“A Look at a Population’s Trust in Automation in Healthcare”

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INTRODUCTION

In the healthcare system of the United States, 250,000 deaths each year are attributed to medial errors. (Anderson, 2017) Taking this into account and the fact that human factors principles have been implemented in the healthcare system since 1999 (Institute of Medicine, 2000), there is an essential need for improvement in the healthcare sector. With the advancements in automation (i.e. Artificial Intelligence) in recent decades, the application of autonomous technologies in healthcare has been made possible. To understand the application of automation in healthcare, it is important to know what automation exactly means. Automation is technology that actively selects information, remodels data, makes decisions, or manages processes. (Lee, 2004) In healthcare, automation has the capability to enhance clinical decision making, facilitate disease diagnosis, identify previously unrecognized imaging or genomic patterns associated with patient phenotypes, and aid in surgical interventions for various human diseases. (Yu, 2018) When looking at the application of automation in healthcare in practical setting, applying this technology in a primary care setting has great benefits in rural areas. In communities without large numbers of specialized primary care physicians, utilizing prediction based artificial intelligence systems can enhance the diagnosis capability of minor to critical illnesses with high precision and accuracy. Therefore, considering the capabilities artificial intelligence possesses and the demand for primary care in communities lacking specialized doctors, applying automation in healthcare can lead to significant improvements in healthcare and save lives. To safely and appropriately achieve this, it is imperative that the collaboration of humans and automation be built on trust. So, what is trust in an intelligent system? There are two critical elements that define the basis of trust:

1) What automation is to be trusted?

2) What information is supporting the trust in automation?

Currently, it is unclear how to design automated systems to ensure a patient's trust in the automation the doctor is using. Therefore, the purpose of this study is to identify the critical factors related to the predict trust in automation regarding patient care. In doing so, it will provide interpretability to the measurement of trust and the predictors that influence trust in the healthcare system.

In the propagation of building trust in automation in healthcare, the doctor-automation patient collaboration should be at the forefront of the design system, but there are multiple challenges related to the behavioral and social aspects of human-AI collaboration which impacts its adoption. (Lai, 2021) Approaches to accumulate this trust can be accomplished by designing a holistic approach to recognize healthcare as a dynamic socio-technical system where sub-elements interact with each other. (Asan, 2020) The SEIPS (Systems Engineering Initiative for Patient Safety) provides a framework for the integration of human factors and ergonomics for healthcare quality and patient safety enhancement. (Carayon, 2020) This model has two principles: 1) the person is the center of the work system and 2) interactions among the work system elements should be designed to support performance and safety and avoid negative outcomes. (Carayon, 2020) Through the framework of SEIPS, the patient is the center of the design, thus presenting difficulties not evident with other products such as cars or planes. Humans, being autonomous and prone to abnormalities, have no set pattern attributable to all subjects, thus providing opportunities for further research to perfect the doctor-automation patient collaboration framework. With this paper researching the factors that influence trust in automation in healthcare, the outcome of this research should provide predictability in the dynamic relationship of the doctor-automation patient collaboration environment.

METHODS

Survey Data Collection

A survey will be used as the method of data collection, and the survey questions are shown in Appendix in Figure 2.1. Questions related to demographics, attitudes towards automation, and complacency in automation are included in the survey. The rating scale questions will determine a numeric measurement of one's trust in the integration of technology in everyday life or one's happiness in integrating Artificial Intelligence in everyday life. The complacency questions will focus on a questionee's complacency rating. (Singh, Molloy, and Parasuraman, 1993) The complacency rating would help determine attitudes towards automated devices and the potential for complacency in automation, but for the sake of this project, the complacency questions will be omitted from the analysis. The questions will be used to build a predictive model which computes the patient's trust in automation in healthcare. The variable, scenario1 is the predictor which will be measured as our target variable and it is measured quantitatively on a 1-10 scale. To make the numeric variable more suitable for data analysis, it will be transformed into a categorical predictor called "trust". This variable will have two levels:

- 0 – patient does not trust automation in healthcare
- 1 – patient does trust automation in healthcare the numeric variable

Changing this variable to be categorical will be more suitable for this type of data analysis and will be used as the target variable for logistic regression analysis and Bayesian binomial models.

About the Researcher

The person conducting the research is Sam Koscelny, a third year Industrial Engineering and Management student at Oklahoma State University. He will administer the data collection during the month of April of 2021 by uploading the survey to the social media websites of Facebook, Twitter, and LinkedIn and text messaging the survey to people of one degree of separation from him. The expected sample size, N, is going to be N = 80.

Exploratory Data Analysis

As a result of the data collection, the data analysis will include constructions of histograms to display the frequency of the specific responses. After the exploratory analysis of the data is implemented, the building of the logistic regression model will begin.

Logistic Regression Analysis

Multiple logistic regression models will be constructed and using stepwise deletion, a final model will be formed through identifying the significant predictors which influence trust the most. This final model will be written in the form of logistic equation where trust is equated based off the significant predictors. From the equation and logistic regression model, interpretability and inference about the factors of trust in automation in healthcare will be discussed. Furthermore, at the completion of the frequentist approach of logistic model building, Bayesian Binomial models will be created.

Bayesian Binomial Analysis

The models will be built off the project data using "trust" as the target variable. By counting the number of occurrences a population trusts automated healthcare and the number of overall responses from the survey, Bayesian binomial models can be constructed using priors, current data, and calculation of the posterior. These models will be compared with different values of the prior to show how changes in the past data compared to new data influence the construction of the posterior. Furthermore, a realistic scenario will be simulated using prior data and new data to display the effectiveness of Bayesian statistics in a real-world situation.

At the completion of building both the logistic regression model and Bayesian binomial model, discussion of the models will take place to compare the advantages and disadvantages of each model.

Results

After the survey was conducted, the dataset was downloaded as a .csv file and uploaded into R Studio to conduct statistical analysis. There was a total of 80 responses with varying degrees of response types. The following histograms were used to gain insight about the dataset:

Figure 1.1 - Histogram of Age

Figure 1.2 - Histogram of Gender

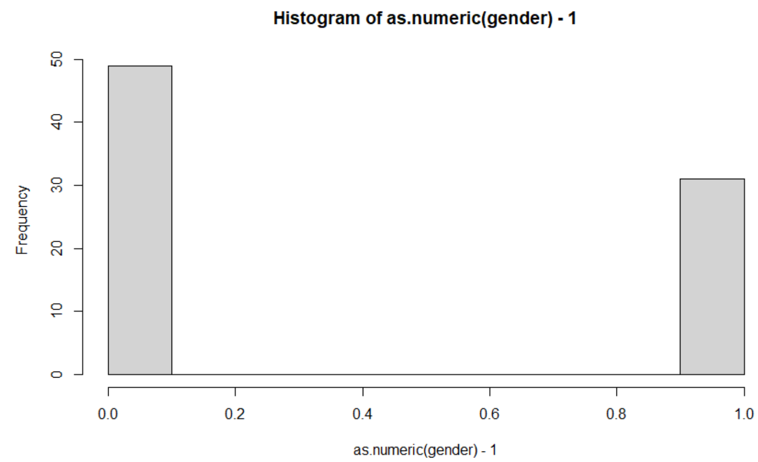
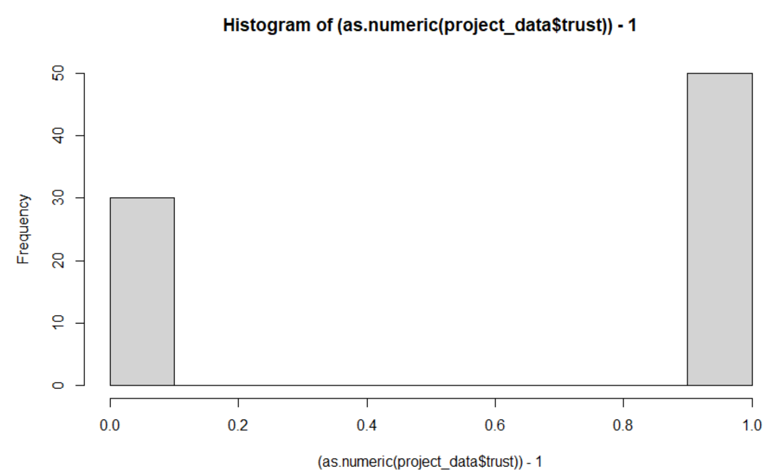


Figure 1.3 – Histogram of Trust in Automation in Healthcare



Analysis of the Exploratory Analysis:

Out the 80 responses, the majority are derived from the age population of 20 – 25 years old. Further, there were more females who answered the survey than men, and 50 responses are determined to trust automation in healthcare, while 30 responses did not indicate a trust in automation in healthcare.

Logistic Regression Analysis:

Following the basic description of the dataset, the logistic regression analysis was performed. Using the Stepwise Deletion method, the most important factors in predicting trust in automation in healthcare are:

- Gender
- Degree
- Political View
- Number of Smart Devices

The output of the logistic regression model is below:

Figure 1.4 – Summary of Logistic Regression Model

```
Call:
glm(formula = trust ~ gender + degree + pol + number_of_smart_devi
    family = "binomial", data = project_data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.0141  -0.9364   0.5023   0.8744   1.7605

Coefficients:
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)              0.06168    0.82857   0.074  0.94066
genderMale               1.36160    0.60565   2.248  0.02457 *
degreeHigh School        0.13694    0.60733   0.225  0.82160
degreeMaster's Degree   -1.23670    0.85220  -1.451  0.14673
degreePh.D. or higher   -3.49006    1.22092  -2.859  0.00426 **
polconservative         -1.53388    0.70497  -2.176  0.02957 *
polliberal              -0.41082    0.82636  -0.497  0.61909
number_of_smart_devices  0.29163    0.14390   2.027  0.04270 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 105.850  on 79  degrees of freedom
Residual deviance:  87.261  on 72  degrees of freedom
AIC: 103.26

Number of Fisher Scoring iterations: 4
```

Analysis of Logistic Regression Summary

Taking the values from the output, a logistic regression model can be derived. Trust is the target variable and in the logistic regression model, and it can be interpreted as percent chance for an individual to trust automation in healthcare. As the modeling of trust gets closer to 1, the likelihood of the patient realistically trusting automation in healthcare increases and as trust gets closer to 0, the likelihood of the patient realistically distrusting automation in healthcare decreases.

Logistic Regression Model of Trust in Automation in Healthcare:

trust = 0.06168 + 1.3616*(X1) – 3.49*(X2) – 1.53388*(X3) + .29163*(X4)

Bayesian Binomial Analysis:

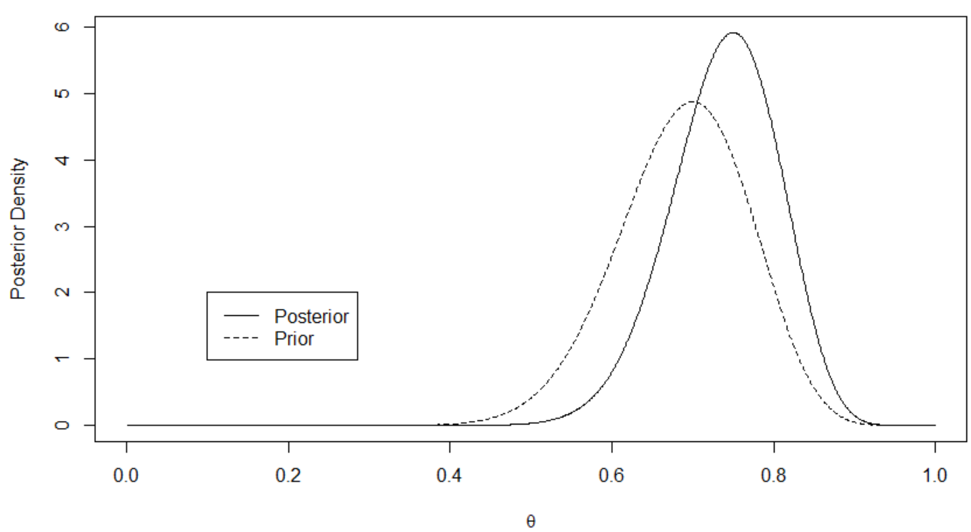
Various Bayesian binomial models were conducted to estimate the impact of the prior on the posterior to optimize the number of prior data needed in order to accurately predict the posterior. A table was constructed to display the varying models constructed:

Figure 1.5	Prior = 20 samples, New Data = 10
Figure 1.6	Prior = 30 samples, New Data = 10
Figure 1.7	Prior = 40 samples, New Data = 10
Figure 1.8	Prior = 50 samples, New Data = 10
Figure 1.9	Prior = 60 samples, New Data = 10
Figure 1.10	Prior = 80 samples, New Data = 10
Figure 1.11	Prior = 60 samples, New Data = 40

Table 1.1 – Table of Figures for the Bayesian Binomial Models

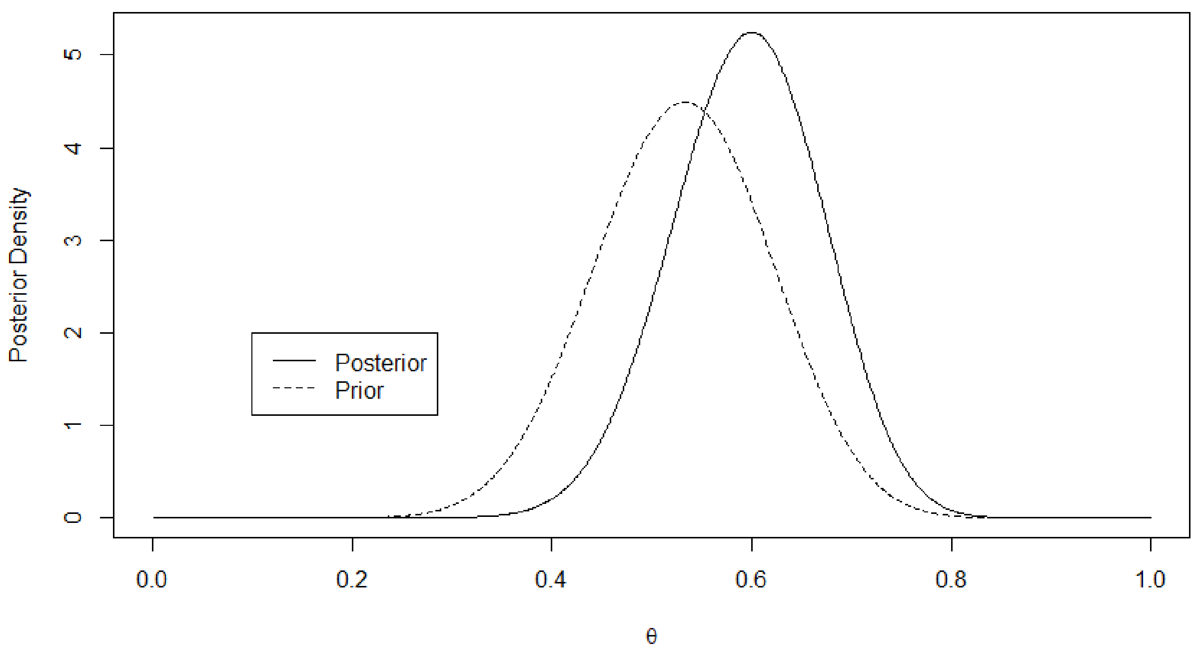
The results are as follows.

Figure 1.5 – Bayesian Binomial Model with Prior = 20 samples



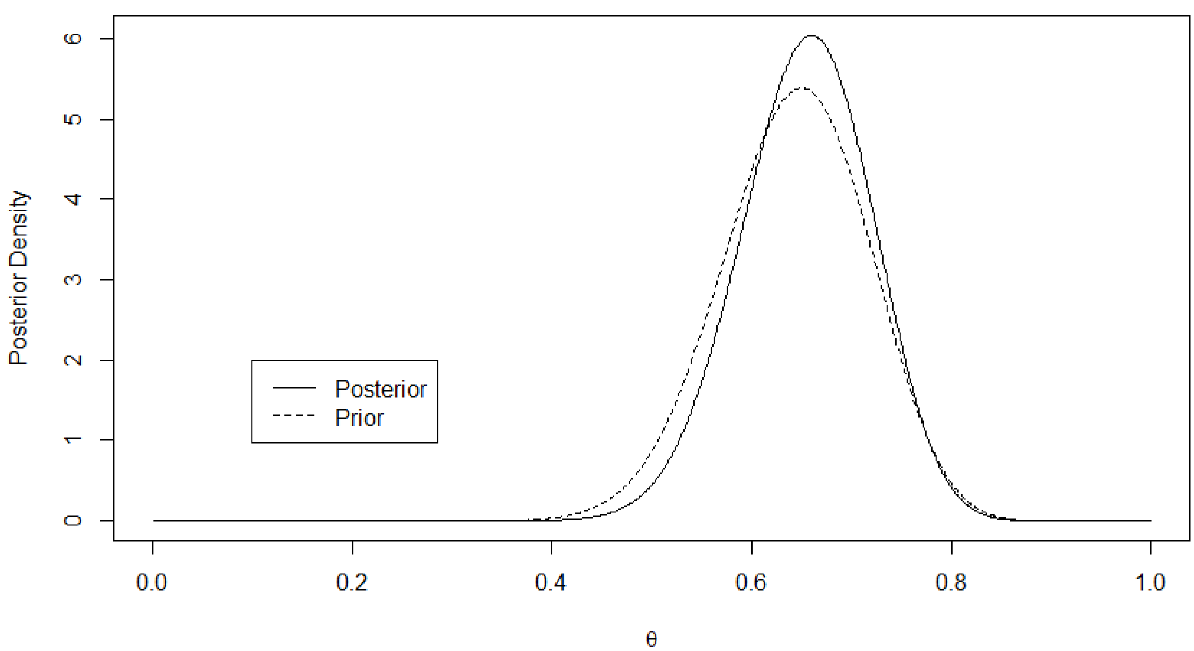
Lower CI	Upper CI	Percent Accuracy
0.6325147	0.9937264	0.9500000

Figure 1.6 – Bayesian Binomial Model with Prior = 30 samples



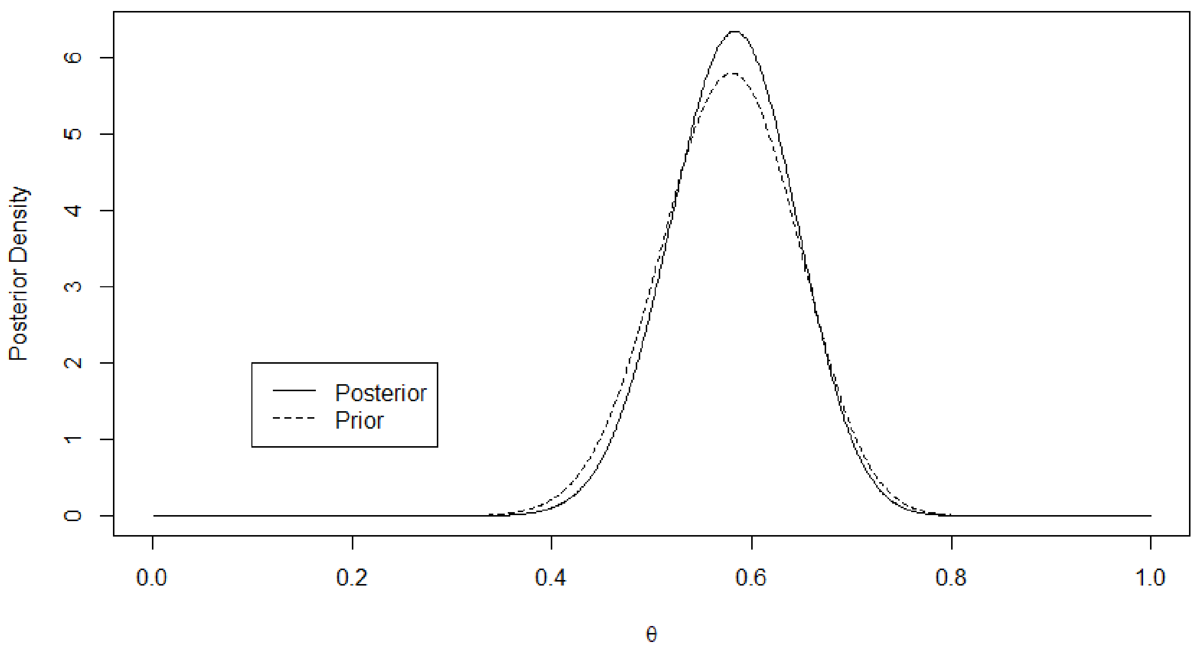
Lower CI	Upper CI	Percent Accuracy
0.5162805	0.9594457	0.9500000

Figure 1.7 – Bayesian Binomial Model with Prior = 40 samples



Lower CI	Upper CI	Percent Accuracy
0.4120577	0.9066268	0.9500000

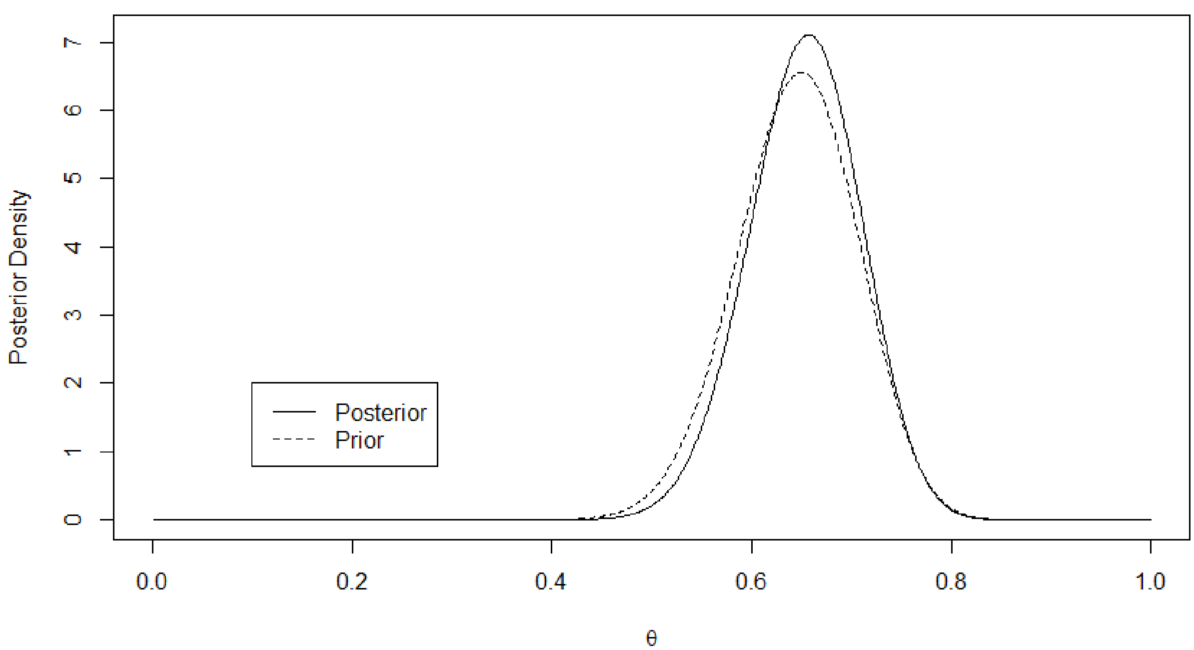
Figure 1.8 – Bayesian Binomial Model with Prior = 50 samples



Lower CI	Upper CI	Percent Accuracy

0.2337926	0.7662074	0.9500000

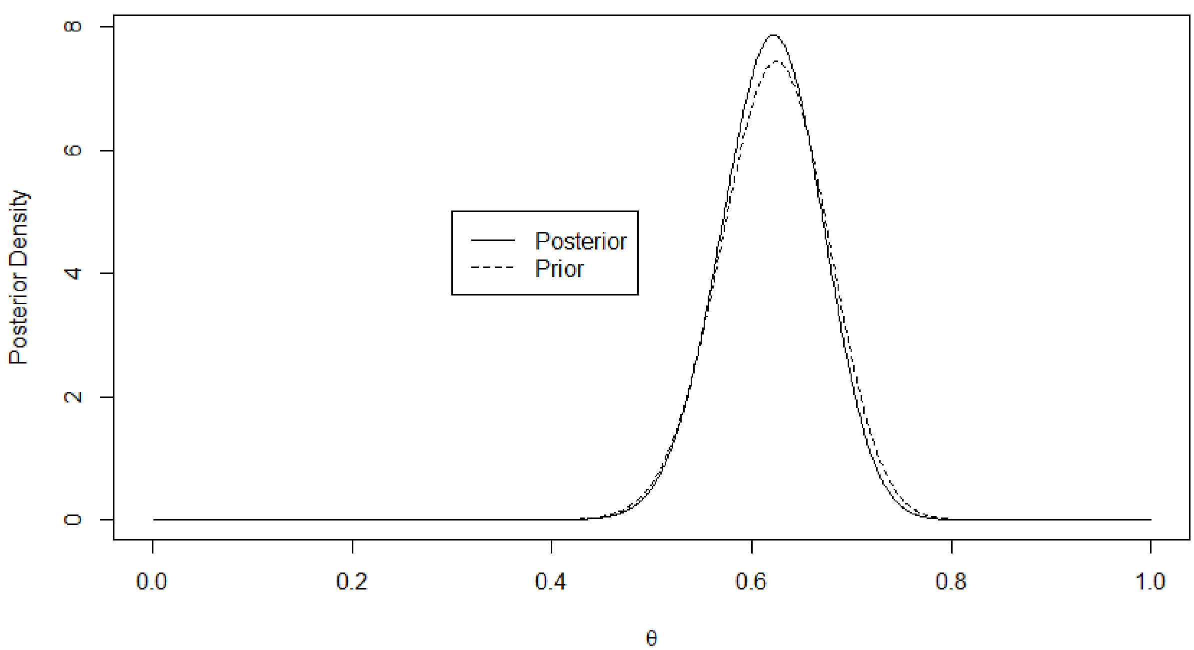
Figure 1.9 – Bayesian Binomial Model with Prior = 60 samples



Lower CI	Upper CI	Percent Accuracy

0.4120577	0.9066268	0.9500000

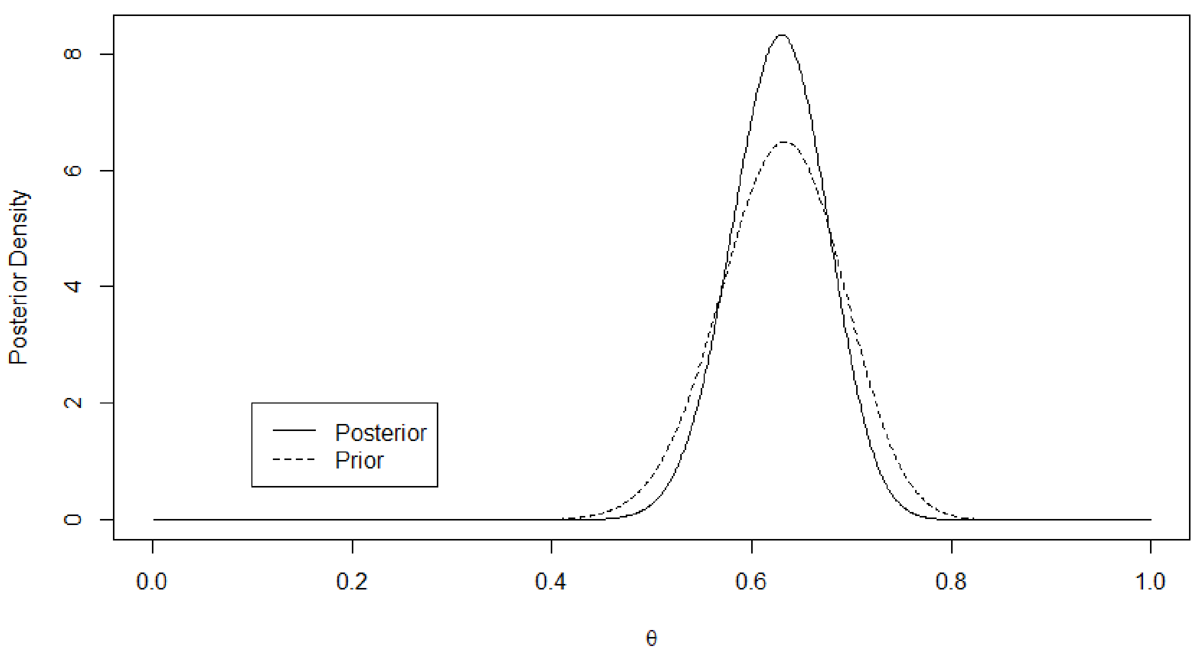
Figure 1.10 – Bayesian Binomial Model with Prior = 80 samples



Lower CI	Upper CI	Percent Accuracy

0.3182255	0.8414229	0.9500000

Figure 1.11 – Bayesian Binomial Model with Prior = 60 samples and New Data = 40



Lower CI	Upper CI	Percent Accuracy

0.4733672	0.7616007	0.9500000

Discussion

Analysis of the results of the Logistic Regression and Bayesian Binomial Model will be presented in this section.

Analysis of the Logistic Regression Model

In Figure 1.4, the summary of the logistic regression model was performed. Where the X variables are: X1 is genderMale, X2 is degreePh.D. or higher, X3 is polconservative, X4 is number_of_smart_devices. To interpret the output, factors which increase the likelihood of trust are when the patient is male and as the number of smart devices increase, likelihood of trust improves. Factors which decrease trust are if the patient holds a Ph.D. degree or degree of higher education and if the patient is conservative. In terms of significance, holding a Ph.D. has the greatest impact on a patient's trust in automation in healthcare, while being politically conservative, one's gender being male, and the number of smart devices are the following factors which decrease in significance.

The intercept of the model, or the baseline model, is composed of the variables genderFemale, degreeBachelors, and polneutral. With the value of 0.06168, it means, when the gender is female, the level education achieved by the patient is a bachelors, and their political leanings are neutral, and the number of smart devices neither increases or decreases (X4=0), the value of 0.06168 can be used to get the expected value of the probability of trust in automation in healthcare.

Validation of the Logistic Regression Model

1) Confusion Matrix

The logistic regression model was split into training and test sets in order to validate the results, and the split was a 50/50 split. The training set was used to train a logistic regression model. The trained model was then tested against the test dataset in order to determine if the trained model can accurately predict if the patient would trust or not trust healthcare in automation in the test dataset. The minority class, not trusting automation in healthcare, is the true positive in the cross validation while trusting automation in healthcare is the true negative. A confusion matrix was then constructed as a table to demonstrate the results. These results are below:

lm.pred1 Confusion Matrix	Actual No	Actual Yes
Predicted No	5	4
Predicted Yes	5	26

Table 1.1 – Confusion Matrix of lm.pred1

From the confusion matrix, the percent correct is 77.5% and the misclassification rate is 22.5%. The calculated F-score is 0.52631.

k-Fold CV

Another method used to validate the results was the k-Fold method. The data was split into 5 and 10 k-Folds with a 50/50 split in the data.

Test Error	Fold
0.225	1
0.250	2
0.200	3
0.225	4
0.250	5
Mean Error	**0.23**

Table 1.2 – k-Fold Results, where k = 5

Test Error	Fold
0.300	1
0.325	2
0.275	3
0.325	4
0.325	5
0.175	6

0.200	7
0.200	8
0.225	9
0.275	10
Mean Error	**0.2625**

Table 1.2 – k-Fold Results, where k = 10

From the two k-Fold methods, the mean error is 0.23 and 0.2625 for k = 5 and k = 10, respectively. This output is consistent with the mean error from the confusion matrix.

Discussion of the Logistic Regression Validation

The results from the confusion matrix are mixed. While the accuracy is 77.5% correct, the F-score is 52.6%. So, while the model is correct 77.5% of the time, its significance is average. The reason for these results is that for the model, it is easier to determine the false positive, i.e. a patient has trust in automation, because there are more occurrences of the false positive in the model. The challenge for the model is accurately predicting the true positive, i.e. a patient does not have trust in automation. While it accurately predicted the true positive 5 times, it made the errors of misclassification 4 times and false alarm 5 times. In other words, it missed 5 patients who did not have trust in automation in healthcare, which with the minority class being not having trust, this is the most critical error. With the model incorrectly identifying people who don't have trust more than it correctly identifies them, it is a critical flaw in the frequentist model. The k-Fold findings are consistent with the results from the confusion matrix, and setting k equal to 5 results in the smallest mean error.

While the model's performance is mixed, the inference of the variables give valuable insight on how trust is constructed within a population. With the previous factors mentioned being key indicators of trust, it begs questions for further research. Questions such as:

In regards to males: What types of males are more prone to trust than others? Are males who play video games or engage in sci-fi fiction more prone to trust than those who don't? Or are males as a population more prone to trust than females?

In regards to number of smart devices: Do specific smart devices influence trust more than others? What impact does virtual reality or augmented reality have on trust?

In regards to the conservative political ideology: Do specific news channels or media outlets influence trust more than others? What fundamental beliefs do conservatives hold that might influence trust in automation in healthcare?

In regards to holders of Ph.D degrees: How has this level of education made one think critically about trust? Do Ph.D. graduates in STEM differ than Ph.D. graduates in the liberal arts?

Asking questions such as this to delve deeper in the factors that influence trust in automation in healthcare, can give a more cohesive and complete perspective on what specific factors influence trust the most. Furthermore, when implementing automation in healthcare across different populations, understanding all of the complex factors which impact trust will be paramount in the success of new healthcare technology.

Analysis of the Bayesian Binomial Model

Following the frequentist perspective of analyzing the dataset, Bayesian analysis was performed. As seen in Figures 1.5 – 1.10, varying Bayesian models were created to demonstrate the effect the prior distribution had on the posterior distribution. Table 1.1 displays the order in which the prior was augmented to demonstrate the effectiveness of the Bayesian models.

Figure 1.5 has the smallest prior size of n = 20, and it was tested on new data of size 10. As seen in the figure, the prior is shifted to the left of the posterior. In a formula this figure is represented as $P(0.63< \theta<0.99 \mid y) = 0.95$. The data which was given to the model calculated that a patient is 63% to 99% likely to trust automation in healthcare with a 95% accuracy. This estimate for a population seems to be too high and not representative of the entire population because while more people are likely to trust automation in healthcare than distrust it, it is likely to not be as prevalent as this Bayesian model predicts.

Figure 1.6 increased the prior size to n = 30, and its distribution is $P(0.52< \theta<0.96 \mid y) = 0.95$. Increasing the prior size seems to have made an impact on the model because now it is more realistic and reliable.

When looking at Figure 1.7, it shows that the prior is accurately modeled by the posterior, so it seems that for this dataset, when the prior reaches a value greater than 40, an accurate distribution can be calculated.

As the prior is increased to size 50 and 60 in Figure 1.8 and 1.9, more accurate models are created, and the final model, Figure 1.10, used the largest n, with n = 80, to generate the model. Yet, as the prior is increased in size, the models only slightly change. In these figures, the prior and posterior are seemingly similar, not entirely the same, but are accurate representations of each other.

This finding is important because it seems to suggest that after a certain sample size for the prior, new data can accurately predict the posterior. To apply this, consider a scenario where health care professionals are attempting to implement an artificial intelligence in a rural, third world country. Also consider that the communities being targeted are around populations of 30 – 50 people. This technology will function as a primary care physician, and in order for automated technology to function at its full capability will require trust on part of the patient for the A.I. to accurately and predictably diagnose correctly. Given a prior, or observed data, of ~ 40 to 60 sample size, from one village, the healthcare professionals can take that data and combine it with new data at the current village to get an accurate posterior estimate of the patients in the rural community's trust in automated healthcare. Figure 1.11 demonstrated this scenario by considering the prior to be 60 samples and the new data to 40 samples. The models of the prior and posterior validly model each other and it provides a realistic distribution of $P(0.47< \theta<0.76 \mid y) = 0.95$.

Comparison of the Logistic Regression Model and Bayesian Binomial Model

The findings from the Bayesian binomial model are very interesting when compared to the logistic regression model. The frequentist approach to analyzing the dataset required a lot of data to even create an accurate model, and to improve upon the model will need even more data collection. This approach can be very expensive in terms of time and cost, and depending on the goal of the researcher, may not even be necessary. Going back to the scenario, if health professionals want to implement trust in automation in healthcare in a population in the most efficient way, the Bayesian binomial approach may be the best choice. This method can accurately predict an individual's chance at trusting automation with a relatively small data collection when compared to the logistic approach.

If the researcher is wanting to investigate the specific factors and their relationship with trust, then the logistic regression method may be a better choice for the research team, given they have appropriate amount of funding and time to collect data.

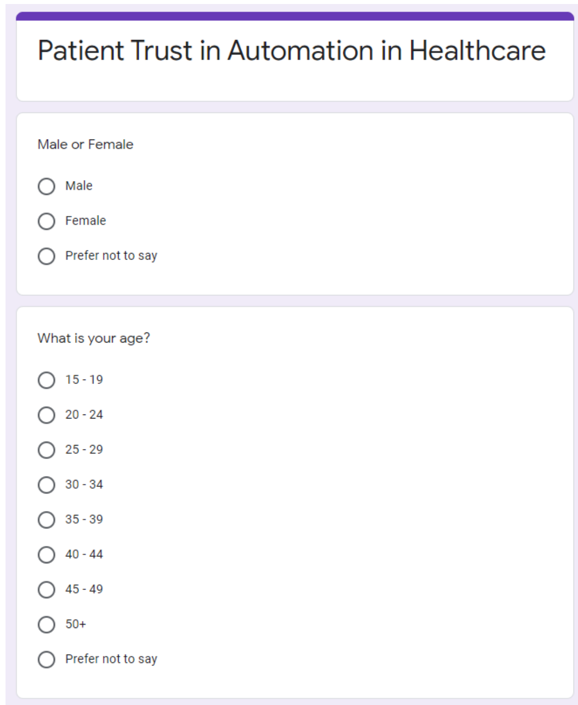
Conclusion

Both the logistic regression model and the Bayesian binomial model are applicable given the correct circumstance. Further research will need to be done to delve deeper into the factors which influence a population's trust in automation in healthcare. Yet, as further technology is developed and society progresses, the factors which influence trust today may not be the factors which influence it tomorrow. It is important for researchers to actively gauge the populations trust levels to observe how it changes over time. Quantifying trust in automation is not an easy task, but the factors found in this research may lead to finding factors in the future which significantly impact trust in automation in healthcare. As that research is being conducted, the findings of today can be implemented to be consciousness of the patient's trust in order to improve their experience in the healthcare sector.

List of Appendices

Appendix A – Survey Questionnaire

Figure 2.1 – Patient Trust in Automation in Healthcare Survey



Patient Trust in Automation in Healthcare

Male or Female

- Male
- Female
- Prefer not to say

What is your age?

- 15 - 19
- 20 - 24
- 25 - 29
- 30 - 34
- 35 - 39
- 40 - 44
- 45 - 49
- 50+
- Prefer not to say

Please specify your ethnicity.

- Caucasian
- African-American
- Latino or Hispanic
- Asian
- Native American
- Native Hawaiian or Pacific Islander
- Two or More
- Other/Unknown
- Prefer not to say

What is the highest degree or level of education you have completed?

- Some High School
- High School
- Bachelor's Degree
- Master's Degree
- Ph.D. or higher
- Trade School
- Prefer not to say

What is your current employment status?

- Employed Full-Time
- Employed Part-Time
- Seeking opportunities
- Retired
- Prefer not to say

How would you describe your political view?

- Very Liberal
- Slightly Liberal
- Slightly Conservative
- Very Conservative
- Prefer not to say

How often do you use a computer?

- Very often
- Often
- Neutral
- Not often
- Not very often

How many hours a day do you use a computer?

- Less than 1 hour
- Between 1 and 2 hours
- Between 2 and 3 hours
- Between 3 and 4 hours
- Between 4 and 5 hours
- More than 6 hours

I think that automated devices used in medicine, such as CT scans and ultrasound, provide very reliable medical diagnosis.

- Strongly Disagree
- Disagree
- Neither Disagree nor Agree
- Agree
- Strongly Agree

If I need to have a tumor in my body removed, I would choose to undergo computer-aided surgery using laser technology because it is more reliable and safer than manual surgery.

- Strongly Disagree
- Disagree
- Neither Disagree nor Agree
- Agree
- Strongly Agree

Automated systems used in modern aircraft, such as the automatic landing system, have made air journeys safer.

- Strongly Disagree
- Disagree
- Neither Disagree nor Agree
- Agree
- Strongly Agree

ATMs provide a safeguard against the inappropriate use of an individual's bank account by dishonest people.

- Strongly Disagree
- Disagree
- Neither Disagree nor Agree
- Agree
- Strongly Agree

Automated devices used in aviation and banking have made work easier for both employees and customers.

- Strongly Disagree
- Disagree
- Neither Disagree nor Agree
- Agree
- Strongly Agree

Even though the automatic cruise control in my car is set at a speed below the speed limit, I worry when I pass a police radar speed trap in case the automatic control is not working properly.

- Strongly Disagree
- Disagree
- Neither Disagree nor Agree
- Agree
- Strongly Agree

Manually sorting through card catalogues is more reliable than computer-aided searches for finding items in a library.

- Strongly Disagree
- Disagree
- Neither Disagree nor Agree
- Agree
- Strongly Agree

I would rather purchase an item using a computer than have to deal with a sales representative on the phone because my order is more likely to be correct using the computer.

- Strongly Disagree
- Disagree
- Neither Disagree nor Agree
- Agree
- Strongly Agree

Bank transactions have become safer with the introduction of computer technology for the transfer of funds.

- Strongly Disagree
- Disagree
- Neither Disagree nor Agree
- Agree
- Strongly Agree

I feel safer depositing my money at an ATM than with a human teller.

- Strongly Disagree
- Disagree
- Neither Disagree nor Agree
- Agree
- Strongly Agree

I have to tape an important TV program for a class assignment. To ensure that the correct program is recorded, I would use the automatic programming facility on my VCR rather than manual taping.

- Strongly Disagree
- Disagree
- Neither Disagree nor Agree
- Agree
- Strongly Agree

Do you trust the integration of technology in everyday life?

	1	2	3	4	5	6	7	8	9	10	
Not at all	○	○	○	○	○	○	○	○	○	○	Absolutely

On a scale from 1 - 10, would you be happy to see the integration of artificial intelligence in everyday life?

	1	2	3	4	5	6	7	8	9	10	
Not happy	○	○	○	○	○	○	○	○	○	○	Very happy

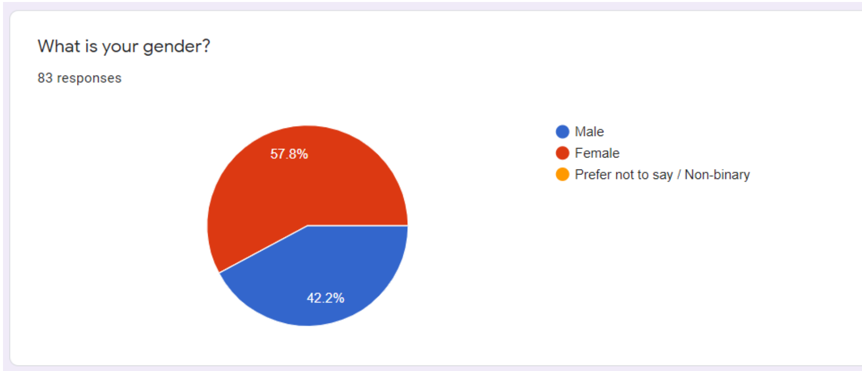
On a scale from 1 - 10, how comfortable would you be if a doctor performed surgery with the assistance from an automotive robot?

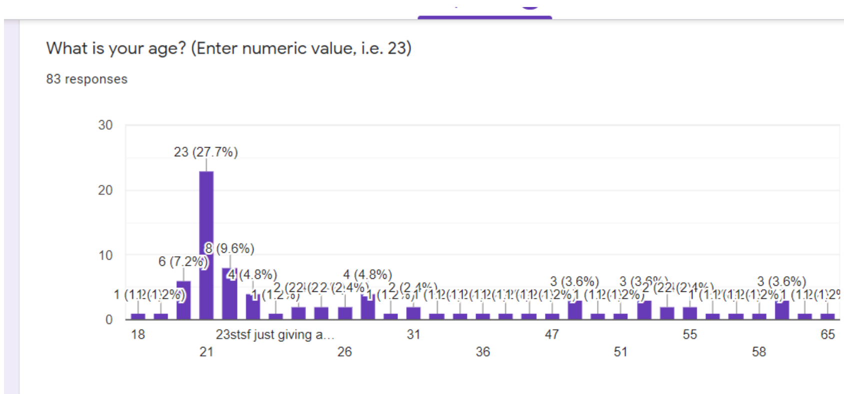
	1	2	3	4	5	6	7	8	9	10	
Not comfortable	○	○	○	○	○	○	○	○	○	○	Very comfortable

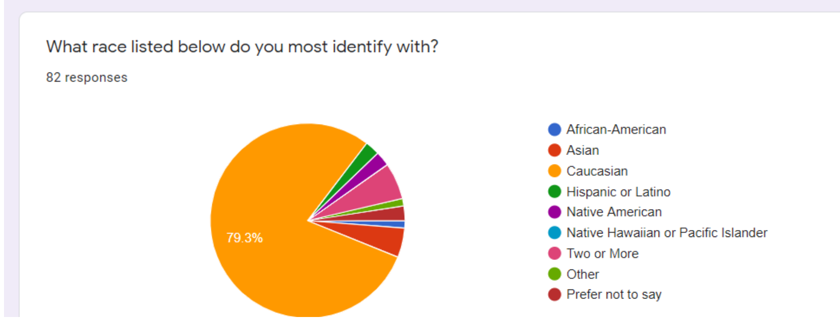
On a scale from 1 - 10, how comfortable would you be if a robot performed surgery without the assistance of a doctor

	1	2	3	4	5	6	7	8	9	10	
Not comfortable	○	○	○	○	○	○	○	○	○	○	Very comfortable

Appendix B – Survey Responses

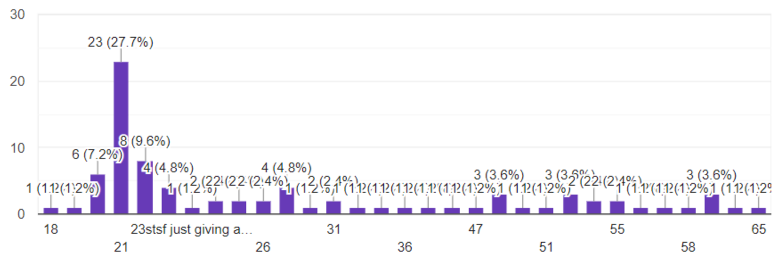






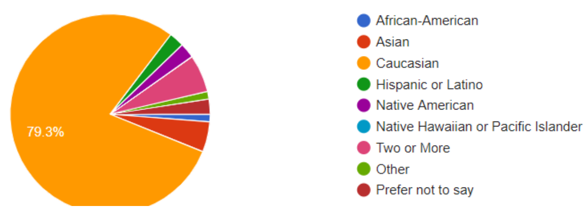
What is your age? (Enter numeric value, i.e. 23)

83 responses



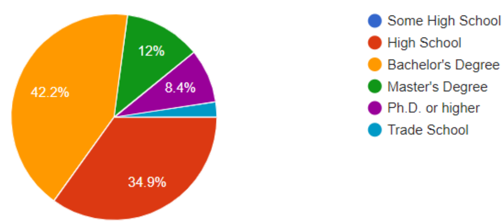
What race listed below do you most identify with?

82 responses



What is the highest degree or level of education you have completed?

83 responses



What is your occupation?

82 responses

Reservoir Engineering

Business development manager

Health Program Administrator

Occupational therapists

Risk and Safety Specialist

Technical Analyst

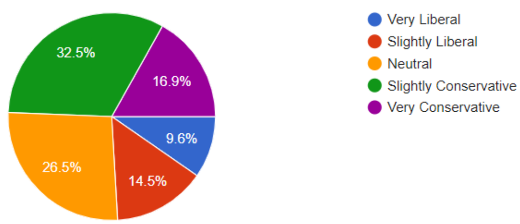
Accounting

Student worker

PA

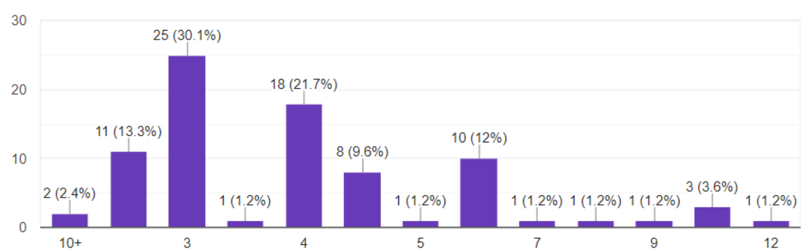
How would you describe your political view?

83 responses



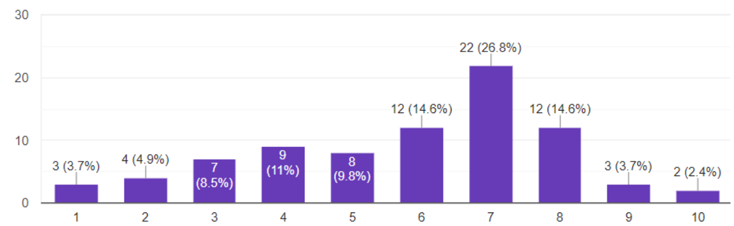
How many smart devices do you own? (e.g.), smartphone, computer, tablet, watch, home automation devices, automotive automation, etc. (Enter numeric value, i.e., 3)

83 responses



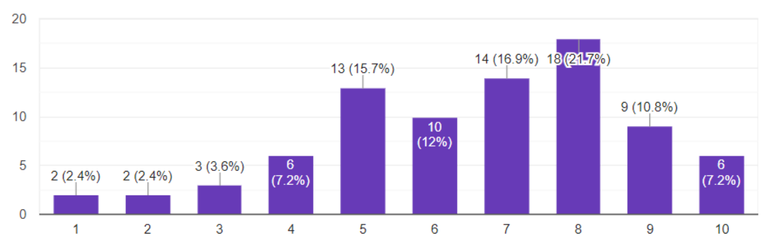
Consider a scenario where you visit your primary care provider for an annual health examination. You present unusual cardiac symptoms and your Primary Care Provider cannot refer to a cardiologist therefore they used an automated assistant to diagnose you. The algorithm takes in your symptoms and demographics and outputs a diagnosis and recommendation that your Primary Care Provider confirms. On a scale of 1-10 how much do you trust the assisted automations diagnosis?

82 responses



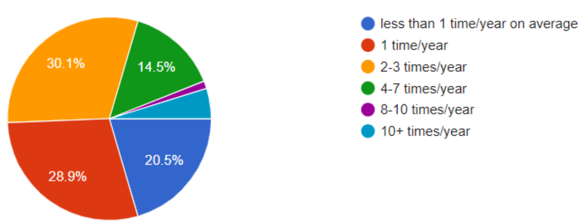
Consider a scenario where you visit your primary care provider for an annual health examination. You present normal cardiac symptoms and your Primary Care Provider cannot refer to a cardiologist therefore they used an automated assistant to diagnose you. The algorithm takes in your symptoms and demographics and outputs a diagnosis of your risk for developing heart disease. On a scale of 1-10 how much do you trust the assisted automations diagnosis?

83 responses



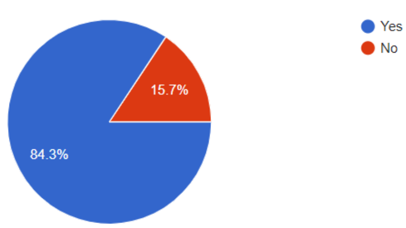
How often do you see a doctor? (can be Primary Care Provider, specialty, women's health, mental health, etc.)

83 responses



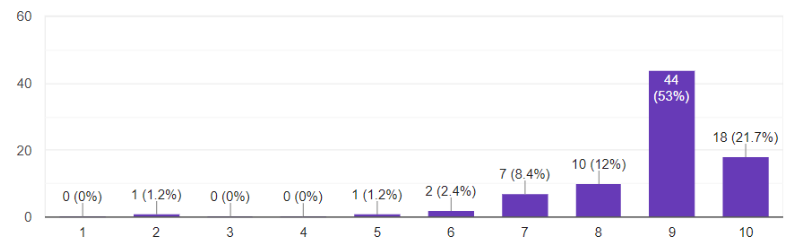
Have you ever used the internet to check health related symptoms such as WebMD?

83 responses



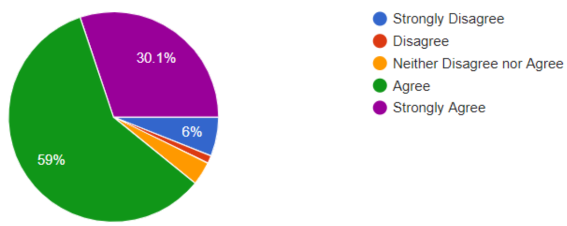
On a scale of 1-10, how much do you trust a GPS system to provide you driving instructions to a destination? (This assumes you only input the destination and do not interfere with the GPS automation until you've reached your destination.)

83 responses



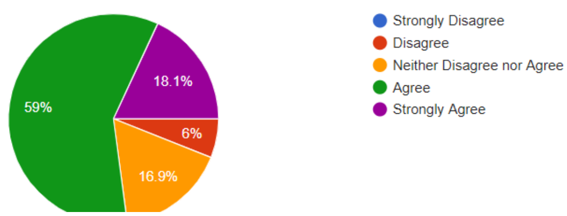
I think that automated devices used in medicine, such as CT scans and ultrasound, provide very reliable medical diagnosis.

83 responses



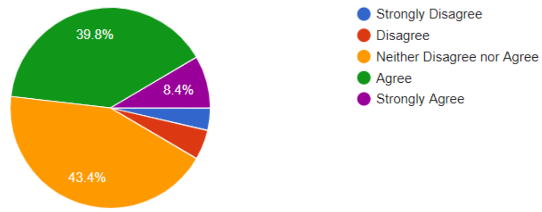
Automated devices in medicine save time and money in the diagnosis and treatment of disease.

83 responses



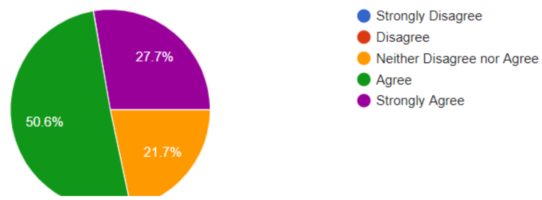
If I need to have a tumor in my body removed, I would choose to undergo computer-aided surgery using laser technology because it is more reliable and safer than manual surgery.

83 responses



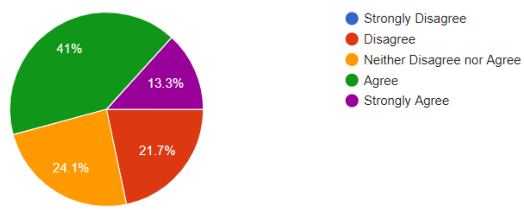
Automated systems used in modern aircraft, such as the automatic landing system, have made air journeys safer.

83 responses



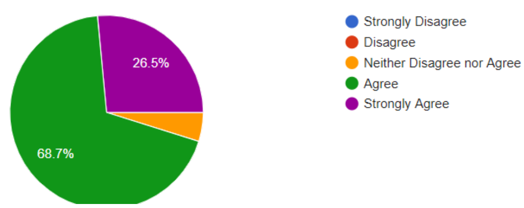
ATMs provide a safeguard against the inappropriate use of an individual's bank account by dishonest people.

83 responses



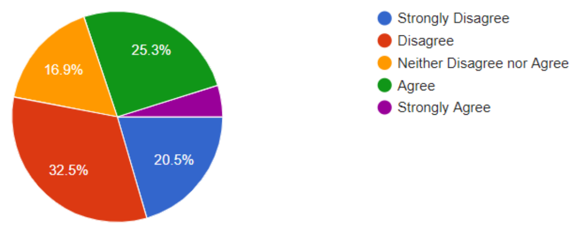
Automated devices used in aviation and banking have made work easier for both employees and customers.

83 responses



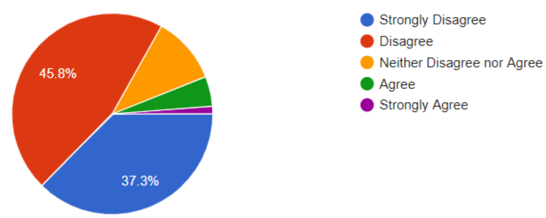
Even though the automatic cruise control in my car is set at a speed below the speed limit, I worry when I pass a police radar speed trap in case the automatic control is not working properly.

83 responses



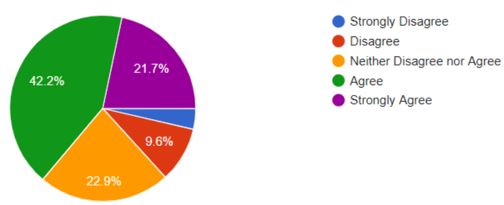
Manually sorting through card catalogues is more reliable than computer-aided searches for finding items in a library.

83 responses



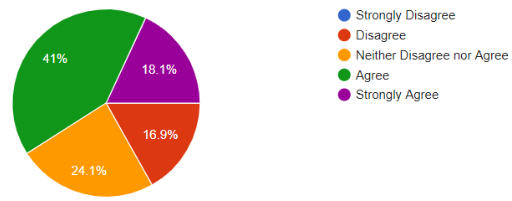
I would rather purchase an item using a computer than have to deal with a sales representative on the phone because my order is more likely to be correct using the computer.

83 responses



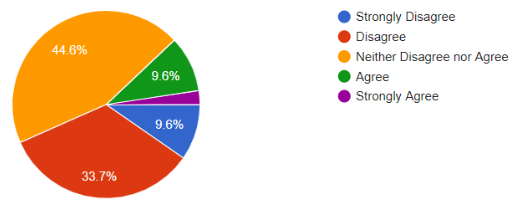
Bank transactions have become safer with the introduction of computer technology for the transfer of funds.

83 responses



I feel safer depositing my money at an ATM than with a human teller.

83 responses



Appendix C – Outputs in R

Figure 2.2 – Confusion Matrix of lm.pred1

```
lm.pred1  0  1
       0  5  4
       1  5 26
```

Figure 2.3 – k-Fold, where k = 5

```
> error_df
  test_error fold
1      0.225    1
2      0.200    2
3      0.275    3
4      0.250    4
5      0.175    5
> mean(error_df$tes
[1] 0.225
```

Figure 2.4 – k-Fold, where k = 10

```
> error_df
   test_error fold
1       0.300    1
2       0.325    2
3       0.275    3
4       0.325    4
5       0.325    5
6       0.175    6
7       0.200    7
8       0.200    8
9       0.225    9
10      0.275   10
> mean(error_df$test_error)
[1] 0.2625
```

Appendix D – R Code

```
library(readxl)
rm(list=ls())
###Logistic Regresssion Analysis
project_data = read.csv("/Users/skoscel/Documents/OSU Spring 2021/IEM 5990/Patient Trust in
AI Doctors (Responses)_use.csv", colClasses=c('factor', 'numeric', 'factor', 'factor', 'factor',
'factor', 'numeric','numeric', 'numeric', 'factor','factor', 'numeric', 'factor', 'factor',
'factor','factor','factor','factor','factor','factor','factor','factor','factor'))
project_data
attach(project_data)

###Exploratory data analysis
hist(age)
hist(as.numeric(gender) - 1 )
hist(as.numeric(project_data$trust) - 1)

contrasts(gender)
contrasts(occupation)

var(scenario1)
boxplot(scenario1)
var(scenario2)
boxplot(scenario2)

###Make scenario1 cateogrical with 0 being not trust and 1 being trust
project_data$trust=1
project_data$trust[which(project_data$scenario1==0)]=0
project_data$trust[which(project_data$scenario1==1)]=0
project_data$trust[which(project_data$scenario1==2)]=0
project_data$trust[which(project_data$scenario1==3)]=0
project_data$trust[which(project_data$scenario1==4)]=0
project_data$trust[which(project_data$scenario1==5)]=0
project_data$trust=as.factor(project_data$trust)


###make often_do_see_doctor categorical with levels of high and low
project_data$docfreq="high"
project_data$docfreq[which(as.character(project_data$often_do_see_doctor)=="less than 1
time/year on average")]="low"
project_data$docfreq[which(as.character(project_data$often_do_see_doctor)=="1
time/year")]="low"
project_data$docfreq=as.factor(project_data$docfreq)
```

```
###Make pol (political ideaology of patient) categorical with levels of liberal, conservative and, neutral
project_data$pol="liberal"
project_data$pol[which(as.character(project_data$political_view)=="Slightly Conservative")]="conservative"
project_data$pol[which(as.character(project_data$political_view)=="Very Conservative")]="conservative"
project_data$pol[which(as.character(project_data$political_view)=="Neutral")]="neutral"
project_data$pol=as.factor(project_data$pol)

project_data$pol=relevel(project_data$pol, ref="neutral")


###count the number of times the patient trust and do not trust in the survey
count(project_data$trust)


###fit logistic regression model
###used stepwise deletion to fit the model to the best fit
lm.fit1=glm(trust~gender+degree+pol+number_of_smart_devices, data=project_data, family="binomial")

###get signficant factors of the model
summary(lm.fit1)


###get second model to see how to behaves
###did not use in project
lm.fit2=glm(trust~gender+degree+pol+number_of_smart_devices + race, data=project_data, family="binomial")

summary(lm.fit2)

###compare the models
###did not use in project
lrtest(lm.fit1, lm.fit2)


##### LOGISTIC REGRESSION VALIDATION  ###########
#split into training and test sets
set.seed(5)
n=nrow(project_data)
train=sample(1:n,.5*n)
test=(-train)
train=project_data[train,]
test=project_data[test,]
```

```
###Fit the model with test data
lm.fit_train=glm(trust~gender+degree+pol+number_of_smart_devices, data=test,
family="binomial")
summary(lm.fit_train)

##Construct the confusion matrix
lm.probs1=predict(lm.fit_train, data=test, type = "response")
lm.probs1[1:10]
contrasts(project_data$trust) ## yes corresponds to a higher probability bc its associated with a 1
lm.pred1=rep("0",40) #creates a vector of n no elements
lm.pred1[lm.probs1 >= 0.5]="1" #transforms everything with prob above 0.5 to Up
lm.table1=table(lm.pred1,test$trust) #the diag is correct predictions and off-diag is incorrect
lm.correct1=mean(lm.pred1==test$trust)
lm.misclass1=mean(lm.pred1!=test$trust)

##confusion matrix table
lm.table1

###accuracy calculatoin
lm.correct1
###error calcualtion
lm.misclass1

###accuracy function
accuracy = function(tp, fp, tn, fn) {


  accuracy = (tp + tn) / (tp + tn + fp + fn)
  print(accuracy)

}

###outputs .775
accuracy(5,4,26,5)


###fscore calculation
Fscore = function(tp, fp, tn, fn) {

  precision = tp / (tp +fp)
  recall = tp / (tp + fn)
  Fscore = (2*(precision*recall))/(precision + recall)
  print(Fscore)

}
```

```
###outputs .5263158
Fscore(5,4,26,5)


##### k fold CV
library(caret)
### change the "times" argument to your number of folds (k)
split_index=createDataPartition(project_data$trust, p = 0.5, list = FALSE, times = 5)
head(split_index)
error_df= data.frame(matrix(ncol = 2, nrow = ncol(split_index)))
colnames(error_df) = c('test_error', 'fold')
y.test=rep(0,nrow(project_data[-(split_index[,1]),]))
errors=rep(0,nrow(project_data[-(split_index[,1]),]))

for(i in 1:nrow(error_df)){
  # use ith column of split_index to create feature and target training/test sets
  train=project_data[ split_index[,i],]
  test=project_data[-split_index[,i],]
  y.true=as.character(test$trust)


  # Fit the model and predict
  lm.fit=glm(trust~gender+degree+pol+number_of_smart_devices, data=test, family="binomial")
  fit.pred=predict.glm(lm.fit, test, type="response")

  # Calculate error and store it
  for (j in 1:length(fit.pred)) {
    if (fit.pred[j]>0.5) {y.test[j]= 1}
    else {y.test[j]= 0}
    if (y.test[j]==y.true[j]) {errors[j]=1}
    else {errors[j]=0}

  }

  misclass=1-(sum(errors)/length(errors))
  error_df[i,'test_error']= misclass
  error_df[i, 'fold'] =i
}
###kFold Results
error_df
mean(error_df$test_error)
```

```
##################################################################################

###Bayesian Regression
Analysis###########################################################



#### Using same project data
rm(list=ls())
par(mfrow=c(1,1))



#PART 1 -Bayseian with prior = 20
# so we will use the original newdat3 as our prior data and let's use another 10 people as our new
data
newdat4=sample(data,10)
y=sum(newdat4)
n=length(newdat4)
#create an array for all values of theta, we know that it falls between 0 and 1
theta = seq(0.001, 0.999, by = 0.001)
#i have my original uniform prior from the original 80 data points as a and b
a=1
b=1
newdat3=sample(data,20)
yprior=sum(newdat3)
nprior=length(newdat3)
aprior=yprior+a
bprior=nprior-yprior+b
plot(theta, dbeta(theta,y+aprior,n-y+bprior),t="l",lty=1,ylab="Posterior Density",
    xlab=expression(theta))
lines(theta, dbeta(theta, aprior,bprior), lty=2)
legend(0.1, 2, c("Posterior", "Prior"), lty=c(1,2))

apost=y+aprior
bpost=n-y+bprior
mean=apost/(apost+bpost)
mode=(apost-1)/(apost+bpost-2)
mean
mode



#PART 2 - Bayseian with prior = 30
```

```
# so we will use the original newdat3 as our prior data and let's use another 10 people as our new
data
newdat4=sample(data,10)
y=sum(newdat4)
n=length(newdat4)
#create an array for all values of theta, we know that it falls between 0 and 1
theta = seq(0.001, 0.999, by = 0.001)
#i have my original uniform prior from the original 80 data points as a and b
a=1
b=1
newdat3=sample(data,30)

yprior=sum(newdat3)
nprior=length(newdat3)
aprior=yprior+a
bprior=nprior-yprior+b
plot(theta, dbeta(theta,y+aprior,n-y+bprior),t="l",lty=1,ylab="Posterior Density",
    xlab=expression(theta))
lines(theta, dbeta(theta, aprior,bprior), lty=2)
legend(0.1, 2, c("Posterior", "Prior"), lty=c(1,2))

apost=y+aprior
bpost=n-y+bprior
mean=apost/(apost+bpost)
mode=(apost-1)/(apost+bpost-2)
mean
mode



h.final<-optimize(Dev.HPD.beta.h,c(0,1),y=y,n=n,alpha=0.05)$minimum
HPD.beta.h(y, n, h.final, plot=F)



#PART 3 - Bayseian with prior = 40
# so we will use the original newdat3 as our prior data and let's use another 10 people as our new
data
newdat4=sample(data,10)
y=sum(newdat4)
n=length(newdat4)
#create an array for all values of theta, we know that it falls between 0 and 1
theta = seq(0.001, 0.999, by = 0.001)
#i have my original uniform prior from the original 80 data points as a and b
a=1
b=1
```

```
newdat3=sample(data,40)
yprior=sum(newdat3)
nprior=length(newdat3)
aprior=yprior+a
bprior=nprior-yprior+b
plot(theta, dbeta(theta,y+aprior,n-y+bprior),t="l",lty=1,ylab="Posterior Density",
    xlab=expression(theta))
lines(theta, dbeta(theta, aprior,bprior), lty=2)
legend(0.1, 2, c("Posterior", "Prior"), lty=c(1,2))

apost=y+aprior
bpost=n-y+bprior
mean=apost/(apost+bpost)
mode=(apost-1)/(apost+bpost-2)
mean
mode


h.final<-optimize(Dev.HPD.beta.h,c(0,1),y=y,n=n,alpha=0.05)$minimum
HPD.beta.h(y, n, h.final, plot=F)



#PART 4 - Bayseian with prior = 50
# so we will use the original newdat3 as our prior data and let's use another 10 people as our new
data
newdat4=sample(data,10)
y=sum(newdat4)
n=length(newdat4)
#create an array for all values of theta, we know that it falls between 0 and 1
theta = seq(0.001, 0.999, by = 0.001)
#i have my original uniform prior from the original 80 data points as a and b
a=1
b=1
newdat3=sample(data,50)
yprior=sum(newdat3)
nprior=length(newdat3)
aprior=yprior+a
bprior=nprior-yprior+b
plot(theta, dbeta(theta,y+aprior,n-y+bprior),t="l",lty=1,ylab="Posterior Density",
    xlab=expression(theta))
lines(theta, dbeta(theta, aprior,bprior), lty=2)
legend(0.1, 2, c("Posterior", "Prior"), lty=c(1,2))

apost=y+aprior
bpost=n-y+bprior
```

```
mean=apost/(apost+bpost)
mode=(apost-1)/(apost+bpost-2)
mean
mode

h.final<-optimize(Dev.HPD.beta.h,c(0,1),y=y,n=n,alpha=0.05)$minimum
HPD.beta.h(y, n, h.final, plot=F)


#PART 5 - Bayesian with prior = 60
# so we will use the original newdat3 as our prior data and let's use another 10 people as our new
data
newdat4=sample(data,10)
y=sum(newdat4)
n=length(newdat4)
#create an array for all values of theta, we know that it falls between 0 and 1
theta = seq(0.001, 0.999, by = 0.001)
#i have my original uniform prior from the original 80 data points as a and b
a=1
b=1
newdat3=sample(data,60)
yprior=sum(newdat3)
nprior=length(newdat3)
aprior=yprior+a
bprior=nprior-yprior+b
plot(theta, dbeta(theta,y+aprior,n-y+bprior),t="l",lty=1,ylab="Posterior Density",
    xlab=expression(theta))
lines(theta, dbeta(theta, aprior,bprior), lty=2)
legend(0.1, 2, c("Posterior", "Prior"), lty=c(1,2))

apost=y+aprior
bpost=n-y+bprior
mean=apost/(apost+bpost)
mode=(apost-1)/(apost+bpost-2)
mean
mode

h.final<-optimize(Dev.HPD.beta.h,c(0,1),y=y,n=n,alpha=0.05)$minimum
HPD.beta.h(y, n, h.final, plot=F)

####PART 5 - Bayesian with prior = 80
# so we will use the original newdat3 as our prior data and let's use another 10 people as our new
data
newdat4=sample(data,10)
y=sum(newdat4)
n=length(newdat4)
```

```
#create an array for all values of theta, we know that it falls between 0 and 1
theta = seq(0.001, 0.999, by = 0.001)
#i have my original uniform prior from the original 80 data points as a and b
a=1
b=1
data = as.numeric(project_data$trust) - 1
data
yprior=sum(data)
nprior=length(data)
aprior=yprior+a
bprior=nprior-yprior+b
plot(theta, dbeta(theta,y+aprior,n-y+bprior),t="l",lty=1,ylab="Posterior Density",
    xlab=expression(theta))
lines(theta, dbeta(theta, aprior,bprior), lty=2)
legend(0.3, 5, c("Posterior", "Prior"), lty=c(1,2))

apost=y+aprior
bpost=n-y+bprior
mean=apost/(apost+bpost)
mode=(apost-1)/(apost+bpost-2)
mean
mode



h.final<-optimize(Dev.HPD.beta.h,c(0,1),y=y,n=n,alpha=0.05)$minimum
HPD.beta.h(y, n, h.final, plot=F)

###############################################
### SCENARIO DESCRIBED IN PROJECT
###Bayesian with prior = 50, new data = 40
# so we will use the original newdat as our prior data and let's use another 30 people as our new
data

newdat4=sample(data,40)
y=sum(newdat4)
n=length(newdat4)
#create an array for all values of theta, we know that it falls between 0 and 1
theta = seq(0.001, 0.999, by = 0.001)
#i have my original uniform prior from the original 80 data points as a and b
a=1
b=1
newdat3=sample(data,60)
yprior=sum(newdat3)
nprior=length(newdat3)
aprior=yprior+a
```

```
bprior=nprior-yprior+b
plot(theta, dbeta(theta,y+aprior,n-y+bprior),t="l",lty=1,ylab="Posterior Density",
    xlab=expression(theta))
lines(theta, dbeta(theta, aprior,bprior), lty=2)
legend(0.1, 2, c("Posterior", "Prior"), lty=c(1,2))

apost=y+aprior
bpost=n-y+bprior
mean=apost/(apost+bpost)
mode=(apost-1)/(apost+bpost-2)
mean
mode

h.final<-optimize(Dev.HPD.beta.h,c(0,1),y=y,n=n,alpha=0.05)$minimum
HPD.beta.h(y, n, h.final, plot=F)




##################################################################
# Function: Computes the HPD interval associated with a
#          particular height variable h which ranges between
#          0 and 1.

HPD.beta.h = function(y, n, h=.1, a=1, b=1, plot=T, ...){
  apost= y + a
  bpost= n - y + b
  if (apost > 1 & bpost > 1) {
    mode = (apost - 1)/(apost + bpost - 2)
    dmode = dbeta(mode, apost, bpost)}
  else return("mode at 0 or 1: HPD not implemented yet")
  lt = uniroot(f=function(x){
    dbeta(x,apost, bpost)/dmode - h},
    lower=0, upper=mode)$root
  ut = uniroot(f=function(x){ dbeta(x,apost, bpost)/dmode - h},
             lower=mode, upper=1)$root
  coverage = pbeta(ut, apost, bpost) - pbeta(lt, apost, bpost)
  if (plot) {
    th = seq(0, 1, length=1000)
    plot(th, dbeta(th, apost, bpost),
         t="l", lty=1,xlab=expression(theta),
         ylab="Posterior Density", ...)
    abline(h=h*dmode)
    segments(ut,0,ut,dbeta(ut,apost,bpost))
    segments(lt,0,lt,dbeta(lt,apost,bpost))
```

```
    title(bquote(paste("P(", .(round(lt, 2))," < ", theta, " < ",
                  .(round(ut,2)), " | " , y, ") = ",
                  .(round(coverage, 2)))))
  }
  return(c(lt,ut,coverage,h))
}


###############################################################################
# HPD based interval:
# Note: h here is between 0 and 1 and each value of h in this region
#       provides and HPD interval with the coverage reported by the
#       function HPD.beta.h(....)


# Lets get the exact HPD interval

Dev.HPD.beta.h<-function(h, y, n, alpha){
  cov<-HPD.beta.h(y, n, h, plot=F)[3]
  res<-(cov-(1-alpha))^2
  return(res)
}

h.final<-optimize(Dev.HPD.beta.h,c(0,1),y=y,n=n,alpha=0.05)$minimum
HPD.beta.h(y, n, h.final, plot=F)
```

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