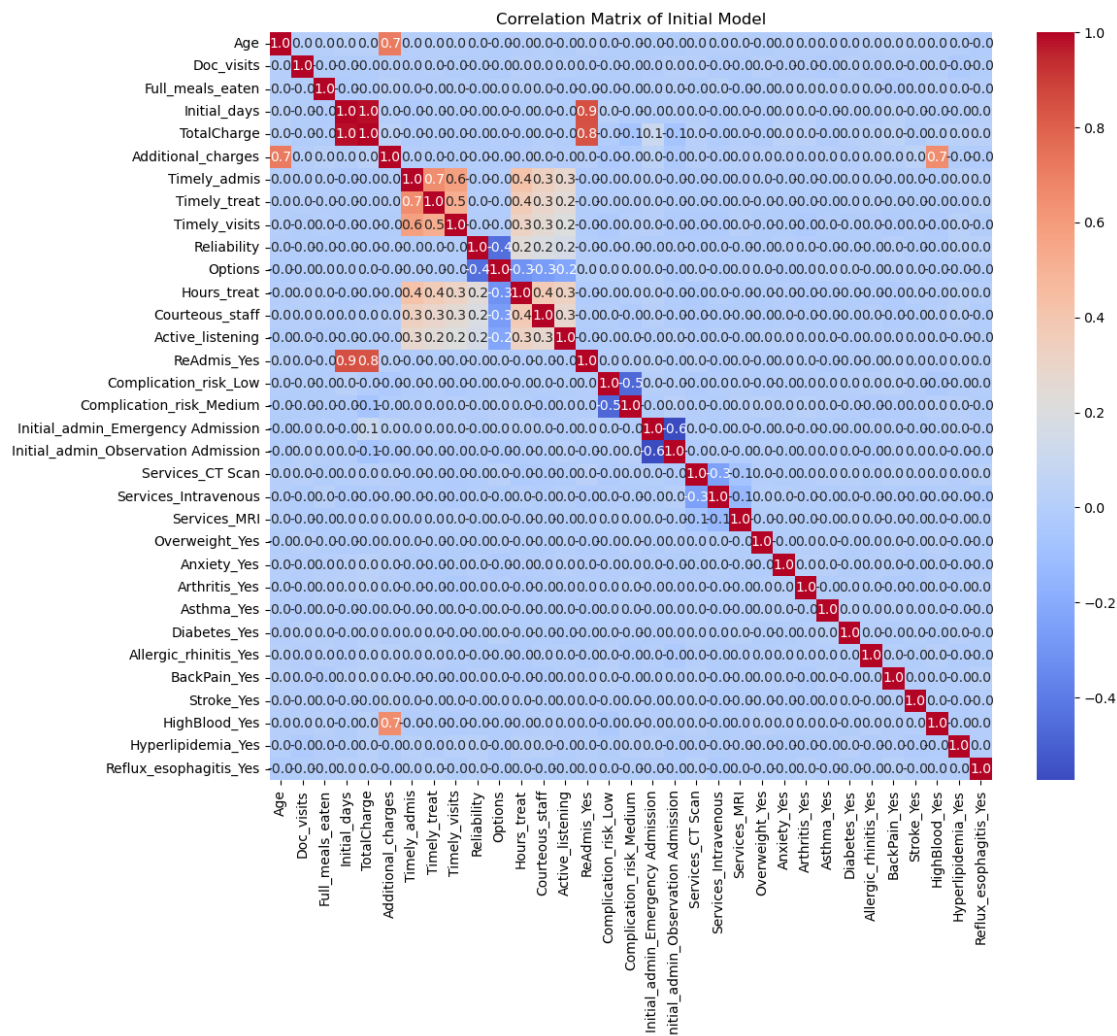
Hyperlipidemia_Yes	0.011739	-0.009049	
Reflux_esophagitis_Yes	-0.007816	-0.007731	
	BackPain_Yes	Stroke_Yes	HighBlood_Yes \
Age	0.021081	0.012035	0.007147
Doc_visits	0.008514	-0.002230	0.008967
Full_meals_eaten	-0.015676	0.002784	0.014784
TotalCharge	0.035828	-0.003694	0.019910
Additional_charges	0.014245	0.035140	0.654316
Timely_admis	-0.011687	0.001948	-0.011017
Timely_treat	-0.005413	-0.007706	-0.007745
Timely_visits	-0.015480	0.001304	-0.015244
Reliability	0.012723	-0.013430	-0.004075
Options	0.006659	0.005025	-0.013292
Hours_treat	-0.016056	0.004282	-0.002369
Courteous_staff	-0.015781	-0.005280	0.007277
Active_listening	0.000213	0.000040	0.002601
ReAdmis_Yes	0.013313	0.000918	0.002270
Complication_risk_Low	0.019759	-0.001537	-0.027906
Complication_risk_Medium	-0.009920	0.000886	0.014528
Initial_admin_Emergency Admission	0.000535	-0.009743	-0.001440
Initial_admin_Observation Admission	0.009861	0.005543	0.006006
Services_CT Scan	0.016757	0.013635	0.011772
Services_Intravenous	-0.013446	-0.019871	-0.008408
Services_MRI	-0.000353	-0.003580	0.001681
Overweight_Yes	0.010083	-0.001011	0.026231
Anxiety_Yes	0.009289	-0.013801	0.008303
Arthritis_Yes	-0.018804	-0.018438	0.007314
Asthma_Yes	0.014261	0.002443	0.006174
Diabetes_Yes	-0.013405	0.005792	-0.005858
Allergic_rhinitis_Yes	0.004023	-0.004837	0.011709
BackPain_Yes	1.000000	0.003602	0.003048
Stroke_Yes	0.003602	1.000000	0.007568
HighBlood_Yes	0.003048	0.007568	1.000000
Hyperlipidemia_Yes	-0.000963	-0.014847	-0.009529
Reflux_esophagitis_Yes	0.016036	-0.000054	0.001150
	Hyperlipidemia_Yes \		
Age	0.003736		
Doc_visits	-0.026730		
Full_meals_eaten	0.000688		
TotalCharge	0.017565		
Additional_charges	-0.002475		
Timely_admis	0.019393		
Timely_treat	0.000697		
Timely_visits	0.018551		
Reliability	0.020022		
Options	-0.009352		

Hours_treat	0.017648
Courteous_staff	0.016202
Active_listening	-0.001970
ReAdmis_Yes	0.004307
Complication_risk_Low	-0.005972
Complication_risk_Medium	0.010995
Initial_admin_Emergency Admission	0.018941
Initial_admin_Observation Admission	-0.009077
Services_CT Scan	0.000600
Services_Intravenous	-0.003848
Services_MRI	-0.002363
Overweight_Yes	-0.006102
Anxiety_Yes	-0.013178
Arthritis_Yes	-0.007130
Asthma_Yes	-0.009106
Diabetes_Yes	0.011739
Allergic_rhinitis_Yes	-0.009049
BackPain_Yes	-0.000963
Stroke_Yes	-0.014847
HighBlood_Yes	-0.009529
Hyperlipidemia_Yes	1.000000
Reflux_esophagitis_Yes	0.001580

	Reflux_esophagitis_Yes
Age	-0.019609
Doc_visits	-0.005330
Full_meals_eaten	-0.000562
TotalCharge	0.026284
Additional_charges	-0.011405
Timely_admis	0.011367
Timely_treat	0.017425
Timely_visits	-0.005584
Reliability	0.016277
Options	-0.011764
Hours_treat	0.009729
Courteous_staff	-0.013657
Active_listening	-0.003236
ReAdmis_Yes	0.005422
Complication_risk_Low	0.000652
Complication_risk_Medium	-0.005622
Initial_admin_Emergency Admission	-0.000126
Initial_admin_Observation Admission	-0.008650
Services_CT Scan	0.017628
Services_Intravenous	-0.022007
Services_MRI	0.001986
Overweight_Yes	-0.012240
Anxiety_Yes	-0.007566
Arthritis_Yes	0.014894

Asthma_Yes	-0.001458
Diabetes_Yes	-0.007816
Allergic_rhinitis_Yes	-0.007731
BackPain_Yes	0.016036
Stroke_Yes	-0.000054
HighBlood_Yes	0.001150
Hyperlipidemia_Yes	0.001580
Reflux_esophagitis_Yes	1.000000

```
[10]: # plotting the initial_model correlation matrix
correlation_matrix = X_with_target.corr()
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".1f")
plt.title("Correlation Matrix of Initial Model")
plt.show()
```



```
[8]: import numpy as np

vif_data = pd.DataFrame()
vif_data["Variable"] = X.columns

vif_values = []
for i in range(len(X.columns)):
    vif = variance_inflation_factor(X.values, i)
    vif_values.append(vif)

vif_data["VIF"] = vif_values

# pulling p-values from the model
p_values = model.pvalues

# add p-values to the vif dataframe
vif_data['P-Value'] = vif_data['Variable'].apply(lambda var: p_values.get(var, np.nan))

print(vif_data)
```

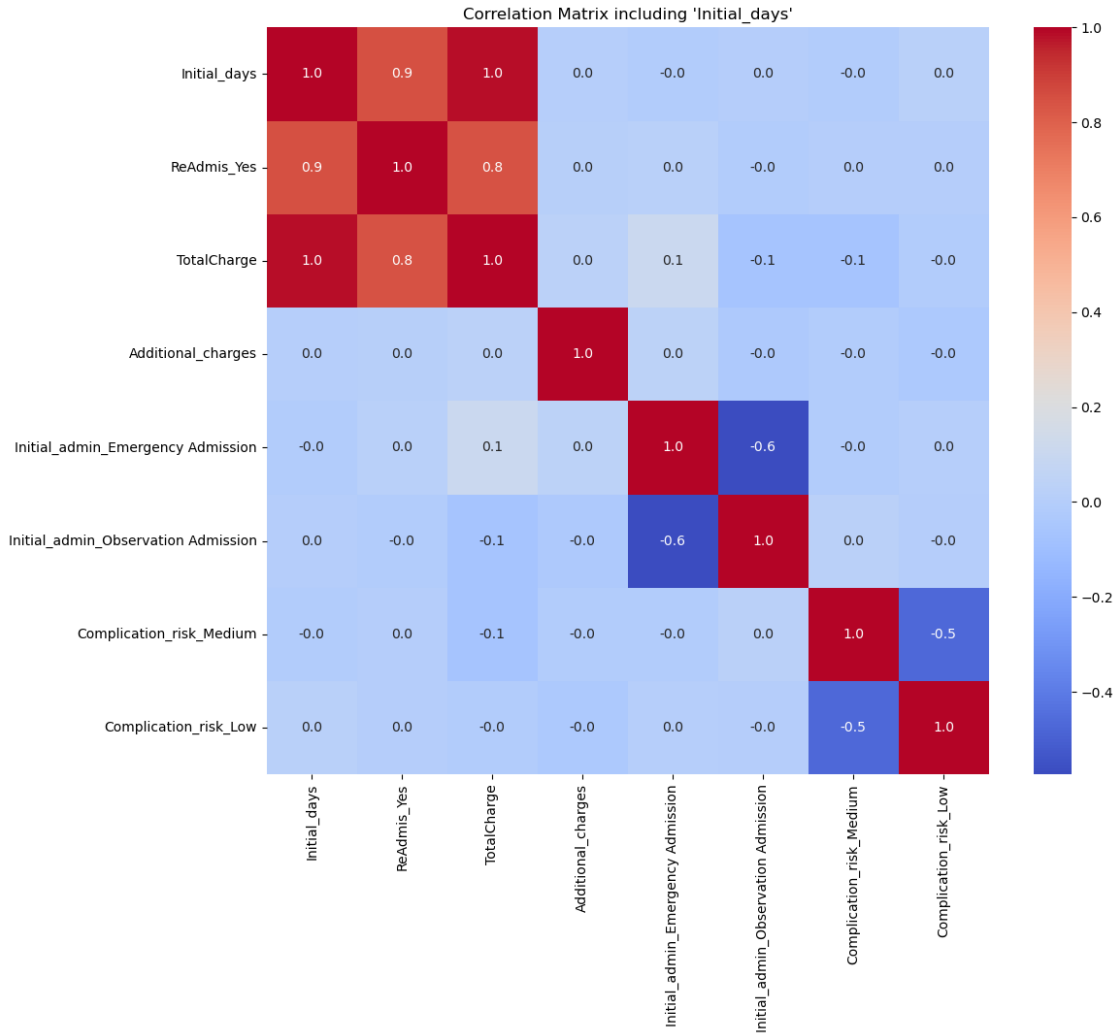
	Variable	VIF	P-Value
0	Age	68.480567	0.181855
1	Doc_visits	19.941977	0.687606
2	Full_meals_eaten	1.978869	0.178170
3	TotalCharge	23.757244	0.000000
4	Additional_charges	78.307975	0.090644
5	Timely_admis	27.940825	0.944225
6	Timely_treat	23.599967	0.114698
7	Timely_visits	19.957174	0.136150
8	Reliability	13.129180	0.939779
9	Options	11.956790	0.398910
10	Hours_treat	18.638020	0.696698
11	Courteous_staff	16.070136	0.684208
12	Active_listening	14.358288	0.878522
13	ReAdmis_Yes	5.512167	0.161024
14	Complication_risk_Low	1.658864	0.000000
15	Complication_risk_Medium	2.400300	0.000000
16	Initial_admin_Emergency Admission	3.095585	0.000000
17	Initial_admin_Observation Admission	1.951168	0.892261
18	Services_CT Scan	1.233743	0.774173
19	Services_Intravenous	1.585907	0.413132
20	Services_MRI	1.073312	0.402218
21	Overweight_Yes	3.391201	0.950970
22	Anxiety_Yes	1.477685	0.000000
23	Arthritis_Yes	1.562574	0.000000
24	Asthma_Yes	1.408097	0.512425
25	Diabetes_Yes	1.381342	0.000000

26	Allergic_rhinitis_Yes	1.652144	0.000000
27	BackPain_Yes	1.707121	0.000000
28	Stroke_Yes	1.256522	0.650942
29	HighBlood_Yes	12.980122	0.000000
30	Hyperlipidemia_Yes	1.510806	0.000000
31	Reflux_esophagitis_Yes	1.705367	0.000000

As seen in the above heatmap, we can use this to find any variables with correlation to the Initial_days variable. We see that the ReAdmis and TotalCharge variables are strong Initial_days predictors, we will include Additional_charges as well. From the table of variance inflation factor's and P-values we see that the dummy variables for Initial_admin and Complication_risk had low P-values and low variance inflation factor numbers and thus will be kept. We use the variables mentioned to generate a new heatmap, and a new variance inflation factors table with P-values:

```
[12]: # reduced_model columns
selected_columns = ['Initial_days', 'ReAdmis_Yes', 'TotalCharge',
                    ↪ 'Additional_charges',
                    ↪ 'Initial_admin_Emergency Admission',
                    ↪ 'Initial_admin_Observation Admission', 'Complication_risk_Medium',
                    ↪ 'Complication_risk_Low']
filtered_data = X[selected_columns]

# plotting the new correlation matrix
correlation_matrix = filtered_data.corr()
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".1f")
plt.title("Correlation Matrix of reduced model")
plt.show()
```



```
[36]: import numpy as np

selected_columns = ['ReAdmis_Yes', 'TotalCharge', 'Additional_charges',
                    'Initial_admin_Emergency Admission',
                    'Complication_risk_Medium', 'Complication_risk_Low']
vif_cols = X[selected_columns]

vif_data = pd.DataFrame()
vif_data["Variable"] = vif_cols.columns

vif_values = []
for i in range(len(vif_cols.columns)):
    vif = variance_inflation_factor(X.values, i)
    vif_values.append(vif)
```

```

vif_data["VIF"] = vif_values

# pulling p-values from the model
p_values = model.pvalues

# Add p-values to vif dataframe
vif_data['P-Value'] = vif_data['Variable'].apply(lambda var: p_values.get(var,
↪np.nan))

print(vif_data)

```

	Variable	VIF	P-Value
0	ReAdmis_Yes	23.438315	0.161024
1	TotalCharge	3.609938	0.000000
2	Additional_charges	3.678486	0.090644
3	Initial_admin_Emergency Admission	2.072822	0.000000
4	Complication_risk_Medium	1.032847	0.000000
5	Complication_risk_Low	1.323609	0.000000

As we can see above, the only P-value that was of issue was the ReAdmis variable but checking our heatmap and correlation matrix we can see there appears to be a linear relationship between the number of days a patient was initially admitted and their readmission. It also shows a relationship between initial_days and the patient's total charges. The new multiple linear regression model will be run with these now-reduced set of variables.

D3. Reduced Linear Regression Model

A reduced linear regression model can be run with the narrowed down values mentioned earlier. The output of which can be seen along with further analysis continued below:

```

[37]: import pandas as pd

data1 = pd.read_csv('prepared-data.csv')
pd.set_option('display.max_columns', None)

selected_columns = ['Initial_days', 'ReAdmis_Yes', 'TotalCharge',
↪'Additional_charges',
                    'Initial_admin_Emergency Admission',
↪'Complication_risk_Medium', 'Complication_risk_Low', 'Age']

data2 = data1[selected_columns]

X = data2.drop('Initial_days', axis=1)
X = sm.add_constant(X)

# our dependent variable
y = data2['Initial_days']

```

```
# initial ols model
reduced_model = sm.OLS(y, X).fit()

# summary of the initial model
print(reduced_model.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          Initial_days    R-squared:                0.998
Model:                  OLS             Adj. R-squared:          0.998
Method:                 Least Squares    F-statistic:             6.845e+05
Date:                  Tue, 09 Jan 2024   Prob (F-statistic):       0.00
Time:                  20:08:42          Log-Likelihood:          -16014.
No. Observations:      10000            AIC:                    3.204e+04
Df Residuals:          9992             BIC:                    3.210e+04
Df Model:              7
Covariance Type:       nonrobust
=====
```

```
=====
                                coef    std err          t      P>|t|
-----
[0.025    0.975]
-----
const                -29.8795      0.058   -514.049    0.000
-29.993   -29.766
ReAdmis_Yes           0.4313      0.047     9.113    0.000
0.339     0.524
TotalCharge           0.0121    1.06e-05   1144.217    0.000
0.012     0.012
Additional_charges    -0.0001    2.64e-06   -52.558    0.000
-0.000    -0.000
Initial_admin_Emergency Admission -6.1609      0.024   -252.440    0.000
-6.209    -6.113
Complication_risk_Medium 4.9182      0.028    177.195    0.000
4.864     4.973
Complication_risk_Low  4.8927      0.034    145.946    0.000
4.827     4.958
Age                   0.0305      0.001     36.501    0.000
0.029     0.032
=====
```

```
=====
Omnibus:              121.461    Durbin-Watson:           1.993
Prob(Omnibus):        0.000     Jarque-Bera (JB):        120.583
Skew:                 -0.249     Prob(JB):                6.54e-27
Kurtosis:             2.798     Cond. No.:               8.65e+04
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

specified.

[2] The condition number is large, 8.65e+04. This might indicate that there are strong multicollinearity or other numerical problems.

Based on the reduced model above, our R-squared is now 0.998 which means the model still accounts for 99.8% of the variance. We now have a new reduced model equation as follows:

$$\hat{Y} = -29.8795 - 6.1609 * \text{Initial_admin_Emergency Admission} + 0.4313 * \text{ReAdmis_Yes} + 0.0121 * \text{TotalCharge} - 0.0001 * \text{Additional_charges} + 4.9182 * \text{Complication_risk_Medium} + 4.8927 * \text{Complication_risk_Low} + 0.0305 * \text{Age}$$

E. Reduced Model Analysis

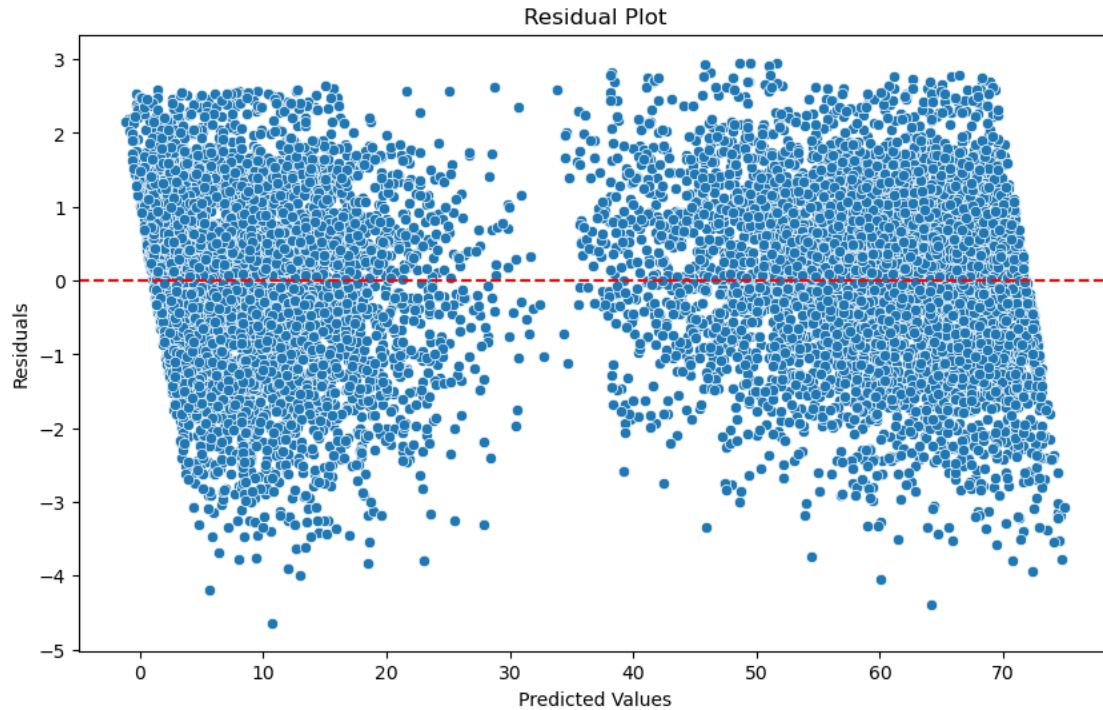
The strategy for the variable selection was an analysis of the correlation matrix, heatmap, variance inflation factors, and P-values. These tools helped to identify the variables that had a correlation with the initial_days variable. A new regression model was ran with the R-squared results shown above along with the new reduced model equation. New variance inflation factors and p-values were also generated. Lastly we will need to generate a residual plot and calculate the residual standard error:

```
[31]: import seaborn as sns
import matplotlib.pyplot as plt

# calculating residuals
residuals = y - reduced_model.predict(X)

# plotting residual plot
plt.figure(figsize=(10, 6))
sns.scatterplot(x=reduced_model.predict(X), y=residuals)
plt.axhline(y=0, color='red', linestyle='--')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.title('Residual Plot')
plt.show()

# calculating residual standard error
RSE = (sum(residuals ** 2) / (len(y) - X.shape[1])) ** 0.5
print("Residual Standard Error:", RSE)
```



Residual Standard Error: 1.20061821423433

E2. Output and Calculations of Analysis

All output and calculation analysis are noted in the above sections and visualizations.

E3. Linear Regression Code

The code used to create the multiple regression models, both the initial and reduced versions can be found below:

```
[32]: import statsmodels.api as sm

columns = ['Age', 'Doc_visits', 'Full_meals_eaten',
          'Initial_days', 'TotalCharge', 'Additional_charges', 'Timely_admis',
          'Timely_treat', 'Timely_visits', 'Reliability', 'Options',
          'Hours_treat', 'Courteous_staff', 'Active_listening', 'ReAdmis_Yes',
          'Complication_risk_Low', 'Complication_risk_Medium',
          'Initial_admin_Emergency Admission',
          'Initial_admin_Observation Admission', 'Services_CT Scan',
          'Services_Intravenous', 'Services_MRI', 'Overweight_Yes', 'Anxiety_Yes',
          'Arthritis_Yes', 'Asthma_Yes', 'Diabetes_Yes',
          'Allergic_rhinitis_Yes', 'BackPain_Yes', 'Stroke_Yes', 'HighBlood_Yes',
          'Hyperlipidemia_Yes', 'Reflux_esophagitis_Yes']

data = data[columns]
```



```

X = data.drop('Initial_days', axis=1)
X = sm.add_constant(X)

# our dependent variable
y = data['Initial_days']

# initial ols model
model = sm.OLS(y, X).fit()

# summary of the initial model
print(model.summary())

```

OLS Regression Results

```

=====
Dep. Variable:          Initial_days    R-squared:                1.000
Model:                  OLS             Adj. R-squared:          1.000
Method:                 Least Squares   F-statistic:             2.116e+16
Date:                   Tue, 09 Jan 2024 Prob (F-statistic):       0.00
Time:                   19:08:41         Log-Likelihood:          1.1236e+05
No. Observations:      10000           AIC:                    -2.247e+05
Df Residuals:          9967            BIC:                    -2.244e+05
Df Model:               32
Covariance Type:        nonrobust
=====
=====

```

		coef	std err	t	P> t

const		-27.6939	3.74e-07	-7.41e+07	0.000
-27.694	-27.694				
Age		6.291e-09	4.71e-09	1.335	0.182
-2.94e-09	1.55e-08				
Doc_visits		1.232e-08	3.06e-08	0.402	0.688
-4.77e-08	7.24e-08				
Full_meals_eaten		-4.278e-08	3.18e-08	-1.347	0.178
-1.05e-07	1.95e-08				
TotalCharge		0.0122	2.84e-11	4.3e+08	0.000
0.012	0.012				
Additional_charges		-3.336e-11	1.97e-11	-1.692	0.091
-7.2e-11	5.28e-12				
Timely_admis		-3.225e-09	4.61e-08	-0.070	0.944
-9.36e-08	8.71e-08				
Timely_treat		-6.709e-08	4.25e-08	-1.578	0.115
-1.5e-07	1.63e-08				
Timely_visits		5.85e-08	3.93e-08	1.490	0.136
-1.84e-08	1.35e-07				

Reliability	-2.642e-09	3.5e-08	-0.076	0.940
-7.12e-08 6.59e-08				
Options	3.107e-08	3.68e-08	0.844	0.399
-4.11e-08 1.03e-07				
Hours_treat	1.482e-08	3.8e-08	0.390	0.697
-5.97e-08 8.93e-08				
Courteous_staff	-1.456e-08	3.58e-08	-0.407	0.684
-8.48e-08 5.56e-08				
Active_listening	5.151e-09	3.37e-08	0.153	0.879
-6.09e-08 7.12e-08				
ReAdmis_Yes	1.777e-07	1.27e-07	1.402	0.161
-7.08e-08 4.26e-07				
Complication_risk_Low	5.0464	8.99e-08	5.61e+07	0.000
5.046 5.046				
Complication_risk_Medium	5.0464	7.44e-08	6.78e+07	0.000
5.046 5.046				
Initial_admin_Emergency Admission	-6.2526	7.95e-08	-7.87e+07	0.000
-6.253 -6.253				
Initial_admin_Observation Admission	1.235e-08	9.12e-08	0.135	0.892
-1.66e-07 1.91e-07				
Services_CT Scan	2.916e-08	1.02e-07	0.287	0.774
-1.7e-07 2.28e-07				
Services_Intravenous	5.913e-08	7.23e-08	0.818	0.413
-8.25e-08 2.01e-07				
Services_MRI	1.424e-07	1.7e-07	0.838	0.402
-1.91e-07 4.76e-07				
Overweight_Yes	4.336e-09	7.05e-08	0.061	0.951
-1.34e-07 1.43e-07				
Anxiety_Yes	-1.0510	6.86e-08	-1.53e+07	0.000
-1.051 -1.051				
Arthritis_Yes	-0.8781	6.69e-08	-1.31e+07	0.000
-0.878 -0.878				
Asthma_Yes	-4.627e-08	7.06e-08	-0.655	0.512
-1.85e-07 9.22e-08				
Diabetes_Yes	-0.9178	7.19e-08	-1.28e+07	0.000
-0.918 -0.918				
Allergic_rhinitis_Yes	-0.7394	6.56e-08	-1.13e+07	0.000
-0.739 -0.739				
BackPain_Yes	-1.0392	6.52e-08	-1.59e+07	0.000
-1.039 -1.039				
Stroke_Yes	3.639e-08	8.04e-08	0.452	0.651
-1.21e-07 1.94e-07				
HighBlood_Yes	-1.3708	1.82e-07	-7.52e+06	0.000
-1.371 -1.371				
Hyperlipidemia_Yes	-1.1471	6.78e-08	-1.69e+07	0.000
-1.147 -1.147				
Reflux_esophagitis_Yes	-0.7284	6.51e-08	-1.12e+07	0.000
-0.728 -0.728				

```
=====
Omnibus:                405.752    Durbin-Watson:                1.985
Prob(Omnibus):           0.000    Jarque-Bera (JB):           1309.867
Skew:                    0.013    Prob(JB):                    3.68e-285
Kurtosis:                4.773    Cond. No.                    1.81e+05
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.81e+05. This might indicate that there are strong multicollinearity or other numerical problems.

```
[58]: import pandas as pd

pd.set_option('display.max_columns', None)

selected_columns = ['Initial_days', 'ReAdmis_Yes', 'TotalCharge',
                    ↪ 'Additional_charges',
                    'Initial_admin_Emergency Admission',
                    ↪ 'Complication_risk_Medium', 'Complication_risk_Low', 'Age']

data2 = data[selected_columns]

X = data2.drop('Initial_days', axis=1)
X = sm.add_constant(X)

# our dependent variable
y = data2['Initial_days']

# initial ols model
reduced_model = sm.OLS(y, X).fit()

# summary of the initial model
print(reduced_model.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          Initial_days    R-squared:                0.998
Model:                  OLS             Adj. R-squared:          0.998
Method:                 Least Squares    F-statistic:             6.845e+05
Date:                   Tue, 09 Jan 2024  Prob (F-statistic):      0.00
Time:                   21:05:07         Log-Likelihood:          -16014.
No. Observations:       10000           AIC:                    3.204e+04
Df Residuals:           9992           BIC:                    3.210e+04
Df Model:                7
Covariance Type:        nonrobust
=====
```

=====		coef	std err	t	P> t
[0.025 0.975]					

const		-29.8795	0.058	-514.049	0.000
-29.993	-29.766				
ReAdmis_Yes		0.4313	0.047	9.113	0.000
0.339	0.524				
TotalCharge		0.0121	1.06e-05	1144.217	0.000
0.012	0.012				
Additional_charges		-0.0001	2.64e-06	-52.558	0.000
-0.000	-0.000				
Initial_admin_Emergency Admission		-6.1609	0.024	-252.440	0.000
-6.209	-6.113				
Complication_risk_Medium		4.9182	0.028	177.195	0.000
4.864	4.973				
Complication_risk_Low		4.8927	0.034	145.946	0.000
4.827	4.958				
Age		0.0305	0.001	36.501	0.000
0.029	0.032				
=====					
Omnibus:	121.461	Durbin-Watson:		1.993	
Prob(Omnibus):	0.000	Jarque-Bera (JB):		120.583	
Skew:	-0.249	Prob(JB):		6.54e-27	
Kurtosis:	2.798	Cond. No.		8.65e+04	
=====					

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 8.65e+04. This might indicate that there are strong multicollinearity or other numerical problems.

F. Data Summary and Implications

The final regression model can be found below along with the coefficients interpretations:

$$\hat{Y} = -29.8795 - 6.1609 * \text{Initial_admin_Emergency Admission} + 0.4313 * \text{ReAdmis_Yes} + 0.0121 * \text{TotalCharge} - 0.0001 * \text{Additional_charges} + 4.9182 * \text{Complication_risk_Medium} + 4.8927 * \text{Complication_risk_Low} + 0.0305 * \text{Age}$$

Using the equation, the coefficients seem to show a high correlation with the initial_days variable. Each coefficient was found to have affected the Initial_days:

- Age: increase of Initial_days by 0.0305 units
- Complication_risk_Low: increase of Initial_days by 4.8927 units
- Complication_risk_Medium: increase of Initial_days by 4.9182 units
- Initial_admin_Emergency Admission: decrease of Initial_days by 6.1609 units
- Additional_charges: decrease of Initial_days by 0.0001 units

- TotalCharge: increase of Initial_days by 0.0121 units
- ReAdmis_Yes: increase of Initial_days by 0.4313 units

The P-values in all of the variables above also indicated significance aside from the ReAdmis & Additional_charges columns. It indicates that some of these variables impact the Initial_days variable, it may also indicate that Initial_days may change depending on if these variables increase or decrease. The model found that a patient's total charges and being readmitted has a correlation with the Initial_days variable. In a practical sense, these variables identified can be monitored to help predict patient readmissions. If a patient's total charges are high and they've been readmitted, the model is showing that there is a good chance their Initial_days will be high too. The same logic can be applied if a patient is being readmitted as well (high Initial_days and total charges).

The analysis does have limitations, the majority of our P-values were 0.000 but not all of them. We used Additional_charges as it may relate to TotalCharge in some way and the patient's readmission status. This analysis is meant to represent only this subset of variables. The independent variables may need to change if a different dependent variable is selected. Using only one model on a subset of variables may not lead to an entirely accurate answer to other research questions. If there are other variables not recorded by the hospital these may also change the results of the analysis.

F2. Recommended course of action

Based on the regression analysis conducted above, hospitals should work to reduce the likelihood of a patient being readmitted to the hospital, and their total charges. The longer the patient remains in the hospital, the more of a burden it becomes on the patient. Financially, it is in the best interest of the patient for hospital staff to diagnose and treat patients as soon as they can. Other factors such as the Complication_risk and Initial_admin may also play a role in the time a patient spends in the hospital. Ensuring the patient is classified under the correct complication risk and initial admission would help. Other multiple regression models should be run using different independent variables for a more accurate analysis. Hospitals can develop programs for patients that are at higher-risk of readmission based on these models and can treat them accordingly.

G. Panopto Video <https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=a5c35e1a-4c54-4cc9-bb2b-b0f30049b98e>

H. Third-party Code References

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