MSCI 718 - Statistics for Data Analysis

Analyzing the Influence of Exposure to Autonomous Vehicle Technology on its Safety Perception

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Introduction

The introduction of autonomous vehicles (AVs) indicates a transformative shift in the landscape of transportation, promising to revolutionize the driving experience in aspects of safety and efficiency. With the increase of AV technology in public roadways, it has become vital to understand the public perception of its safety. Social acceptance derived from the safety perception of AVs is a critical factor influencing their successful deployment. This research article aims to examine how exposure to autonomous vehicle technology is affecting the perceptions of road users, especially cyclists and pedestrians, in regard to safety.

AV technology interactions can significantly shape public opinion and acceptance. Research has indicated that personal experience with and education about AVs can result in more positive opinions and an increased chance of adoption. (Tapia et al., 2023) (Classen et al., 2023). On the other hand, minimal exposure may result in skepticism and increased safety concerns (Yang et al., 2022). Given the complex relationship between exposure and perception, conducting a comprehensive analysis is important. This analysis aims to enlighten stakeholders, such as policymakers, manufacturers, and the general public, about the elements contributing to the acceptance of AVs. As the automation levels of cars grow it is essential to ensure that vulnerable road users can safely interact with AVs and feel safe at the prospect of sharing the road with AVs – this is important to make the technology acceptable for mass deployments (Imanishimwe & Kumar, 2023).

In this report, Bayesian logistic regression has been used to understand the influence of technological familiarity with AV on its safety perception and how people feel sharing roads with AVs. We will be employing a dataset from a survey conducted in Pittsburgh, which records the feedback from bicyclists and pedestrians regarding their engagements with AVs (Data.Gov., 2021). This dataset provides a distinctive opportunity to study the perspectives of an often underrepresented group in AV research, non-vehicular road users, who have been significantly impacted by the technology's implementation. The model revealed that familiarity with tech behind AVs lead to a higher safety perception, feel comfortable sharing roads with AV and believe it will play a positive role in preventing traffic injuries.

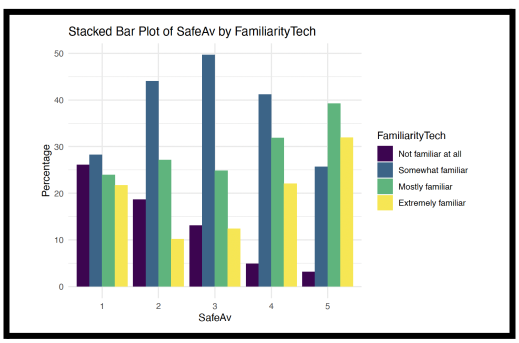
Methodology

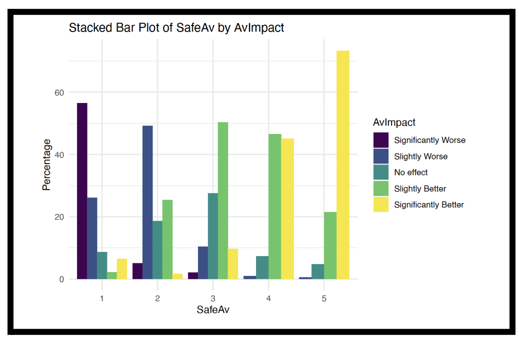
Data Collection

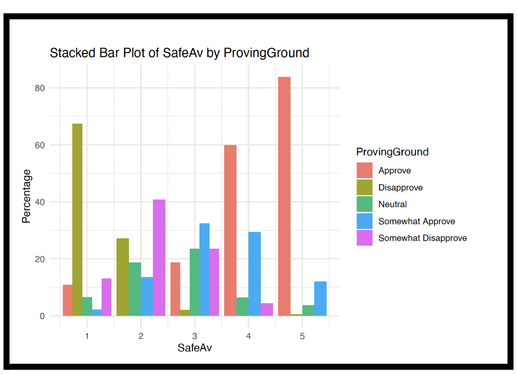
The data used in this study was obtained using an open data site from the United States government. The data is regarding a survey that was conducted in Pittsburgh in 2019 by the BikePGH organization to understand how residents of Pittsburgh feel about sharing roads with autonomous vehicles. The old survey was conducted in 2017 when Uber first launched AVs on the road in Pittsburgh, but it had different variables. The 2019 survey is not available on sites like Kaggle but is only available on the US Govt open data portal and BikePGH member website. The survey was conducted in two parts. Firstly, it was filled out by BikePGH donors, and secondly, it was filled out by residents of Pittsburgh. There were a total of 798 responses in the survey, but according to the scope of the study and defined variables, the final data comprised 645 responses.

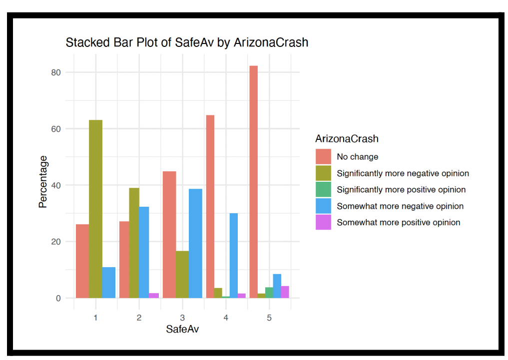
Conventional survey method analysis was used to conduct an extensive analysis of the data to understand how familiarity with AV tech influences an individual's safety perception. Since survey questions are mostly independent of each other, simpler models were used. Additionally, a majority of statistical methods are limited to the single variable effect; thus, the clustering or group effect is often not considered. The variables used in the study and their conceptual definition are listed in Table 1 in the appendix.

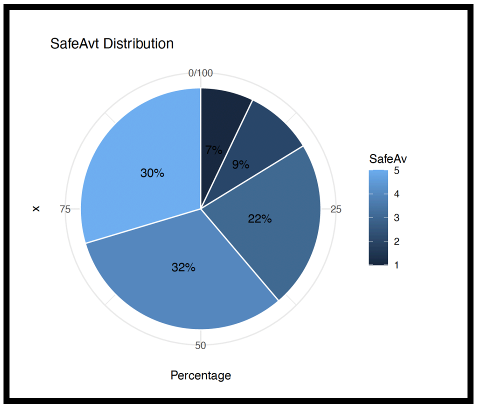
Exploratory Data Analysis

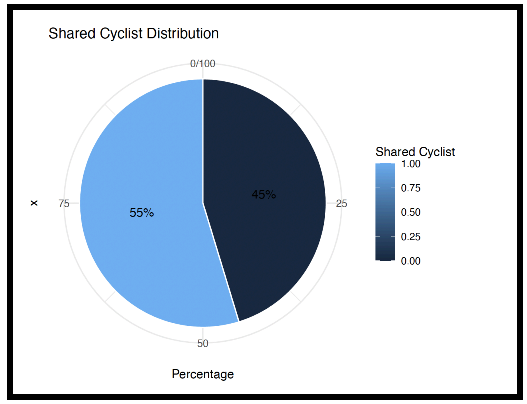












The figures above highlight summary statistics and distribution regarding the data. The stacked bar plot is in Figure 1. This shows that an individual who is more familiar with the technology behind autonomous vehicles will perceive them as safe. The stacked bar plot is in Figure 2. Shows that people who perceive AVs will play a positive role in decreasing traffic injuries perceive it as a safe vehicle on the road. The group of people who believe AV is not safe would not allow roads to be a test vicinity for the AVs. Moreover, respondents who believe that AVs are safe and are comfortable sharing roads with AVs had little to no impact of the Arizona crash incident by AV on their safety perception. In addition, the heatmaps Figure 10 & 11 in the appendix shows the correlation between different variables. This visualization helps identify potential links between tech familiarity and SafeAv perception, suggesting that people more familiar with tech feel safer with sharing the road with autonomous vehicles.

Since the data is categorical, a Chi-Square test was conducted to select the appropriate variables with respect to an individual's safety perception for data analysis.

The figure below shows the results of the Chi-Square Test.

Pearson's Chi Square Test		
Safe AV and Familiarity Tech		
X-squared	**df**	**P value**
74.553	12	2.88e-11

Pearson's Chi Square Test		
Shared Cyclist and Shared Pedestrian		
X-squared	**df**	**P value**
37.831	1	7.714e-10

Pearson's Chi Square Test		
Shared Cyclist and Safe Av		
X-squared	**df**	**P value**
32.01	4	1.89e-6

Pearson's Chi Square Test		
Familiarity Tech and Av Impact		
X-squared	**df**	**P value**
23.166	4	0.0001173

The results of the Chi-Square test show that all of the variables are statistically significant, and these later gave direction to make Bayesian regression models using MCMC or HMC for Single regression and generalized linear regressions. The regression model used in this study was Bayesian Ordered Logistic Regression with cumulative family. This is because the variables being used are categorical, and the dependent variable is ordinal. Based on the exploratory data analysis, past literature and Chi Square test the variables were selected for model development.

$$\log\left(\frac{P(Y \leq j)}{1 - P(Y \leq j)}\right) = \log\left(\frac{P(Y \leq j)}{P(Y > j)}\right) = \alpha_j - x\beta$$

The logit link function was used in the Bayesian analysis, similar to multinomial logistic regression. This is because in multivariate link function models, the logit link provides better fit in the presence of extreme independent variable levels which is mostly evident in survey data Chambers and Cox (1967).

Results & Analysis

Model A

This model predicts the safety perception of autonomous vehicles based on the level of familiarity with AV technology. The aim is to understand if familiarity with AV technology is adequate to explain the variations in their safety perception or if inclusion of additional variables explain this relationship in a better way. The model is based on a major hypothesis of the study and previous literature that familiarity with AV technology positively influences safety perception of an individual.

$$Y = \beta_0 + \beta_1 FamiliarityTech + \varepsilon$$

Model A Results							
	Estimate	**Est.Error**	**l-95% CI**	**U-95% CI**	**Rhat**	**Bulk ESS**	**Tail ESS**
Intercept.1	-2.56	0.16	-2.87	-2.25	1.00	11974	11033
Intercept.2	-1.58	0.11	-1.80	-1.3	1.00	16090	13413
Intercept.3	-0.31	0.09	-0.49	-0.13	1.00	15671	13335
Intercept.4	1.12	0.10	0.92	1.32	1.00	15076	13669
FamiliarityTech.L	1.49	0.20	1.10	1.89	1.00	14318	12072
FamiliarityTech.Q	-0.39	0.17	-0.73	-0.07	1.00	15380	11881
FamiliarityTech.C	0.02	0.13	-0.23	0.28	1.00	16469	11360

The formula SafeAv ~ FamiliarityTech indicates that the perceived safety of autonomous vehicles (SafeAv) is modeled as a function of an individual's level of familiarity with technology (FamiliarityTech).

Since the initial EDA showed more weight towards the positive side, a prior was added centered around 1 for SafeAv and around 0 for Familiarity Tech. The intercept [1] of -2.56 refers to the log odds of being in the SafeAV's “very unsafe” category when FamiliarityTech is held constant at the reference level “Not Familiar at all.” As $e^{-2.56} = 0.077$ and 1/0.077 is 12.98, it means that at the reference level, there is a 12.98 times lower log odds of being in the higher category. The credibility intervals (-2.87 to - 2.25) show that this effect is significant as there is no 0 between the lower and upper 95% intervals, and it has a low gap as well. In addition, the estimated error is 0.16, indicating that the model has moderate to good precision. Moreover, the value of 1 shows good convergence, and Bulk/ Tail ESS measures the number of independent draws from posterior distribution; large values show a good amount of independent draws in the model.

Going towards intercept [4], the values decrease, and at intercept [4], the value is 1.12. This refers to the log odds of being in the second-highest category of SafeAV (mostly safe) compared to the lower categories, keeping the FamiliarityTech variable constant at the reference level. The value of $e^{1.12} = 3.06$ and 1/ 3.06 is 0.327 times higher odds ratio to be in this category at the reference level.

The coefficient of FamiliarityTech.L shows a linear positive relation with SafeAV. As the coefficient is 1.49 or $e^{1.49} = 4.44$ and 1/ 4.44 is 0.225, a unit change in the FamiliarityTech.L leads to a 0.225 times higher odds ratio to be in the higher category, holding everything else constant. The other parameters show that the effect is statistically significant, the model has converged well, and a good amount of independent draws from the posterior distribution were conducted. The coefficient for FamiliarityTech.Q is -0.39, which represents a negative quadratic effect of "FamiliarityTech" on the log odds of being in a higher "SafeAv" category. A one-unit change in FamiliarityTech leads to a 1.5 times lower odds ratio to be in a higher category, everything else constant. This implies that at higher levels of the linear trend, the positive linear effect of familiarity may reach a point of diminishing returns at very high levels of technological familiarity. To further investigate the negative quadratic impact other relevant variables such as Av Impact or interaction terms can be added to understand potential causal effects. Moreover, the model plot given in the appendix visualizes the uncertainty in coefficients estimated in the regression model. Wider density on the left indicates higher uncertainty in coefficient values. The trace plots (bottom) ideally show well-mixed lines suggesting the model converged and explored the parameter space effectively.

Model B

This model predicts the safety perception of autonomous vehicles based on the level of familiarity with AV technology and individual perception regarding the effect of AV on traffic injuries using an nomothetic causal relationship approach. The goal is to expand the model by including AvImpact to investigate its potential role as a mediator or moderator in the relationship between FamiliarityTech and SafeAv. The rationale behind this expansion comes from theoretical reasoning and practical implications. From a theoretical standpoint, AvImpact could serve as an intermediary variable (mediator) through which FamiliarityTech influences SafeAv. Alternatively, AvImpact might modify the strength or direction of the relationship between FamiliarityTech and SafeAv (moderator).

$$Y = \beta_0 + \beta_1 FamiliarityTech + \beta_2 AVImpact + \varepsilon$$

Model B Results							
	Estimate	**Est.Error**	**l-95% CI**	**U-95% CI**	**Rhat**	**Bulk ESS**	**Tail ESS**
Intercept.1	-2.68	0.22	-3.13	-2.25	1.00	11228	10597

Intercept.2	-0.86	0.17	-1.18	-0.53	1.00	15528	13077
Intercept.3	1.30	0.17	0.98	1.63	1.00	11477	12776
Intercept.4	3.31	0.19	2.94	3.69	1.00	10805	12437
FamiliarityTech.L	0.75	0.22	0.32	1.18	1.00	15343	12521
FamiliarityTech.Q	-0.23	0.18	-0.58	0.12	1.00	15831	11615
FamiliarityTech.C	-0.11	0.14	-.038	0.17	1.00	16446	11668
AvImpact.L	5.82	0.40	5.06	6.63	1.00	8792	10057
AvImpact.Q	-0.80	0.31	-1.45	-.021	1.00	9529	9783
AvImpact.C	0.37	0.23	-0.09	0.83	1.00	9923	11001
AvImpact.E	0.26	0.21	-0.15	0.68	1.00	14600	11803

In this model, AVImpact is also added to FamiliarityTech. The Intercepts represent the log-odds of being in the SafeAV's "very unsafe" category when FamiliarityTech and AVImpact are at their reference level. When AvImpact is included, the intercepts in Model 2 likely reflect the combined effects of both FamiliarityTech and AvImpact on the baseline log odds of being in each safety category. In addition, the inclusion of AvImpact has led to some positive influence previously attributed to FamiliarityTech in Model 1. This could explain the overall shift in the baseline log-odds towards lower values. The direction of relationships between the variables is similar to Model 1. However, Intercept [3] has changed from -0.3 to 1.31 due to this addition, which is interesting. AVImpact might capture factors related to the perceived impact of autonomous vehicles that weren't considered in Model 1. These factors could be influencing the baseline for the "somewhat safe" category Intercept[3]. For example, if people perceive AVs with higher potential impact (captured by AvImpact) as being more likely to avoid accidents, this could contribute to a higher baseline log-odds of being in the "somewhat safe" category for SafeAV.

AvImpact.L represents a very strong positive linear effect with SafeAV. The coefficient of AvImpact.L is 5.82 or $e^{5.82} = 336.9$, indicating that as AvImpact increases by one unit, the log-odds of being in a higher "SafeAv" category increase substantially by 336.9 times holding other variables constant. The credibility intervals (5.06 and 6.63) indicate that this relationship is statistically significant. Moreover, the value of 1 shows good convergence, and Bulk/ Tail ESS measures the number of independent draws from posterior distribution; large values show a good number of independent draws in the model. As the variables strengthen the direct relationship, as shown in Model A, we can say that AvImpact acts as a moderator in this relationship. To confirm this, further analysis needs to be conducted as current evidence is not sufficient to present the verdict regarding its moderation.

However, the negative quadratic effect of AvImpact suggests that the positive impact of AvImpact diminishes at higher levels, similar to the pattern observed for FamiliarityTech in model 1. The AvImpact E4 is positive, and it suggests that additional categories beyond the coded levels, such as "very impactful" or "extremely impactful," might have a positive influence on the log odds of being in a higher SafeAv category, but it is statistically insignificant.

Model C

Othman (2021) reviewed public acceptance and safety perception of AVs. It discusses how interaction with AVs on the road affects safety perception. Based on this research and insights from the previous model, the model predicts the safety perception of autonomous vehicles based on the level of familiarity with AV technology and how often they have experience sharing the road with AVs, being on bikes, and as pedestrians. The model aims to investigate the idiographic causal relationship for a specific group that shares roads with AVs in pittsburg.

$$Y = \beta_0 + \beta_1 FamiliarityTech + \beta_2 AVImpact + \beta_3 (SharedCyclist \times SharedPedestrian) + \varepsilon$$

Model C Results							
	Estimate	**Est.Error**	**l-95% CI**	**U-95% CI**	**Rhat**	**Bulk ESS**	**Tail ESS**
Intercept.1	-1.86	0.19	-2.24	-1.5	1.00	15323	12752
Intercept.2	-0.86	0.16	-1.18	-0.55	1.00	16139	14061
Intercept.3	0.47	0.16	0.16	0.78	1.00	14752	13639
Intercept.4	1.96	0.17	1.63	2.3	1.00	14209	13327
FamiliarityTech.L	1.19	0.21	0.79	1.61	1.00	17704	12541
FamiliarityTech.Q	-0.19	0.17	-0.53	0.14	1.00	20146	10947
FamiliarityTech.C	-0.06	0.14	-0.33	0.2	1.00	21283	11566
SharedCyclist	1.28	0.24	0.8	1.76	1.00	113117	11878
SharedPedestrian	0.97	0.22	0.54	1.4	1.00	13520	11902
SharedCyc:SharedPed	-1.10	0.31	-1.71	-0.5	1.00	12286	11825

This model analyzes the interaction effect of SharedCyclist and SharedPedestrian on the relationship being studied in this research. All intercepts are significant, with relationships similar to those of prior models. The effect of FamiliarityTech isn't much affected by the addition of this interaction. The SharedCyclist coefficient of 1.28 shows a positive relationship with SafeAv. Coefficient 1.28 or $e^{1.28}$ = 3.59 and 1/ 3.59 is 0.0.278, which indicates that as the unit of SharedCyclist changes by one unit, it leads to a 0.28 times higher odds ratio to be in the higher category of SafeAv, all other variables held constant. The coefficient of SharedPedestrian is 0.97 or $e^{0.97}$ = 2.64, and 1/ 2.64 is 0.0.38, which indicates that as the unit of SharedPedestrian changes by one unit, it leads to a 0.38 times higher odds ratio to be in the higher category of SafeAv, all other variables held constant.. It also has a positive relationship with SafeAv.

The SharedCyclist: SharedPedestrian interaction term has a negative interaction coefficient (-1.10), which suggests that the positive effects of SharedCyclist and SharedPedestrian on the log-odds of being in a higher "SafeAv" category are not independent of each other. In other words, the effect of one variable depends on the level of the other variable.

LOOIC Modeling Bayesian Regression

Leave-one-out cross-validation was also done to check interaction and error was less and it was successful. Results are shown below for all three models

LOOIC	Model 1	Model 2	Model 3
elpd_loo	-923	-723.1	-905.7
p_loo	7.1	11.4	10.3
looic	1846	1446.2	1811.4

Among all three models, Model 2 appears to have the best predictive power. has the highest elpd_loo value (-723.1) and the lowest LOOIC value (1446.2) However, it's also important to consider the complexity of the models. Model 2 has a p_loo value of 11.4, which is higher than both Model 1 (7.1) and Model 3 (10.3). This suggests that Model 2 is a more complex model. Depending on the modeling goals, a balance between accuracy and complexity might be necessary. However, a more comprehensive analysis considering factors like standard errors and the intended use case of the model would be recommended for a definitive conclusion.

Discussion

Our analysis yielded several key insights discussed in the section above. This part of the report will look at the future practical implications related to the study. The rationale behind model development and justification for expanding models along with the selection of variables is also added in the analysis above. Overall, models show that people who are familiar with AV technology do perceive it to be safe and are comfortable sharing the road with AVs. This implies that in the future, countries with high-tech AVs are expected on the road, especially in countries that have domain knowledge in this field. Moreover, a prior centered around 1 was also added in Model A, providing additional regularization to the model, resulting in adjusted parameter estimates while maintaining the overall interpretability and trends in the relationship between the predictors and the outcome variable. Individuals who are bullish on AV safety on the road with respect to traffic incidents perceive AVs as being much safer. Another important variable was the interaction, so an individual's own experience with AVs really defines how safe they feel. Model B also tried to understand the mediating relationship of AvImpact between AV safety and its tech familiarity among individuals.

Finally, Model C highlights that direct experience sharing the road with AVs, either as a cyclist or pedestrian, fosters a more positive safety perception. This study also evaluated the opinions of participants about AV safety from the perspective of other relevant measures. The results show that AV safety ratings have been widely varied based on the type of traits in the responses. Moreover, Arizona Crash as a variable was added to the model to further check impact on safety perception. ArizonaCrash was significant but did not affect the prior model results. This means that the individuals who favor AVs as safe transport are not worried about the Uber fatal crash.These findings suggest that public outreach campaigns promoting AV safety benefits and encouraging real-world interaction could be crucial for fostering trust and wider adoption of autonomous vehicles.

In conclusion, it implies that AV companies can explore developed countries whose populations are interested in tech. This area requires more research to help electric companies build the AVs for the right markets. Further research can include more variables, which can be quantitative research based on facts and figures rather than perception only. Some further topics that can be explored in this domain are media coverage's effect on AV safety perception, the role of marketing campaigns, and how policymakers can leverage these findings to promote public acceptance and the safe integration of AVs into the transportation system.

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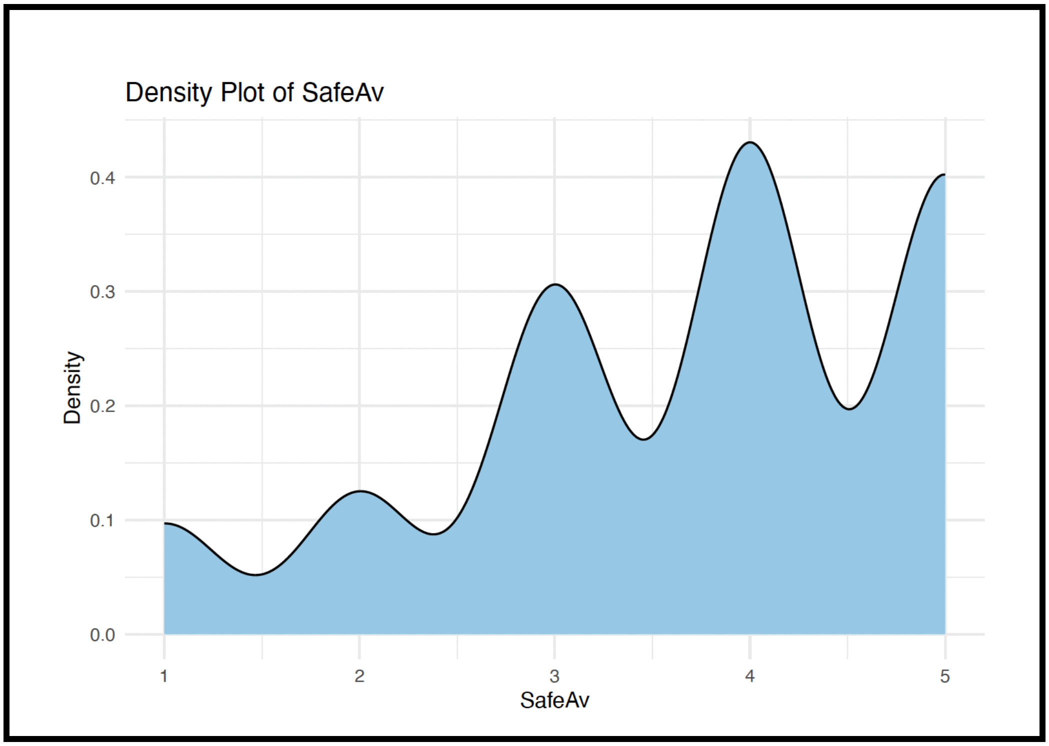
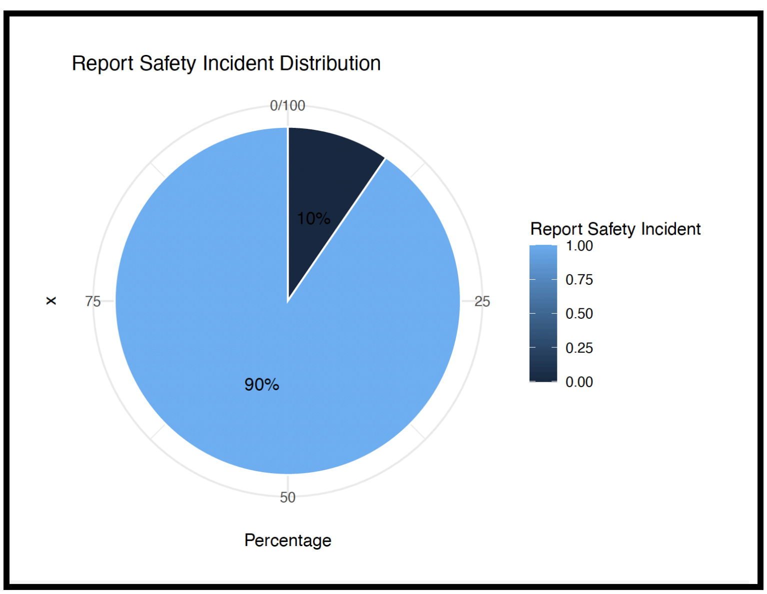
Appendix

Variable	Definition	Scale of Familiarity
Familiarity Tech	How familiar are you with the technology behind autonomous vehicles?	Extremely Familiar; Mostly Familiar; Somewhat Familiar; Not Familiar at all
Shared Cyclist	Have you shared the road with an Autonomous Vehicle (AV) while riding your bicycle on the streets of Pittsburgh?	Yes; No; Not Sure
Shared Pedestrian	Have you been near an AV while walking or using a mobility device (wheelchair; etc) in Pittsburgh?	Yes; No; Not Sure
Safe Av	On a typical day; how safe do you feel sharing the road with autonomous vehicles?	1 being very unsafe and 5 being very safe
Safe Human	On a typical day; how safe do you feel sharing the road with human-driven cars?	1 being very unsafe and 5 being very safe
Av Impact	What effect do you think AVs will have on traffic injuries and fatalities?	Significantly Better; Significantly Worse; Slightly Better; Slightly Worse; No Effect
Proving Ground	What do you think about the use of Pittsburgh's public streets as a proving ground for Autonomous Vehicles?	Approve; Somewhat Approve; Neutral; Somewhat Approve; Somewhat Disapprove
Arizona Crash	In March of 2018; an AV struck and killed Elaine Herzberg; a pedestrian; in Tempe; AZ. As a pedestrian and/or bicyclist; how did this event and its outcome change your opinion about sharing the road with AVs?	Significantly more negative opinion; Somewhat more negative opinion, No change; Somewhat more positive opinion; Significantly more positive opinion

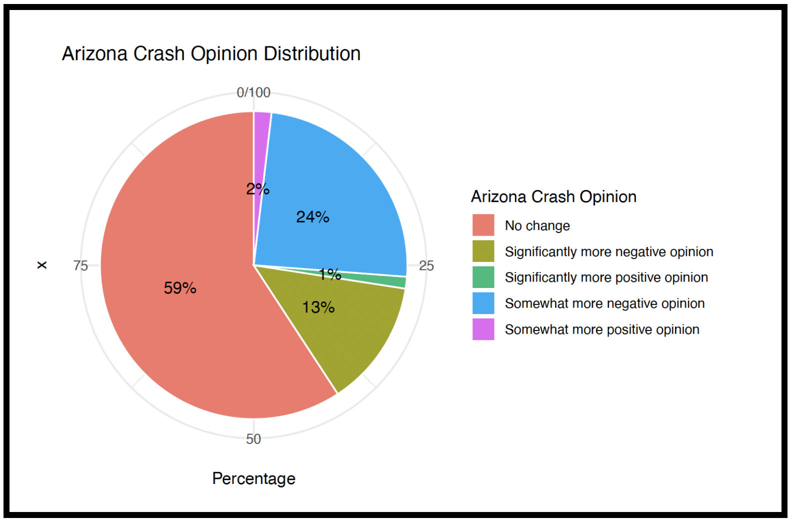
Table 1



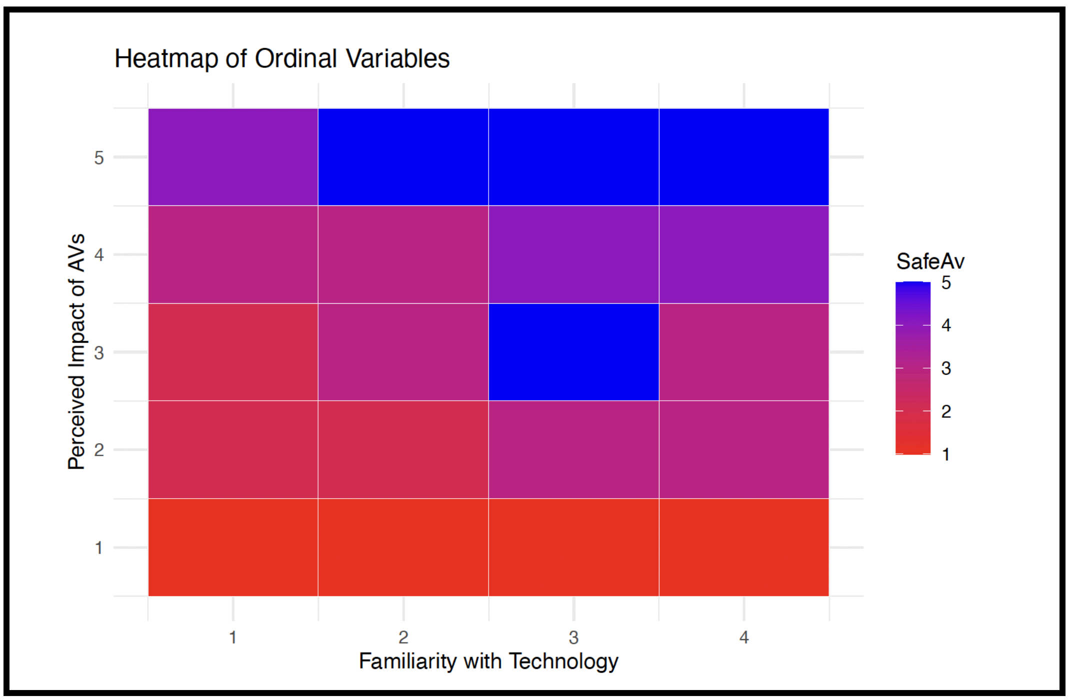
Density Plot of SafeAV



Pie Chart of Report Safety Incident Distribution

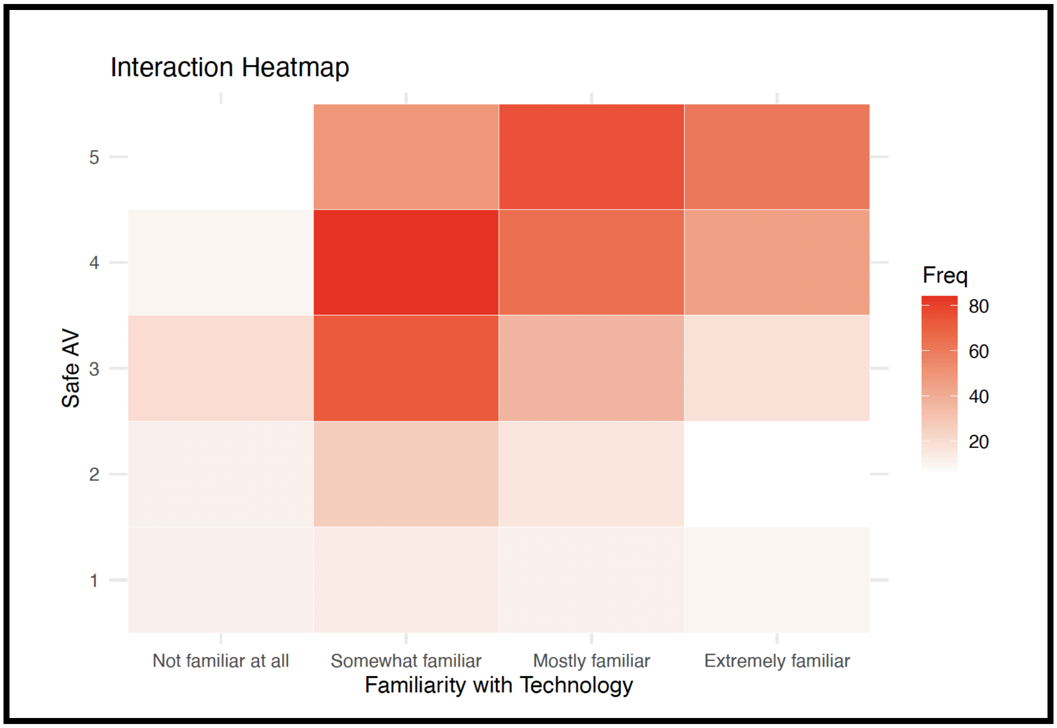


Pie Chart of Arizona Crash Opinion Distribution



Heatmap of Ordinal Variables

The heat map above depicts the relationship between perceived impact of AVs (y-axis), familiarity with technology (x-axis), and different levels of "SafeAv" represented by the color gradient from red (level 1) to blue (level 5), allowing for visual analysis of patterns and correlations among these ordinal variables.



Heatmap of Interactions

The heat map above depicts the relationship between SafeAv (y-axis) and Familiarity with Technology (x-axis). Lighter shades of red indicate lower frequencies, primarily clustered in the bottom-left corner, suggesting low SafeAv and low tech familiarity. As SafeAv and tech familiarity increase towards the top-right, frequencies increase. This visualization helps identify potential links between tech familiarity and SafeAv perception, suggesting that people more familiar with tech feel safer with sharing the road with autonomous vehicles.