DISSERTATION

ACCEPTANCE OF SELF-DRIVING VEHICLES IN THE UNITED STATES: EXPECTATIONS, WILLINGNESS TO PAY, SUPERVISION CAPABILITY, AND FUNDING OVERSIGHT

Submitted by

Eric Stewart

Department of Systems Engineering

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Doctoral Committee:

Advisor: Erika Gallegos

Steven Conrad
Jeremy Daily
Yanlin Guo
Greg Marzolf

ABSTRACT

ACCEPTANCE OF SELF-DRIVING VEHICLES IN THE UNITED STATES: EXPECTATIONS, WILLINGNESS TO PAY, SUPERVISION CAPABILITY, AND FUNDING OVERSIGHT

As technology has advanced to a level that supports a potential transition of the private and corporate vehicle fleets from human-operated vehicles to vehicles with self-driving capability, research and development efforts have typically focused on improving the technology and system integration of self-driving vehicles (SDVs). This emphasis has often come at the expense of attention to other systems within the broader self-driving vehicle ecosystem. One of these key systems is the potential SDV consumer, who would serve as the catalyst of any potential vehicle fleet transition. Research gaps currently exist regarding reliability and safety expectations for self-driving vehicles, how potential juries may assign blame for negative events involving SDVs, and how safety oversight and SDV-required infrastructure improvements can be funded with the least-opposed new or increased taxes and fees. Other research regarding human interaction with SDVs, such as willingness to pay, has also become outdated as these values change over time. Addressing these research gaps and refreshing relevant data is critical to supporting a transition to SDVs.

To mitigate these gaps and provide updated SDV-relevant data, several experiments were conducted with participants residing in the United States. In one experiment, data was collected regarding how participants would assign blame for traffic collisions and other negative incidents involving SDVs, and how manufacturer advertising claims would impact their blame

assignments. This research found that a majority of the sample population was primarily inclined to blame the driver of the SDV, though claims by the manufacturer about human oversight not being needed led a majority of participants to assign additional blame to the manufacturer. In another experiment, participants were asked to select between competing feature packages that addressed safety and reliability architecture elements. Results from this experiment found that rate of takeover requests and methods of alerting the driver to system failures were primary decision drivers, while the vehicle's failsafe behavior was not a primary factor in decision making. On economic issues, experimental data indicated that the percentage of the population willing to pay a premium for self-driving technology was increasing, as was the mean premium participants were willing to pay. However, the median premium value was lower than what was found in previous studies. The data also showed that increases in vehicle purchase prices or subscription fees for self-driving capability were the preferred methods of funding safety oversight and SDV-supporting infrastructure, compared to increases in fuel, mileage, or vehicle taxes. In a final experiment, human oversight of autonomous systems was found to be ineffective, with participants detecting an average of only 15% of induced system errors, regardless of how system capability was framed or how errors were distributed.

The experimental results contained within this dissertation provide support for systems engineering efforts in support of the development and integration of SDVs within the ground transportation system-of-systems. Specifically, this research better defines potential consumer expectations for safety and reliability architecture elements, which can be translated into system design requirements for future SDVs. In parallel, this work finds that human oversight of SDVs is ineffective, suggesting that assumptions about humans being able to observe and correct SDV errors may be unrealistic. Updated willingness to pay values provide insight into the cost constraints for future SDV products relative to otherwise equivalent human-driven vehicles, while funding preference information provides policy guidance on which fees or taxes authorities could implement to fund oversight and infrastructure improvements. Finally, this dissertation provides a mapping of predictors that can be used to estimate willingness to pay, the impact of manufacturer advertising, primary blame assignments for SDV incidents, and preferences for safety and reliability architecture features, while also identifying predictors that have second-order effects on other predictors.

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DEDICATION

This dissertation is dedicated to the continued growth of the body of human knowledge, to the scholars who have contributed to that knowledge in the past, and to the scholars who will contribute in the future.

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Chapter 1. Introduction

Recent advancements in Artificial Intelligence (AI), vehicle-mounted onboard computing capability, and vehicle mounted sensors have enabled numerous automotive companies to pursue commercially viable self-driving vehicle (SDV) designs with near term product introduction timelines. Companies such as Tesla and Waymo are leaders within this space, offering products such as Tesla Autopilot as a self-driving beta capability and autonomous taxi services in select cities. In support of these efforts, considerable research and development has been invested into ways to improve the hardware, software, and AI elements needed to ensure viable consumer-ready product offerings. While these efforts are needed and value-added from a product development standpoint, research into the human consumer preferences and behaviors that could significantly influence the success and rate of widespread SDV adoption has been limited.

There are several influences that the SDV consumer and the SDV non-consumer can have on the environment that impact the long-term commercial viability of SDVs. As one example, one of the larger risks SDV manufacturers face is potential legal judgements stemming from accidents or traffic regulation violations involving their SDVs while the vehicles are in self-driving mode. In such scenarios, a product that complies with all of the technical requirements for an SDV could become a cautionary tale if the vehicle manufacturer is hit with a significant class-action judgement after a non-zero number of product owners suffer physical or monetary injury due to low-probability product failures. As another example, if the cost of making a vehicle capable of self-driving exceeds the premium that a consumer is willing to pay for a self-driving car versus a car with only advanced driver-assist features, that technically acceptable

SDV product would not be a commercial success. To make the cost versus willingness to pay (WTP) balancing act more challenging, WTP has been shown to have a temporal element where WTP fluctuates with the passage of time.

Another major environmental influence that consumers exert on SDVs that warrants additional study is human oversight of the autonomous systems. In many safety architectures, it is assumed that a trained operator will be able to recognize when a system (automated or otherwise) is not functioning properly and take the required actions necessary to address the system failure safely. One challenge that is somewhat unique to SDVs is that one of the selling points for the technology is that the “driver” of the SDV would be able to engage in activities other than driving or system supervision, which would reduce the assumed effectiveness of human intervention in the event of the SDV encountering a situation where prompt response from the driver is warranted. Other factors, such has system over-trust caused by positive capability framing or complacency due to infrequent error occurrences, could also have a negative effective on human oversight effectiveness. Given the importance of human supervision of SDV systems (at least in the early adoption phases) and the influences that could negatively affect the effectiveness of this supervision, additional research into the accuracy of human supervision assumptions is needed.

This dissertation addresses some of the research gaps that exist regarding the potential impacts humans can have on the SDV environment, both as a SDV consumer and as a non-consumer who is impacted by widespread adoption of SDVs. These research gaps include providing a refresh of WTP for full-self driving capability in the United States, identifying how the experiment population would assign primary blame for SDV-involved traffic collisions and violations of traffic regulations, determining the optimal feature levels for safety and reliability features for SDVs, and determining how oversight of SDV technology and SDV-supporting infrastructure improvements can be funded using the least opposed / most tolerated tax and fee structures. Results from this research provides insight to manufacturers regarding reliability, safety, and value requirements for future SDVs, support funding decisions for critical oversight and infrastructure programs, validate or correct assumptions regarding the effectiveness of human oversight of SDV systems, and allow for better assessment of legal risks manufacturers could face with their SDV products.

1.1. Research Aims and Research Questions

This dissertation is organized around five research aims and utilizes data collected from both a survey study and a simulated traffic sign recognition (TSR) experiment. These research aims are organized around gaining a better understanding of how SDVs may be treated by juries in a legal setting, refreshing the willingness of potential American consumers of SDVs to pay a premium for self-driving vehicles, identifying American reliability and safety behavior expectations regarding SDVs, identifying what methods for funding oversight and infrastructure improvements for SDVs would be least opposed, and evaluating the effectiveness of human oversight of autonomous systems and possible influences of that oversight effectiveness. When combined, these factors will have a significant impact on the likelihood and long-term viability of mass adoption of SDVs within the United States.

1.1.1. Aim 1 – Perceptions of SDV Legal Culpability

As self-driving vehicles (SDVs) become more frequently involved in traffic collisions and moving violations, understanding how potential jury pools would assign blame for those events becomes critical to understanding the risk profiles for SDV manufacturers. To identify how Americans may assign blame for SDV-caused collisions, as well as identify predictors for those blame assignments, an online anonymous survey was conducted that contained sections to identify respondent characteristics as well as a section to identify how the respondents would assign blame in four hypothetical SDV-involved traffic collisions or moving violations. The results of this experiment effort were published in Stewart & Gallegos (2025a). The following research questions are addressed in Research Aim 1:

- **RQ1.1:** Who would the average American assign blame to if an SDV was involved in a traffic collision or traffic law violation?
- **RQ1.2:** Are risk tolerance, SDV familiarity, SDV comfort, or demographic factors significant predictors of views of legal culpability for SDV-involved traffic incidents?

1.1.2. Aim 2 – Reliability and Safety Expectations

Development of reliability and safety requirements for current and future SDV designs is dependent on having a full understanding of consumer expectations regarding vehicle reliability, failure behavior, and alert methods. To identify American consumer expectations for SDV reliability, resilience, and safety as well as identify predictors for those expectations, an online anonymous survey was conducted that contained sections to identify respondent characteristics and a Conjoint analysis to determine system reliability, resilience, and safety expectations. The results of this experiment effort were published in Stewart & Gallegos (2025b). The following research questions are addressed in Research Aim 2:

- **RQ2.1:** What are customer expectations for SDV system accuracy and resilience?
- **RQ2.2:** Are risk tolerance, SDV familiarity, SDV comfort, or demographic factors significant predictors of views of legal culpability for SDV-involved traffic incidents and expectations on system performance and resilience?

1.1.3. Aim 3 – Willingness to Pay for SDVs

The transition to SDVs will require the commercial viability of SDVs. To be commercially viable, the difference in cost between a vehicle capable of self-driving and a standard human-driven vehicle must be less than or equal to the willingness to pay of the intended consumer for that additional capability. Since this willingness to pay can vary between and within consumer populations and has a temporal component, each population needs to surveyed to evaluate WTP for each level of autonomous vehicle capability. This drives a need for an updated survey of potential American consumers. Given these observations, an experiment was conducted to measure willingness to pay for SDV capability and evaluate how the willingness varies with system supervision requirements and consumer characteristics. The following research questions are addressed in Research Aim 3:

- **RQ3.1:** How much is a potential SDV buyer in the United States willing to pay for an SDV versus a traditional vehicle?
- **RQ3.2:** How much does that premium change based on the level of driver supervision required for the SDV?
- **RQ3.3:** Are risk tolerance, SDV familiarity, SDV trust, or demographic factors significant predictors of willingness to pay in the United States?

1.1.4. Aim 4 – Tax and Fee Preferences for Oversight and Infrastructure Funding

The transition to SDVs will require investments in the necessary infrastructure and oversight required to ensure safe operations of large numbers of SDVs on existing roadways. To understand how these investments and oversight costs can be funded, research data is needed on tolerance of fees or taxes needed for funding the necessary oversight and infrastructure improvements needed to support safe operation of SDVs at scale. Potential funding methods include fuel taxes, vehicle taxes, and subscription fees to utilize self-driving capabilities. The methods of funding selected need to be tolerated by the population being expected to pay these taxes and fees in order to avoid feeding opposition to the widespread adoption of SDVs. Given these observations, a survey experiment was conducted to evaluate the most preferred, or least opposed, fee and tax structure to support SDV adoption. The following research questions are addressed in Research Aim 4:

- **RQ4.1:** What method of funding for the regulatory framework and infrastructure is least opposed by the general population of the United States?
- **RQ4.2:** Are risk tolerance, SDV familiarity, SDV trust, or demographic factors significant predictors of preferences for funding methods for SDV oversight and infrastructure investment in the United States?

1.1.5. Aim 5 – Effectiveness of Human Oversight on Autonomous Systems

One of the key architectural elements of the safety architecture of the future SDV dominated transportation system is the oversight provided by a human operator of the SDV. This architecture assumes that oversight provided by passengers in the SDV would be sufficiently accurate and effective to ensure that artificial intelligence failures within the SDV systems would not lead to injuries, property damage, or violations of local traffic laws. At the same time, SDV manufacturers would be incentivized to downplay the level of oversight required in order to make the technology more appealing to a broader pool of potential customers and potentially secure higher prices for the vehicles they produced. There is also potential for users to become complacent in their oversight of their SDVs if the SDVs go long periods of time without any noticeable errors in their performance. To determine the impacts of framing and error rates on human oversight of automated systems, and to assess general effectiveness of human oversight, an experiment involving simulated traffic sign recognition (TSR) data was conducted. The results of this research aim have been submitted for publication in Stewart & Gallegos (2026). The following research questions are addressed in Research Aim 5:

- **RQ5.1:** What impact, if any, does positive framing have on the effectiveness of driver oversight of a TSR AI on an SDV?
- **RQ5.2:** What impact, if any, does a frequency of errors by a TSR AI have on the effectiveness of driver oversight of that system?
- **RQ5.3:** What impact, if any, does framing of TSR capability and TSR error frequency have on user trust of a TSR system?
- **RQ5.4:** Are Manchester DBQ values, SDV familiarity, SDV trust, or demographic factors significant predictors of oversight effectiveness?

Chapter 2. Background

There are several interconnected and mutually influencing factors the contribute to the public perception of SDVs and define the environment in which current and future SDVs will need to operate. These factors include the value proposition for SDVs, which defines the expected return on investments for changing from human-driven vehicles to SDVs, the willingness of consumers to pay more for a vehicle capable of self-driving versus a conventional human-driven vehicle, and how SDVs will be treated within the legal system when these vehicles are involved in incidents involving property damage, injuries, or fines. Additionally, consumer expectations regarding SDV reliability and safety influence their willingness to purchase a self-driving vehicle, and need to be taken into account as design requirements for SDVs. While research exists for each of these factors, gaps exist in the current body of knowledge warrant additional research to address.

2.1. Value Proposition for SDVs

Each year, tens of thousands of people lose their lives on United States roadways. The U.S. Department of Transportation National Highway Traffic Safety Administration documents the grim toll, with 38,824 fatalities recorded in 2020 (National Highway Traffic Safety Administration, 2022). The National Safety Council, a traffic safety advocacy group, estimated greater death tolls in later years, with 46,300 fatalities in 2022 and 44,450 fatalities in 2023; a 13.6% fatality rate increase from 2019 (National Safety Council, 2024). This equates to 1.44 fatalities per 100 million vehicle miles traveled (National Safety Council, n.d.), and in 45% of these fatal accidents the drivers were engaged in one of the following behaviors: speeding, impaired driving, or not wearing a seatbelt (National Highway Traffic Safety Administration, 2022). Recent modeling studies have also shown that demographic factors such as age and gender can influence injury severity outcomes in traffic crashes (Nickkar et al., 2024). Traffic crashes also cause significant injuries that require costly medical attention. In 2022, an estimated 5.2 million injuries requiring medical attention were attributed to 3.6 million vehicle-related collisions in the United States costing $481.2 billion in medical costs, property damage, and lost economic activity (National Safety Council, n.d.). A further 9.2 million crashes involved property damage but no significant injuries (National Safety Council, n.d.).

Human error is given primary blame for up to 96% of crashes (Triki, Karray, & Ksantini, 2023), with human recognition error, decision error, and performance error accounting for approximately 79% of all traffic crashes (National Highway Traffic Safety Administration, 2015). Within this context, recognition error involved a driver misinterpreting a traffic control device or other indicator, a decision error involved miscalculating when it was safe to perform a lane change, merge operation, or similar driving function, and a performance error involved errors including not initiating braking soon enough to avoid a collision. SDVs could potentially address these deficiencies, with simulation-based research showing that a 100% adoption of Connected and Autonomous Vehicles (CAVs) can reduce the number vehicle impacts by 90-94% versus human operated vehicles (Papadoulis, Quddus, & Imprialou, 2019). Assuming an equal reduction in injuries and fatalities from traffic collisions, 40,000 lives could be saved, 4.68 million injuries could be prevented, and $433 billion in economic losses could be avoided annually.

Additional benefits beyond reduced traffic collisions could be gained by a transition to a near 100% SDV vehicle mix. For example, the existence of an SDV taxi service could allow

low-income individuals who lack access to reliable mobility options to get to medical appointments they would have missed or delayed otherwise, leading to a reduction in medical care costs that are often carried by government-provided insurance programs (Nunes et al., 2020). Savings could also be realized from reductions in motor vehicle crashes that involve low-income individuals, as some estimates suggest that $18 billion in public revenues are spent each year to pay for the consequences of these crashes (Nunes et al., 2020). For these benefits to be realized, owners of human-operated vehicles must make the transition to owning an SDV or decide to abandon personal vehicle ownership in favor of on-demand SDV rideshare services. For this transition to occur, a positive return on investment for the decision is needed. For many potential users of SDVs, especially those with more limited incomes, subsidies for either SDV ownership or utilization of an SDV rideshare program would be needed, along with subsides for ride share services such as SDV taxis (Nunes & Hernandez, 2020) and investments in supporting infrastructure, such as SDV taxi staging areas and access to passenger pickup locations. These subsidies and investments would need to be offset by increases in revenue generation by impacted government entities.

2.2. Willingness to Pay (WTP) for SDVs

A central challenge for SDV development is determining how much additional cost potential buyers are willing to pay compared with a conventional human-operated vehicle. The value proposition for consumers typically being improved safety, convenience, and productivity. However, if consumers' WTP does not exceed the incremental cost of adding the required automation technologies, widespread SDV adoption is economically infeasible. Previous studies have identified the high cost of autonomous systems as a primary barrier to SDV deployment (Nickkar et al, 2020).

In addition, WTP varies substantially across populations and regions, suggesting that market potential for SDVs will not be uniform. Some demographic or geographic segments may support viable SDV markets, while others may not. Understanding both the mean and median WTP within a target population, and the characteristics of consumers most receptive to SDV technology, is therefore essential for identifying feasible market entry points and guiding effective outreach strategies.

2.2.1. Observed Past Willingness to Pay for Full Self-Drive

Several survey-based studies have been performed worldwide that included a series of WTP questions intended to identify frequency and magnitude of WTP. These studies have largely focused on SAE Level 3 and Level 4 automation, with Level 3 automation as "conditional driving automation" where self-driving technologies are active, but a human driver may be asked to takeover at any time, and Level 4 is that the automation features can operate reliably without the need for human driver intervention (SAE International, 2021). The results of these surveys suggest a wide variance in general SDV WTP and WTP magnitude across populations. These studies are described below and summarized in Table 1.

Australia. A study conducted by Cunningham et al. (2019) noted that more than 55% of participants had zero WTP for either a partially-automated car or a fully-automated car compared to the same vehicle without any SDV capabilities. At the opposite end of the spectrum, roughly 8% of participants expressed a high WTP magnitude through Likert responses to WTP questions. From a quantitative standpoint, Cunnigham et al. (2019) found a mean WTP value for full self-driving of AUD 14,919 (~9,250 USD) with a median WTP of AUD 5,000 (~3,100 USD).

China. There are two primary reference studies that included questions regarding WTP for vehicle automation. In a 2019 study, Liu et al. (2019) reported that 26.3% of respondents had zero WTP and that the mean WTP for full self-driving was approximately USD 2,900 (19,300 yuan). In a subsequent 2022 study by Wang et al. (2022), respondents from Meishan and Jiading reported mean WTP values of USD 1,072 (7,510 yuan) and USD 1,990 (13,936 yuan), respectively. While these later results appear lower than the earlier national estimate, this difference may reflect regional economic variation as well as temporal change – both factors likely influencing the observed decline in mean WTP over time.

Japan. Based on a sample collected in 2017, the estimated mean WTP is 209.8 thousand yen ($1853 USD) for Level 3 and 279.9 thousand yen ($2473 USD) for Level 4 (Morita & Managi, 2020).

Germany. A study by Weigl, Eisele, & Riener (2022) estimated a WTP for both males and females for full self-driving technology and driver assist technology (SAE Level 3). For driver assist, they reported a mean WTP for males of 10.8% (median 10%) and females of 10.7% (median 10%) over the cost of a non-SDV vehicle. For full SDV technology, the study found that males had a mean WTP of 14.9% (median 11%) over a non-SDV vehicle, and similarly females had a WTP of 13.8% (median 10%).

United States. U.S. studies have observed trends similar to those found in other nations. In one 2014 survey that collected data in Austin Texas, average WTP was $7,253 for L4 full automation, and $3,300 for L3 partial automation (Bansal et al, 2016). In a follow-up 2015 study by Bansal & Kockelman (2017) that collected data across the U.S., 58.7% of participants had zero WTP for Level 4 automation, and the average WTP for Level 4 technology across all participants was $5,847. Another study in the same timeframe found that their respondent pool had both a large zero WTP population for full self-driving and a respondent subset with a WTP of greater than $10,000 (Daziano et al, 2017).

Table 1. Synthesis of Literature for WTP of Level 4 Automation

Country	Year	Mean WTP (USD)	"0" WTP (%)	Median WTP (USD)	Source
Australia	2019	9,250	55	3,100	Cunningham et al. (2019)
China	2019	2,900	26.3	N/A	Liu et al. (2019)
China	2022	1,072 – 1,990	0	N/A	Wang et al. (2022)
Japan	2017	2,473	0	N/A	Morita & Managi (2020)
United States	2014	7,253	N/A	N/A	Bansal et al. (2016)
United States	2017	5,847	N/A	N/A	Bansal & Kockelman (2017)
United States	2017	1,422 – 6,580	>0	N/A	Daziano et al. (2017)

A review of these previous studies reveals several consistent quantitative trends across populations when analyzing WTP for full self-driving capability. First, a substantial portion of respondents reported zero WTP for Level 4 automation: 58.7% in the US (Daziano et al, 2017; Bansal & Kockelman, 2017), 26.3% in China (Liu et al., 2019), and 55% in Australia (Cunningham et al, 2019). Second, the mean WTP values show wide variation across regions and time, ranging from approximately USD 1,072-1,990 in the 2022 China sample (Wang et al., 2022) to USD 9,250 in Australia (Cunningham et al., 2019) and USD 4,900-7,253 in earlier US studies (Bansal et al, 2016; Daziano et al, 2017). Third, these averages are often skewed by high outlier values, with small subsets of respondents reporting WTPs exceeding USD 10,000, which inflates the overall mean relative to the median. Lastly, many of these studies were performed when partially automated technology and advanced driver assistance systems (ADAS) were in early market stages, thereby potentially limiting their perceived value and realism among participants.

2.3. Predicted Additional Costs of Widespread SDV Adoption

While widespread SDV adoption may lead to significant benefits as the result of increased road safety, reduced transportation congestion, and improved freedom of mobility, the transition to widespread use of SDVs will also have associated costs that must be accounted for in future infrastructure and government operation budgets. Sources of these costs include additional and unique wear and tear on existing infrastructure, increased costs associated with oversight of SDV technology and SDV manufacturers, the need for government investment in SDV adoption in the form of subsidies and shared roadway digital twin data, and the need for new infrastructure improvements to support SDV safety in mixed road fleets.

2.3.1. Impact of Self-Driving Vehicles on Infrastructure

Emerging research on the impact of adoption of self-driving vehicles (SDVs) indicates that the introduction of these vehicles will generate additional cost burdens for governments and agencies responsible for roadway maintenance and operations. Cost drivers include upgrades to infrastructure, including:

1. **Data capturing smart features**: Adding smart features to existing road structures to provide SDVs with information regarding driving environment, roadway characteristics, and the location and direction of travel of other vehicles would enhance the ability of SDVs to navigate the roadways safely (Chen et al., 2023).
2. **Enhanced lighting in tunnels and underpasses**: SDV traffic sign recognition systems could have difficulty interpreting signs in low-light conditions found in tunnels and underpasses (Konstantinopoulou et al., 2020). To address this problem, enhanced lighting would be needed in these locations.
3. **Updates to sign placement relative to lights for nighttime conditions**: Traffic sign recognition systems are sometimes challenged by low-light conditions (Shladover & Bishop, 2015). These limitations require that traffic signs be located

near sufficient artificial light sources to ensure high probability of traffic sign recognition system success.

4. **Need for "safe harbor" locations for safe transition from self-driving to human-operation**: SDVs require safe places to stop or restart in an emergency or when reaching the exit of an automated operation area (Liu et al., 2019). This requirement mandates that autonomous operation zones have sufficient road shoulders, pull off areas, or other exits to allow for a safe restart of self-driving or a safe transition to human operation.

5. **Updated placement requirements for traffic control signs**: Traffic sign recognition systems have the ability to detect signs that are located near a roadway, but are not applicable to traffic utilizing that roadway, such as signs on frontage roads and exit ramps (Roper et al., 2018). These failure modes necessitate updates to sign placement regulations, updates to placements of existing traffic control signs, and updates to commercial sign regulations for signs near roadways.

6. **Need to update traffic control sign standards**: The U.S. Department of Transportation is investigating what changes should be made, if any, to the Manual on Uniform Traffic Control Devices (MUTCD) standard to assist in the transition to SDVs (U.S. Department of Transportation, 2021). Any changes to the MUTCD standards will require replacement of signs impacted by the standards update.

7. **Road work and emergency signage**: Traffic sign recognition (TSR) systems often face challenges when exposed simultaneously to both permanent road

signage as well as temporary roadwork or emergency signage (Roper et al., 2018). SDVs can act on the incorrect signage for the situation in these situations based on limitations of their algorithms. To address this issue, additional, machine-readable signage may be required to provide the SDV with sufficient information to select the correct driving behavior for the situation.

8. **Machine-readable variable message signs**: TSRs have difficulty reading human-readable signs due to variations in size, height, light color, and light output for these signs (Roper et al., 2018). These signs would not be readable by unaided human drivers (Tengilimoglu et al., 2023), so duplications of variable message signage would be required so long as there were mixed fleets of vehicles.

Additional sources of expense from SDV adoption include wear impacts on existing and future infrastructure, to include:

1. **Bridge loading**: Increased loading on bridges due to the use of heavy vehicle platooning (Liu et al, 2019), which would lead to increased wear and potential bridge failure for bridges with longer span lengths (Yarnold & Weidner, 2019).
2. **Infrastructure data needs**: Additional data gathering and existing infrastructure analysis requirements to account for SDV-influenced bridge loading, to include instrumentation of bridges, analysis of combined fleet vehicle travel patterns, and other analysis efforts (Sayed et al., 2020; Ulrich et al., 2019; Tengilimoglu et al., 2023; Liu et al., 2019).

3. **Road wear concentration**: Increased frequency of road resurfacing operations due to advanced lane-keeping by SDVs concentrating loading and wear and tear on a smaller portion of the total road surface (Liu et al., 2019).
4. **Signage maintenance**: Increased inspection and replacement of traffic control signs may be required as TSRs can be challenged by the effects of weathering, vandalism, and damage on signs (He et al., 2020; Triki et al., 2023; Batool et al., 2023; Roper et al., 2018).

2.3.2. Need for a Digital Twin of Existing Traffic Control Infrastructure

Existing literature highlights the need for a digital twin of the road system to support the safe introduction and operation of SDVs. This digital twin should include highly accurate digital maps of roadways with detailed information from traffic controls (Ulrich et al., 2019; Tengilimoglu et al., 2023). In addition to highly accurate maps, the digital twin must incorporate data from transmitters that assist SDVs in navigating challenging driving conditions, such as adverse weather, occluded traffic control devices, or loss of connectivity to Global Navigation Satellite Systems (Chen et al., 2023). The digital twin can also facilitate virtual testing of self-driving systems before road trials (Wang et al., 2024). After passing virtual evaluations, SDVs could be tested in real-world scenarios at specialized test sites, allowing for the validation of edge cases. This hybrid testing and verification approach can reduce testing costs for both SDV manufacturers and government oversight entities.

2.3.3. Need for Independent Oversight of SDVs

New technologies introduce regulatory challenges in ensuring consumer safety. Regulations often fail to keep pace with the technology, resulting in a temporary absence of appropriate legal restrictions needed to control the risks associated with the new technology

(Moses, 2007). As SDVs become a greater part of the vehicle mix, effective safety regulation will ensure the safety of both the passengers of the SDVs and other road users.

One of the more recent and well publicized failures of a new technology that lacked appropriate oversight was the loss of two Boeing 737 MAX aircraft in which 346 lives were lost due to malfunctions of the Maneuver Characteristics Augmentation System (MCAS) (U.S. Senate Committee on Commerce, Science, and Transportation, 2021). The U.S. Federal Aviation Administration (FAA) had oversight authority on the 737 MAX aircraft and its MCAS, but much of that oversight had been delegated to members of the Boeing Outside Designated Authority (ODA) unit, who were employees of Boeing acting on behalf of the FAA (Warren & Alp, 2024). Post-crash investigations observed the following issues with this oversight approach:

1. The FAA lacked the expertise to provide oversight (U.S. Department of Transportation Office of the Inspector General, 2021).
2. Boeing ODA members were pressured to prioritize meeting schedule over ensuring safe aircraft operations (U.S. Department of Transportation Office of the Inspector General, 2021).
3. Boeing assumed pilots would be able to handle MCAS failures, without telling the pilots about MCAS failure modes (U.S. Department of Transportation Office of the Inspector General, 2021).
4. Congressional action had to be taken to prevent a recurrence of this oversight failure (Cook, 2020; Aircraft Certification Reform and Accountability Act, 2020).

The MCAS analog demonstrates the need for oversight of vehicle control technologies whose failures can result in human casualties, and the need for that oversight to be independent.

Since SDV failures could result in human casualties, independent oversight of this technology is needed.

2.3.4. Cost of Training Data for SDV Oversight

One of the important elements of an SDV system is the ability of the SDV to identify safety critical traffic signs using an onboard or networked traffic sign recognition (TSR) system. The TSR system must be sufficiently robust to handle a wide range of image-related challenges that can occur during normal operations, such as sign deterioration, damage, or vandalism, weather impacts (e.g., ice, snow, rain, haze, smoke, etc.), camera issues (e.g., dirty lens, broken lens, overexposure, underexposure, dead pixels, etc.), lighting conditions (e.g., low light, direct sun, shadows, etc.), sign occlusion, and other challenges (He et al, 2020; Triki et al, 2023; Batool et al., 2023; Atif et al, 2022). To develop and certify such a TSR system, labeled images of every sign and challenge permutation need to be available for both the training set of data and a separate set of test data. Given the large number of images required for these datasets, and the large costs associated with gathering and properly labeling images (He et al., 2020), the government agency responsible for SDV oversight will need a robust funding mechanism to fund the data capture, data labeling, and test activities required to provide effective oversight.

2.3.5. Expectations for New Technology Oversight

A review of the literature shows a general agreement that standards need to be developed for SDV technology, and that there is some contention on what basis should be used to establish the standards. One side of the debate advocates for technology-based standards that regulate the elements of the SDV, such as sensors, processing capability, and artificial intelligence used to enable self-driving, since performance-based standards and regulation present challenges when standards are not well defined or the mandated level of performance is difficult to measure

(Coglianese et al., 2003). Those in opposition to technology-based standards argue that such standards limit innovation and stifle the emergence of competing technological approaches, and advocate for a performance-based set of standards that mandate a certain outcome, but now how that outcome is achieved should be developed (Coglianese et al., 2003). Researchers in both camps agree that the standards must be based on scientific risk assessments, economic calculations comparing cost of compliance to cost of failures of the technology, and a high level of public trust in the ability of the standards to ensure their safety (Merchant et al., 2009).

In addition to standards development, previous research also suggests that the oversight and regulation of SDV technology must also achieve the following:

1. Providing methods to obtain legal remedies to those harmed by SDV failures, assigning responsibility for potential damages in a manner that is transparent and generally viewed as reasonable, and ensuring accountability measures for SDV manufacturers (Weimer & Marin, 2016; McCool, 2019).
2. Avoid undue burdens on SDVs that would reduce rate of SDV adoption through the use of oversight frameworks that balance cost avoidance, safety assurance, and technology adoption support, or through government subsidies to mitigate cost of oversight (Mandel, 2009; Merchant et al., 2009; Roca et al., 2017).

2.4. Legal Culpability for SDVs

A significant area of risk and uncertainty for the widespread implementation of SDVs is the potential for legal actions against SDV manufacturers to cause significant financial damage. Specifically, if an SDV misreads a traffic sign and is then involved in a crash with injuries and property damage, who would be found to have primary fault for the crash: the driver of the vehicle (assuming human intervention is possible) or the manufacturer of the SDV? One method to estimate the potential liability is to examine existing case law, and the potential for class action lawsuits against the SDV manufacturers.

2.4.1. Past and Current Legislation Involving Crashes with SDVs

There is limited case law to draw from regarding assignment of SDV crash blame, and the defendant in most of these cases, Tesla, has argued that their current technology offerings are not fully autonomous and that human drivers need be ready to take over driving at a moment's notice. In one case in Mountain View, California, Tesla was sued after a driver was killed when their Tesla, utilizing Autopilot functionality, veered into a concrete barrier at high speed. During trial, Tesla attorneys argued the software was not capable of performing the maneuver that led to the crash, that Tesla informed the driver via the user's manual of required driver supervision of Autopilot, and that human error caused the crash (Ewing, 2023). In this case, Tesla was successful in getting the lawsuit dismissed.

In another case in Florida, Tesla was sued by the survivors of Jeremy Banner who was killed in a collision in 2019 when his Tesla drove under a semitruck while the Autopilot feature was engaged (Romo, 2023). As with the California case, Tesla argued Banner was using Autopilot in a manner that violated the limits described in the user manual, and that Banner was not sufficiently supervising the system. Unlike the California case, Palm Beach County Judge Reid Scott ruled that there was rea-sonable evidence to suggest that Tesla was aware of the limitations of their Autopilot system, that these limitations could put drivers as risk, and that Tesla continued to sell the vehicles and overstate the capabilities of the Autopilot (Romo, 2023). With that ruling, the Banner family was allowed to continue their litigation.

This defensive strategy by Tesla for these lawsuits has opened up additional legal vulnerabilities, as Tesla owners are arguing that Tesla is not delivering on promised vehicle capability. In one case in California, the plaintiff alleged that he purchased a Tesla vehicle due to marketing claiming Tesla vehicles had required hardware and would only need software updates to become fully self-driving. This claim was later ruled sufficiently false by the court as Tesla vehicles at the time lacked Lidar systems required to achieve SAE Level 4 automation (Tesla Advanced Driver Assistance Systems Litigation, 2024). Similar legal action was taken by the State of California against Tesla, where the state alleged Tesla made several false or misleading statements in advertisements regarding the autonomous capabilities of their vehicles (Department of Motor Vehicles, State of California, 2022). These lawsuits have forced Tesla to modify its online and advertising messages to state the limitations of the Autopilot system (Tesla, 2024).

These crashes and others have been subject of National Transportation Safety Board (NTSB) investigations focusing on the Autopilot system. These investigations have shown that the Autopilot system is being used outside of the operational domain of the vehicle in most of these crashes, and that Tesla is not sufficiently limiting when the system can be used (National Transportation Safety Board, 2020). In the Mountain View case, the NTSB found that crash was due in part due to failure of the Autopilot to steer correctly onto the highway exit, overreliance by the driver on the Autopilot system, and distracted driving by the driver accessing entertainment on his phone at the time of the crash (National Transportation Safety Board, 2020). These investigation results have the potential to support future lawsuits against Tesla and other manufacturers.

2.4.2. Potential for Class Action Lawsuits

Another threat to SDV manufacturers is the prospect of losing a large-scale judgement in a class action lawsuit resulting from damages and injuries caused by failures of the SDV, or by accusations of false advertising. With class action lawsuits, even if the class claim is weak, the sheer number of class members along with the possibility a sympathetic jury will hear the case can cause defendants to settle cases to limit the financial damage (Messner v. Northshore University Health System, 2012). Additionally, there are incentives for class counsels to pursue class actions against well-resourced corporations to secure large attorney's fees (Morrison, 2011). There have already been attempts in current civil suits against Tesla to gain class-action status, including a California case involving drivers who purchased a Tesla based on promises made regarding self-driving capability that was never delivered (Brodkin, 2024).

2.4.3. Predicting Jury Opinions

There is limited research regarding how a potential jury pool may view legal culpability for traffic collisions that involve SDVs operating without input from human drivers. Without knowing who a potential jury pool would blame, it is difficult to quantify the potential legal exposure an SDV manufacturer would have regarding class action lawsuits if their products were involved in accidents.

2.5. Expectations for Safety and Reliability of SDVs for American Consumers

As SDVs become increasingly common on roadways and more available to consumers, concerns about safety for both passengers and other road users have emerged as key barriers to SDV adoption (Kim et al, 2022; Wang et al, 2020). Incidents' involving SDVs in traffic collisions, particularly with associated injuries and fatalities, have also limited growth in consumer demand (Kim et al, 2022). These trends highlight the need for SDV designs that enhance public perception of system safety and reliability to support continued market growth. However, achieving this design objective is complicated by the non-uniform perception of SDV safety among the general population. Research shows that individuals identifying as female, non-White, or older, express greater concerns regarding personal safety with SDVs than other gender, age, and ethnic groups (Lee et al, 2022). Similarly, drivers in rural and urban areas report higher safety concerns than those living in suburban areas (Lee et al, 2022). Perceived safety benefits have been shown to significantly influence trust in SDVs (Li et al, 2024). Yet, other research suggests that trust alone does not predict people's willingness to actually ride in one (Fink et al, 2025). Comfort with using SDVs for passenger transport, where passengers cannot intervene, is also heterogenous. One study found that younger respondents, males, and urban residents were more willing than other groups to allow their children to be transported in SDVs (Lee et al, 2020).

2.5.1. Design Features Associated with Reliability and Safety

Several design features influence perceptions of SDV reliability and safety. The following subsections review four commonly discussed design elements: disengagement rates, takeover request (TOR) methods, failure response behavior, and system reliability.

2.5.1.1. Disengagement Rates

Several design elements influence perceptions of SDV reliability and safety. One key measure of reliability is disengagement rate, which represents the number of times a hu-man must intervene when the SDV encounters errors or engages in potentially dangerous driving behavior (Wang et al, 2020; Kohanpour et al, 2025). Current SDV technology exhibits a wide range of disengagement rates, with one study reporting values ranging from 0.0002 to 3.0 disengagements per mile, depending on the vehicle manufacturer (Wang et al, 2020). Analysis of data from the California DMV (the only regulatory agency currently mandating collection and publication of dis-engagement data) from 2019 to 2022 found an average of 0.0028 disengagements per mile, or one disengagement per 359 miles traveled (Kohanpour et al, 2025). Of the more than 39,000 disengagements documented in the California DMV data, only 0.22%

resulted in a collision (Kohanpour et al, 2025). While this data provides valuable insight into current SDV reliability, it reflects conditions specific to California's testing environment and reporting requirements. Differences in road infra-structure, climate, traffic density, and regulatory oversight across regions may limit the generalizability of these findings to broader U.S. or international contexts. Nevertheless, these values illustrate the variability in current SDV reliability performance and under-score the importance of understanding what disengagement rates potential consumers would find acceptable. Despite the low number of collisions associated with SDV disengagements, manufacturers must ensure disengagement rates that are equal to or less than the frequency that would be tolerated by potential consumers.

2.5.1.2. Takeover Request (TOR) Method

Another factor associated with perceived safety of SDVs is the method of notifying the driver of a takeover request (TOR), which alerts the driver to intervene in response to failures or challenges within the self-driving system. Potential modes for TOR alerts include heads-up displays (HUDs) on the windshield, strip lighting on the perimeter of the windshield, console displays, audio alerts, and haptic signals to the driver (Tan et al, 2025). Previous literature has identified a need for multimodal TOR design, along with a tailored approach for modal selection and modal combinations based on the scenario being encountered (Deng et al, 2024). Cross-cultural studies of automated driving have found substantial variation in driver takeover response times, highlighting the challenges associated with relying on human supervision of automated systems (Strle et al., 2021). This suggests that SDVs will need multimodal TOR alert capabilities, such as visual and audio alert mechanisms, to ensure safe operation of the self-driving system.

2.5.1.3. Failure Response Behavior

Failure response behavior is another critical factor influencing perceptions of SDV safety. Current safety architectures for SDVs typically assume the presence of a driver with the capability to take control of the vehicle when there is a self-driving system failure (Mature-Peaspan et al, 2020). Concurrently, research is underway to improve SDV failure mode and danger mitigation behavior, such as enabling SDVs with position receiver failures to identify safe routes to roadway shoulders versus merely slowing to a stop within their current lane (Mature-Peaspan et al, 2020). Other enhancements include the development of decision-making algorithms that allow self-driving systems to identify safe responses to road conditions that include lane changes and slower speeds (Lee & An, 2023).

2.5.1.4. System Resilience

The final aspect of SDV safety is system resilience, defined as the number of critical sensors within the self-driving system that would be tolerated to fail before the self-driving system was not able to operate safely. The assumption is that a system with redundant sensor architecture, which allows some sensors to fail before safety is compromised, would be perceived as having greater safety than a system with no such sensor redundancy.

2.6. Gaps in Literature

While the existing literature provides valuable insights on SDVs, important gaps remain regarding consumer willingness to pay for SDV technologies, preferences for funding SDV-related infrastructure and oversight, preferences for measurable safety and reliability features, and the role of human oversight in automated driving systems. The following subsections identify these gaps and outline how they are addressed in this dissertation.

2.6.1. Perceptions of SDV Legal Culpability

A significant area of risk and uncertainty for the widespread implementation of SDVs is the potential for legal actions against SDV manufacturers to cause significant financial damage. Specifically, if an SDV misreads a traffic sign and is then involved in a crash with injuries and property damage, who would be found to have primary fault for the crash: the driver of the vehicle (assuming human intervention is possible) or the manufacturer of the SDV? While several cases are currently being litigated in courts around the United States regarding liability for SDV manufacturers such as Tesla, few have reached jury verdicts. In one of these cases, the family of a Mountain View, California driver killed sued Tesla after the driver's Tesla vehicle, while utilizing Autopilot functionality, veered into a concrete barrier at high speed. At trial, Tesla attorneys argued the software was not capable of performing the maneuver that led to the crash, that Tesla informed the driver via the user's manual of required driver supervision of Autopilot, and that human error caused the crash (Ewing, 2023). In this case, Tesla's legal arguments led to the dismissal of the case.

In case in Florida involving the death of Jermey Banner, Tesla was sued by Banner's after he was killed in a 2019 collision involving his Tesla droving under a semitruck while the Autopilot feature was engaged (Romo, 2023). As with the California case, Tesla argued Banner was using Autopilot in a manner that violated the limits described in the user manual, and that Banner was not sufficiently supervising the system. Unlike the California case, Palm Beach County Judge Reid Scott ruled that there was reasonable evidence to suggest that Tesla was aware of the limitations of their Autopilot system, that these limitations could put drivers as risk, and that Tesla continued to sell the vehicles and overstate the capabilities of the Autopilot (Romo, 2023). With that ruling, the Banner family was allowed to continue their litigation.

This defensive strategy by Tesla for these lawsuits has opened up additional legal vulnerabilities, as Tesla owners are arguing that Tesla is not delivering on promised vehicle capability. In one case in California, the plaintiff alleged that he purchased a Tesla vehicle due to marketing claiming Tesla had required hardware and would only need software updates to become fully self-driving. This claim was later ruled sufficiently false by the court as Tesla vehicles at the time lacked Lidar systems required to achieve SAE Level 4 automation (Tesla Advanced Driver Assistance Systems Litigation, 2024). Similar legal action was taken by the State of California against Tesla, where the state alleged Tesla made several false or misleading statements in advertisements regarding the autonomous capabilities of their vehicles (Department of Motor Vehicles, State of California, 2022). These lawsuits have forced Tesla to modify its online and advertising messages to state the limitations of the Autopilot system (Tesla, 2024).

These crashes and others have been subject of National Transportation Safety Board (NTSB) investigations focusing on the Autopilot system. These investigations have shown that the Autopilot system is being used outside of the operational domain of the vehicle in most of these crashes, and that Tesla is not sufficiently limiting when the system can be used (National Transportation Safety Board, 2020). In the Mountain View case, the NTSB found that crash was due in part due to failure of the Autopilot to steer correctly onto the highway exit, overreliance by the driver on the Autopilot system, and distracted driving by the driver accessing entertainment on his phone at the time of the crash (National Transportation Safety Board, 2020). These investigation results have the potential to support future lawsuits against Tesla and other manufacturers.

Another threat to SDV manufacturers is the prospect of losing a large-scale judgement in a class action lawsuit resulting from damages and injuries caused by failures of the SDV, or by accusations of false advertising. With class action lawsuits, even if the class claim is weak, the sheer number of class members along with the possibility a sympathetic jury will hear the case can cause defendants to settle cases to limit the financial damage (Messner v. Northshore University Health System, 2012). Additionally, there are incentives for class counsels to pursue class actions against well-resourced corporations to secure large attorney's fees (Morrison, 2011). There have already been attempts in current civil suits against Tesla to gain class-action status, including a California case involving drivers who purchased a Tesla based on promises made regarding self-driving capability that was never delivered (Brodkin, 2024).

The ability of SDV manufacturers to assess their potential legal risk regarding these cases is limited by a lack of research regarding how a potential jury pool may view legal culpability for traffic collisions that involve SDVs operating without input from human drivers. Without knowing who a potential jury pool would blame, manufacturers cannot quantify the potential legal exposure from potential class action lawsuits if their products were involved in accidents. As part of Research Aim 1, this dissertation analyzes who experiment participants would initially blame for SDV-involved traffic accidents and traffic regulation violations, and how claims made by manufacturers regarding human supervision of their products would influence blame assignment to the manufacturer. Additionally, various demographic factors and other respondent attributes were evaluated as potential predictors of primary blame assignment and the influence of the blame assigned to the manufacturer.

2.6.2. Reliability and Safety Expectations

Review of the literature identified several survey studies that utilized conjoint analysis experiments to evaluate elements associated with SDV safety and reliability. However, most prior work examined these attributes in qualitative or indirect terms, such as perceived safety, willingness to pay for safety features, or preferences for interface design. For instance, Kang et al. (2025) explored driver display communication modes, while Nikkar and Lee (2022) assessed willingness to pay for safety functions such as emergency stop and exit assistance. Other studies, including Pronay et al. (2025), incorporated general safety features without quantifying specific performance levels. A common limitation across these studies is that they did not evaluate quantitative performance attributes or system behavior metrics that more directly captures the operational safety characteristics of SDVs.

While traditional conjoint and discrete choice approaches have been used to model consumer preferences for vehicle technologies, these methods typically estimate feature utilities independently and do not incorporate systematic variable selection or hierarchical modeling of demographic effects. As a result, they may obscure the relative influence of correlated predictors or understate cross-group variability. Hierarchical Bayesian extensions have been proposed to address these issues by modeling individual-level heterogeneity, but these approaches require informative priors and are computationally intensive for larger datasets. In contrast, integrating conjoint analysis with modern regularization and mixed-effects techniques, such as LASSO regression and generalized linear mixed models, provides a more transparent, data-driven means of identifying dominant features and subgroup effects. This combined framework enhances both precision and interpretability while maintaining computational efficiency for large-scale datasets.

These gaps reveal a need for a quantitative, scalable framework that links measurable SDV safety features with underlying demographic and behavioral indicators of preference. Building on these prior efforts, research seeks to advance the understanding of how consumers evaluate measurable, system-level safety features in self-driving vehicles. Specifically, within Stewart and Gallegos (2025b), Research Aim 2 aims to determine the reliability and safety feature levels SDV consumers expect in their SDVs, which features levels have the highest utility, and which features are most important in consumer decisions.

2.6.3. Willingness to Pay for SDVs

Despite previous research efforts on full self-driving vehicle WTP, gaps exist in the current literature. First, there can be pronounced differences between populations with regards to WTP. This makes it challenging to predict population WTP using data from dissimilar regions or population characteristics. Second, as was seen in the studies from China, both the overall population WTP and WTP magnitude change and tend to decrease over time. This necessitates resampling of populations to update WTP and WTP magnitude predictions. Based on these first observations, an updated sample of the population of the United States is needed. Third, current literature suggests that the risk preference of the respondent and their comfort level with full self-driving vehicles could be predictors for WTP, but there is a deficiency in studies that capture risk and comfort levels for the respondents or examine the predictive significance of those levels. Fourth, while previous studies have looked at classes of vehicle users (such as personal automobile only versus public transportation only), there is a deficit in studies that examine if vehicle type is a predictor of WTP for full self-driving vehicles. Finally, there is a lack of studies looking into the assignment of blame for full SDV traffic collisions and mishaps as a predictor of WTP for vehicle automation. Given these observed gaps, this dissertation looks to survey a sample of the population of the United States to determine both WTP and its predictors.

As part of Research Aim 3, Stewart and Gallegos (2026) addresses this research gap by (1) generating an updated willingness to pay (WTP) profile for full self-driving and advanced driver-assist technology for a sampled U.S. respondent population and (2) evaluating how individual characteristics such as demographics, SDV trust levels, risk preferences, vehicle ownership, and perceptions of manufacturer advertising predict likelihood of being willing to pay a premium for SDV technology and the monetary magnitude of that willingness to pay.

2.6.4. Tax and Fee Preferences for Oversight Funding

The transition to SDVs as the majority contributor to vehicle mixes on the roadways will induce significant additional expenses for infrastructure improvements and effective government oversight of SDV manufacturers and SDV-enabling technologies. To fund these additional expenditures, a dedicated source of revenue needs to be secured via either taxation, fees, or additional levies on the cost of vehicles. At the same time, the selected revenue formula needs to be tolerated by those impacted by the additional costs in order for the revenue streams to be stable and predictable. Currently, a gap exists in the current literature regarding funding preferences for vehicle infrastructure in the context of supporting SDV adoption.

As part of Research Aim 4, Stewart et al. (2026) addresses this research gap by (1) evaluating preferences for fuel taxes, mileage taxes, vehicle taxes, and self-drive subscription fees via a Conjoint analysis experiment and (2) evaluating predictors for these preferences, with candidate predictors including trust in SDVs, vehicle ownership, annual miles driven, and highest level of education achieved.

2.6.5. Effectiveness of Human Oversight on Autonomous Systems

Gaps currently exist in the literature regarding how system capability framing and the frequency of errors in automated systems, such as TSR systems, affect the reliability of human oversight in self-driving vehicles. Since capability framing can impact both SDV manufacturer liability and user trust in the system, and because trust may in turn affect the accuracy of human oversight, there is a need to better understand how framing may hinder or enhance a user's ability to effectively monitor automated systems. Additionally, further research is needed to determine whether the frequency and temporal proximity of errors within an automated system influence the effectiveness of human supervision. Understanding these dynamics is essential for evaluating how drivers respond to real-world system imperfections. Research Aim 5 addresses these gaps by measuring the effectiveness of participant oversight of a simulated TSR system and evaluating if TSR capability framing or error concentrations are significant predictors of oversight accuracy.

Chapter 3. Common Experimental Methods

3.1. Introduction

This dissertation utilized two separate experiments to evaluate and answer the research aims of this research. Specifically, a survey was conducted with 403 respondents and used for Research Aims 1 – 4, identified as Experiment 1. A separate experiment (i.e., Experiment 2) was conducted for Research Aim 5 with 62 participants, which included a survey as part of the experimental design that had similar sets of questions as the survey used in Research Aims 1 – 4. While each of these experimental approaches had some unique elements, there were several common data collection and analysis methods that were common across both. In order to support document conciseness and single sources of data, this section provides descriptions of these common experimental attributes and experimental results that were utilized in more than one research aim.

3.2. Demographics Information

Experiment respondents were asked to provide information regarding how they identified themselves in several demographic categories, including race or ethnic identify, gender, household income level, highest level of education achieved, marital status, type of vehicle they owned, driving frequency, and their estimated number of miles driven each year.

3.2.1. Method of Capture

With the exception of the number of miles driven per year, respondent answers for the demographic categories were limited to a defined list of values as shown in Table 2. Experiment respondents provided their demographic information remotely through an online computer interface.

Table 2. Demographic Attribute Levels

Attribute	Levels
Gender	Male; Female; Non-Binary / Other Gender; Prefer not to say
Race or Ethnicity	Hispanic; Latino; African American; White / Non-Latino; Asian; Pacific Islander; Native American / Alaskan Native; Other; Prefer not to answer
Marital Status	Single; Married; Divorced; Widow/Widower; Prefer Not to Answer
Education	Less Than High School; High School Diploma; Some College; Associate's Degree; Bachelor's Degree; Master's Degree; Doctorate Degree; Professional Degree
Income Level	Less than $10,000; $10,000-$19,999; $20,000-$29,999; $30,000-$39,999; $40,000-$49,999; $50,000-$59,999; $60,000-$69,999; $70,000 - $79,999; $80,000-$89,999; $90,000-$99,999; $100,000-$149,999; More than $150,000
Drive Frequency	Daily; 4-6 times a week, 2-3 times a week; Once a week; Never
Type of Vehicle	Vehicle using gasoline or diesel fuel (Internal Combustion Engines); Vehicle using fuel other than gasoline or diesel (hydrogen, natural gas, etc.); Hybrid electric/gas vehicle (battery + gasoline powered engine); Electric vehicle (battery only); Do Not Own a Vehicle

3.2.2. Experiment 1 Participant Demographics

Participants were recruited and paid through a paid survey panel through the Prolific platform. In total, 413 participants began the survey, and 403 participants provided fully complete and valid responses meeting all screening criteria. Inclusion criteria required respondents be living in the United States and be over 18 years old. Prolific recruited participants that closely matched US Census demographics based on gender, race/ethnicity, and marital status. The sample comprised of 197 males (48.9%), 198 females (49.1%), 7 non-binary (1.74%) and 1 prefer not to answer (0.25%). Ages ranged from 18 to 79 years old (mean = 45.5, SD = 15.6). Most participants reported owning a vehicle (N = 367, 91.1%), with 324 owning an internal combustion engine vehicle, 25 owning a hybrid vehicle, 10 owning a battery electric vehicle, and 8 owning another fuel type vehicle (e.g., hydrogen, natural gas, etc.). Self-reported driving frequencies of the sample were as followed: daily (N = 194, 48.1%), 4-6 times a week (N = 86, 21.3%), 2-3 times a week (N = 65, 16.1%), once a week (N = 22, 5.5%), and never (N = 36, 8.9%).

Following the collection of the respondent demographic data for Experiment 1, the demographic composition of the experiment population was compared to the estimated demographic characteristics of the general population of the United States as defined by the U.S. Census American Community Survey and past decennial census data (U.S. Census Bureau (a-e), n.d.). This comparison is shown in

Table 3 and

Table 4.

Table 3. Survey Sample Gender, Race/Ethnicity, and Martial Status

Attribute	**Survey Response Data**		**US Census**
	N	%	%
	Gender		
Male	197	48.88	49.58
Female	198	49.13	50.42
Non-Binary / Other Gender	7	1.74	N/A
Prefer Not to Answer	1	0.25	N/A
	Race or Ethnicity		
Hispanic / Latino	55	13.65	18.7
African American	56	13.90	12.40
White / Non-Latino	244	60.55	61.60
Asian	24	5.96	6.00
Pacific Islander	1	0.25	0.20
Native American / Alaskan Native	4	0.99	1.10
Other	16	3.97	8.40
Prefer Not to Answer	3	0.74	N/A
	Marital Status		
Single	168	41.69	36.00
Married	179	44.42	48.00
Divorced	40	9.93	10.50
Widow/Widower	12	2.98	5.50
Prefer Not to Answer	4	0.99	N/A

Table 4. Survey Sample Education and Income

Attribute	**Survey Response Data**		**US Census**
	N	%	%
	Education		
Less Than High School	0	0.00	10.40
High School Diploma	57	14.14	26.10
Some College	91	22.58	19.10
Associate's Degree	52	12.90	8.80
Bachelor's Degree	139	34.49	21.60
Master's Degree	46	11.41	
Doctorate Degree	5	1.24	14.00
Professional Degree	13	3.23	
	Income		
$0 - $9,999	40	9.93	5.50
$10,000 - $19,999	16	3.97	
$20,000 - $39,999	70	17.37	28.50
$40,000 - $59,999	42	10.42	
$50,000 - $59,999	37	9.18	
$60,000 - $79,999	64	15.88	29.00
$80,000 - $99,999	41	10.17	
$100,000 - $149,999	57	14.14	16.90
More than $150,000	52	12.90	20.20

3.3. SDV Trust as a Predictor

One common hypothesis across both experiments was the theory that the concept of trust in self-driving vehicles would be a predictor of factors such as willingness to pay for SDVs and the assignment of blame for SDV-involved collisions and violations of traffic regulations. In this context, SDV trust evaluates the extent to which an experiment participant would be willing to own and utilize an SDV, and their level of willingness to allow SDVs to be used in various driving locations and scenarios. To evaluate this hypothesis, a method of assessing SDV trust was developed and utilized within both experiments.

3.3.1. SDV Trust and Willingness to Pay for SDVs

Several studies suggest the concept of trust in autonomous or fully self-driving vehicles can significantly impact WTP. Wang et al. (2024) examined participants' level of trust and their WTP for full self-driving vehicles both before and after riding in a Level 4 autonomous vehicle. The study found that mean trust in the technology increased by 17.5% across the study population following the ride. This increase in trust corresponded to a mean WTP rise of 13.8% for male non-drivers and 13% for male drivers. In contrast, female participants experienced a 5.7% decrease in WTP for drivers and a modest decrease for non-drivers after the ride (Wang, Hu, Sun, & He, 2024).

Another study by Orthman (2023) highlights the impact of comfort with fully self-driving vehicles on WTP. In their study, Orthman collected WTP data from participants and then presented the respondents with images and details of traffic collisions involving SDVs. After viewing the traffic collisions, respondents were again questioned on their WTP for fully autonomous technology. This study found mean WTP dropped by 28.1% (from $11,724 to $8,428) among respondents who were unfamiliar with the traffic collisions shown to them prior to the study, and mean WTP dropped by 29.5% (from $6,166 to $4,347) for respondents who were familiar with the traffic collisions prior to the study (Othman, 2023).

Similarly, Dong et al (2019) evaluated the effects of trust and found that people with prior knowledge of driverless cars expressed a higher willingness to ride driverless buses. The effects of trust were further explored in VENTURER Trial 3, a UK government funded project that examined the level of trust that drivers, pedestrians, and cyclists had with autonomous vehicles, and demonstrated that trust plays a significant role in defining interactions between road users and autonomous vehicles (Venturer Project Partners, 2018).

Based on the results of these studies, it is hypothesized that the trust level a respondent has with Level 4 automation can serve as a predictor of respondent WTP for the technology.

3.3.2. SDV Trust and Human Oversight of Autonomous Technologies

Trust plays a critical role in how humans interact with automated systems controlled by artificial intelligence (AI) (Kim & Song, 2022). Users with low trust in an automated system are less likely to adopt the technology, while users with unwarranted or excessive trust in the system may be less effective at supervising the system or responding appropriately when errors occur (Li et al., 2025; Miller et al., 2019). This balance highlights the importance of maintaining an appropriate level of trust that is aligned with system reliability and performance, particularly for SDV road safety (Gao et al., 2024). Such calibrated trust depends on effective and accurate communication of system capabilities and limitations (Kim & Song, 2022). To assess the role of trust in human supervision of a TSR system, this research considers trust as a factor influencing how users engage with and oversee SDV technologies.

3.3.3. Assessment of SDV Trust

Experiment participants were asked to answer a total of eight questions, using a 5-point Likert scale for agreement, about their trust level regarding SDVs, including whether or not they would be willing to purchase a self-driving vehicle, if they would be willing to use the self-driving functionality, and whether they would share the road with SDVs in a variety of contexts. For the questions shown in Table 5, answers are assigned a point score based on the agreement point value scheme (Strongly Agree = 5, Strongly Disagree = 1), while the question shown in Table 6 uses the disagreement point value scheme (Strongly Agree = 1, Strongly Disagree = 5). Respondents with the highest level of trust with SDVs will get a score of 40 points while a respondent with the least trust with SDVs would get a score of 8.

Table 5. SDV Trust Level Questions (Agreement Preferred)

Question Text
I would be willing to share the road with Self-Driving vehicles.
I would feel safe using Self-Driving capability within the next year on a Highway/Freeway with moderate traffic.
I would feel safe using Self-Driving capability within the next year on a Highway/Freeway in gridlock.
I would feel safe using Self-Driving capability within the next year in a residential neighborhood.
I would feel safe using Self-Driving capability within the next year in a school zone.
I would feel safe using Self-Driving capability within the next year in a busy parking lot.
I would feel safe using Self-Driving capability within the next year on urban/city streets.

Table 6. SDV Trust Level Questions (Disagreement Preferred)

Question Text
Limits should be placed on when Self-Driving can be used.

3.3.3.1. Trust Results from Experiment 1

The distribution of total SDV trust scores for the first experiment population is shown in Figure 1. The mean of the SDV trust scores was 20.78, with a median trust score of 20. Given the range of trust scores possible is 8 – 40, this suggests that the general population generally has a lower level of trust with SDVs.

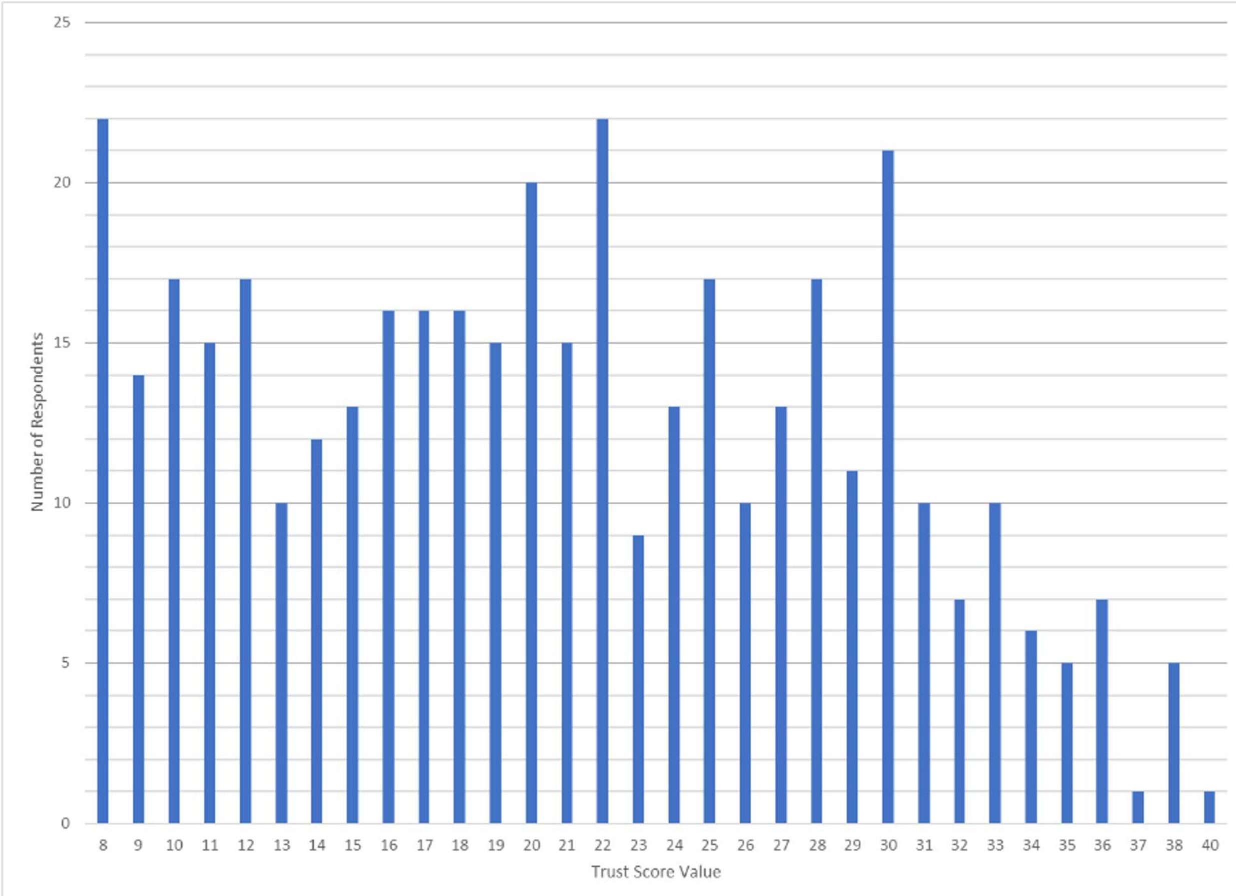


Figure 1. SDV Trust Score Distribution for Experiment 1 Population

3.3.3.2. Linear Regression Analysis of Trust Score with Demographics as Predictors

A linear regression analysis was performed on the first experiment trust score data to determine if any demographic factors were statistically significant predictors of total trust score. There was no statistically significant impact on trust score from the following predictors: education, income, marital status. There was statistical significance on trust score from gender and race/ethnicity as shown in Table 7.

Table 7. Summary of Statistically Significant Predictors for Trust Score

Coefficient	**Estimate**	**Std Error**	**t-value**	**p-value**
(Intercept)	27.23	2.96	9.20	0.001
Gender Not Male (ref. male)	-8.46	1.56	-5.44	0.001
Race/Ethnicity - Asian (ref. White)	7.82	3.38	2.32	0.021
Race/Ethnicity - African American (ref. white)	4.19	2.29	1.83	0.068

*All other factors for Race or Ethnicity were not significant predictors of trust scores.

The strongest predictor for SDV trust score is gender identify, with individuals not identifying as male scoring significantly lower than individuals identifying as male, with the average SDV trust score of those identifying as a gender other than male being 8.46 points less than the average score of individuals identifying as male. Figure 2 shows the trust score distributions by gender for the Experiment 1 population.

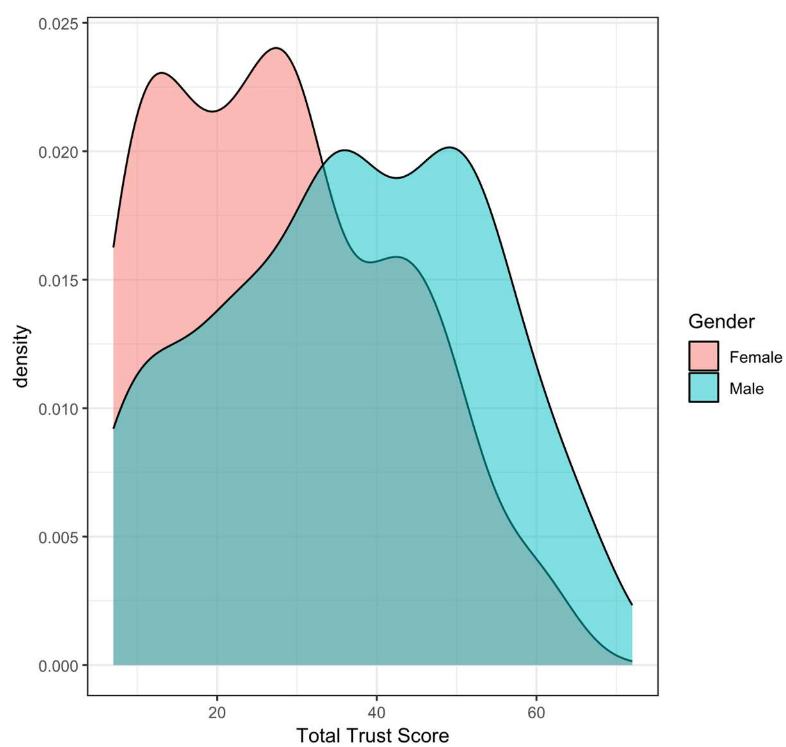


Figure 2. Trust Score Distributions by Gender

The predictor of race or ethnicity also plays a role in the prediction of SDV trust scores, with Asians having an average SDV trust score value that is 7.82 points higher than the average of individuals identifying as White / Non-Latino (p = 0.0211). Individuals identifying as African Americans had a marginally significant (p = 0.068) higher SDV trust score than White / Non-Latino respondents, with the average SDV trust score of African American being 4.19 points higher.

3.3.3.3. Trust Results for Experiment 2

The distribution of total SDV trust scores for the Experiment 2 respondent population is shown in Figure 3. The mean of the SDV trust scores was 25.85, with a median trust score of 28. Given the range of trust scores possible is 8 – 40, this suggests that the general population generally has a lower level of trust with SDVs.

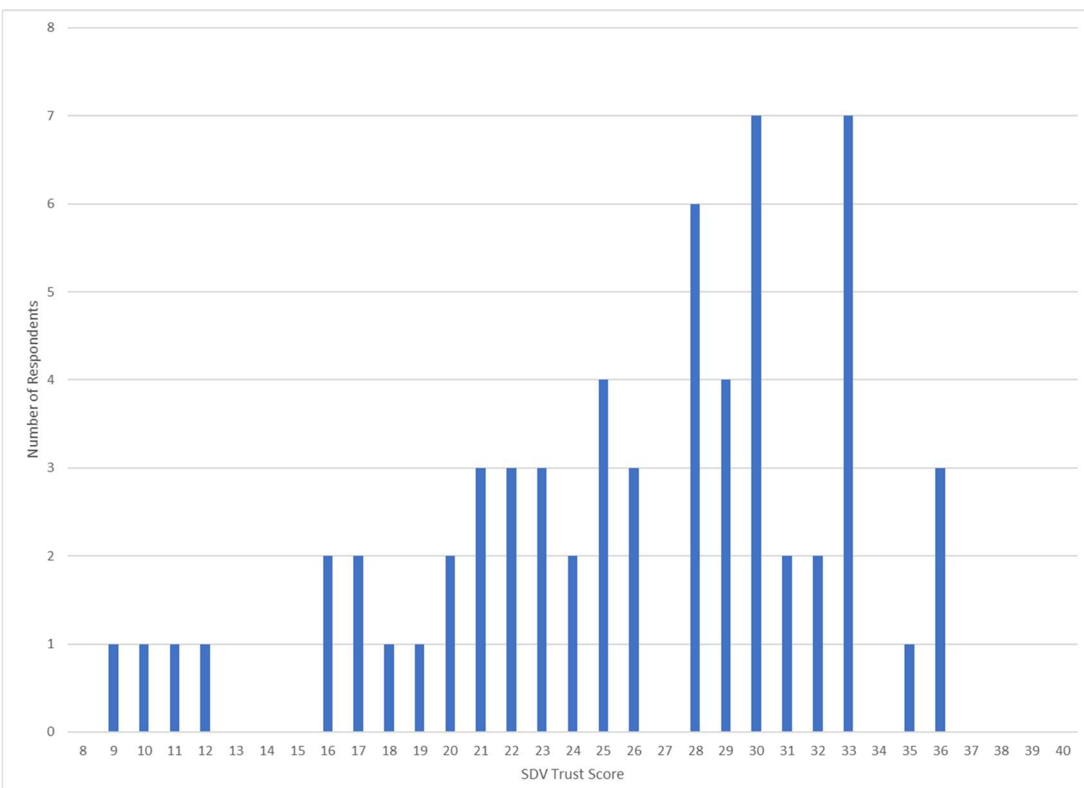


Figure 3. SDV Trust Score Distribution for Experiment 2 Participant Population

3.4. Risk Preference as a Predictor

Another hypothesis present in both experiments was the theory that risk preference would be a predictor of factors such as willingness to pay for SDVs and the assignment of blame for SDV-involved collisions and violations of traffic regulations. In this context, risk was defined by the General Risk Propensity Scale (GRiPS) defined by Zhang et al (2019). To evaluate this hypothesis, a risk information was collected from both experiment populations and evaluated as a predictor for experiment outcomes.

3.4.1. Risk Preference and Willingness to Pay

One potential predictor for WTP for full SDV technology, motivated by Orthman (2023), was the risk preference of the respondent. In Orthman (2023), the mean WTP of the respondents decreased after being shown traffic collisions involving full self-driving vehicles, but the WTP did not drop to zero. This suggests that a portion of the respondent pool was willing to accept the risks associated with full SDV technology, even after seeing potential negative outcomes related to using the technology. In another study, researchers found that risk perception impacted user intent to adopt self-driving/autonomous vehicles, with respondents seeing SDVs as higher risk being less likely to adopt the technology (Ho et al, 2023). Other studies found risk perception, and by extension risk tolerance, as a predictor of willingness to adopt SDV technology, with performance and privacy risk (Kenesei et al., 2022) and personal risk perception of SDVs (Ribeiro et al, 2021) being analyzed. These studies suggest that those who are not willing to accept the perceived risks regarding SDVs would have a WTP of or near $0. For future studies regarding WTP for full self-driving vehicles, assessing respondent risk preference and evaluating the risk preference as a predictor of WTP may yield statistically significant results.

3.4.2. Assessment of Risk Preference

Experiment 1 participants were asked the eight risk preference questions defined in the General Risk Propensity Scale (GRiPS) (Zhang, Highhouse, & Nye, 2019). The questions were asked using a 5-point Likert scale for each question, ranging from "Strongly Agree" (point allocation of 5) to "Strongly Disagree" (point allocation of 1). Higher scores indicate a higher preference for risk, while lower scores are indicative of risk aversion, with possible scores ranging from 8 (most risk-averse) to 40 (most risk-tolerant).

3.4.3. Risk Distribution for Experiment 1

The distribution of total risk scores for the Experiment 1 participant population is shown in Figure 4. The mean of the risk scores was 20.41, with a median risk score of 20. Given the range of risk scores possible is 8 – 40, this suggests that the general population is well distributed across risk adverse (low risk score) to risk seeking (high risk score).

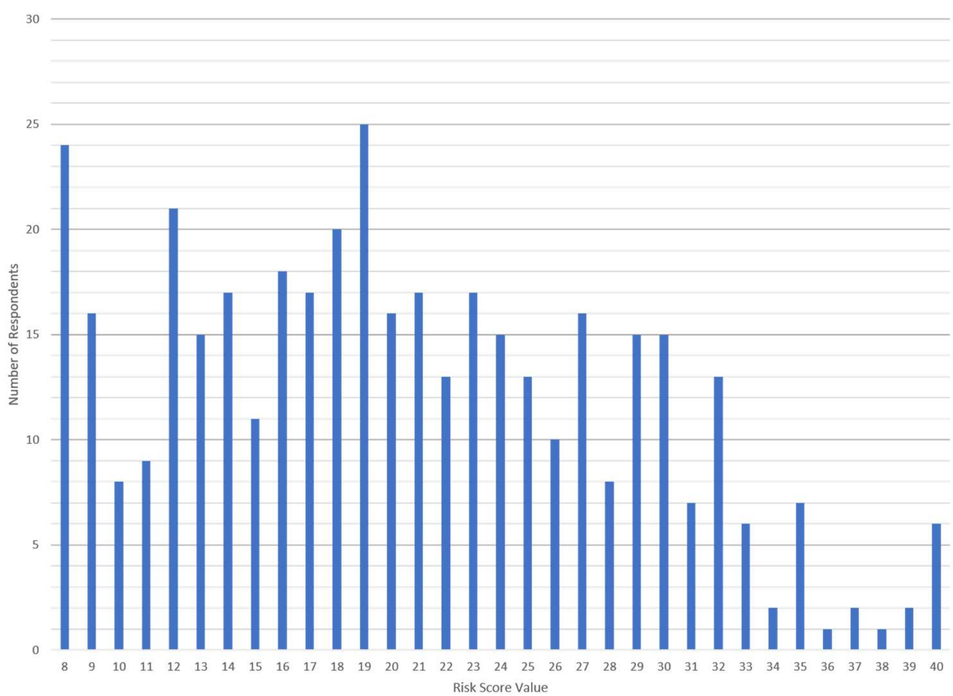


Figure 4. Risk Scores Distribution for Experiment 1 Population

3.4.4. Demographics as Predictors of Risk Score

A linear regression analysis was performed on the survey data to determine if any demographic factors were statistically significant predictors of total risk score. There was no statistically significant impact on risk score from the following predictors: education, income, race/ethnicity, or marital status. There was statistical significance on risk score from gender, with respondents who do not identify as male having an average risk score that is 4.31 points less than the average risk score for males ($p < 0.001$), as shown in Table 8.

Table 8. Summary of Statistically Significant Predictors for Risk Score

Coefficient	**Estimate**	**Std Error**	**t-value**	**p-value**
(Intercept)	13.47	1.51	8.93	0.001
Gender Not Male (ref. male)	-4.31	0.79	-5.43	0.001

3.5. SDV Familiarity as a Predictor

As part of this dissertation, a theory was put forth that the level of familiarity an experiment participant had with SDVs could have predictive value for outcomes such as blame assignment for SDV-involved traffic collisions. In this context, SDV familiarity includes knowledge of existing self-driving technology, past exposure to SDVs through rides in self-driving vehicles, and knowledge of the potential limitations of self-driving technology. To evaluate this hypothesis, a method of assessing SDV familiarity was developed and utilized within both experiments.

3.5.1. Assessment of SDV Familiarity

Survey respondents were presented questions to capture their level of familiarity the respondent has with SDVs. The six questions shown in Table 9 were presented to the respondent with a 5-point Likert-Scale ranging from Strongly Agree (5 points) to Strongly Disagree (1 point). The maximum familiarity score is 30 points, while the lowest familiarity score is 6 points.

Table 9. SDV Familiarity Questions

Question Text
I know about the concept of Self-Driving Vehicles.
I am willing to buy a vehicle that is capable of Self-Driving.
Limits should be placed on when Self-Driving can be used.
I would be willing to share the road with Self-Driving vehicles.
I know of the potential limitations of Self-Driving vehicles.
I have traveled in a vehicle using Self-Drive, such as Tesla Autopilot or like technology.

3.5.2. Familiarity Score Results from Experiment 1

The distribution of SDV familiarity scores for the experiment population is shown in Figure 5. The mean of the SDV familiarity scores was 20.36, with a median familiarity score of 20. Given the range of familiarity scores possible is 6-30, this suggests that the general population is generally has a higher level of familiarity with SDVs.

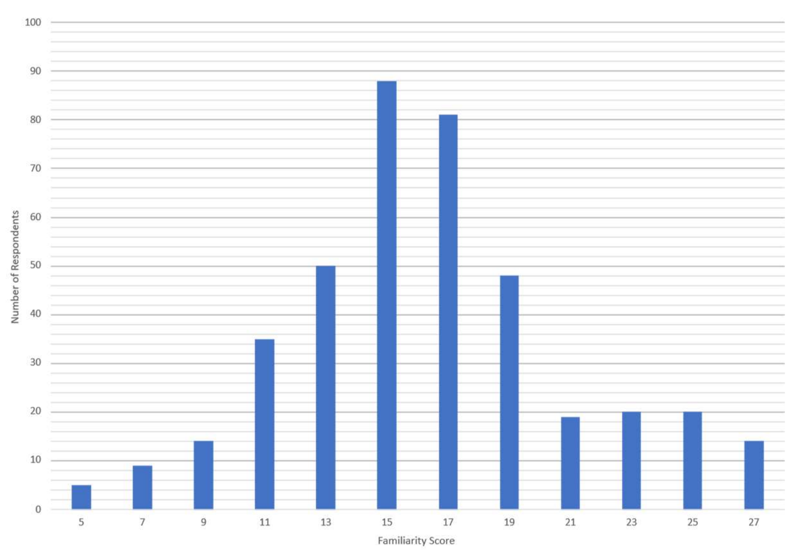


Figure 5. Familiarity Score Distribution for Experiment 1 Survey Respondent Population

3.5.2.1. Linear Regression Analysis of Familiarity Score with Demographics as Predictors

A linear regression analysis was performed on the familiarity score data to determine if any demographic factors were statistically significant predictors of total familiarity score. There was no statistically significant impact on familiarity score from the following predictors: education or marital status. There was statistical significance on familiarity score from gender, with respondents who do not identify as male having an average familiarity score that is 1.13 points less than the average familiarity score for males ($p < 0.001$) as shown in Table 10. Figure 6 shows the distribution of familiarity scores by gender.

Race or ethnicity also plays a role in the prediction of SDV familiarity scores, with respondents identifying as other for race or ethnicity having a SDV familiarity score value that is 1.78 points higher than the average for individuals identifying as White/ Non-Latino ($p = 0.011$). Additionally, while not statistically significant, with an income of greater than $150,000 had an average familiarity score that was 0.95 points more than the average comfort score for respondents reporting incomes of between $40,000 - $59,999.

Table 10. Summary of Statistically Significant Predictors for Familiarity Score

Coefficient	**Estimate**	**Std Error**	**t-value**	**p-value**
(Intercept)	7.08	0.52	13.69	0.001
Gender Not Male (ref. male)	-1.14	0.27	-4.19	0.001
Race or Ethnicity Other (ref. White / Not Latino)	1.78	0.70	2.56	0.011
Income More than $150,000 (ref. $40,000-$59,999)	0.95	0.51	1.85	0.065

*All other factors for Race or Ethnicity and Income were not significant predictors of familiarity scores.

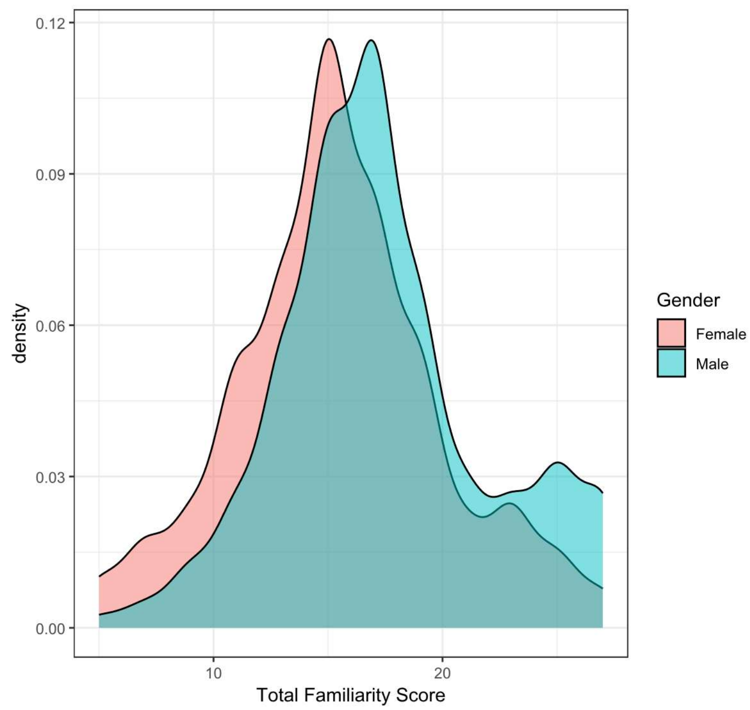


Figure 6. Familiarity Score Distribution by Gender for Experiment 1

3.5.2.2. Familiarity Score Results from Experiment 2

The distribution of total SDV familiarity scores for the first survey respondent population is shown in Figure 7. The mean of the SDV trust scores was 23.13, with a median familiarity score of 23. Given the range of familiarity scores possible is 6 – 30, this suggests that the general population generally has a higher level of familiarity with SDVs.

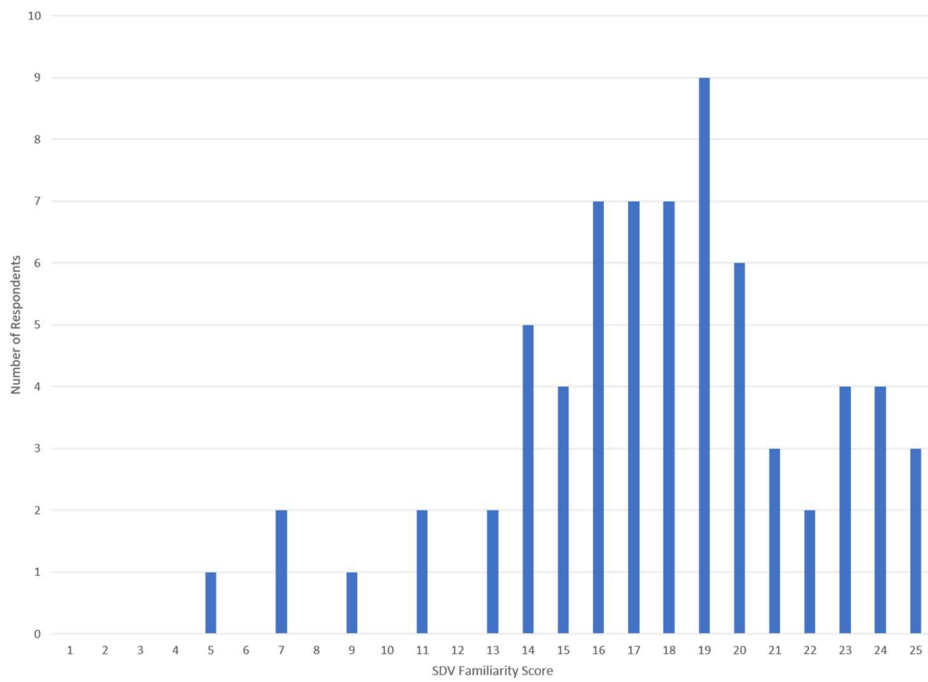


Figure 7. Familiarity Score Distribution for Experiment 2 Survey Respondent Population

3.6. Reliability of Novel Predictor Methods

The introduction of new and previously unused predictors within this dissertation introduced a need to ensure the internal consistency of these new variables as well a need to evaluate the level of correlation between potentially similar variables, such as SDV trust and SDV familiarity values. To evaluate the internal consistency of these new predictors, the Cronbach Alpha of each new variable was evaluated using the 403 data values collected in first experiment. To evaluate potential correlation between the two variables, a Spearman analysis was conducted.

3.6.1. Cronbach's Alpha

One of the more widely used measures of "internal consistency" of questionnaire-based survey data is Cronbach's alpha reliability (Cronbach, 1951), which describes the reliability of a sum (or average) of q measurements where the q measurements may represent questionnaire/test items (Bonnet & Wright, 2014; Cronbach, 1951). Acceptable values for Cronbach's alpha have been defined by George & Mallery (2003) as shown in Table 11.

Table 11. Cronbach's Alpha Qualitative Range Evaluations

Range	**Qualitative Assessment**
$\alpha > 0.9$	Excellent
$0.8 > \alpha > 0.9$	Good
$0.7 > \alpha > 0.8$	Acceptable
$0.6 > \alpha > 0.7$	Questionable
$0.5 > \alpha > 0.6$	Poor
$\alpha < 0.5$	Unacceptable

Given that the question set used to assess respondent SDV trust and familiarity levels were generated for the purpose of this experiment and had not been independently evaluated prior to use in the experiment, a Cronbach alpha calculation on both the SDV trust and SDV familiarity questions was evaluated using R code and the response data from the first survey experiment. Additionally, the Cronbach alpha was calculated for the GRiPS risk tolerance questions. The results of these calculations are shown in Table 12.

Table 12. Cronbach's Alpha Results

Variable	**Cronbach Alpha (α)**	**Qualitative Assessment**
SDV Trust	$\alpha = 0.724$	Acceptable
SDV Familiarity	$\alpha = 0.524$	Poor
Risk	$\alpha = 0.903$	Excellent

The risk and SDV trust questions were evaluated to have "Excellent" or "Acceptable" values (respectively) for Cronbach's alpha, while the SDV Familiarity questions yielded a "Poor" Cronbach's alpha evaluation. While the $\alpha = 0.524$ is not ideal per George and Mallery (2003), the value can still be considered acceptable based on the early stages of research on "familiarity" as a predictor. Per Nunally (1967), early research on predictor tests or hypothesized measures of a construct, reliabilities of 0.60 or 0.50 suffice. Taber (2018) also provides support for the familiarity Cronbach's alpha being acceptable, positing that values of 0.45 can be adequate for research instruments designed to offer insight into samples of a population of interest. Taber further suggested that much lower values may be acceptable if the instrument's purpose is descriptive or hypothesis-generating versus diagnostic. Finally, Loewenthal (2001) suggests that for cales with a small number of items (<10), it may be possible to accept a lower alpha coefficient, perhaps as low as 0.60.

3.6.2. Spearman Analysis

The Spearman rank correlation measures the strength and direction of the association between two ranked variables (Wisniewski & Brannan, 2024). This measure is not as sensitive to outliers versus a Pearson analysis (Maher et al, 2013), and the range of this correlation is -1 to +1. To utilize this method, the survey data must be transformed so that the data values are ranked. In these experiments, the questions used to determine SDV trust, SDV familiarity, and Risk were presented to respondents as 5-point Likert options, allowing for a data transformation where responses were ranked in effectiveness from 1 to 5 ("Strongly Disagree" = 1, "Strongly Agree" = 5). This transformation allowed the Spearman approach to be used for testing correlation between risk and SDV trust, and SDV trust and SDV familiarity.

Spearman rank correlation was evaluated using R code based on the survey results from the first experiment. The results are summarized in Table 13. Statistically significant correlations were observed between SDV trust and risk, and SDV trust and SDV familiarity, though the correlations were only moderate in magnitude. These correlations appear to be reasonable, as familiarity is a reasonable contributor to trust, and higher risk tolerance would allow for greater trust in emerging technologies.

Table 13. Spearman Rank Correlation Results

Correlation Pair	**r**	**p-value**
SDV Trust vs Risk	0.158	0.001
SDV Trust vs SDV Familiarity	0.237	>0.001

3.7. Assessment of Driving Frequency

Experiment participants in both experiments were asked to identify how often they drove in a typical week, using a single-choice question with five levels: never, once a week, 2-3 times a week, 4-6 times a week, and daily. Responding to this question was mandatory.

3.8. Assessment of Miles Driven

Experiment participants in both experiments were asked to estimate how many miles they would drive a personal vehicle (car, truck, van, etc.) in an average year. Respondents entered the value of miles driven into a text box within the survey. Responding to this question was mandatory.

3.9. Assessment of Vehicle Ownership Type

Vehicle ownership type was included as a categorical predictor variable. Respondents identified their primary vehicle type from the following categories: do not own vehicle; gasoline or diesel fuel vehicle (internal combustion engine vehicle, ICEV); battery electric vehicle; hybrid electric vehicle, or vehicle using other fuel types. The ICEV category served as the reference group in all regression models.

Vehicle ownership was divided into three categories for the model as follows:

1. **Do Not Own Vehicle:** Respondents do not own a personal vehicle and rely on other transportation options.
2. **Electric / Hybrid Vehicle:** Respondent owns either an electric vehicle (battery only) or a hybrid vehicle using both battery stored energy and a gasoline engine.
3. **ICE Vehicle:** Respondent owns an internal combustion engine (ICE) vehicle that uses either gasoline or diesel fuel. This was the reference category for the models.

3.10. Statistical Analysis Methods

Both experiments conducted as part of this dissertation had overlap on statistical analysis methods used in the data analysis. To support conciseness within this dissertation, methods common to both experiments are described here. Methods unique to a single experiment are described within the relevant research aims methods chapter.

3.10.1. Generalized Linear Mixed Effects Models (GLMMs)

Binary logistic mixed effects models (a type of generalized linear mixed model, GLMM) were used to evaluate the effects of demographic and self-reported attribute data on SDV safety feature preference. This method was selected over hierarchical Bayesian alternatives due to the absence of informative prior distributions, which are typically required to take full advantage of Bayesian estimation. In the absence of such priors, Bayesian methods tend to yield results nearly identical to frequentist models in both magnitude and interpretation (Lesaffre & Lawson, 2012). Prior studies have shown that for large datasets (N = 672 – 1250), frequentist and Bayesian mixed-effects approaches produce comparable outcomes when data completeness is high (Perez-Millan et al, 2022; Le et al, 2021; Yee-Flores et al, 2022). Given that our conjoint analysis had more than 2,400 observations with no missing data, the GLMM framework provided an equally robust yet more computationally efficient means of modeling individual-level heterogeneity.

In these models, the dependent variable was whether the choice package, which consisted of a human interventions value, failure allowance value, failure behavior, and alert method, was selected (yes/no) in each choice task. Fixed effects included measured impact of advertising, WTP, self-reported drive frequency, and demographics. Random intercepts for participant ID and survey block ID were included to account for within-participant variation and potential dependencies created by grouping survey questions. This analysis was conducted using RStudio (R version 4.5.1) with the lme4 package.

This statistical technique has been utilized in previous studies to address unobserved heterogeneity across individual respondents while also accounting for repeated choice observations within the respondent pool (Bhat & Castelar, 2002). Review of previous literature also found that GLMMs are acceptable for low complexity models (Matuschek et al, 2017) and for models where normality can be assumed for random effects (McCulloch & Neuhaus, 2011).

3.10.2. Linear Regression Analysis

Linear regression analysis fits a linear equation to observed data, allowing for predictions of results based on the effects of predictor variables (Roustaei, 2024). This type of regression analysis allows for the investigation of relationships between dependent and independent variables where linear relationships are expected, and allow for prediction of dependent variable values based on independent variable inputs (Ali & Younas, 2021, Schober & Vetter, 2021). Linear regression models are commonly used to identify general underlying patterns connecting independent and dependent variables, quantify relationships between these variables, and predict expected values for dependent variables based on specified values for the independent variables (Roustaei, 2024).

Existing literature suggests that Likert-scale data from survey studies can be analyzed using linear regression methods. Carifio & Perla (2007) noted that Likert scales are not strictly ordinal, and that multi-item Likert responses that are properly constructed can be treated as interval data for the purpose of parametric analysis like linear regression. Their research showed that aggregated 5-point scales exhibit equal-interval properties sufficient for regression analysis. Norman (2010) provided additional support for this observation, with his research showing through simulation and prior studies that there were no practical differences in results for Likert items from parametric and non-parametric approaches. Norman concluded that violations of interval assumptions with Likert items did not invalidate linear regression outcomes when real-world scenarios were being examined. Additional support is also provided by Sullivan & Artino (2013) who asserted that linear regression analysis can be applied to ordinal Likert data so long as the aggregate score distribution is nearly normal and the sample size includes at least 5-10 observations per group. Finally, Huh & Gim (2025) found through simulation studies that 5-point Likert scales used as response or explanatory variables could be treated as continuous for parametric models, though the simulations showed the required sample sizes needed to be increased by 10% to achieve equivalent power. Correlation and model fit were preserved, and type I error rates stayed near 0.05 (Hug & Gim, 2025).

Linear regression analysis was used in situations where explanatory/ independent variables were reasonably normal in distribution and where a linear relationship was expected between the dependent and independent variables.

3.11. Data Cleaning

Due to the use of an online anonymous experiment interface for both experiments used in this dissertation, a data cleaning effort was necessary to ensure data provided by respondents was valid, and that the responses were provided by humans. This section describes the methods for data evaluation and criteria for data inclusion for each experiment.

3.11.1. Experiment 1

Several methods were used to ensure a clean dataset for this experimental dataset. First, incomplete responses were eliminated from the response data, as were responses from participants who identified that they lived outside of the United States. U.S. residency was further checked through metadata analysis captured by the Qualtrics online platform. In addition, the quality of data was verified with pattern checks (such as consistently selecting the middle option or following a repeating answer pattern) on Likert question responses and comparison of the amount of time the respondent needed to complete the survey against the time needed to complete the survey by reliable beta-testers. This allowed elimination of responses where respondents appeared to have rushed through the survey. Finally, the experiment also included a Likert question and free form question pair covering the topic of WTP, with the Likert question asking for level of agreement on WTP generally, and the free form question asking for a quantitative WTP value. Responses where the Likert response did not correlate to the quantitative WTP would have been removed.

3.11.2. Experiment 2

Data cleaning for the online experiment responses collected occurred in two steps: 1) Screening questions within the experiment that captured inclusion criteria for the participants, and 2) Data screening of collected responses to ensure participants were human and were deliberate in their responses. In the initial screening, question responses were evaluated to determine if respondents met the requirements to be included in the experiment, including the requirement that participants reside in the United States and drive a personal vehicle at least once weekly. Following data collection, responses were evaluated by the Google ReCAPTCHA functionality included within the Qualtrics experiment platform. ReCAPTCHA values of less than 0.5 were flagged as likely bot responses within the Qualtrics platform, and were deleted from the analysis dataset. After the ReCAPTCHA screen, responses were evaluated for final inclusion based on full completion of the experiment, verified interaction with the video portion of the experiment through selection of a "Start Video" button on a separate browser window, and duration of participation that would allow full interaction with the experiment video portion and reasoned responses to the other experiment elements. Only those responses that meet all inclusion criteria were included in the analysis.

3.12. Experiment 1 Design, Approval, and Distribution Method

The first experiment performed in support of this dissertation provided data that was utilized in four of the five research aims of this dissertation. To support conciseness of this dissertation, the description of design, human subject research approval, and distribution of the survey was consolidated into a single section to avoid duplication within the four research aims.

3.12.1. Experiment 1 Design

A copy of the survey can be found in Appendix A. Experiment 1 consisted of the following elements that captured information from experiment participants:

1. Section 1 – Consent and Screening: This section included informed consent capture and experiment eligibility screening questions. The only screening question for this experiment was verification that the participant resided in the United States.
2. Section 2 – Risk Tolerance: This section captured participant responses to the GRiPS questions using a 5-point Likert scale.

3. Section 3 – SDV Familiarity: This section consisted of the SDV familiarity framework described in Section 3.5.
4. Section 4 – SDV Trust: This section consisted of the SDV trust framework described in Section 3.3.
5. Section 5 – Blame Assignment and Impact of Advertising: This section captured data required to support the assessment of the questions in Research Aim 1.
6. Section 6 – Discrete Choice Experiment on Funding Methods: This section captured data required to support the assessment of the questions in Research Aim 4.
7. Section 7 – Safety and Reliability Conjoint Analysis: This section captured data required to support the assessment of the questions in Research Aim 2.
8. Section 8 – Demographics: This section captured the demographics information described in Section 3.2.

3.12.2. Experiment 1 Human Subject Research Approval

Since Experiment 1 involved the use of human subjects as respondents to the online survey, the survey went through IRB approval through the Colorado State University Institutional Review Board IRB. Approval was granted under protocol #5825, and followed ethical human subject testing principles.

3.12.3. Experiment 1 Distribution

Experiment participants were provided by Prolific, which sent registered participants links to an online anonymous experiment developed and deployed using the Qualtrics platform. The experiment took approximately 15-minutes to complete. After data cleaning, the experiment had 403 respondents, and all participants lived in the United States. A statistically representative sample of the United States in terms of demographic factors was targeted using the registered user pool available to Prolific.

Chapter 4. Aim 1 Methods – Perceptions of SDV Legal Culpability

4.1. Introduction

To assess how a sampled experiment population would assign blame when a SDV is involved in a traffic collision, a series of hypothetical scenarios was created where the experiment respondent was provided information about a collision or regulation violation that involved an SDV. Information provided included how a traffic sign recognition (TSR) system failed, the behavior of the SDV during the incident, and the outcome of the TSR failure. Within the experiment, each participant was asked to assign primary blame to one of the parties involved (directly or indirectly) with the incident.

To evaluate the impact of claims made in manufacturer advertising on blame assignment to the manufacturer when their SDVs are involved in collisions and violations of traffic regulations, experiment participants were prompted after each assigning primary blame in each scenario

4.2. SDV Collision and Traffic Violation Scenarios for Primary Blame Assignment

The experiment presented participants with scenarios where an SDV is involved in a traffic collision (2 scenarios) or a moving violation (2 scenarios) and asked a series of questions to determine the impact of vehicle manufacturer advertising of SDV capabilities on their blame assignment for the incidents. In the first three scenarios, participants were able to assign primary blame to one of the following: 1) vehicle driver, 2) vehicle manufacturer, or 3) sign maintainer. In the fourth scenario, blame could only be assigned to either the vehicle driver or the vehicle manufacturer as there was no damage or vandalism to the traffic signs involved in the scenario. These scenarios are shown in Figure 8 - Figure 11.

4.2.1.1. Scenario 1 (Vandalized Sign + Driver's Console)

For this traffic collision scenario, a Traffic Sign Recognition (TSR) failure occurs due to traffic sign vandalism, and the TSR information is displayed on the driver console. The red car is operating as a SDV and crosses into the intersection without stopping due to the TSR not recognizing the Stop sign as a Stop sign. The TSR mistake is displayed on the driver's console, but the driver does not react to the error. The red car crashes into the blue car. The respondent has the option to assign primary blame on either the driver of the red car, the manufacturer of the red car, or the party responsible for maintaining the Stop sign. This scenario is illustrated in Figure 8.

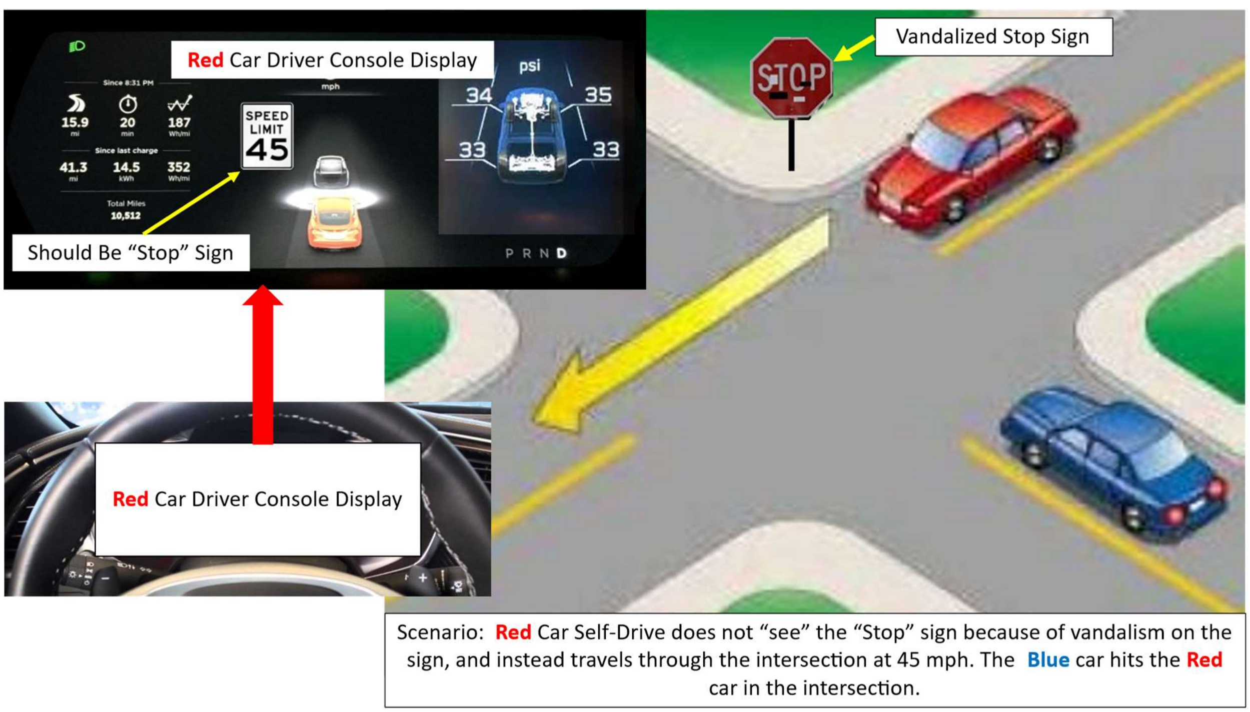


Figure 8. Scenario 1 – Collision Due to TSR Failure, Display on Driver Console

4.2.1.2. Scenario 2 (Vandalized Sign + HUD)

In this second traffic collision scenario, a TSR failure occurs due to traffic sign vandalism, and the TSR information is presented on a driver Heads Up Display (HUD). The red car is operating as an SDV and crosses into the intersection without stopping due to the TSR not recognizing the Stop sign as a Stop sign. The TSR mistake is displayed on the driver's HUD, but the driver does not react to the error. The red car crashes into the blue car. The respondent has the option to assign primary blame on either the driver of the red car, the manufacturer of the red car, or the party responsible for maintaining the Stop sign. This scenario is illustrated in Figure 9.

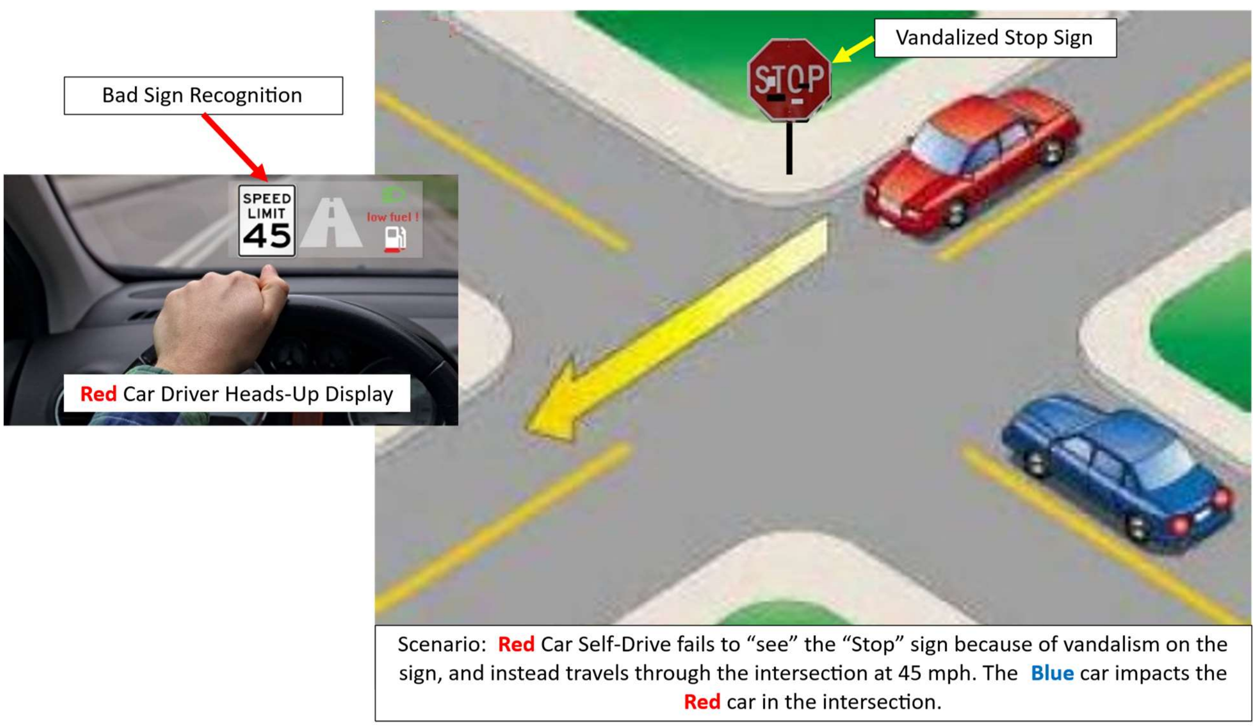
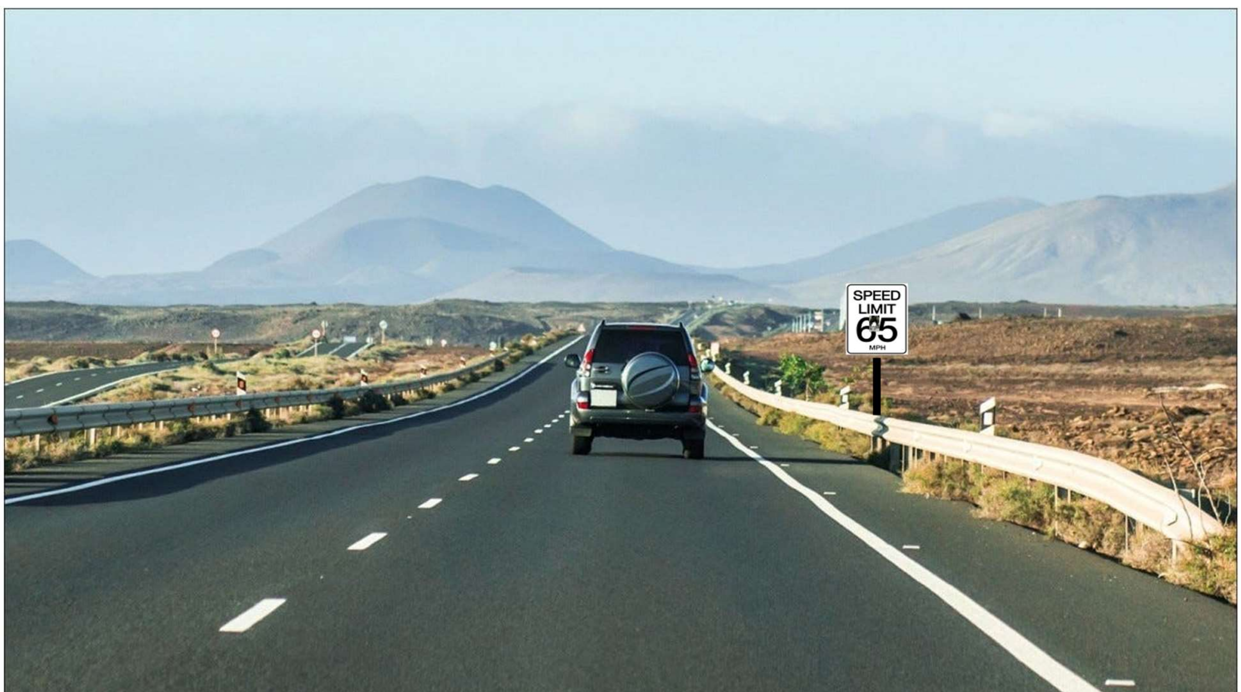


Figure 9. Scenario 2 – Collision Due to TSR Failure, Driver Heads-Up Display (HUD)

4.2.1.3. Scenario 3 (Damaged Sign + Speeding Ticket)

In this moving violation scenario, a TSR failure occurs due to traffic sign damage with the driver not noticing the TSR error. In this scenario, the vehicle is operating as an SDV and passes a damaged Speed Limit 65 sign. Due to the damage on the sign, the TSR interprets the speed limit as 85 mph and the vehicle accelerates to that speed. The driver does not notice this error, and the vehicle is pulled over by a police officer for speeding. The driver is issued a speeding ticket. The respondent has the option to assign primary blame on either the driver of the vehicle, the manufacturer of the vehicle, or the party responsible for maintaining the speed limit sign. This scenario is illustrated in Figure 10.



Event: Vehicle is driving along a highway with little traffic in Self -Driving mode. The vehicle passes a damaged 65 mph sign that the computer interprets to be an 85 mph speed limit sign. The vehicle speeds up to 85 mph. A cop pulls over the vehicle and issues a speeding ticket to the driver.

Figure 10. Scenario 3 – Traffic Law Violation (Speeding) Due to Traffic Sign Damage

4.2.1.4. Scenario 4 (Wrong Sign + Speeding Ticket)

In this moving violation scenario, a TSR failure occurs where the TSR selects the wrong speed limit sign. The vehicle is operating as an SDV and passes a pair of speed limit signs where the governing sign is dependent on if workers are present or not. The TSR cues off the Speed Limit 75 sign despite there being workers present and the vehicle accelerates to that speed. The driver does not notice this error, and the vehicle is pulled over by a police officer for speeding. The driver is issued a speeding ticket. The respondent has the option to assign primary blame on either the driver of the vehicle or the manufacturer of the vehicle. This scenario is illustrated in Figure 11.

Event: Vehicle is traveling along a highway in Self -Driving mode and drives by two speed limit signs: One for a 75 mph speed limit and one for a 45 mph speed limit when workers are working. The vehicle only recognizes the 75 mph speed limit sign and maintains that speed. Workers are working in the work zone, and vehicle is pulled over by cop for speeding and the driver is given a speeding ticket.

Figure 11. Scenario 4 – Traffic Law Violation (Speeding), Selecting Wrong Speed Limit Sign

4.3. Assessment of Impact of Manufacturer Advertising on Manufacturer Blame Assignment

Current literature suggests that a driver's willingness to pay for an SDV is influenced by the amount of supervision the driver must provide while the vehicle is in motion. As a result, there is an incentive for an SDV manufacturer to downplay the amount of supervision a driver must provide during driving to improve sales and sale prices. Given this observation, the experiment presented a follow-on question for each scenario where the participant was informed that the SDV manufacturer had advertised that the vehicle did not require supervision while driving, and asked to state if this would increase, decrease, or not impact manufacturer liability for the incident. The format of the question followed the template shown below:

If the vehicle manufacturer for the vehicle in this event had shown commercials that the self-drive feature allows the driver to multi-task and not focus on road conditions or on how the self-driving car was driving, how would this information change your opinion on how much the vehicle manufacturer was to blame for [the event]?

The available prompt responses and assigned point values for each response is shown in Table 14. A total impact for advertising score was calculated for each respondent, with possible scores ranging from -4 (manufacturer had no additional fault) to 4 (manufacturer at more fault for all scenarios). The intent of this question series was to qualitatively determine if overpromising the capability of a vehicle's self-driving capability increases the legal risk for a vehicle manufacturer.

Table 14. Legal Culpability Point Assessments

Possible Answers	**Point Value**
Vehicle manufacturer would have more blame for [event].	1
Vehicle manufacturer would have the same amount of blame for [event].	0
Vehicle manufacturer would have less blame for [event].	-1

4.4. Statistical Analysis Methods

The following statistical methods were used in the analysis of the data collected from Experiment 1 regarding primary blame assignment and influence of advertising on blame assignment for SDV manufacturing. The results generated using these methods supported answering the research questions associated with Research Aim 1.

4.4.1. Ordered Logistic Analysis

Ordinal logistic regression is a statical method used to model the relationship between one or more independent variables and an ordinal dependent variable, which has multiple categories with a natural ordering (low/medium/high, more/equal/less, etc.) (Liang et al, 2020; Ananth & Kleinbaum, 2020). This regression method assumes either parallel regression or proportional odds when generating the regression model, which allows a direct extension of the binary logistic model to scenarios with an ordinal outcome variable (Liang et al, 2020; Ananth & Kleinbaum, 2020). Proportional odds models are the most common type of ordinal logistic regression models (O'Connell, 2006), and ordinal logistic models are often appropriate scenarios where the outcome variable is categorical with ordered categories (O'Connell, 2006). These models are robust as they only incorporate the order information of response variables and are therefore invariant to any monotonic transformation of outcomes (Liu et al, 2017).

In Experiment 1, ordered logistic analysis was used to evaluate potential predictors for how SDV manufacturer advertising would influence assignment of blame against the manufacturer for traffic collisions and moving violations that involve SDVs. For each of the legal culpability scenarios, respondents for Experiment 1 were asked if advertising suggesting the driver would not need to supervise the SDV would change their assignment of blame to the manufacturer for collisions or moving violations, with the option of saying more blame would be assigned, the same amount of blame would be assigned, or less blame would be assigned. This generated an ordinal dependent variable and made ordered logistic analysis appropriate.

4.4.2. Multinomial Logistic Regression Analysis

Multinomial logistic regression analysis is a method that provides interpretable results, such as odds ratios (Hashimoto et al, 2020), for models were the dependent variable consists of several categories (Liang et al, 2020). Multinomial logistic regression models using multinomial logistic regression provide an extension of the binomial model with a logit link function, appropriate for analysis situations where the response variable have at least three possible allowable outcomes (Hashimoto et al, 2020). This type of logistic regression and model can be used to describe the relationship between an independent variable(s) (either continuous or not) and a dichotomous or multi-categorical dependent variable as a supplementary variable to the standard linear regression (Liang et al, 2020).

This analysis method was used in Experiment 1 to evaluate predictors for assignment of primary blame for SDV-involved traffic collisions or moving violations where three separate groups or individuals are identified as options for primary blame assignment. Specifically, this method was used to find significant predictors of blame assignment in Scenarios 1-3 of the legal culpability analysis as part of Experiment 1.

Chapter 5. Aim 2 Methods –Reliability and Safety Expectations

5.1. Introduction

To assess American reliability and safety expectations for self-driving vehicles, participants in Experiment 1 were presented with a Conjoint experiment evaluating four common elements of SDV safety and reliability, including frequency of Takeover Requests (TORs) and methods of alerting the driver to issues with the self-driving systems. Using data collected from the Conjoint experiment, feature utility levels were determined using integrated Qualtrics analysis tools. An additional LASSO analysis was utilized to identify any examined features that were non-impactful to participant decisions, and to determine which features had the greatest impact on participant choices.

5.2. Safety and Reliability Conjoint Experiment

Conjoint analysis is a market research technique used to identify consumer preferences and the product trade-offs they are willing to make. In this approach, respondents evaluate packages composed of different feature values and indicate which package they prefer (Getting Stared with Conjoint Projects, 2025). The resulting data can be used to predict the optimal product or service configuration based on the perceived importance of each feature within the package. Conjoint analysis has been applied in previous research examining preferred features in vehicles, including hybrid-electric vehicles (HEVs) (Silaen & Windasari, 2022), hydrogen fuel cell vehicles (Li et al., 2024), and autonomous vehicles (Kang et al, 2025).

In the first survey experiment, the conjoint analysis assessment was developed and administered using the Qualtrics survey platform's conjoint analysis tool, which also calculated relative utility values for each feature.

5.2.1.1. Conjoint Analysis Features and Feature Levels

There were four features relating to SDV safety evaluated within the Conjoint analysis. Participants were provided a detailed description of each feature upon beginning the conjoint analysis section of the survey. Each feature is defined as follows, and the levels of each feature are provided in Table 15:

1. Human Interventions (4 options) – Total number of times within a five-year period that a driver must take over for the self-driving functionality; representing reliability.
2. Failure Allowance (4 options) – Portion of sensors, as a percentage of the total sensors needed for the self-driving system, that are allowed to fail before the system is no longer capable of self-driving; representing resilience.
3. Failure Behavior (3 options) – Action the vehicle takes when the self-driving system has encountered an error that requires a transfer of control from the self-driving system back to the human driver.
4. Alert Method (4 options) – Method in which the vehicle alerts the driver to alerts or warnings from the self-driving system, to include visual and/or audio warnings.

Table 15. Features and levels for conjoint analysis

Feature Name	Feature Levels
Human Interventions	1x per 5 years 100x per 5 years 500x per 5 years 1000x per 5 years
Failure Allowance	5% 10% 15% 20%
Failure Behavior	Vehicle Stops Safely Vibration Alert & TOR Visual Alert & TOR
Alert Method	No Alert Visual Audio Audio & Visual

For "Human Interventions", respondents were presented with the feature "How Often Driver Must Take Over", with choice options as shown in Table 15. This construct parallels the term "disengagement event" commonly used in autonomous vehicle reliability literature (Min et al, 2022; Bas Kaman & Olmus, 2024; Khattak et al, 2021). The purpose of this feature was to assess respondents' preferences regarding system reliability. Participants were presented with the following description for "How Often Driver Must Take Over":

How Often the Driver Must Take Over: This represents the number of times the driver will need to take over driving the vehicle from the computer during the time the driver owns the vehicle.

For "Failure Allowance", respondents viewed the feature "Sensor Repair Timings", with each choice set including one of the failure allowance levels shown in Table 15. This feature was designed to evaluate preferences related to sensor resilience. Participants were presented with the following description for "Sensor Repair Timings":

Sensor Repair Timings: Self driving relies on cameras and other items on the vehicle to "see" the world and allow for safe travel. Sometimes these cameras break and need to be repaired. This feature asks you how many cameras should be allowed to break, as a percentage of the total, before repairing the broken cameras is needed.

For "Failure Behavior", respondents were shown the feature "What the Vehicle Does When Self-Driving Fails", with each choice set displaying a level from Table 15. This feature was designed to capture respondents' preferences regarding SDV failure behavior. Participants were presented with the following description for "What the Vehicle Does When Self-Driving Fails":

What the Vehicle Does When Self-Driving Fails: This feature talks about what the vehicle will do if self-driving stops working. The vehicle can safely come to a complete stop, or the vehicle can alert you with a warning you can see and have you take over driving, or alert you with a touch warning (vibration) and have you take over driving.

Finally, for "Alert Method", respondents were presented with the feature "Method of Alerting Driver to Alerts", with options corresponding to levels provided in Table 15. This feature was designed to assess respondents' preferences for how the self-driving system communicates alerts during a failure event. Participants were presented with the following description for "Method of Alerting Driver to Alerts":

Method of Alerting Driver to Alerts: This feature talks about how the vehicle will let the driver know about messages or alerts from the self-driving computer. Options for how the vehicle can let the driver know about messages or alerts include a visual alert, a sound alert, both a visual alert and a sound alert, or no alert at all.

5.2.1.2. Rationale for Experiment Feature Selections

These four safety-related features (i.e., reliability, resilience, failure behavior, and alert method) were intentionally selected to focus on technical system attributes that directly influence the operational safety and user trust of SDVs. Prior literature has consistently identified these dimensions as central to public perceptions of SDV safety and reliability (Kim et al, 2022; Wang et al, 2020; Lee et al, 2022; Lee et al, 2020; Kohanpour et al, 2025; Tan & Zhang, 2025; Deng et al, 2024; Mature-Peaspan et al, 2020; Lee & An, 2023). In contrast, attributes such as cost, convenience, or aesthetic design were excluded to minimize potential confounding effects between safety perceptions and market-oriented trade-offs. Including economic or convenience factors would have likely shifted respondent attention away from the core research objective of identifying how measurable system-level safety features influence consumer preferences.

5.2.1.3. Conjoint Analysis Feature Sets

The conjoint analysis contained feature sets (or packages) comprised of one option from each feature. Participants completed a series of choice tasks in which two packages were presented side-by-side, and they indicated their preferred option for an SDV.

The combination of features and levels yielded 192 unique feature sets possible. Each participant completed six choice tasks, each involving a pairwise comparison of two feature sets. A priori sample size calculations indicated that a minimum of 340 respondents was required; the final dataset included 403 valid responses, exceeding this threshold. To further validate the required sample size, the approach outlined by de Bekker-Grob et al. (2015) for binary discrete choice experiments was utilized. The sample size N was then estimated using Equation 1.

$$N = \frac{\left(z_\alpha + z_\beta\right)^2 \times \sigma^2}{\delta^2} \tag{1}$$

Where $z_\alpha = 1.96$ for a two-tailed significance level of 0.05, $z_\beta = 0.84$ for 80% statistical power, and $\sigma^2 = 1.0$ as the standard multinomial logit utility variance in discrete choice experiments. The term δ represents the desired effect size, and N is the required sample size.

Statistical power was then computed by Equation 2 as:

$$Power = 1 - \Phi\left[\left(1.96 \times \sqrt{\frac{1}{N}}\right) - \delta\right] \tag{2}$$

Where Φ is the cumulative distribution function of the standard normal distribution. Effect sizes (δ) between 0.2 and 0.5 were evaluated, incorporating a 0.7 adjustment factor (i.e., N = 282) to account for unobserved heterogeneity (de Bekker-Grob et al, 2015). The resulting sensitivity analysis is summarized in Table 16.

Table 16. Sensitivity Analysis Results to Determine Sample Size

Effect Size δ	**Odds Ratio**	**Required N (80% Power)**	**Power for N = 403**	**Power at Effective N = 282**
0.2	1.22	196	97%	95%
0.3	1.35	87	99+%	99+%
0.5	1.65	31	99+%	99+%

These results confirm that our sample size of N = 403 provides approximately 97–99% power at $\alpha = 0.05$ to detect an effect size of $\delta = 0.2$ (odds ratio = 1.22), exceeding the 80% minimum requirement (de Bekker-Grob et al, 2015). After adjusting for unobserved heterogeneity (effective N = 282, 95% power), the power remains above 95%, indicating that the sample size was sufficient to detect meaningful differences in feature preferences.

5.2.1.4. Feature Level Utility Values

Qualtrics uses a multinomial logit model to estimate the individual utilities of choice attribute levels using the choice variable (i.e., which package of options was chosen) as the dependent variable. Using a Bayes Hierarchical variation for the logit model, Qualtrics analyzes the survey response data to calculate a part-worth utility value for each feature level (Qualtrics, 2025). These utility values are standardized, such that the mean value between all feature levels is centered at 0, allowing for relative evaluation of feature levels against one another. For the utility values, the higher the score, the more weight it carries in the decision-making process.

5.3. LASSO Regression Analysis

The Least Absolute Shrinkage and Selection Operator (LASSO) is a statistical method originally developed as an alternative to subset selection and ridge analysis and used for shrinkage and selection in regression problems (Tibshirani, 1996). LASSO has become a popular statistical technique for simultaneous estimation and variable selection (Zou, 2006), though it may suffer from inconsistency under some conditions due to the LASSO regularization parameter not being optimally chosen (Desboulets, 2018). For scenarios where a small number of large effects are present in the data, or a small to moderate number of medium-sized effects exist, LASSO has been shown to be superior to ridge regression and subset selection techniques (Tibshirani, 1996).

Previous studies have used LASSO methods and LASSO-type coefficient penalties in conjoint analysis to identify choice features that have the most significant impact on package selection. For example, LASSO has been used to identify important factors for electric vehicle adoption in the United States (Archsmith et al, 2022) and in the United Kingdom (Filip, 2021). In Experiment 1, LASSO regression analysis was performed on the survey data to determine the relative importance of each SDV safety feature examined in the study. This analysis was conducted using Rstudio (R version 4.5.1)

Chapter 6. Aim 3 Methods – Willingness to Pay for SDVs

6.1. Introduction

Willingness to pay information was collected from the participants of Experiment 1 through the use of a free-form answer question within the user interface of the online experiment. Separate questions were used to collect WTP data for full-self driving functionality, and for advanced driver-assist technology.

6.2. Assessment of Willingness to Pay

Willingness to Pay (WTP) for SDVs was measured in US dollars (USD) for two different levels of automation: full self-driving, corresponding to SAE Level 5 automation, and driver assist, aligned with SAE Level 3 automation. WTP data were collected using an open-text field that allowed respondents to enter any numeric or text response.

Respondents to the survey were presented with questions to capture what premium, if any, they would be willing to pay for self-driving capability or driver assist technology on their next vehicle, above the price of the vehicle without the technology. Respondents entered the premium they were willing to pay for each level of self-driving capability into an open-ended text box following a question prompt within the survey. This yielded a monetary value for how much they would be willing to pay for each level. A response to this question was mandatory.

For self-driving vehicle premium, respondents were prompted with the following question:

How much more would you be willing to pay (in dollars), for a vehicle capable of self-driving safely without you having to keep track of the vehicle's movement, versus a normal vehicle?

For driver assist premium, respondents were prompted with the following question:

How much more would you be willing to pay (in dollars), for a vehicle capable of self-driving technology but requires you to keep track of the vehicle's movement in order to ensure the safety of the vehicle and passengers, versus a normal vehicle?

The wording of these questions intentionally omitted descriptions of how the vehicles would achieve self-driving to avoid requiring the respondents to provide a value evaluation for specific technologies. Instead, the intent of the questions was to evaluate the perceived value of a functional capability versus a specific technology implementation.

Willingness to pay thus resulted in three dependent variables evaluated in support of Research Aim 3: 1) willingness to pay for full self-drive ($ amount); 2) willingness to pay for driver assist ($ amount); and 3) willing to pay for full self-drive (yes/no). Including both monetary WTP and binary WTP provided a more complete picture of consumer acceptance. The binary measure captures overall willingness to adopt SDV technology, while the monetary measure reflects the magnitude of that willingness, allowing us to distinguish between broad acceptance and the practical limits of what consumers are prepared to pay. Post-survey data clean-up included updating values such as "none" and "not one cent" into number values of $0.

Chapter 7. Aim 4 Methods – Tax and Fee Preferences for Oversight and Infrastructure Funding

7.1. Introduction

The widespread adoption of SDVs has the potential of creating new oversight and infrastructure maintenance and improvement costs that will require new or additional taxes and fees to fund. Oversight authorities and entities tasked with maintaining infrastructure systems need guidance on which taxes and fees that are candidates to fund these expenditures are least opposed. To address this question, a Discrete Choice Experiment (DCE) was formulated to evaluate four candidate funding methods.

7.2. Discrete Choice Experiment Design

A discrete choice experiment was used for identifying preferences and utility of revenue options. This experimental approach is based on the attribute theory of value and consumer choice put forward by Lancaster (1966) who posited that consumers derive satisfaction from the attributes of a purchased good. Additionally, this approach has a basis in econometrics through the random utility theory proposed by McFadden (1973). Choice experiments have been used in similar studies, such as Visaria, Jensen, Thorhauge, and Mabit (2022) that assessed preferred methods for paying for EV charging infrastructure, and Mihilova et al (2022) that assessed preferred implementations for positive energy districts in Switzerland.

7.2.1. Attribute Selection and Funding Sources

A total of five different funding methods were utilized in various combinations in the funding profiles used in the DCE. A definition for each of these were provided to participants before beginning the DCE, as well as included as a footnote for each question. The definitions presented to the participants are as follows:

- **Fuel Tax:** Added tax on the cost of a gallon of fuel (gasoline, diesel, hydrogen, etc.) that would be in addition to existing federal and state fuel levies.
- **Mileage Tax:** Tax based on the number of miles a vehicle is driven in a given year, collected at the time of vehicle registration renewal.
- **Self-Driving Subscription Fee:** Monthly fee for a service that enables self-driving. If the service is not paid for by the driver, the driver will not be able to use the self-driving feature.
- **Vehicle Purchase Tax:** One-time tax paid on a new vehicle at the time of purchase.
- **Increase in Vehicle Price:** Vehicle manufacturers increase the upfront cost of vehicles to pay for the costs of putting into place self-driving.

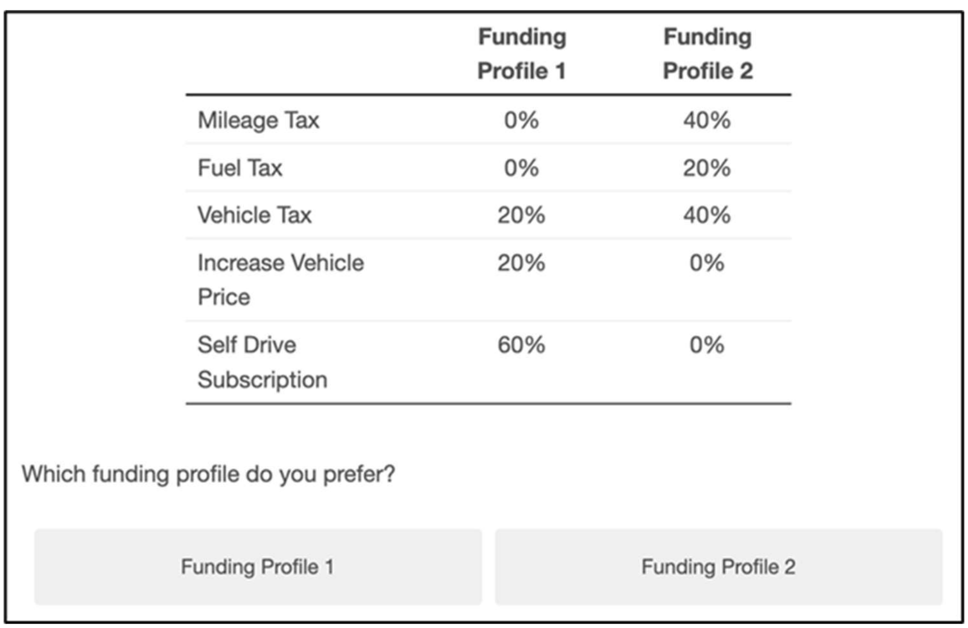
7.2.2. Funding Profile Generation

Attribute levels in the DCE were set to present funding profile options where each funding method could contribute a percentage of the required revenue toward the total cost of SDV implementation. This allocation was used since the total annual cost of SDV oversight is neither a known quantity nor a value that would remain constant from year to year. Funding levels were then generated using the five identified funding sources by assigning percentages of funding generated from each source expressed as decimals, with values limited to (0.0, 0.2, 0.4, 0.6, 0.8, 1.0), with the sum of the contributions from each funding source in the funding profile equaling a total of 1.0. Based on five funding methods and six values for each method, a total of 7,776 unique funding profiles (6 x 6 x 6 x 6 x 6) are possible, of which only 126 unique combinations are equal to 1.0. An example of six possible funding profiles is shown in Table 17.

Table 17. Example DCE Funding Profiles

Funding Profile Example	Fuel Tax	Mileage Tax	Self-Driving Subscription	Vehicle Purchase Tax	Increase in Vehicle Price
1	1.0	0.0	0.0	0.0	0.0
2	0.2	0.2	0.2	0.2	0.2
3	0.8	0.0	0.2	0.0	0.0
4	0.0	0.6	0.2	0.2	0.0
5	0.0	0.2	0.2	0.2	0.4

The design of the DCE presented each survey respondent with competing pairs of funding profiles that contained funding methods that are currently in use by government entities, with the respondent being required to select the preferred (or most tolerated) option for each pair of funding profiles. An example question from the survey is provided in Figure 12.



	Funding Profile 1	Funding Profile 2
Mileage Tax	0%	40%
Fuel Tax	0%	20%
Vehicle Tax	20%	40%
Increase Vehicle Price	20%	0%
Self Drive Subscription	60%	0%

Which funding profile do you prefer?

Funding Profile 1

Funding Profile 2

Figure 12. Example DCE Question from Survey

7.2.3. Evaluation of D-Efficiency for DCE

Due to the need to ensure 100% coverage of costs without overages or shortages, only 126 funding combinations out of the potential 7,776 funding profile permutations meet this constraint. Unfortunately, using only 126 unique combinations results in a R-code evaluated D-efficiency score of 0.116, which is typically considered non-ideal for a discrete choice experiment. This low D-efficiency value would cause the experiment to be considered suspect for experiments where previous studies are available for review and comparison.

For situations where previous studies are not available, such as this experiment, Walker et al. (2018) found that low D-efficiency ratings can be acceptable. Other research has shown that pure random experiments are capable of having higher efficiency of parameter estimation (when measured based on D-efficiency and A-efficiency values) as compared to experiments designed with D-efficient methods (Burris & Patil, 2009). Based on this previous research, a random selection of 62 unique funding profiles from these possible 126 was selected for inclusion in this survey. D-efficiency evaluations using R found this 62-funding profile set had a D-efficiency value of 0.083.

7.2.4. Experiment Blocking

Participants were not exposed to all 62 profiles. Instead, each participant was presented with a total of six questions, with each question comparing two funding profiles, for a total of 12 profiles shown to each respondent. There were six different blocks (i.e., sets of questions) created, such that participants exposed to a specific block would get the same set of questions as the other participants exposed to that block. The survey was designed to present each respondent with only a single block of questions and capture their responses. Respondents were randomly assigned question blocks, and the survey was designed to level-load each question block with a similar number of randomly assigned survey respondents.

Chapter 8. Aim 5 Methods – Effectiveness of Human Oversight on Autonomous Systems

8.1. Introduction

Human oversight is seen as one of the key elements of the safety architecture of SDVs, so much so that requirements for such oversight are often the cornerstone of the legal strategy used by SDV manufacturers when defending themselves in court against product liability claims. One of the key assumptions with this safety architecture is that human operators will be able to detect and react to autonomous system failures before those failures results in damages, injuries, or fatalities. To test the validity of this assumption, a video experiment was developed to measure how well experiment participants would be able to detect induced errors within a TSR system, and if the environmental factors of system capability descriptions or rate of system failures would influence the accuracy of that oversight. Video Based Human Oversight Experiment Design

An experiment was conducted to understand the impact of SDV system capability framing and frequency of TSR system errors on both respondents' trust in the system and their performance in identifying errors in the TSR system. The experimental design consisted of a 2 (framing: positive, negative) x 2 (error rate: random, concentrated) factorial design. The study adhered to ethical principles for human subject testing and had approval from the university's Institutional Review Board (IRB).

8.1.1. Participants

Participants were randomly assigned by the software program to a framing condition (between-subject) and error rate condition (between-subject) upon beginning the study. Periodic data cleaning was conducted during data collection to ensure that a minimum of 12 complete responses were obtained per group combination. Once this minimum number was reached, data collection was closed. As a result of the software randomization occurring independent of data cleaning, the number of participants per group was not equal, see Table 18.

Table 18. Number of Participants per Experimental Condition

Framing	**Error Rate**	
	Random	Concentrated
Positive	12	20
Negative	15	15

8.1.2. TSR Videos

Each participant viewed four driving videos, totaling 15.7 minutes of footage. This video duration, while lengthy, is in line with previous experiments involving evaluation of human trust and interventions in SDVs, including one that utilized 20 video clips with a clip duration of up to 50 seconds per clip (Merriman et al., 2023).

Participants were told that they were watching actual video data from a real TSR system and were instructed to identify when they believed the TSR system made a detection and/or identification error. Within the videos, traffic sign detections were simulated by placing a yellow box around traffic signs, and sign identifications were simulated by overlaying images of traffic signs onto the video, as shown in Figure 13.

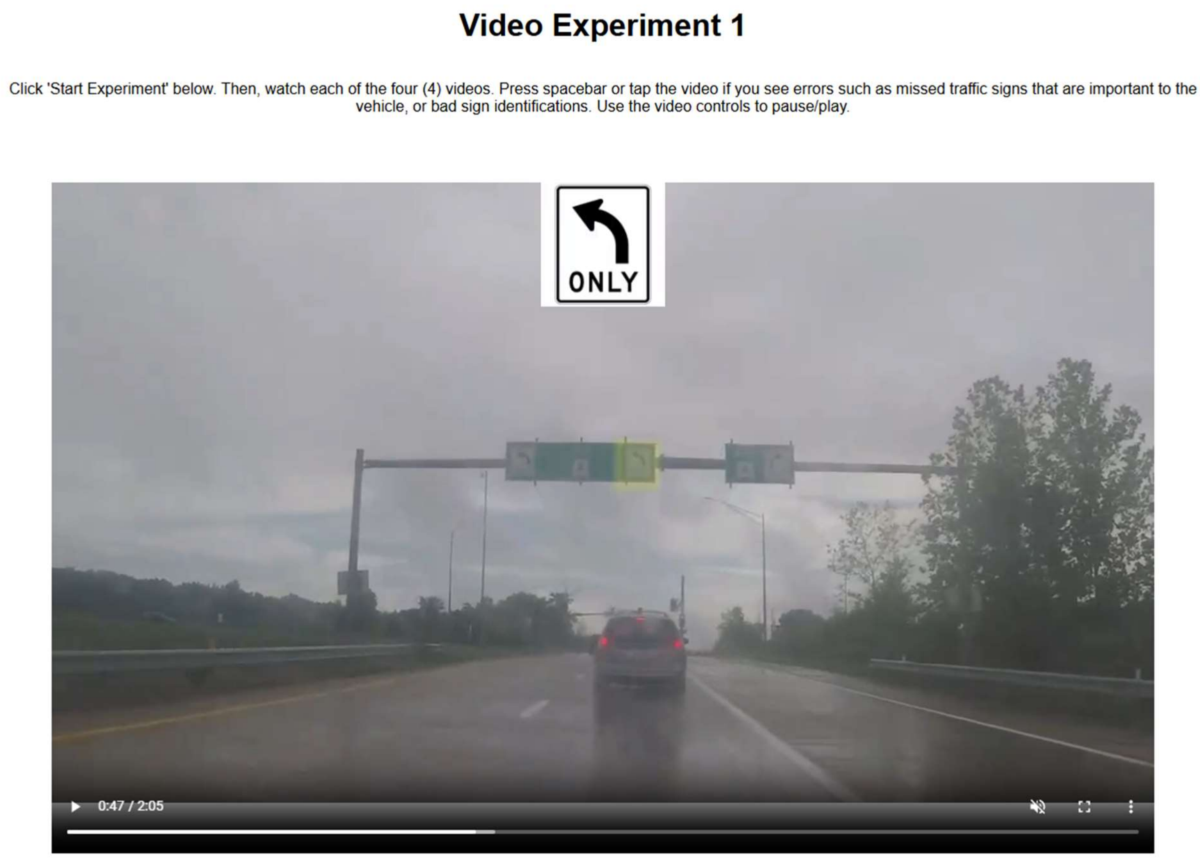


Figure 13. Video User Interface for TSR Supervision Experiment

The TSR videos were synthetically created using driving footage collected by the research team. Video was captured using a Hero 4 GoPro™ camera mounted on the dashboard of a Subaru Outback as the vehicle was traveling on local roads and highways in Missouri, US. Raw video was edited using the open-source ShotCut™ software to create individual scenario videos with simulated TSR detections and identifications. The videos were presented to the respondents via a Cloudflare-hosted website.

Regardless of experimental condition, all participants watched the same set of four driving scenarios to avoid introducing additional variability. The only difference being that the overlaid TSR errors occurred at different times in the videos depending on the error rate group.

The scenarios varied in weather induced visibility and road type, but all featured low to moderate traffic conditions.

Scenario 1 (125 seconds) involved travel along a state-maintained highway within a small city, followed by an exit onto an off-ramp. Weather conditions were overcast with rain, reducing visibility on the video. The TSR system primarily attempted to detect and identify typical traffic control signs (e.g., speed limit, direction of travel) along the route.

Scenario 2 (304 seconds) involved travel along a city street that transitioned into a state-maintained highway. Weather included both overcast skies and rain. The TSR primarily attempted to detect and identify speed limit and caution signs along the path of travel.

Scenario 3 (206 seconds) involved travel along a state-maintained multi-lane road that transitioned to an interstate with significant construction. Weather conditions were overcast with no precipitation. The TSR primarily attempted to detect and identify speed limit and construction signage within a reduced-lane construction zone.

Scenario 4 (305 seconds) involved travel along a rural road with no shoulders and numerous hills and curves. Weather conditions were overcast with rain. The TSR primarily attempted to detect and identify speed limit and caution signs along the route, which included frequent detections and identifications.

8.1.3. Framing

For this experiment, framing referred to how the reliability and accuracy of the TSR system were described to participants. Participants received either positive (N = 32) or negative (N = 30) framing, which was provided in written form immediately before participants watched the driving videos. These descriptions were as follows:

- *Positive:* This traffic sign finding AI **has been in development for over a year**, and **recent tests have shown that the system is very reliable and accurately identifies important regulatory and warning signs**, ensuring the safety of the vehicle and its passengers. This AI was put through its final approval tests recently, and a significant amount of test data was collected. A random selection of this data will be shown to you in a video format. Please review the four (4) videos for any detection or identification errors.
- *Negative:* This traffic sign finding AI is **still in early development**, and the **developers believe there may still be some bugs in the software**. This AI was tested recently using a human-driven vehicle with a camera mounted to the front of the car. The AI processed the video from the camera and attempted to detect road signs, identify the type of road sign, and highlight signs that were relevant to the human-driven car. A random selection of this data will be shown to you in a video format. Please review the four (4) videos for any detection or identification errors as this will help the developers further improve the AI.

8.1.4. Error Rate

To simulate TSR errors, two failure modes were implemented: (1) missed detection, in which a traffic sign relevant to the vehicle was not detected (i.e., no yellow box was displayed), and (2) incorrect identification, in which a relevant sign was detected but misidentified by the system (i.e., yellow box displayed with an incorrect sign overlay). An example of each failure mode is shown in Figure 14.

Figure 14. Sample TSR Errors Incorrect Identification (Left) and Missed Detection (Right)

A total of seven simulated TSR errors occurred across the experiment. Depending on error rate group assignment, participants experienced these errors at different times throughout the videos. Participants in the concentrated error rate group (N = 35) experienced five of the seven errors in close temporal proximity, occurring later in the videos. Participants in the random error rate group (N = 27) experienced the errors more evenly distributed across the videos, with a relatively greater number occurring earlier to present a more random pattern. A comparison of error timing across conditions is shown in Figure 15.

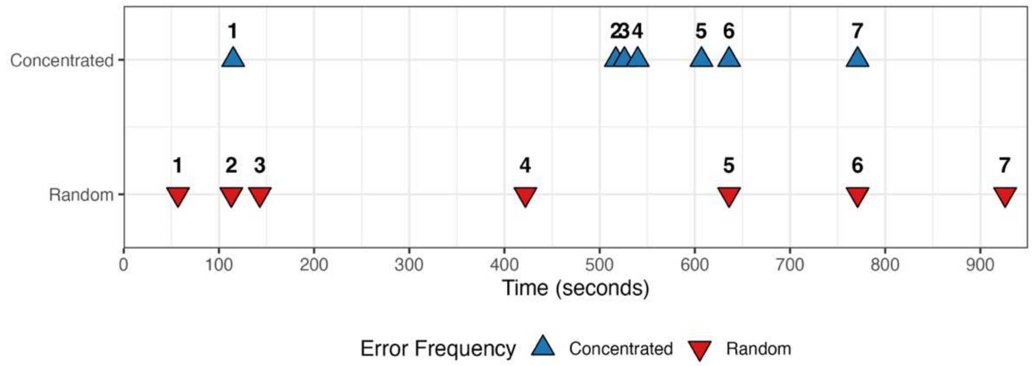


Figure 15. Timeline of Error Events Across Conditions

Chapter 9. Aim 1 Results - Perceptions of SDV Legal Culpability

9.1. Introduction

The potential for legal culpability regarding SDV-involved traffic collisions and traffic regulation violations poses a significant risk for SDV manufacturers. Case law regarding the extent of SDV manufacturer liability in these negative events is still developing as civil cases are litigated within the courts. Until this case law is better established, there is a need to experimentally assess the population of potential jurors and identify their stated beliefs regarding responsibility for traffic collisions and moving violations that involve SDVs. The data from this experimental effort can help answer the following research questions:

- **RQ1.1:** Who would the average American assign blame to if an SDV was involved in a traffic collision or traffic law violation?
- **RQ1.2:** Are risk tolerance, SDV familiarity, SDV comfort, or demographic factors significant predictors of views of legal culpability for SDV-involved traffic incidents?

The results of this chapter were presented at the 2026 INCOSE International Symposium in Ottawa, Canada, and subsequently published in the conference proceedings titled "What would I see in court? A survey analysis of who Americans would blame for self-driving vehicle crashes and traffic violations" (Stewart & Gallegos, 2025a).

9.2. Primary Blame Assignment for SDV Collisions and Moving Violations

The distribution of primary blame assignments for each scenario for the survey respondent population is shown in Figure 16. When examining the consistency in blame assignment among the respondent population, the driver was blamed in all scenarios by 156 respondents, the vehicle manufacturer by 28 respondents, and the sign maintainer (for Scenarios 1-3) by 9 respondents. On the opposite end of the spectrum, the driver escaped primary blame in all four scenarios with 43 respondents, the vehicle manufacturer with 199 respondents, and the sign maintainer with 303 respondents. Additional distribution information is shown in Table 19.

The primary blame assignments shown in Figure 16 shows a consist majority regarding assignment of blame against the driver of the SDV in all four scenarios. Additionally, the primary blame for the vehicle driver for the scenario involving vandalism of the stop sign increased when the error was presented to the driver via a HUD (Scenario 2) versus on the driver console (Scenario 1), suggesting SDV manufacturers can potentially lower their legal risk by displaying TSR results prominently to the driver.

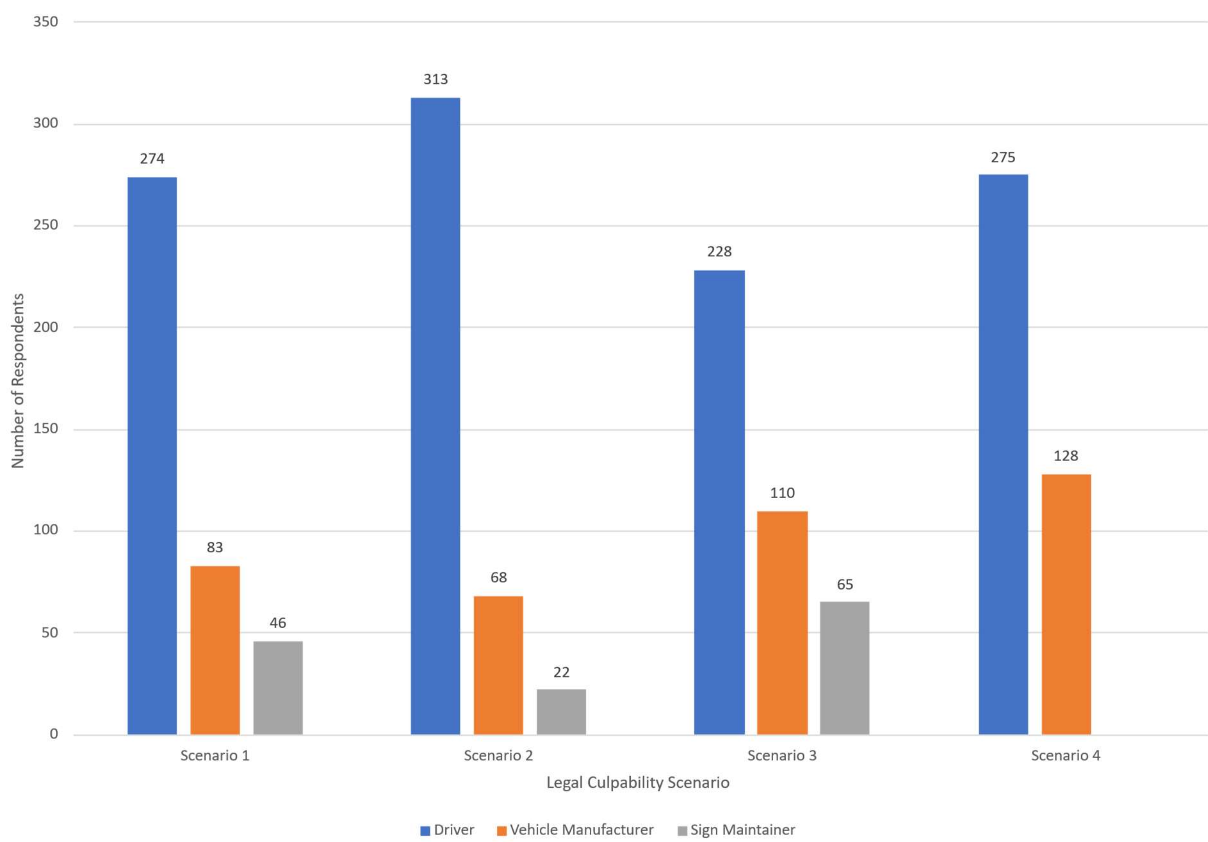


Figure 16. Primary Blame Distribution by Legal Culpability Scenario

Table 19. Frequency of Assignment of Primary Blame for Legal Culpability Scenarios

Agent	Frequency of Blame		
	Always	Sometimes	Never
Driver	156	204	43
Vehicle Manufacturer	28	176	199
Sign Maintainer	9	91	303

9.3. Impact of Advertising on Manufacturer Blame Assignment

The distribution of impact of advertising scores for the survey respondent population is shown in Figure 17. The mean of the impact of advertising scores was 1.66, with a median score of 2.0. Given the range of impact of advertising scores possible is -4 to 4, this suggests that the general population is generally more likely to apply additional blame to the vehicle manufacturers who advertise that supervision of their SDV vehicles is not required (impact of advertising score ≥ 0) versus less likely (SDV familiarity score < 0).

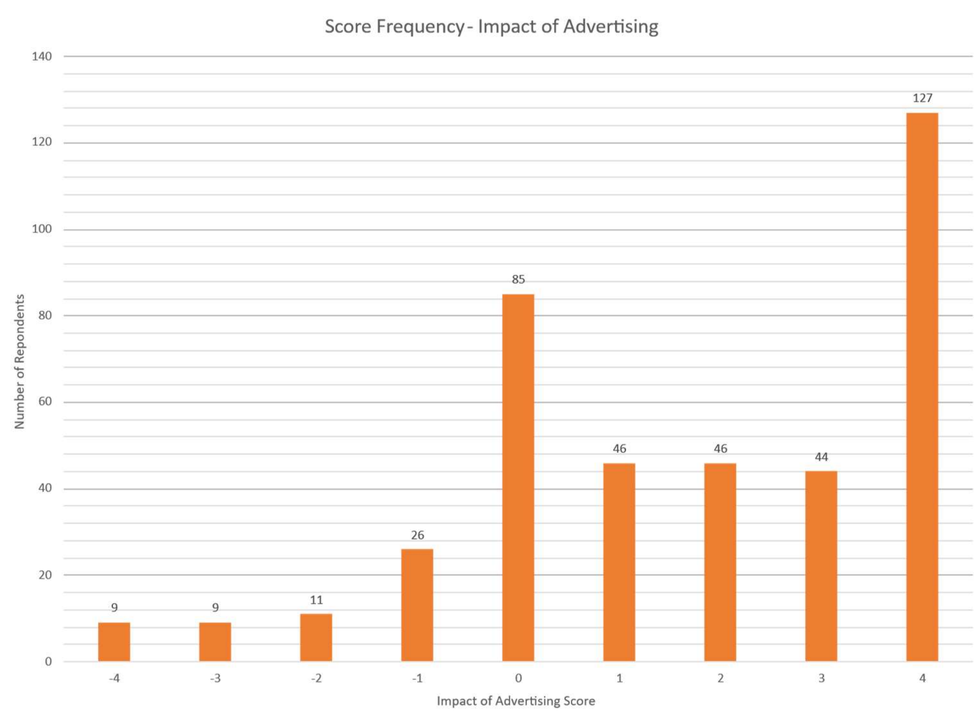


Figure 17. Advertising Impact Score Frequency for Survey Respondent Population

The distribution of advertising impact for each of the scenarios is shown in Figure 18. With the exception of Scenario 3 (Damaged Sign + Speeding Ticket), at least half of survey respondents would assign additional blame for the SDV-involved traffic accident or moving violation to the SDV vehicle manufacturer based on the claims made in the marketing / advertising campaign for the SDV. Additionally, 127 respondents (31.2%) of respondents assigned additional blame to the vehicle manufacturer in all scenarios based on the content of the advertising / marketing campaign.

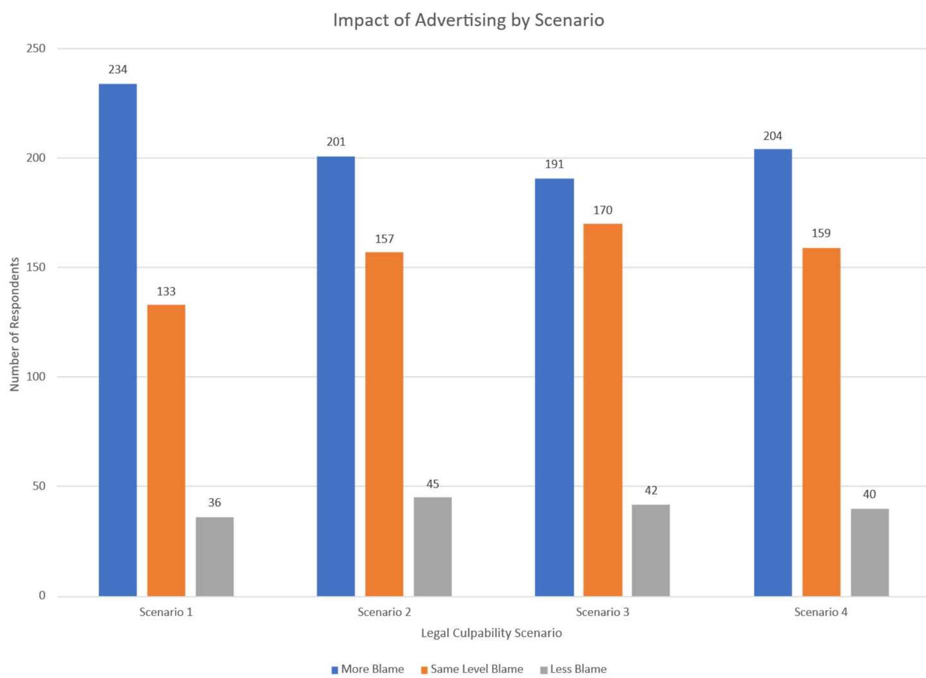


Figure 18. Advertising Impact Selection Frequency for Survey Respondent Population

9.4. Predictors of Primary Blame Assignment and Impact of Manufacturer Advertising

Multinomial logistic regression and ordinal logistic regression analysis approaches were used to evaluate demographic attributes, risk scores, SDV familiarity scores, SDV trust scores, and other attributes as potential predictors of primary blame assignment or impact of advertising.

These analyses utilized the participant response data from Experiment 1 ($n = 403$) and used $p < 0.05$ as the threshold for significance.

9.4.1. Risk as a Predictor (Primary Blame)

A multinomial logistic regression analysis was performed on the experiment data to determine if risk score was a statistically significant predictor of primary blame assignment for each of the four scenarios. Risk score was found to be statistically significant ($p = 0.015$) predictor for blame of the vehicle manufacturer in Scenario 1 (Vandalized Sign + Driver's Console), with vehicle manufacturer blame decreasing with increasing total risk score. Figure 19 illustrates the probability of blame assignment for Scenario 1 based on total risk score.

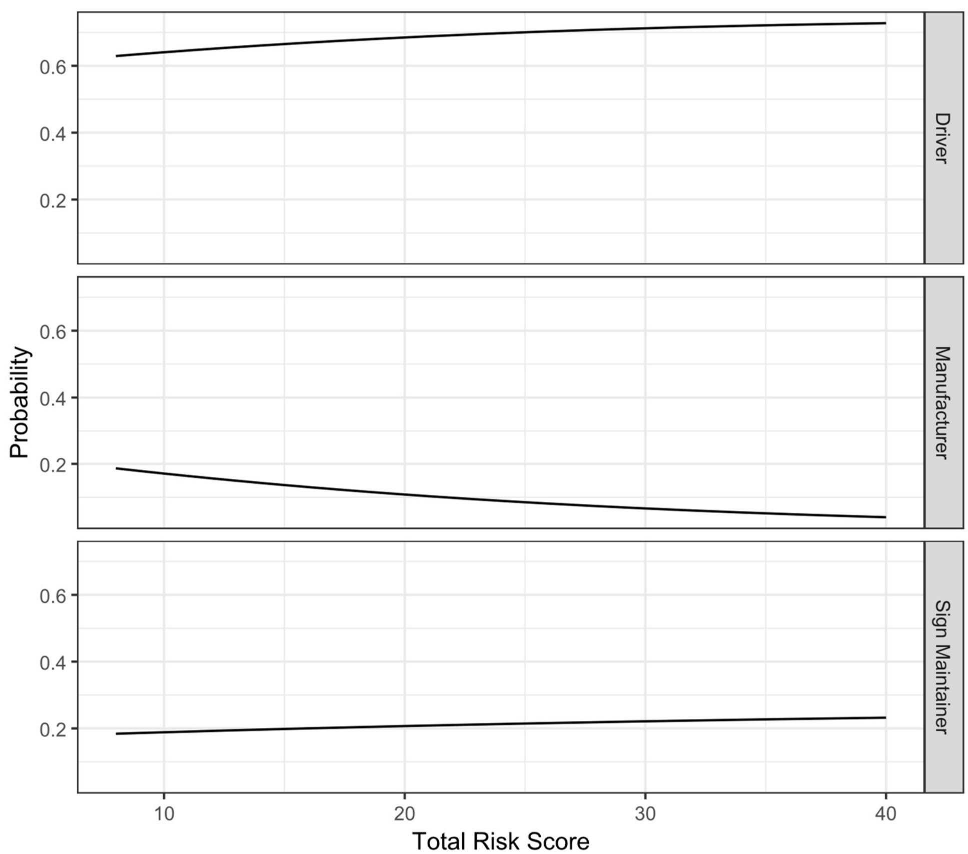


Figure 19. Blame Probability by Total Risk Score - Scenario 1 (Vandalized Sign + Console)

Risk Score was also statistically significant ($p = 0.032$) predictor for blame of the vehicle manufacturer in Scenario 2 (Vandalized Sign + HUD), with vehicle manufacturer blame decreasing with in-creasing total risk score. Figure 20 illustrates the probability of blame assignment for Scenario 2 based on total risk score. Note that as the probability of blame for the vehicle manufacturer increased, the probability of blame for the driver increased.

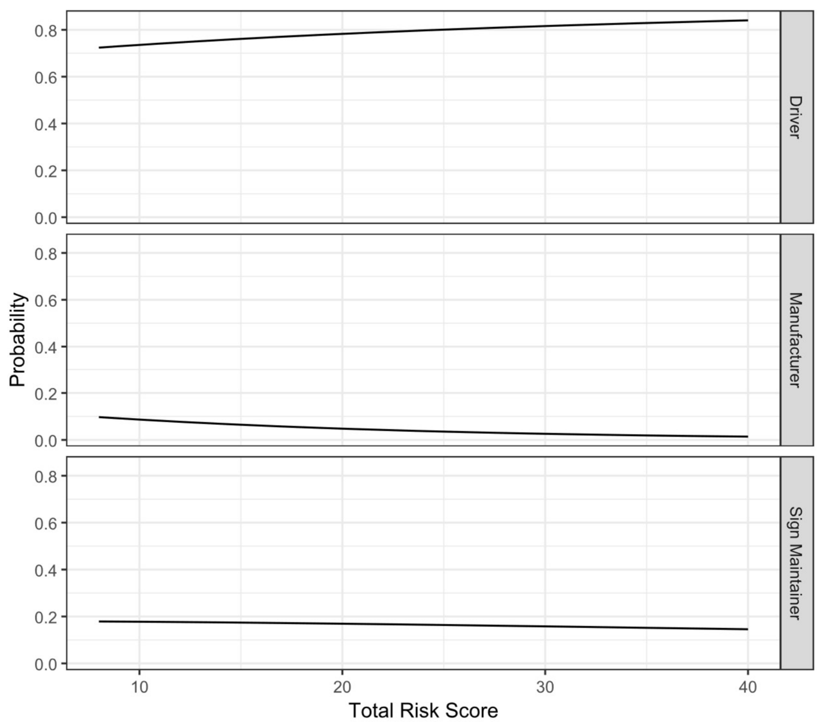


Figure 20. Blame Probability by Total Risk Score - Scenario 2 (Vandalized Sign + HUD)

9.4.1.1. Implications of Demographic Predictor Results

For both Scenario 1 and Scenario 2, the probability of blame assignment against the vehicle manufacturer decreased with increasing risk score, while the probability of the driver receiving primary blame increased. Based on these observations and the statistically significant predictors of total risk score described in Section 3.4.4, the data suggests that an attorney wanting to shield a vehicle manufacturer from legal liability would prefer a jury composition that was more male than not male as the survey predicts a total risk score, on average, of 4.31 points less for a not male potential juror versus a male potential juror.

9.4.2. Trust Score as a Predictor of Primary Blame Assignment

A multinomial logistic regression analysis was performed on the first experiment survey data to determine if trust score was a statistically significant predictor of primary blame assignment for the legal culpability scenarios. Trust score was a statistically significant ($p = 0.030$) predictor for blame of the vehicle manufacturer in Scenario 2 (Vandalized Sign + HUD), with vehicle manufacturer blame and sign maintainer blame increasing with increasing trust score. Figure 21 illustrates the probability of blame assignment for Scenario 2 based on trust score.

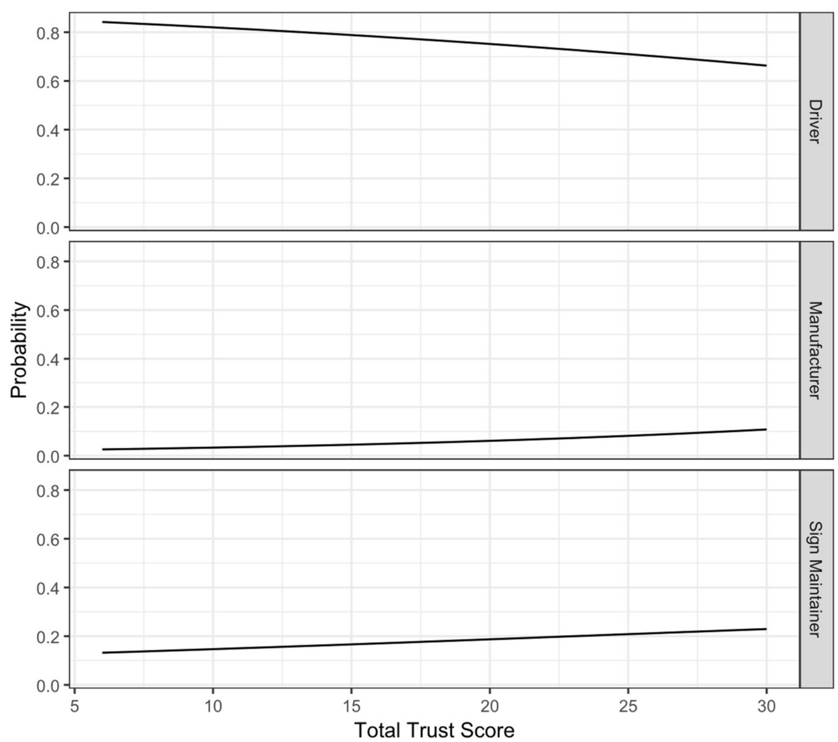


Figure 21. Blame Probability by Total Trust Score - Scenario 2 (Vandalized Sign + HUD)

Trust score was also a statistically significant (p = 0.021) predictor for blame of the vehicle manufacturer in Scenario 3 (Damaged Sign + Speeding Ticket), with vehicle manufacturer blame increasing with increasing trust score. Figure 22 illustrates the probability of blame assignment for Scenario 3 based on trust score.

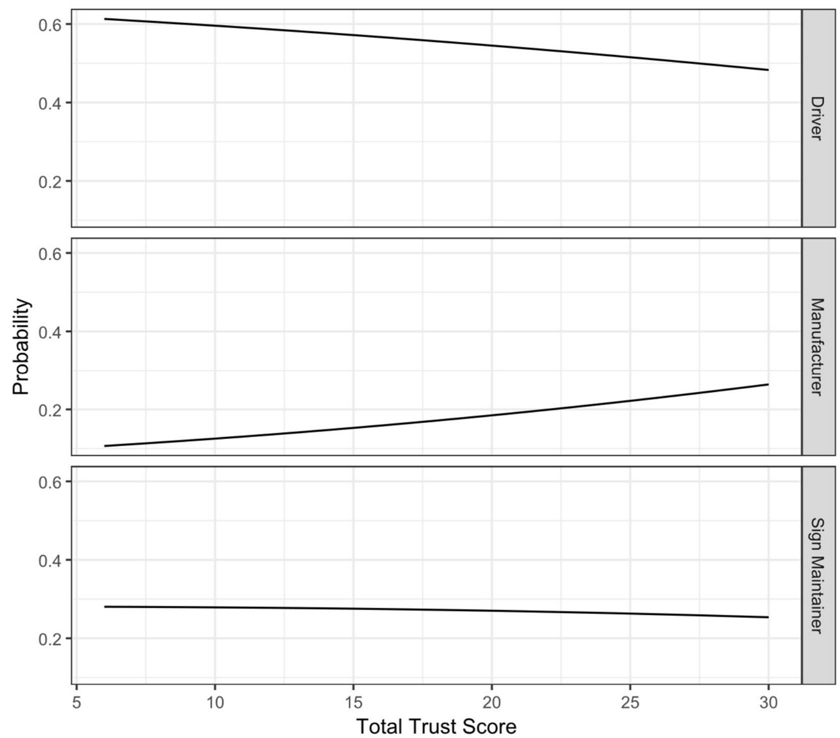


Figure 22. Blame Probability by Total Trust Score - Scenario 3 (Damaged Sign + Speeding)

9.4.2.1. Implications of Demographic Predictor Results

In Scenarios 2 (Vandalized Sign + HUD) and 3 (Damaged Sign + Speeding Ticket), trust score was a statistically significant predictor for blame assignment against the vehicle manufacturer, with probability of the vehicle manufacturer taking primary blame increasing with increasing trust score. Combining this information with the statistically significant predictors for trust score described in Section 3.3.3.2 suggests that an attorney wanting to shield a vehicle manufacturer from liability for an SDV-involved collision or traffic violation would prefer a jury that is less male in terms of gender, and would prefer a jury that more identifies as White/ Non-Latino versus Asian or African American. Conversely, the data suggests that an attorney wanting to shield a driver from blame would prefer a jury that is more male and Asian or African American.

9.4.3. Familiarity Score as a Predictor of Primary Blame Assignment

A multinomial logistic regression analysis was performed on the survey to determine if familiarity score was a statistically significant predictor of primary blame assignment for the legal culpability scenarios. Familiarity score was not a statistically significant predictor of blame assignment for any scenarios.

9.4.4. Predictors of Impact of Advertising on Primary Blame Assignment

An ordered logistic analysis was performed on the survey data to evaluate if risk score, SDV trust score, or SDV familiarity score predicted the impact of advertising on the assignment of blame to the vehicle manufacturer (i.e., less, same, more). A separate model was fit for each scenario. The results of these analysis runs are shown in

Table 20 -

Table 23.

Table 20. Ordered Logit for Scenario 1 (Vandalized Sign + Driver's Console) Ad Blame

Coefficient	Estimate	Std Error	t-value	p-value
SDV Trust Score	0.043	0.017	-2.427	0.0151
SDV Familiarity Score	0.101	0.033	3.025	0.0024
Risk Score	-0.010	0.013	-0.805	0.4206
Manufacturer Less | Same	-1.180	0.585	-2.018	0.0436
Manufacturer Same | More	0.852	0.577	1.476	0.1399

Trust score and familiarity score were both statistically significant predictors of when the vehicle manufacturer blame assignment would be influenced by advertisements. For both predictors, a higher score predicted more blame being assigned to the vehicle manufacturer. Using the model output, Equation (3) is valid for Scenario 1 (Vandalized Sign + Driver's Console) for predicting impact of advertising on vehicle manufacturer blame:

$$\text{Score} = 0.043(\text{Trust Score}) + 0.101(\text{Familiarity Score}) - 0.010(\text{Risk Score}) \quad (3)$$

Where: Score < -1.180 → Manufacturer has less blame

-1.180 ≤ Score ≤ 0.852 → Manufacturer has same blame

Score > 0.852 → Manufacturer has more blame

Table 21. Ordered Logit for Scenario 2 (Vandalized Sign + HUD) Ad Blame

Coefficient	Estimate	Std Error	t-value	p-value
SDV Trust Score	-0.012	0.017	-1.170	0.2421
SDV Familiarity Score	0.090	0.032	2.825	0.0047
Risk Score	-0.008	0.013	-0.608	0.5428
Manufacturer Less | Same	-0.725	0.558	-1.300	0.1935
Manufacturer Same | More	1.384	0.557	2.486	0.0129

Familiarity score was a statistically significant predictor of when the vehicle manufacturer blame assignment would be influenced by advertisements. A higher familiarity score predicted more blame being assigned to the vehicle manufacturer. Equation (4) provides the model for Scenario 2 (Vandalized Sign + HUD) for predicting impact of advertising on vehicle manufacturer blame:

$$\text{Score} = -0.012(\text{Trust Score}) + 0.090(\text{Familiarity Score}) - 0.008(\text{Risk Score}) \tag{4}$$

Where: Score < -0.725 → Manufacturer has less blame

-0.725 ≤ Score ≤ 1.384 → Manufacturer has same blame

Score > 1.384 → Manufacturer has more blame

Table 22. Ordered Logit for Scenario 3 (Damaged Sign + Speeding Ticket) Ad Blame

Coefficient	**Estimate**	**Std Error**	**t-value**	**p-value**
SDV Trust Score	-0.038	0.017	-2.211	0.0270
SDV Familiarity Score	0.092	0.033	2.817	0.0048
Risk Score	-0.005	0.012	-0.436	0.6631
Manufacturer Less | Same	-1.002	0.574	-1.747	0.0806
Manufacturer Same | More	1.288	0.571	2.257	0.0240

Trust score and familiarity score were both statistically significant predictors of when the vehicle manufacturer blame assignment would be influenced by advertisements. For trust score, a higher value predicted less blame being assigned to the vehicle manufacturer, while a higher familiarity score predicted more blame for the manufacturer. Equation (5) summarizes this model for Scenario 3 (Damaged Sign + Speeding Ticket) for vehicle manufacturer blame prediction:

$$\text{Score} = -0.038(\text{Trust Score}) + 0.092(\text{Familiarity Score}) - 0.005(\text{Risk Score}) \quad (5)$$

Where: $\text{Score} < -1.002 \rightarrow$ Manufacturer has less blame

$-1.002 \leq \text{Score} \leq 1.288 \rightarrow$ Manufacturer has same blame

$\text{Score} > 1.288 \rightarrow$ Manufacturer has more blame

Table 23. Ordered Logit for Scenario 4 (Wrong Sign + Speeding Ticket) Ad Blame

Coefficient	Estimate	Std Error	t-value	p-value
SDV Trust Score	-0.003	0.017	-0.180	0.8567
SDV Familiarity Score	0.063	0.063	1.956	0.0504
Risk Score	-0.012	0.012	-0.931	0.3517
Manufacturer Less | Same	-1.222	0.573	-2.132	0.0329
Manufacturer Same | More	0.978	0.567	1.724	0.0846

Familiarity score was a statistically significant predictor of when the vehicle manufacturer blame assignment would be influenced by advertisements. A higher familiarity score predicted more blame being assigned to the manufacturer. Equation (6) summarizes the model for Scenario 4 (Wrong Sign + Speeding Ticket) for predicting impact of advertising on manufacturer blame:

$$\text{Score} = -0.003(\text{Trust Score}) + 0.063(\text{Familiarity Score}) - 0.012(\text{Risk Score}) \qquad (6)$$

Where: Score < -1.222 → Manufacturer has less blame

-1.222 ≤ Score ≤ 0.978 → Manufacturer has same blame

Score > 0.978 → Manufacturer has more blame

9.5. Discussion

This experiment examining of the views of the adult population of the United States with regards to legal culpability for crashes and moving violations caused by SDVs utilized a participant pool of 403 respondents. The analysis examined the impacts of risk tolerance, SDV comfort, and SDV familiarity on primary blame assignment to the driver, vehicle manufacturer, or sign maintainer in the event of a SDV mishap. The analysis also evaluated the impact of advertising on blame assigned to the vehicle manufacturer. Table 24 summarizes the scenarios in which risk, comfort, and familiarity were statistically significant predictors of the results.

Risk score was found to be a statistically significant predictor for primary blame assignment in Scenarios 1 (Vandalized Sign + Driver's Console) and 2 (Vandalized Sign + HUD), where the probability of primary blame assignment to the driver increased with increasing risk-taking tendencies. SDV comfort score was a statistically significant predictor of primary blame assignment in Scenarios 2 (Vandalized Sign + HUD) and 3 (Damaged Sign + Speeding Ticket), with the probability of primary blame being assigned to the driver decreasing with increasing comfort with SDVs. These summaries relate to the Primary column under each scenario for Table 24.

Familiarity and comfort scores were statistically significant predictors for the impact of advertising on vehicle manufacturer blame, with increasing familiarity with SDVs resulting in a higher likelihood of the manufacturer receiving more blame due to advertising. In contrast, increasing comfort with SDVs often resulted in the likelihood of the manufacturer receiving less blame due to advertising. These summaries relate to the Ad column under each scenario for Table 24.

Table 24. Summary of Statistically Significant Predictors for Primary and Ad Blame

Predictor	**Scenario 1 (Vandalized Sign + Driver's Console)**		**Scenario 2 (Vandalized Sign + HUD)**		**Scenario 3 (Damaged Sign + Speeding Ticket)**		**Scenario 4 (Wrong Sign + Speeding Ticket)**	
	Primary	**Ad**	**Primary**	**Ad**	**Primary**	**Ad**	**Primary**	**Ad**
Risk Score	yes	no	yes	no	no	no	no	no
Trust Score	no	yes	yes	no	yes	yes	no	no
Familiarity Score	no	yes	no	yes	no	yes	no	yes

The results of this experiment provide insights into both how potential jurors may respond to questions of legal culpability involving SDVs, and how vehicle manufacturers can protect themselves from blame assignment. First, the data suggests that advertisements can have a significant additive impact on vehicle manufacturer blame assignment if those advertisements suggest that drivers do not have to supervise the SDV. This suggests manufacturers could be putting themselves at greater legal risk based on the content of their advertisements. Based on the experiment data, this risk can possibly be reduced by increasing the general population's familiarity with SDVs. Additionally, the data suggests that manufacturers can increase their likelihood of prevailing against legal actions if they increase the average risk tolerance scores of the jury and select jurors with higher comfort scores. This can be accomplished by taking into account demographic factor impacts on risk tolerance and SDV comfort that were identified in this survey analysis.

Chapter 10. Aim 2 Results - Reliability and Safety Expectations

10.1. Introduction

Future SDV designs will need to meet the safety and reliability expectations of consumers in order to be viable commercial products. Evaluating and quantifying these expectations required the use of a Conjoint analysis experiment where four key characteristics for safety and reliability were evaluated for feature utility and overall feature importance based on the experiment data provided by 403 respondents. This data was analyzed to answer the following research questions in support of Research Aim 2:

- **RQ2.1:** What are customer expectations for SDV system accuracy and resilience?
- **RQ2.2:** Are risk tolerance, SDV familiarity, SDV comfort, or demographic factors significant predictors of views of legal culpability for SDV-involved traffic incidents and expectations on system performance and resilience?

The results of this chapter were published in the journal *Future Transportation* titled "Reliability, Resilience, and Alerts: Preferences for Autonomous Vehicles in the United States" (Stewart & Gallegos, 2025b).

10.2. Expectations for Reliability and Safety for SDVs

Conjoint experiment response data was evaluated to determine feature level utility values and the optimal feature package using data analysis capabilities inherent to the Qualtrics platform. Additionally, relative feature importance was evaluated using LASSO regression analysis performed within R.

10.2.1. Utility Values for Experiment 1 Data

Perceived importance of each feature and levels within each feature were com-pared across the entire 403 response sample. Standardized utility values represent how strongly each feature level influenced respondents' choices, adjusted to a common scale so that differences in preference can be compared directly across features. Analyses within and between feature levels were standardized so that results could be compared consistently, for example, from alert method levels to failure allowance levels, ensuring all values were expressed on the same baseline and scale of variability.

10.2.1.1. Comparison of Features

Figure 23 presents the utility values with 95% confidence intervals of the four features based on responses from the full survey sample. Across the respondents, method of alerting drivers to alerts and warnings and human intervention frequency (i.e., reliability) were the most influential features in choice-set selection. In contrast, sensor failure allowance (i.e., resilience) and failure behavior were comparatively less important.

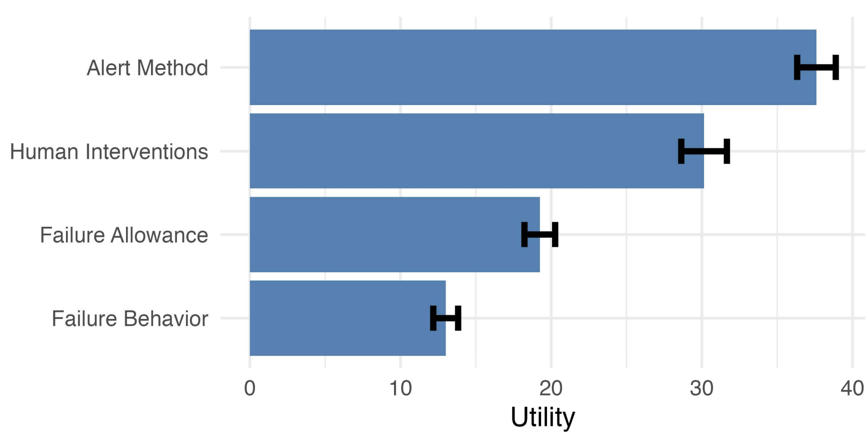


Figure 23. Feature Importance (95% CI) for the Four Features (Total Respondent Population)

10.2.1.2. Comparison of Levels within Features

The standardized utility values for each level, with 95% confidence intervals, are provided in Figure 24, enabling both within- and between-feature comparisons. Positive utility values indicate a preference for the feature level, while negative utility values reflect lower perceived importance. Key observations include a strong preference for human intervention frequencies between 1 and 100 times over a five-year period, as well as a preference for the SDV to stop safely in the event of a system failure. Respondents also expressed clear disapproval of having no alert system for notifications of an SDV system alert, favoring instead a combined audio and visual alert. Finally, the data suggests a willingness to accept relatively low system resiliency, with preference for requiring sensor repairs when as few as 5% of the sensors have failed.

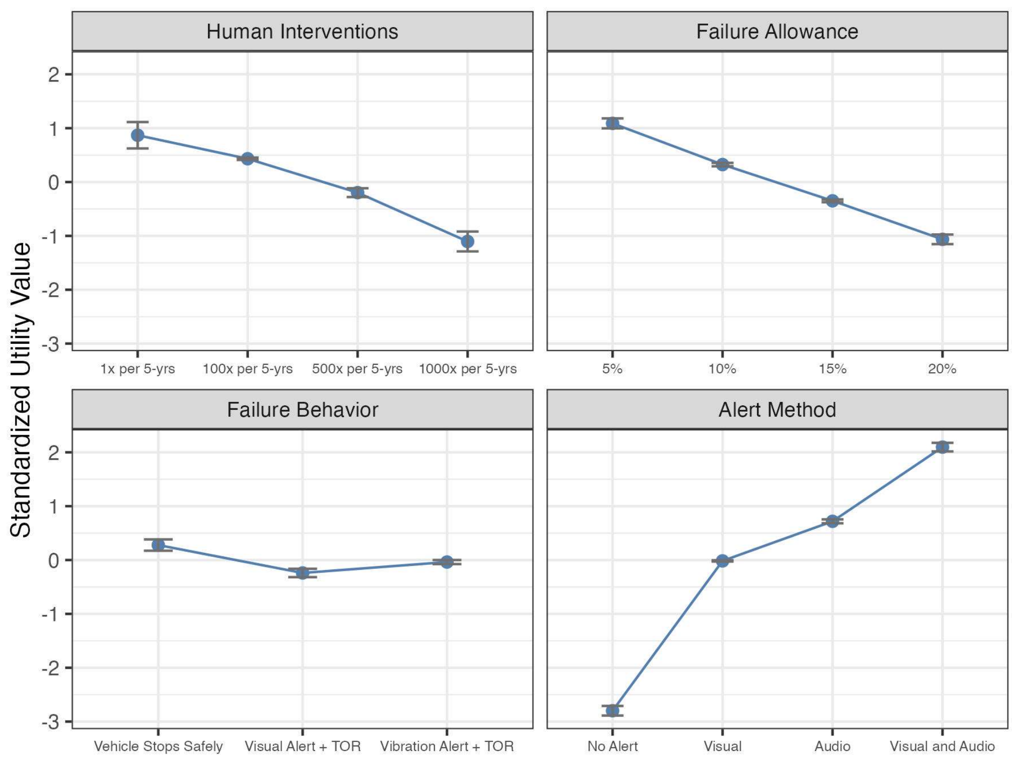


Figure 24. Standardized Utility Values (95% CI) for SDV Features Across Sample Population

10.2.1.3. Optimal Reliability and Safety Feature Levels

Table 25 captures the optimal feature package observed across the total respondent population. This was determined by selecting the level within each feature with the highest utility value.

Table 25. Optimal Feature Package Values for Total Respondent Population

Feature	Optimal Package Value
Human Interventions	1x per 5-years
Failure Allowance	5%
Failure Behavior	Vehicle Stops Safely
Alert Method	Audio & Visual Alert

10.2.2. Utility Values by Experiment Population Sample Subsets

Several binary logistic mixed effects models were used to identify significant predictors of feature level preferences. To simplify the tables, only the significant predictors are retained, while the insignificant predictors from the model are removed from each table. These predictors were then used to compare utility values across the feature levels within each significant factor.

10.2.2.1. Feature Level Utility by WTP

Before conducting the utility analysis based on WTP, survey responses were screened for outliers in both the self-driving and driver-assist WTP data. Because responses were collected through open-text fields, some participants entered extremely high or nonnumeric values. To identify and exclude these outliers, the interquartile range (IQR) method was applied separately to each dataset. Observations falling below 1.5 × IQR below the first quartile or above 1.5 × IQR above the third quartile were classified as outliers and re-moved from subsequent analyses.

For self-driving WTP, 32 outliers were identified, ranging from \$50,000 to \$400,000. For driver-assist WTP, 45 outliers were identified, ranging from \$25,000 to \$300,000. These extreme or implausible values were excluded to prevent distortion of model estimates.

After cleaning, WTP remained a significant predictor of feature level selection for human intervention frequency and system resilience, see Table 26. Since WTP was expressed in continuous dollar amounts, the resulting coefficients were small in magnitude, reflecting incremental changes in preference with each dollar increase. Respondents with higher WTP for full self-driving functionality were less likely to prefer higher intervention frequencies (100-1000 interventions per five years). Conversely, those with higher WTP for driver-assist automation were more likely to tolerate higher intervention frequencies and preferred greater system resilience (15% failure allowance).

Table 26. Feature Level Preference by Willingness to Pay for SDV Functionality

WTP by Automation Level	**Feature**	**Level**	**Coeff**	**p-value**
Full Self-Drive	Human Interventions	100x per 5 years	-7.29×10^{-05}	< .001
Full Self-Drive	Human Interventions	1000x per 5 years	-1.51×10^{-04}	< .001
Full Self-Drive	Human Interventions	500x per 5 years	-8.81×10^{-05}	< .001
Driver Assist	Human Interventions	100x per 5 years	1.13×10^{-04}	.041
Driver Assist	Human Interventions	1000x per 5 years	2.53×10^{-04}	< .001
Driver Assist	Human Interventions	500x per 5 years	1.68×10^{-04}	.002
Driver Assist	Failure Allowance	15%	1.87×10^{-04}	< .001

10.2.2.2. Feature Level Utility by Impact of Manufacturer Advertising

Impact of manufacturer advertising was found to significantly predict feature level selection for human intervention frequency, as shown in Table 27. Specifically, participants with higher impact of advertising scores had a lower preference for a system reliability level of 1000 interventions per 5-year period than those with lower impact of advertising scores.

Table 27. Feature Level Preference by Impact of Advertising

Variable	Feature	Level	Coeff	p-value
Impact of Advertising Score	Human Interventions	1000x per 5 years	-0.08	.040

10.2.2.3. Feature Level Utility by Risk Score

Risk score was also to be a significant predictor of feature level selection for alert method, as shown in Table 28. Specifically, participants with higher risk propensity preferred visual and audio alert systems versus respondents with lower risk propensity scores.

Table 28. Feature Level Preference by Risk Score

Variable	Feature	Level	Coeff	p-value
Risk Score	Alert Method	Audio & Visual	0.027	.013

10.2.2.4. Feature Level Utility by Drive Frequency

Drive frequency emerged as a significant predictor of feature level selection for alert method and system resilience, as shown in Table 29. For this model, drive frequency of daily was the reference level. Respondents who reported driving 2-3 times per week had a lower preference for no alert compared to those who drive daily. Respondents who reported never driving had a lower preference for a 5% system resilience level versus daily drivers. However, those who drove 4-6 times per week showed a higher preference for a 5% system resilience rate when compared to daily drivers.

Table 29. Feature Level Preference by Drive Frequency

Drive Frequency	Feature	Level	Coeff	p-value
2-3x per week	Alert Method	No Alert	-0.50	.048
Never	Failure Allowance	5%	-0.77	.012
4-6x per week	Failure Allowance	5%	0.46	.043

10.2.2.5. Feature Level Utility by Household Income

Household income level was a significant predictor of feature level selection for both human intervention frequency and alert method, as shown in Table 30. The baseline for this model was respondents with a household income between \$40,000 - \$59,999, meaning that each comparison was relative to the \$40k - \$60k level. In all cases, coefficients were positive for significant variables, suggesting that each group was more likely to prefer the respective feature compared to the reference income group. Specifically, the alert option of no alert was more preferred by those with household earnings between \$60,000 - \$79,999 or \$100,000 to \$149,999 than the baseline group. Moreover, those having a household income of \$100,000 to \$149,999 reported a higher preference for a visual alert system compared to the baseline group.

Table 30. Feature Level Preference by Income Group

Income Level	Feature	Level	Coeff	p-value
\$60k - \$79,999	Alert Method	No Alert	0.79	.007
\$100k - \$149,999	Alert Method	No Alert	0.74	.014
\$100k - \$149,999	Alert Method	Visual Alert	0.71	.014

A point of interest from the income analysis was that the optimized feature list for those reporting a household income of \$100,000 - \$149,999 varied slightly from the total sample's optimized feature list. As shown in Table 31, the preferred failure behavior for participants reporting a \$100,000 - \$149,999 income range was to have a vibration warning followed by a

TOR request versus the vehicle bringing itself to a safe stop. All utility values [standardized] for this income group is shown in Figure 25, where the largest utility value within each feature yields the optimal feature list for the group.

Table 31. Optimal Feature Package Values for Income Group $100,000 - $149,999

Feature	Income $100,000-149,999	Entire Sample
Human Interventions	1x per 5 years	1x per 5 years
Failure Allowance	5%	5%
Failure Behavior	Vibration Alert + TOR	Vehicle Stops Safely
Alert Method	Audio & Visual Alert	Audio & Visual Alert

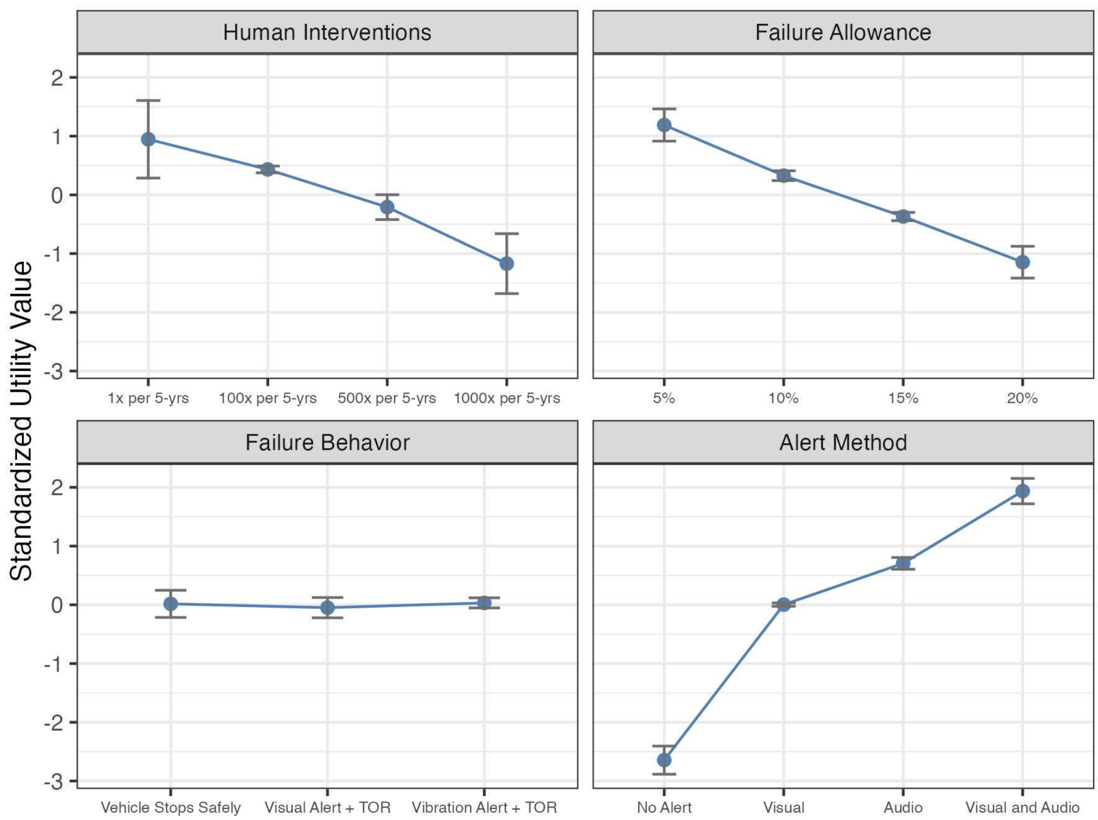


Figure 25. Standardized Utility Values (95% CI) for SDV Features, $100k - $149,999 Income

10.2.2.6. Feature Level Utility by Race/Ethnicity

Race/ethnicity also emerged as a significant predictor of feature level selection for human intervention frequency and alert method, as shown in Table 32. The baseline for this model was respondents identifying as White/Non-Latino. Participants identifying as Hispanic or African American showed a greater preference for a system reliability level of 1000 human interventions per 5-year period versus the baseline group. For the feature of alert method, participants identifying as Hispanic had a lower preference for no alert compared to the reference group.

Table 32. Feature Level Preference by Race/Ethnicity

Race/Ethnicity	**Feature**	**Level**	**Coeff**	**p-value**
African American	Human Interventions	1000x per 5 years	0.56	.028
Hispanic	Human Interventions	1000x per 5 years	0.72	.015
Hispanic	Alert Method	No Alert	-1.00	.002

Those identifying as Hispanic also had an optimal feature package list that varied slightly from the total sample's optimized feature list. As shown in Table 33, the preferred system reliability for Hispanic respondents was 100 human interventions per 5-year period versus 1 human intervention per 5-year period for the total sample. Figure 26 illustrates the standardized utilities across each feature for this group.

Table 33. Optimal Feature Package Values for Hispanic Respondents

Feature	**Hispanic Respondents**	**Entire Sample**
Human Interventions	100x per 5 years	1x per 5 years
Failure Allowance	5%	5%
Failure Behavior	Vehicle Stops Safely	Vehicle Stops Safely
Alert Method	Audio & Visual Alert	Audio & Visual Alert

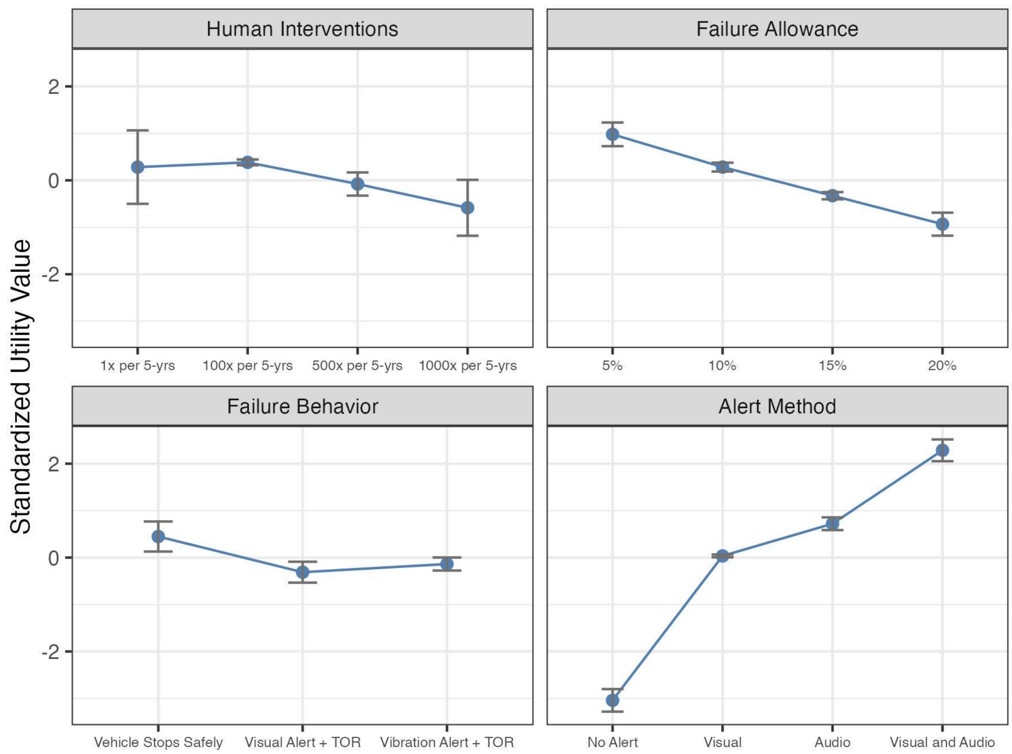


Figure 26. Standardized Utility Values (95% CI) for SDV Features for Hispanic Respondents

10.2.2.7. Feature Level Utility by Marital Status

Marital status was also a significant predictor of feature level selection for human intervention frequency and SDV failure behavior, as shown in Table 34. The baseline for this model was participants identifying as married. Respondents identifying as single showed greater preference for human intervention frequency levels of 100x and 500x per 5 years compared to married individuals.

Table 34. Feature Level Preference by Marital Status

Marital Status	**Feature**	**Level**	**Coeff**	**p-value**
Single	Human Interventions	100x per 5 years	0.65	.033
Single	Human Interventions	500x per 5 years	0.83	.006

10.2.2.8. Feature Level Utility by Education Level

Education level also significantly predicted feature level selection for human intervention frequency and alert method, as shown in Table 35. The baseline for this model was participants with the highest completed education level of high school diploma. Participants with an associate's degree had a greater preference for a visual warning alert system versus those with a high school diploma. Those with some college completed also showed a higher preference for a system reliability level of 100 times per 5-year period versus the baseline group.

Table 35. Feature Level Preference by Education Level

Education Level	**Feature**	**Level**	**Coeff**	**p-value**
Associate's Degree	Alert Method	Visual Warning	0.58	.043
Some College	Human Interventions	100x per 5 years	0.80	.006

10.2.2.9. Synthesis of All Predictors

Figure 27 provides an integrated summary of the subgroup analyses, illustrating how demographic and behavioral predictors relate to feature-level preferences and highlighting consistent patterns across groups. Independent variable predictors are shown in purple text, and the dependent feature levels are shown in black text. A blue arrow with a positive polarity indicates that the independent variable is a positive predictor, increasing the likelihood of selecting that feature level. Conversely, a red arrow with a negative polarity indicates a negative predictor, decreasing the likelihood of selection.

Feature levels without any significant predictors were excluded from the diagram. These include: human interventions (1x in 5 years), failure allowance (10%; 15%), failure behavior (vibration alert + TOR), and alert method (visual alert; audio alert).

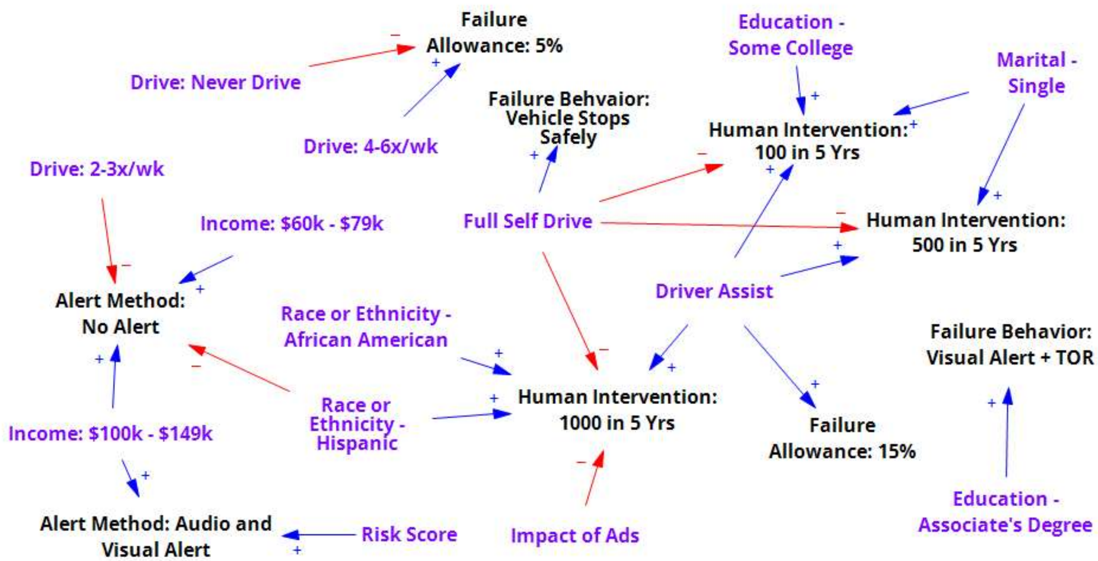


Figure 27. Visualization of Significant Predictors of Feature Preference Across All Subgroups

10.2.3. LASSO Analysis

The previously described feature utility analysis quantified the relative utility of each feature level, allowing comparisons among levels within the same feature. However, this approach was limited in that it did not permit direct comparison of the relative importance of entire features against one another when participants selected among feature packages. For example, the utility analysis could not determine whether system reliability mattered more than the method of alerting the driver about a self-driving system failure. To address this limitation, a LASSO analysis was conducted on the conjoint experiment data. Unlike the utility analysis, LASSO identifies which features and levels meaningfully influenced respondents' choices and which variables were not retained as significant predictors.

Within the LASSO analysis the reference levels of each feature were as follows:

- Human Interventions: 1x per 5 years

- Failure Allowance: 10%
- Failure Behavior: Vibration Alert + TOR
- Alert Method: Audio alert

The results of the LASSO analysis are presented in Table 36. Predictors that were shrunk to zero by LASSO are omitted from the table for clarity. The analysis shows that the feature levels with the greatest influence on package selection were human intervention frequency (1000x per 5 years, compared to 1x per 5 years), failure allowances (20% and 5%, compared to 10%), and alert method (no alert, visual alert, and visual + audio alert, compared to audio alert). Negative coefficients indicate that inclusion of a feature level decreased the likelihood of a package being selected, while positive coefficients indicate that inclusion increased the likelihood of selection. Feature levels not appearing in the table were effectively irrelevant to respondents' decisions. Notably, all SDV failure behavior levels had coefficients of zero, suggesting they were not important factors in the decision-making process.

Table 36. LASSO Coefficients and Odds Ratios for Non-Zero Feature Levels

Feature Level	**Level**	**Coefficient**	**Odds Ratio**
Human Interventions	1000x per 5 years	-0.30	0.74
Failure Allowance	20%	-0.19	0.83
Failure Allowance	5%	0.22	1.24
Alert Method	No Alert	-0.88	0.41
Alert Method	Visual & Audio	0.41	1.50
Alert Method	Visual	-0.05	0.95

The results of the relative feature importance analysis are summarized in Table 37. Among the four attributes, alert type was the most influential factor of choice, accounting for 64.7% of the decision process. This attribute also exhibited the widest coefficient range (1.29), indicating that the difference between the least preferred level (no alert) and the most preferred level (visual + audio) had the greatest effect on respondents' selections. Failure allowance was the second most important driver, explaining 20.3% of choice decisions, with a more modest range of 0.405 across coefficient levels. Human interventions contributed 15.0% of the decision process, with a coefficient range of 0.300. Finally, failure behavior was not retained in the LASSO analysis (range = 0, 0% importance), suggesting that respondents were either not influenced by the failure behavior in their choice selections, or were inconsistent in their choices based on failure behavior.

Table 37. Relative Feature Importance Values from LASSO

Feature	**Coefficient Range**	**Relative Importance (%)**
Human Interventions	0.300	15.0
Failure Allowance	0.405	20.3
Failure Behavior	0	0
Alert Type	1.29	64.7

One common concern about LASSO analysis, especially when one strongly dominates, as seen here with the alert method variable, is the potential for coefficient instability due to correlations among predictors. In such cases, LASSO may arbitrarily select among correlated variables or produce unstable coefficient estimates (Tibshirani et al., 1996; Hebiri & Lederer, 2013). To assess this risk, polychoric correlations among the four predictors were calculated. Pairwise correlations were very low ($|r| < 0.02$), with the highest correlation observed between human interventions and failure allowance ($r = -0.019$). These results indicate minimal multicollinearity and thus, low risk of instability in the LASSO coefficient estimates.

10.3. Discussion

This experiment aimed to evaluate which safety features of SDVs most strongly influence consumer preferences, and to evaluate how these preferences vary across demographic and behavioral subgroups. Using a combination of conjoint utility analysis, LASSO regression, and generalized linear mixed models, this manuscript compared the relative importance of system reliability, resilience, failure behavior, and driver alert methods in shaping choice decisions.

When examining subgroup results collectively, several consistent patterns emerge across demographic and behavioral groups. Although some differences were observed, such as higher-income respondents showing greater acceptance of vibration-based alerts, Hispanic respondents preferring moderate intervention frequencies, and single respond-ents favoring higher intervention rates, the overall hierarchy of feature importance remained stable. Across all subgroups, multimodal alert methods (audio + visual) and high system reliability consistently dominated choice preferences. This consistency suggests that, while demographic and experiential factors influence sensitivity to specific feature levels, perceptions of SDV safety are broadly shaped by a shared emphasis on clear alerts and predictable, reliable system performance.

The observed preference among higher-income respondents for “no alert” options may indicate greater familiarity or comfort with automation technologies. Individuals in this group may be more likely to have experience with advanced driver-assistance systems and thus perceive alerts as redundant or disruptive to the driving experience. Alternatively, this finding could reflect higher trust in system reliability or differing expectations for seamless user interfaces. This finding aligns with previous research that has shown that drivers’ risk perceptions play an important role in shaping real-world distraction behaviors (Hurwitz et al., 2016). Future research should explore whether these preferences stem from increased technological exposure, risk perception, or differing attitudes toward driver intervention.

The observed utility values for several feature levels suggest that current SDV technology may fall short of respondents' expectations. For example, the strong preference for extremely low intervention rates (1 intervention per 5-year timeframe) highlights a critical gap between consumer expectations and current SDV performance, as demonstrated by the disengagement rates reported by the California DMV (Kohanpour et al., 2025). This finding indicates that additional investments in self-driving system reliability are essential to support continued SDV market pentation.

The most consistent and prominent finding was the dominant influence of driver alert methods. Both the utility estimates and the LASSO regression identified multimodal alerts (visual + audio) as the primary factor driving package selection, accounting for nearly two-thirds of total decision weight. In contrast, the absence of alerts was strongly disfavored. These results align with prior literature emphasizing the importance of multimodal takeover request systems (Tan & Zhang 2025; Deng et al., 2024) and suggest that alert design is a higher consumer priority than more complex failure behaviors.

Interestingly, respondents expressed a stated preference for relatively low levels of resilience, with preferences clustering around requiring repairs after as few as 5% of sensor failures. This finding suggests that consumers may prioritize perceived reliability and system transparency over redundancy or fault tolerance. However, these results reflect stated preferences based on hypothetical scenarios rather than observed behavior. Future research incorporating revealed or behavioral data could help determine whether participants would, in practice, tolerate similarly low resilience levels. For manufacturers, this may indicate that investment in redundant hardware provide limited perceptual benefit compared to improving the clarity and responsiveness of alert systems.

One of the most striking findings was that failure behavior was not retained in the LASSO analysis, indicating minimal influence on overall feature set selection. Since this result was unexpected, we reviewed how this feature was presented to respondents. The failure behavior feature prompted participants: “What the vehicle does when self-driving fails,” with three levels: (1) vehicle stops safely, (2) vehicle provides a visual warning to you and you take over driving, and (3) vehicle provides a touch warning (vibration) to you and you take over driving. In the LASSO model, the baseline was set to Vibration Alert + TOR, against which the other two levels were compared. Given the distinct behavioral differences between a system-commanded stop and a driver takeover, this outcome likely reflects respondents’ prioritization of alert and reliability features over specific failure responses, rather than an effect of question framing or level simplicity.

These findings call into question the potential return on investment for current research focused on more dynamic system failure responses beyond executing a safe stop (Mature-Peaspan et al., 2020; Lee & An, 2023). From the consumer perspective, a simple and predicable safe stop response may be sufficient. Instead, factors such as driver alert methods (accounting for 64.7% of pack-age selections in the experiment), sensor failure allowance (20.3%), and system reliability (15%) had a greater impact on consumer preferences. These results provide insight into what features should receive the most investment and attention by current and future SDV manufacturers. Looking ahead, however, advances in artificial intelligence (AI) and ma-chine learning (ML) are likely to reshape how reliability and resilience are achieved in SDV design, potentially altering both technical priorities and consumer expectations.

For example, recent AI and ML innovations enable predictive maintenance, real-time anomaly detection, and adaptive fault-tolerance architectures that allow vehicles to recon-figure control pathways or sensor inputs when faults occur. Such advances could result in self-healing or self-calibrating systems that maintain safe operation under degraded conditions. As these technologies mature, consumer preferences may shift away from static measures of reliability (e.g., low disengagement rates) toward dynamic capabilities such as predictive diagnostics and autonomous fault management. Future research should therefore examine how awareness of AI-driven reliability and resilience improvements may influence stated and observed preferences for SDV safety features.

In parallel with these technological developments, advances in reliability and resilience modeling are also reshaping how such capabilities are conceptualized and evaluated. Recent work by Pan et al. (2024) highlights the growing importance of reliability and resilience modeling frameworks for autonomous vehicle systems, emphasizing hybrid approaches that integrate probabilistic failure modeling with adaptive control strategies to improve system robustness. These modeling insights complement the findings of this study by underscoring the need for consumer-focused reliability metrics to align with technically grounded reliability and resilience architectures.

Chapter 11. Aim 3 Results – Willingness to Pay for SDVs

11.1. Introduction

Commercial viability of SDVs requires that the increased cost of an SDV relative to a human-driven equivalent vehicle is less than the premium a consumer is willing to pay for a self-driving vehicle versus an equivalent vehicle without self-drive capability. Experiment 1 captured the willingness to pay for both full self-driving and advanced driver assist capability from 403 participants. Analysis of this data helped to answer the following research questions in support of Research Aim 3:

- **RQ3.1:** How much is a potential SDV buyer in the United States willing to pay for an SDV versus a traditional vehicle?
- **RQ3.2:** How much does that premium change based on the level of driver supervision required for the SDV?
- **RQ3.3:** Are risk tolerance, SDV familiarity, SDV trust, or demographic factors significant predictors of willingness to pay in the United States?

The results of this chapter were published in the journal *Transport Engineering* titled "Full Self-Driving in the United States: Willingness to Pay and Its Predictors" (Stewart & Gallegos, 2026).

11.1.1. Willingness to Pay for SDVs

As self-driving vehicles (SDVs) transition from experimental to commercial viability, both civil engineers and vehicle manufacturers face uncertainty about when widespread adoption will occur. For civil engineers, forecasting this adoption is essential to plan infrastructure upgrades and traffic management strategies that accommodate both automated and human-driven traffic. For manufacturers, understanding consumer willingness to pay (WTP) helps determine when production costs align with market demand.

Previous studies have shown that WTP for SDV technology varies widely across populations and has fluctuated over time, potentially reflecting growing familiarity with advanced driver assistance systems (ADAS) now offered as standard features in many vehicles. To provide an updated basis for forecasting adoption, this study measures current U.S. WTP for SDV and driver-assist technologies and examines key individual-level predictors influencing these values.

11.1.2. Current Gaps in the Literature and Research Objective

The transition to SDVs as the majority contributor to vehicle mixes on the roadways will induce significant additional expenses for infrastructure improvements and effective government oversight of SDV manufacturers and SDV-enabling technologies. To fund these additional expenditures, a dedicated source of revenue needs to be secured via either taxation, fees, or additional levies on the cost of vehicles. At the same time, the selected revenue formula needs to be tolerated by those impacted by the additional costs in order for the revenue streams to be stable and predictable. Currently, a gap exists in the current literature regarding funding preferences for vehicle infrastructure in the context of supporting SDV adoption.

The objective of this chapter is to evaluate funding preferences for funding infrastructure improvements and oversight costs for survey respondents in the United States and determine if there are significant predictors for these preferences. Predictors investigated include trust in SDVs, vehicle ownership type, annual miles driven, and highest completed level of education.

11.1.3. Potential Predictors of WTP

Based on a review of the literature, this research identified four predictors with the potential to influence willingness to pay for automated vehicle technology. This section provides an overview of relevant literature to support consideration of these predictors. The predictors are defined as follows: Comfort with self-driving vehicles refers to the degree of ease and reassurance individuals feel when considering riding in SDVs, reflecting a trust-like attitude toward their safety and reliability. Risk preference refers to an individual's tendency to either seek out or avoid uncertain situations, such as adopting emerging technologies like SDVs. Impact of advertising refers to the extent to which manufacturer marketing about SDV capabilities shape consumer perceptions and willingness to pay. Vehicle ownership refers to the classification of the respondent's primary vehicle, which may influence preferences for SDV technology.

11.1.3.1. Impact of Advertisements for SDV Capability as a Predictor

Existing literature indicates that manufacturer advertising can influence both purchase intention and WTP. Such influence has been shown to increase intention to test drive vehicles featuring new technologies, such as electric vehicles (Gong et al, 2024), enhance trust in autonomous vehicles (Lee et al, 2022), and increase acceptance of autonomous vehicles (Hryniewicz & Grzegorczyk, 2020). Additionally, a driver's willingness to pay for an SDV is affected by the level of supervision the driver is expected to maintain while the SDV is in motion (Weigl et al, 2022; Morita & Managi, 2020; Cunningham et al., 2019). This creates a potential incentive for SDV manufacturers to downplay the amount of driver supervision required during operation. However, doing so could expose the vehicle manufacturer to greater legal liability if the SDV is later involved in a collision or moving violation. Hence, it is important to understand how such advertising influences consumer perceptions and purchasing decisions, and to consider regulatory guidelines that ensure marketing messages about driver supervision accurately reflect the vehicle's operational limitations.

11.1.3.2. Vehicle Ownership as a Predictor

Several previous studies suggest that vehicle ownership influences a person's willingness to adopt self-driving vehicle technology. Rahimi et al. (2020) utilized respondents from several U.S. metro areas to determine willingness to adopt and WTP for full self-driving vehicles. One of the significant predictors in that study was the type of transportation used by the respondents: Class 1 (personal vehicle use only), Class 2 (Vehicle owners who also use public transport), and Class 3 (public transport or rideshare only) (Rahimi et al, 2020). In their study, respondents had WTP values between \$0 and \$4,000, with distributions that varied based on the transportation class of the respondent. In another study, respondents in Arlington, Texas were less likely to adopt and utilize a shared autonomous vehicle ride hail service if they owned a private vehicle (Patel et al, 2023) These results support that vehicle ownership can be a predictor of SDV adoption, which would influence SDV WTP.

11.2. Methods

A survey study was conducted to understand consumer willingness to pay for self-driving vehicle functionality, and their preferences for funding infrastructure improvements and oversight of self-driving technologies. The study adhered to ethical principles for human subject testing and had approval from the Colorado State University Institutional Review Board (IRB), protocol #5825.

11.3. Assessment of Willingness to Pay

11.3.1.1. Analysis of Willingness to Pay Data

Data analysis and cleaning were conducted using Excel and RStudio (R version 4.4.0). The dependent measures for WTP were modeled using linear regression ($ value) and binary logistic regression (yes/no). Separate models were created for each of the following predictor groupings, with their included independent variables:

1. **Demographics:** Gender (male, female), Race or Ethnicity (White/Non-Latino, African American, Asian, Hispanic, Latino, Native American, Pacific Islander, Other), Income (<$20k, $20-40k, $40-60k, $60-80k, $80-100k, $100-150k, >$150k), Marital Status (single, married, divorced, widowed), Education (high school diploma, some college, associate's degree, bachelor's degree, post-graduate degree, professional degree)
2. **Risk Preference and SDV Comfort:** Risk score (8 to 40), SDV comfort score (8 to 40)
3. **Vehicle Ownership Type:** Do not own vehicle, Gasoline or diesel fuel vehicle, Electric vehicle, Hybrid vehicle, Vehicle using other fuel
4. **Assessment of SDV Manufacturer Advertising:** Impact of advertising score (-4 to 4)

Additionally, linear regression models were fit on the entire survey population (N = 403), as well as only on the subset of participants whose willingness to pay was greater than $0 (N = 292).

11.4. Survey Population Willingness to Pay (WTP)

A macro analysis was performed to determine the population mean and median WTP for full self-driving capability (no human intervention required) and driver assist capability (driver supervision of the "self-drive" functionality being required). The results of this analysis are shown in the following subsections.

11.4.1. Full Self-Driving Willingness to Pay (WTP)

Table 38 summarizes the descriptive statistics for WTP for full self-driving capability. Across the full respondent population ("Full Dataset"), the mean WTP was $13,842 and the median WTP was $5,000, with 111 of 403 respondents (27.5%) indicating no willingness to pay. Among the respondents with positive WTP values ("Positive Full Self-Drive WTP Only"), the mean increased to $19,104 (median = $10,000). The distribution of these responses is shown in Figure 28.

Outlier values were examined using the interquartile range (IQR) method, where any observation outside of 1.5 x IQR below the first quartile or above the third quartile was considered an outlier. A total of 32 outlier responses were identified within the positive-WTP subset, ranging from $50,000 to $400,000. After removing these outliers, the adjusted mean WTP decreased to $9,650 (median = $5,000), providing a more conservative estimate of central tendency.

Table 38. Survey Response Characteristics for Full Self-Driving Vehicle WTP

Condition	N	Mean	Median	"0" Values
Full Dataset	403	$13,842	$5,000	111 (27.5%)
Positive Full Self-Drive WTP Only	292	$19,104	$10,000	0
Positive Full Self-Drive WTP, No Full Self-Drive WTP Outliers	260	$9,650	$5,000	0

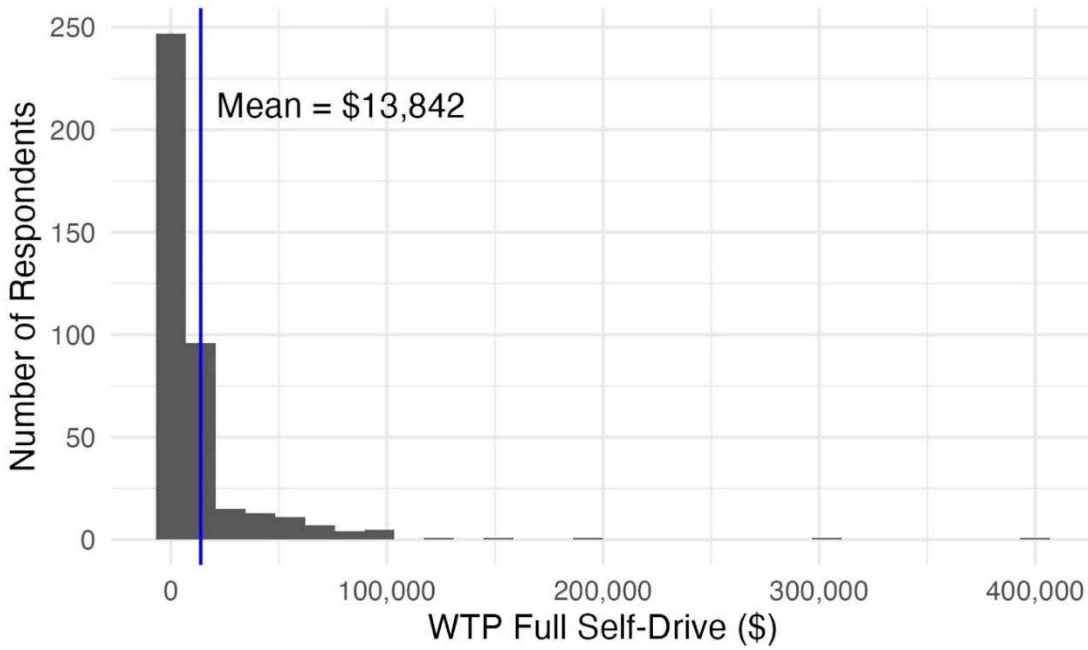


Figure 28. Distribution of responses for willingness to pay for full self-driving.

11.4.2. Driver Assist Willingness to Pay (WTP)

Table 39 summarizes respondents' WTP for driver-assist technology. Across the overall sample ("Full Dataset"), the mean reported WTP was $8,292, with a median of $1,000. About 37.4% (151 of 403 respondents) indicated that they would not pay any premium for this functionality. When limiting the analysis to respondents who reported a positive WTP ("Positive Driver Assist WTP Only"), the mean increased to $13,621 and the median to $4,500, indicating generally lower valuations than those observed for full self-driving capability. The overall response distribution is presented in Figure 29.

To assess the influence of extreme values, the dataset was screened for outliers using the IQR method applied in the previous analysis. Forty-five responses exceeded the 1.5 x IQR threshold, with reported WTP values between $25,000 to $300,000. After excluding these cases, the adjusted mean decreased to $4,385 (median = $2,500), reflecting a more representative estimate of what most consumers are willing to pay for driver-assist features.

Table 39. Survey Response Characteristics for Drive Assist WTP

Condition	N	Mean	Median	"0" Values
Full Dataset	403	$8,292	$1,000	151 (37.5%)
Positive Driver Assist WTP Only	252	$13,261	$4,500	0
Positive Driver Assist WTP, No Driver Assist WTP Outliers	207	$4,385	$2,500	0

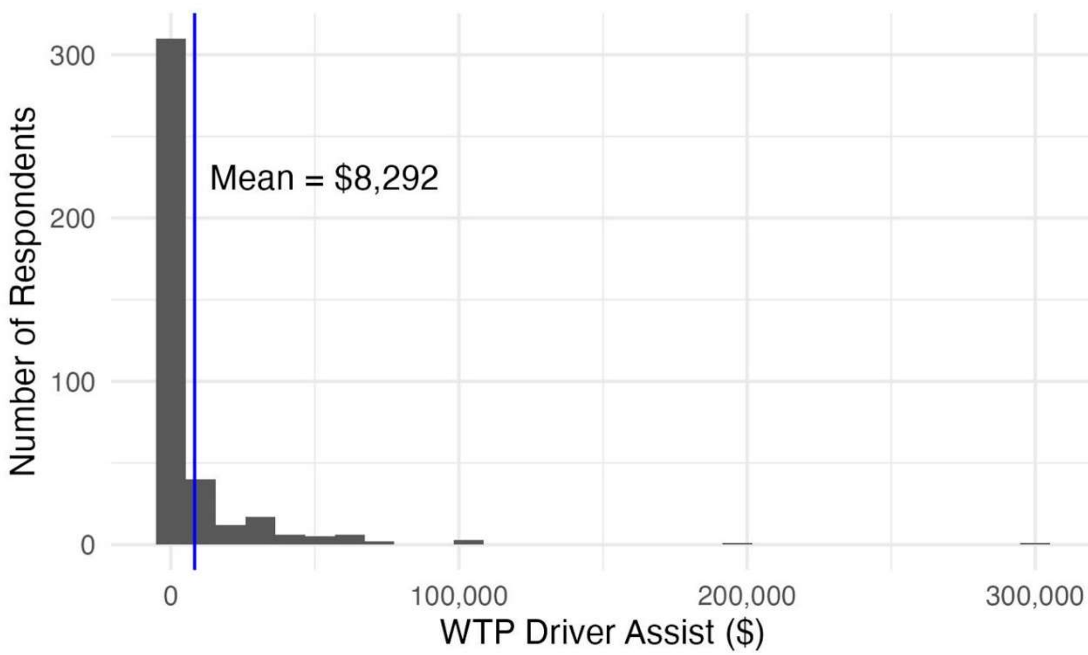


Figure 29. Distribution of responses for willingness to pay for full driver assist

11.5. Predictors of WTP ($) for Full Self-Driving

Linear regression models were used to estimate the direction and magnitude of associations between WTP and individual characteristics. This approach is standard in WTP and behavioral economics research to assess how explanatory factors relate to outcome magnitudes under linear assumptions.

To ensure the appropriateness of both the linear and logistic regression models, diagnostic tests were conducted to verify statistical assumptions. The following checks were performed: (1) multicollinearity (variance inflation factor, VIF), (2) independence (Durbin–Watson test), (3) homoscedasticity (Breusch–Pagan test), (4) normality of residuals (Shapiro–Wilk test), (5) influential outliers (Cook's Distance), (6) linearity, and (7) overall model fit.

The diagnostics indicated low multicollinearity across all models (VIF < 5) and acceptable independence of residuals. Some heteroskedasticity was detected (Breusch–Pagan $p < 0.05$), a common occurrence in WTP survey data due to cross-sectional variability (Jabłońska, 2018; Smetana et al, 2022). Residuals were moderately non-normal, consistent with behavioral economic data, but not severe enough to invalidate inference. To address these deviations, all models were re-estimated using robust standard errors (HC1), providing reliable coefficient estimates.

Model fit indices (Adjusted $R^2 = 0.01–0.06$; Pseudo $R^2 = 0.02–0.22$) were within expected ranges for behavioral survey data (Smetana et al., 2022). While some models contained a higher number of outliers, the robust estimation approach effectively mitigated their influence, ensuring the validity and interpretability of the regression results.

11.5.1. Risk and SDV Trust Scores Predictors for Full Self-Drive WTP

A linear regression analysis was performed to determine if risk score or SDV trust score were predictors for full self-driving WTP when using the full ($n = 403$) participant dataset. There was no statistical significance for SDV trust score on full self-driving WTP, while risk score ($p = 0.038$) was a statistically significant predictor, as shown in Table 40. These results suggest that for each additional point of risk preference, a respondent would have an additional $528.5 in full self-drive WTP.

Table 40. Risk and Trust Score Predictors for Full Self-Drive WTP

Variable	Estimate	Std Error	t-value	p-value
(Intercept)	-6239.5	13568.8	-0.460	0.646
Trust Score	487.6	260.5	1.872	0.062
Risk Score	528.5	253.4	2.086	0.038
Model Fit: F (4, 398) = 7.282, p = 1.146e-05				

11.5.2. Vehicle Ownership Type as Predictor for Full Self-Drive WTP

Linear regression was performed to determine if vehicle type was a predictor for SDV WTP on the reduced dataset (n = 292) of respondents who were willing to pay a premium for full self-driving capability. Vehicle type of do not own a vehicle was a statistically significant predictor (p = 0.046) against a reference of internal combustion engine ownership, as shown in Table 41, where individuals who own these vehicles were willing to pay an additional $11,358 for SDV.

Table 41. Vehicle Ownership Predictors for Full Self-Drive WTP, Positive WTP Responses

Variable	Estimate	Std Error	t-value	p-value
(Intercept)	12612.24	1611.28	7.827	< 0.001
Vehicle Type Reference: Vehicle using gasoline or diesel fuel (Internal Combustion Engines)				
Do not own vehicle	11358.19	5655.72	2.008	0.046
Electric vehicle (battery only)	9759.22	10885.62	0.897	0.371
Hybrid electric/gas vehicle	41257.53	27430.36	1.504	0.134
Vehicle using fuel other than gasoline or diesel	-4557.84	3777.98	-1.206	0.229
Model Fit: F (5,254) = 4.514, p = 0.001				

11.5.3. Impact of Advertising Predictor for Full Self-Drive WTP

A linear regression analysis was performed on the positive WTP only reduced dataset (n = 292) to determine if impact of advertising was a predictor for full self-driving WTP. Impact of advertising was a statistically significant predictor (p = 0.011) on WTP as shown in Table 42. These results suggest that respondents who would shift additional blame to a vehicle manufacturer for SDV collisions and moving violations due to claims made in advertisements will have a lower full self-drive WTP ($2,046 less for each increase in impact of advertising score).

Table 42. Impact of Advertising for Full Self-Drive WTP, Positive WTP Responses

Variable	**Estimate**	**Std Error**	**t-value**	**p-value**
(Intercept)	22608	3175	7.12	0.001
Impact of Advertising	-2046	803	-2.55	0.011
Model Fit: F (1, 290) = 4.141, p = 0.043				

11.6. Predictors of WTP ($) for Driver Assist

11.6.1. Vehicle Ownership Type Predictor for Driver Assist WTP

Linear regression analysis was performed to determine if vehicle type was a predictor for driver assist WTP for the full Experiment 1 respondent pool. There was statistical significance on driver assist WTP for the vehicle types of “do not own a vehicle” (p = 0.013) against a reference of “vehicle using gasoline or diesel fuel,” as shown in Table 43, where non-vehicle owners were willing to pay $9,832 more for an SDV.

Table 43. Vehicle Type Ownership Predictors for Driver Assist WTP

Variable	Estimate	Std Error	t-value	p-value
(Intercept)	4208	1134	3.710	0.001
Vehicle Type Reference: Vehicle using gasoline or diesel fuel (Internal Combustion Engines)				
Do not own vehicle	9832	2942	2.494	0.013
Electric vehicle (battery only)	7485	6779	1.105	0.270
Hybrid electric/gas vehicle	19461	14066	1.384	0.167
Vehicle using fuel other than gasoline or diesel	-2009	3623	-0.555	0.580
Model Fit: F (5,355) = 4. 464, p = 0.001				

11.6.2. Impact of Advertising Predictor for Driver-Assist WTP

A linear regression analysis was performed to determine if the impact of advertising was a predictor for driver assist WTP for the full experiment dataset (n = 403). Impact of advertising is statistically significant (p = 0.004) as shown in Table 44, with results suggest that respondents who would shift additional blame to a vehicle manufacturer will have a lower full self-drive WTP ($1,293 less for each increase in impact of advertising score).

Table 44. Impact of Advertising for Drive Assist WTP

Variable	Estimate	Std Error	t-value	p-value
(Intercept)	10433.4	1641.9	6.354	0.001
Impact of Advertising	-1293.7	440.6	-2.936	0.004
Model Fit: F (1,401) = 5.853, p = 0.016				

11.6.3. Vehicle Ownership Type Predictor for Driver Assist WTP

The linear regression for predicting driver assist WTP on the reduced "Positive Full Self Drive WTP Only" dataset (n = 292) showed significance of vehicle ownership type, as shown in Table 45. Specifically, individuals who do not own a vehicle were willing to pay $9,471 more (p = 0.030) than individuals who own an internal combustion engine vehicle were willing to pay.

Table 45. Vehicle Ownership Predictors for Driver Assist WTP, Positive WTP Responses

Variable	Estimate	Std Error	t-value	p-value
(Intercept)	6469	1114	5.806	0.001
Vehicle Type Reference: Vehicle using gasoline or diesel fuel (Internal Combustion Engines)				
Do not own vehicle	9471	4327	2.189	0.030
Electric vehicle (battery only)	6632	7438	0.892	0.373
Hybrid electric/gas vehicle	24414	17783	1.373	0.171
Vehicle using fuel other than gasoline or diesel	-138	5165	-0.027	0.979
Model Fit: F (5,254) = 4.003, p = 0.002				

11.6.4. Impact of Advertising Predictor for Driver Assist WTP

A linear regression analysis was performed on the "Positive Full Self-Drive WTP Only" subset of the survey response data to determine if the Impact of Advertising was a predictor for driver assist WTP. Impact of advertising is statistically significant ($p = 0.001$) as shown in Table 46, where individuals who are more likely to place blame on the manufacturer are also willing to spend less money on driver assist functionality ($1,856.40 less for each increase in impact of advertising score).

Table 46. Impact of Advertising for Drive Assist WTP, Positive WTP Responses Only

Variable	Estimate	Std Error	t-value	p-value
(Intercept)	14571.9	2218.3	6.569	0.001
Impact of Advertising	-1856.4	573.3	-3.238	0.001
Model Fit: F (1,290) = 6.924, p = 0.009				

11.7. Predictors of WTP (yes/no) for Full Self-Drive

A series of statistical analyses were performed using binary logistic regression on the full dataset of survey responses ($N = 403$) to identify and quantify statistically significant predictors for SDV WTP intention. Note, these models predicted overall willingness to pay for full self-drive (yes/no) rather than the monetary value. SDV WTP responses that were > $0 were assigned "yes" and responses of $0 for SDV WTP were assigned "no." These models were intended to help identify what predictors could be used to assess potential WTP intention within a market segment, and what actions could be taken to increase WTP intention within an evaluated population.

11.7.1. Risk and SDV Trust Scores Predictors for Non-Zero Full Self-Drive WTP

There was statistical significance on premium willingness for comfort score (p = 0.001), but not risk score, as shown in Table 47, where more trust with SDVs was associated with greater WTP intention for SDVs. This suggests that actions with outcomes that increase trust regarding SDV technology could increase the number of population members who have WTP intention.

Table 47. Risk and Trust Score Predictors for Full Self-Drive WTP Willingness

Variable	**Estimate**	**Std Error**	**t-value**	**p-value**
(Intercept)	-2.73	0.62	-4.372	0.001
Trust	0.18	0.02	7.503	0.001
Risk	0.02	0.017	1.056	0.291
Model Fit	**LL**	**DF**	**Chi-Sq**	**p-value**
Model	-188.13	4	98.142	0.001
Null	-237.20	1	--	--

11.7.2. Vehicle Ownership Type Predictor for Non-Zero Full Self-Drive WTP

There was statistical significance on SDV willingness for vehicle type "Do Not Own Vehicle" (p = 0.023), as shown in Table 48. This model did not meet the threshold of significance (p = 0.058), but was retained and reported given that the predictor "Do Not Own a Vehicle" was also a significant predictor in other models.

Table 48. Vehicle Type Ownership Predictors for Full Self-Drive Premium Willingness

Variable	Estimate	Std Error	t-value	p-value
(Intercept)	0.850	0.122	6.966	0.001
Vehicle Type Reference: Vehicle using gasoline or diesel fuel (Internal Combustion Engines)				
Do not own vehicle	1.229	0.55	2.245	0.025
Electric vehicle (battery only)	1.347	1.07	1.262	0.207
Hybrid electric/gas vehicle	0.302	0.49	0.621	0.534
Vehicle using fuel other than gasoline or diesel	-0.339	0.75	-0.456	0.649

Model Fit	LL	DF	Chi-Sq	p-value
Model	-232.63	5	9.146	0.058
Null	-237.30	1	--	--

11.8. Discussion

The survey findings provide evidence of measurable shifts in consumer WTP for SDV technology. Compared to earlier U.S. studies, a larger portion of respondents in this sample expressed some level of willingness to pay, and the average stated dollar amounts were higher overall. These results suggest a growing openness to SDV functionality that may have implications for transportation planning, infrastructure readiness, and long-term technology adoption timelines.

It is important to note, however, that these observed changes represent statistically significant effects within our study sample rather than population-level trends. While the results point to evolving consumer attitudes, they should be interpreted as indicative of potential national patterns rather than definitive estimates.

When compared with previous studies, our results indicate a modest upward shift in both the proportion of respondents expressing WTP for SDV technology and the mean magnitude of that WTP. For example, Rahimi et al. (2020) reported that approximately 30% of respondents unwilling to pay for SDV capability, which is comparable to our finding of 27.5%. Meanwhile, mean WTP values increased relative to prior studies, Bansal et al. (2017) reported $5,857 and Orthman (2023) reported $6,000 to $8,412, whereas our adjusted estimate (after outlier removal) was $9,650. However, the median WTP in our dataset ($5,000) remained below these earlier averages, suggesting that while high-value respondents are raising the mean, most consumers remain cautious about paying large premiums for SDV functionality.

These updated WTP estimates (both mean and median) can assist civil engineers in anticipating when SDV adoption may become economically feasible. Comparing SDV and conventional vehicle price trajectories can help identify inflection points where widespread consumer adoption becomes likely, a key input for infrastructure investment, cost-benefit analyses, and automation-readiness assessments.

For driver assist technology, the mean WTP in our study ($8,292) exceeded the $3,300 reported by Bansal et al. (2016), though the median remained comparatively low ($1,000). These results suggests that while the interest in automated assistance features continues to grow, overall willingness to pay remains limited for much of the population, indicating ongoing price sensitivity.

Advertising effects were statistically significant in three of the five regression models, while SDV comfort and vehicle ownership type were consistently significant predictors of WTP. Respondents more comfortable with SDV technology or without vehicle ownership showed greater willingness to pay for full automation. In contrast, respondents with higher risk preferences tended to have higher WTP magnitudes, and those more inclined to assign manufacturer blame in advertising contexts expressed lower WTP for driver-assist features. Table 49 summarizes the statistically significant predictors for SDV WTP, SDV WTP magnitude, and driver assist WTP magnitude.

Table 49. Summary of Statistically Significant Predictors for Regression Models

Predictor	Full Survey Population			Positive SDV WTP	
	Self-Drive ($)	Driver Assist ($)	Self-Drive (yes/no)	Self-Drive ($)	Driver Assist ($)
Risk and SDV Comfort Scores Models					
Risk Score	yes	no	no	yes	no
SDV Trust Score	no	no	yes	no	no
Vehicle Ownership Type Models (ref. Gas or Diesel)					
Do Not Own Vehicle	yes	yes	yes	yes	yes
Impact of Advertising Models					
Impact of Advertising Score	no	yes	no	yes	yes

The results of this experiment indicate that both the prevalence and magnitude of WTP for SDV technology within the U.S. population continue to evolve. While a growing share of respondents expressed some willingness to pay, the median monetary value decreased relative to previous surveys, suggesting that extreme outliers heavily influence the mean and the broad market affordability remains limited. Ongoing monitoring of WTP trends is therefore recommended to support forecasting of SDV adoption timelines and to inform infrastructure investment and policy planning associated with automated mobility systems.

Given that SDV comfort emerged as a statistically significant predictor of WTP, future surveys should continue to include measures of perceived comfort and trust in automation. Tracking this metric will help quantify how increasing public familiarity with SDVs affects both adoption readiness and willingness to pay over time, factors critical for civil engineers and planners evaluating infrastructure adaptability and safety design standards.

Additionally, advertising influence was found to affect WTP outcomes, underscoring the importance of transparency in communicating SDV capabilities. Accurate public messaging can help maintain consumer trust and support evidence-based infrastructure planning, avoiding mismatches between perceived and actual SDV functionality that could impact roadway operations and safety expectations.

Chapter 12. Aim 4 Results – Tax and Fee Preferences for Oversight and Infrastructure Funding

12.1. Introduction

Commercial viability of SDVs requires that the increased cost of an SDV relative to a human-driven equivalent vehicle is less than the premium a consumer is willing to pay for a self-driving vehicle versus an equivalent vehicle without self-drive capability. Experiment 1 captured the willingness to pay for both full self-driving and advanced driver assist capability from 403 participants. Analysis of this data helped to answer the following research questions in support of Research Aim 4:

- **RQ4.1:** What method of funding for the regulatory framework and infrastructure is least opposed by the general population of the United States?
- **RQ4.2:** Are risk tolerance, SDV familiarity, SDV trust, or demographic factors significant predictors of preferences for funding methods for SDV oversight and infrastructure investment in the United States?

The results of this chapter were submitted to the journal *Transportation Policy* titled "Paying for Autonomous Vehicle Instructure and Effective Oversight: Preferences for Funding Methods" (Stewart et al, TBD).

The integration of Self-Driving Vehicles (SDVs) into transportation systems presents a range of challenges for the agencies responsible for road infrastructure, safety, and transportation policy. As SDVs become more prevalent, their use will require significant investments in regulatory enforcement, infrastructure adaptation, and public adoption incentives. These investments raise critical questions about how these efforts should be funded and which funding mechanisms are most publicly acceptable.

Conventional funding mechanisms typically rely upon economic instruments of taxes and/or user fees. Previous attempts to increase existing fuel taxes or implement mileage taxes in lieu of fuel taxes have been met with public opposition, even when the fees were to improve the quality of infrastructure (Nelson & Rowangould, 2024; Rodriguez & Pulugurtha, 2020; Metcalf, 2023). Ensuring public acceptance of funding mechanisms for SDV implementation is crucial to avoid public resistance that could hinder SDV adoption. Understanding which funding methods are most tolerated, and the factors influencing user acceptance, can help policymakers implement strategies that align with public preferences. To the best of our knowledge, data are not readily available on the acceptance of these methods. To explore these preferences, a survey was conducted with a sample of respondents from the United States that included a funding profile discrete choice experiment. This chapter presents the results of that experiment and identifies funding preferences and their predictors.

12.2. Methods

A discrete choice experiment was conducted to evaluate preferences for funding infrastructure improvements and oversight of self-driving technologies among a respondent population (n = 403). The study adhered to ethical principles for human subject testing and had approval from the Colorado State University Institutional Review Board (IRB), protocol #5825. Respondent demographic data is captured in Section 3.2, the design of the experiment is described in Section 3.12, and data clean up methodology is described in Section 3.11.

Analysis of the data from the discrete choice experiment was conducted using RStudio (R version 4.4.0). Binary logistic regression with mixed effects was used to model funding method preference, using methods similar to previous studies that examined autonomous vehicle adoption (Alnajjar et al., 2023), taxi-driver decision making processes (Szeto et al., 2019), and decisions regarding decoupling parking assignments from apartment leasing (De Gruyter et al., 2024) The dependent variable was the funding profile selection decision (yes/no) for that given participant for the given discrete choice question. Independent variables included demographic factors, SDV trust levels, annual average miles driven, and type of vehicle owned. The model was fit using maximum likelihood estimation (Laplace approximation and included random intercepts for both respondent ID and the Block ID of the block of experiment questions shown to the respondent. These intercepts account for variations within participants, specifically any possible influences of individual preferences or influences caused by the blocking of specific survey questions together. A likelihood ratio test (LRT) was conducted to compare a null model using only random intercepts for participants (ID) and blocks (Block_ID) against the full model to validate model fit.

The fixed effects in the models accounted for the percentage allocations to each of the funding sources. Such that, there was a fixed effect for mileage tax, vehicle tax, fuel tax, and self-drive subscription, with each having possible levels of 0, 0.2, 0.4, 0.6, 0.8, or 1.0. To avoid perfect multicollinearity, the funding option of "increase price of vehicle" was dropped from the model, as the percentage allocation for "increase price of vehicle" could be exactly predicted based on the other four independent variables. The coefficients for mileage tax, vehicle tax, fuel tax, and self-drive subscription represented a comparison to the baseline of an increase in the price of vehicle capable of self-driving. Positive intercept values suggest a preference for the funding method versus paying an increased vehicle price, while a negative intercept value suggests a preference for a higher vehicle price versus the alternative funding method.

The binary logistic models also included interaction terms, allowing the model to determine if the effect of the funding method (Mileage Tax, Fuel Tax, Self-Driving Subscription, or Vehicle Tax) changed with changes in a predictive variable. Models containing interactions for each permutation of funding method and predictive variable were run to identify significant predictors ($p < 0.05$) of funding method tolerance. Investigated predictive variables included demographics variables, SDV trust scores, vehicle ownership type, and annual miles driven. A causal loop diagram was built using Vensim (version 10.3.0) to summarize the significant predictors identified in the binary logistic models.

12.3. Results

This section summarizes the relevant experiment results and analysis supporting Research Aim 4, including results on funding method preferences, predictors of preferences, and numeric values for significant predictors not previously defined in other sections.

12.3.1. Experiment 1 Miles Driven Data

Data was collected regarding average number of miles driven by the Experiment 1 participant population and summarized in Table 50. The participant population includes non-drivers (0 miles driven per year) to heavy drivers who drive up to 100,000 miles per year based on participant estimates. The mean number of miles driven per year by the participant population is 10,400, with a standard deviation of 13,164 miles.

Table 50. Summary of Annual Miles Driven for Experiment 1 Respondents

Characteristic	**Min**	**Max**	**Mean**	**Std Dev**
Annual Miles Driven	0	100,000	10,412	13,164

12.3.2. General Funding Method Preferences

A binary logistic regression analysis with mixed effects was performed to evaluate funding preferences for the total experiment participant participation, with results shown in Table 51. The results of this analysis showed a strong dislike for additional fuel taxes ($\beta = -1.391$, $p < .001$) and a dislike of additional mileage taxes ($\beta = -0.447$, $p < .001$), both compared to an increased vehicle price. Respondents showed a preference for self-driving subscriptions ($\beta = 0.424$, $p < .001$) over increased vehicle prices. However, respondents had no significant preference of vehicle tax compared to an increase in vehicle price ($p = .678$).

Table 51. Funding Method Predictors for Oversight Funding Profile Selection

Variable	**Estimate**	**Std Error**	**z-value**	**p-value**
(Intercept)	0.280	0.082	3.423	< .001
Mileage Tax	-0.447	0.121	-3.682	< .001
Fuel Tax	-1.391	0.127	-10.933	< .001
Vehicle Tax	-0.051	0.124	-0.415	.678
Self-Drive Subscription	0.424	0.121	3.513	< .001
Model Fit	**LL**	**DF**	**Chi-Sq**	**p-value**
Model	-3625.9	7	250.79	< .001
Null	-3571.3	3	--	--

12.3.3. Impact of Vehicle Ownership on Preferences for Funding Methods

The binary logistic models utilized interaction terms to determine the significance of vehicle ownership type on preferences for the candidate funding methods, modeled as an interaction term between vehicle ownership type with each funding method (e.g., vehicle ownership type x fuel tax).

12.3.4. Vehicle Ownership Type as Predictor of Fuel Tax Preference

For respondents who did not own a vehicle, there was a strong preference for fuel taxes versus increased vehicle prices (β = 1.115, $p < .001$). Similarly, for owners of electric / hybrid vehicles, a preference for fuel taxes over increased vehicle prices was observed (β = 0.775, $p = .025$), as shown in Table 52.

Table 52. Vehicle Ownership Type Predictor for Acceptance of Fuel Taxes

Variable	**Estimate**	**Std Error**	**z-value**	**p-value**
(Intercept)	0.332	0.088	3.754	< .001
Mileage Tax	-0.475	0.126	-3.755	< .001
Fuel Tax	-1.638	0.142	-11.495	< .001
Vehicle Tax	-0.056	0.127	-0.441	.659
Self-Drive Subscription	0.419	0.122	3.420	< .001
Vehicle Ownership (reference ICE)				
Do Not Own Vehicle	-0.214	0.118	-1.818	.069
Electric / Hybrid Vehicle	-0.143	0.117	-1.229	.219
Fuel Tax x Vehicle Ownership				
Fuel Tax × Do Not Own Vehicle	1.115	0.338	3.297	< .001
Fuel Tax × Electric / Hybrid Vehicle	0.775	0.346	2.238	.025
Model Fit	**LL**	**DF**	**Chi-Sq**	**p-value**
Model	-3676.5	8	266.86	< .001
Null	-3543.0	1	--	--

12.3.5. Vehicle Ownership Type as Predictor of Mileage Tax Preference

For owners of electric / hybrid vehicles, there was a strong dislike for mileage taxes versus increased vehicle prices observed (β = -2.053, $p < .001$), as shown in

Table 53.

Table 53. Vehicle Ownership Type Predictor for Acceptance of Mileage Taxes

Variable	**Estimate**	**Std Error**	**z-value**	**p-value**
(Intercept)	0.274	0.088	3.104	.001
Mileage Tax	-0.372	0.135	-2.760	.005
Fuel Tax	-1.444	0.131	-10.959	< .001
Vehicle Tax	-0.045	0.127	-0.356	.721
Self-Drive Subscription	0.420	0.122	3.428	< .001
Vehicle Ownership (reference ICE)				
Do Not Own Vehicle	-0.079	0.120	-0.663	.507
Electric / Hybrid Vehicle	0.296	0.121	2.449	.014
Mileage Tax x Vehicle Ownership				
Mileage Tax × Do Not Own Vehicle	0.405	0.347	1.167	.243
Mileage Tax × Electric / Hybrid Vehicle	-2.053	0.755	-2.720	< .001
Model Fit	**LL**	**DF**	**Chi-Sq**	**p-value**
Model	-3540.3	8	272.3	< .001
Null	-3676.5	1	--	--

12.3.6. Vehicle Ownership Type as Predictor of Self-Drive Subscription Preference

Among respondents who did not own a vehicle, there was a strong dislike for self-driving subscriptions versus increased vehicle prices (β = -0.874, p = .008), as shown in

Table 54.

Table 54. Vehicle Ownership Type Predictor for Acceptance of Self-Drive Subscriptions

Variable	**Estimate**	**Std Error**	**z-value**	**p-value**
(Intercept)	0.280	0.088	3.167	.001
Mileage Tax	-0.473	0.126	-3.736	< .001
Fuel Tax	-1.456	0.131	-11.053	< .001
Vehicle Tax	-0.049	0.127	-0.390	.696
Self-Drive Subscription	0.505	0.132	3.828	< .001
Vehicle Ownership (reference ICE)				
Do Not Own Vehicle	0.188	0.121	1.545	.122
Electric / Hybrid Vehicle	0.018	0.119	0.157	.874
Self-Drive Subscription x Vehicle Ownership				
Self-Drive Subscription × Do Not Own Vehicle	-0.874	0.331	-2.634	.008
Self-Drive Subscription × Electric / Hybrid Vehicle	-0.077	0.339	-0.228	.819
Model Fit	**LL**	**DF**	**Chi-Sq**	**p-value**
Model	-3546.6	8	259.21	< .001
Null	-3676.5	1	--	--

12.3.7. Miles Driven as Predictor of Fuel Tax Preference

Respondents with higher annual miles driven preferred fuel taxes versus increased vehicle prices (β = 0.026, p = .043), as shown in

Table 55. It should be noted that all respondents were included in this model, including respondents who did and did not own a personal vehicle.

Table 55. Miles Driven Predictor for Acceptance of Fuel Taxes

Variable	**Estimate**	**Std Error**	**z-value**	**p-value**
(Intercept)	0.304	0.087	3.493	< .001
Mileage Tax	-0.481	0.126	-3.801	< .001
Fuel Tax	-1.461	0.131	-11.081	< .001
Vehicle Tax	-0.058	0.127	-0.454	.649
Self-Drive Subscription	0.407	0.122	3.320	< .001
Miles Driven	-0.041	0.035	-1.174	.240
Fuel Tax × Miles Driven	0.206	0.102	2.021	.043
Model Fit	**LL**	**DF**	**Chi-Sq**	**p-value**
Model	-3547.9	6	257.0	< .001
Null	-3676.5	1	--	--

12.3.8. Miles Driven as Predictor of Mileage Tax Preference

Respondents with higher annual miles driven also disliked mileage taxes versus increased vehicle prices ($\beta = -0.395$, $p = 0004$) as shown in Table 56.

Table 56. Miles Driven Predictor for Acceptance of Mileage Taxes

Variable	**Estimate**	**Std Error**	**z-value**	**p-value**
(Intercept)	0.295	0.086	3.414	< .001
Mileage Tax	-0.476	0.126	-3.755	< .001
Fuel Tax	-1.443	0.131	-10.952	< .001
Vehicle Tax	-0.045	0.127	-0.358	.720
Self-Drive Subscription	0.417	0.122	3.404	< .001
Miles Driven	0.071	0.038	1.840	.065
Mileage Tax × Miles Driven	-0.395	0.137	-2.870	.004
Model Fit	**LL**	**DF**	**Chi-Sq**	**p-value**
Model	-3545.3	6	262.31	< 0.001
Null	-3676.5	1	--	--

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12.3.9. Trust Score as Predictor of Fuel Tax Preference

Respondents with higher SDV trust scores had a preference for fuel taxes versus increased vehicle prices (β = 0.033, p = .009) as shown in Table 57.

Table 57. Trust Score Predictor for Acceptance of Fuel Taxes

Variable	**Estimate**	**Std Error**	**z-value**	**p-value**
(Intercept)	0.422	0.124	3.409	< .001
Mileage Tax	-0.475	0.126	-3.759	< .001
Fuel Tax	-2.157	0.303	-7.106	< .001
Vehicle Tax	-0.055	0.127	-0.438	.661
Self-Drive Subscription	0.414	0.122	3.381	< .001
SDV Trust Score	-0.005	0.004	-1.387	.165
Fuel Tax × SDV Trust Score	0.033	0.012	2.609	.009
Model Fit	**LL**	**DF**	**Chi-Sq**	**p-value**
Model	-3546.6	6	259.6	< .001
Null	-3676.6	1	--	--

12.3.10. SDV Trust Score as Predictor of Self-Drive Subscription Preference

Support for self-drive subscriptions versus increased vehicle prices was less likely for respondents with higher SDV trust scores (β = -0.031, p = .012) as shown in

Table 58. This finding is consistent with the reduced support shown for self-drive subscriptions by owners of electric/hybrid vehicles and respondents who did not own a vehicle, as the mean trust score for electric/hybrid vehicle owners (mean = 23.3) and those who did not own a vehicle (mean = 22.8) were higher than standard vehicle owners (mean = 20.4).

Table 58. Trust Score Predictor for Acceptance of Self-Drive Subscriptions

Variable	Estimate	Std Error	z-value	p-value
(Intercept)	0.162	0.124	1.304	.192
Mileage Tax	-0.473	0.126	-3.741	< .001
Fuel Tax	-1.456	0.131	-11.060	< .001
Vehicle Tax	-0.049	0.127	-0.388	.697
Self-Drive Subscription	1.057	0.286	3.694	< .001
SDV Trust Score	0.006	0.004	1.527	.126
Self-Drive Subscription × SDV Trust Score	-0.031	0.012	-2.505	.012
Model Fit	**LL**	**DF**	**Chi-Sq**	**p-value**
Model	-3546.9	6	259.14	< .001
Null	-3676.5	1	--	--

12.3.11. Education Level on Mileage Tax

Respondents provided the highest level of completed education as part of the survey. For the purposes of the model, education levels of “Master’s Degree”, “Professional Degree”, and “Doctorate Degree” were combined into a single “Graduate Degree” category to account for low respondent numbers for the contributing categories. Reference education level for the model was a high school diploma.

A strong opposition for mileage taxes versus increased vehicle prices was observed for respondents with a Bachelor’s degree ($\beta = -1.238$, $p < 0.001$), a Graduate Degree ($\beta = -1.486$, $p < 0.001$), and Some College ($\beta = -1.251$, $p < 0.001$), and lesser opposition from those with an Associate’s Degree ($\beta = -0.626$, $p < 0.001$), as shown in

Table 59.

Table 59. Education Predictor for Acceptance of Mileage Taxes

Variable	Estimate	Std Error	z-value	p-value
(Intercept)	0.072	0.121	0.594	.552
Mileage Tax	0.572	0.268	2.130	.003
Fuel Tax	-1.445	0.131	-10.956	< .001
Vehicle Tax	-0.045	0.127	-0.359	.719
Self-Drive Subscription	0.422	0.122	3.435	< .001
Education Level (reference HS diploma)				
Some College	0.272	0.116	2.328	.019
Associate’s Degree	0.133	0.132	1.013	.310
Bachelor’s Degree	0.272	0.109	2.484	.012
Graduate Degree	0.322	0.128	2.516	.011
Mileage Tax x Education Level				
Mileage Tax × Some College	-1.251	0.326	-3.832	< .001
Mileage Tax × Associate’s Degree	-0.626	0.372	-1.682	.092
Mileage Tax × Bachelor’s Degree	-1.337	0.311	-4.290	< .001
Mileage Tax × Graduate Degree	-1.486	0.357	-4.152	< .001
Model Fit	**LL**	**DF**	**Chi-Sq**	**p-value**
Model	-3536.7	12	279.44	< .001
Null	-3676.5	1	--	--

12.3.12. Education Level on Self-Drive Subscription

A preference for self-drive subscriptions over increased vehicle prices was observed for respondents with a Bachelor’s degree ($\beta = 1.240$, $p < .001$), a Graduate Degree ($\beta = 1.178$, $p = .001$), and Some College ($\beta = 1.136$, $p < .001$), as shown in

Table 60.

Table 60. Education Predictor for Acceptance of Self-Drive Subscriptions

Variable	Estimate	Std Error	z-value	p-value
(Intercept)	0.498	0.121	4.096	< .001
Mileage Tax	-0.481	0.126	-3.804	< .001
Fuel Tax	-1.449	0.131	-10.999	< .001
Vehicle Tax	-0.053	0.127	-0.419	.674
Self-Drive Subscription	-0.572	0.270	-2.117	.034
Education Level (reference HS diploma)				
Some College	-0.221	0.116	-1.908	.056
Associate's Degree	-0.181	0.131	-1.379	.167
Bachelor's Degree	-0.257	0.109	-2.355	.018
Graduate Degree	-0.231	0.126	-1.824	.068
Self-Drive Subscription x Education Level				
Self-Drive Subscription × Some College	1.136	0.331	3.430	< .001
Self-Drive Subscription × Associate's Degree	0.888	0.375	2.363	.018
Self-Drive Subscription × Bachelor's Degree	1.240	0.310	3.990	< .001
Self-Drive Subscription × Graduate Degree	1.178	0.366	3.221	.001
Model Fit	**LL**	**DF**	**Chi-Sq**	**p-value**
Model	-3541.1	12	271.93	< .001
Null	-3676.5	1	--	--

12.3.13. Synthesis of Results

A causal loop diagram was developed to visualize the interactions among significant predictors from the models above and their influence on funding preferences, see Figure 30. In the diagram, negative signs next to the arrow indicate factors associated with lower preference for a given funding mechanism, while positive arrows indicate factors associated with a higher preference.

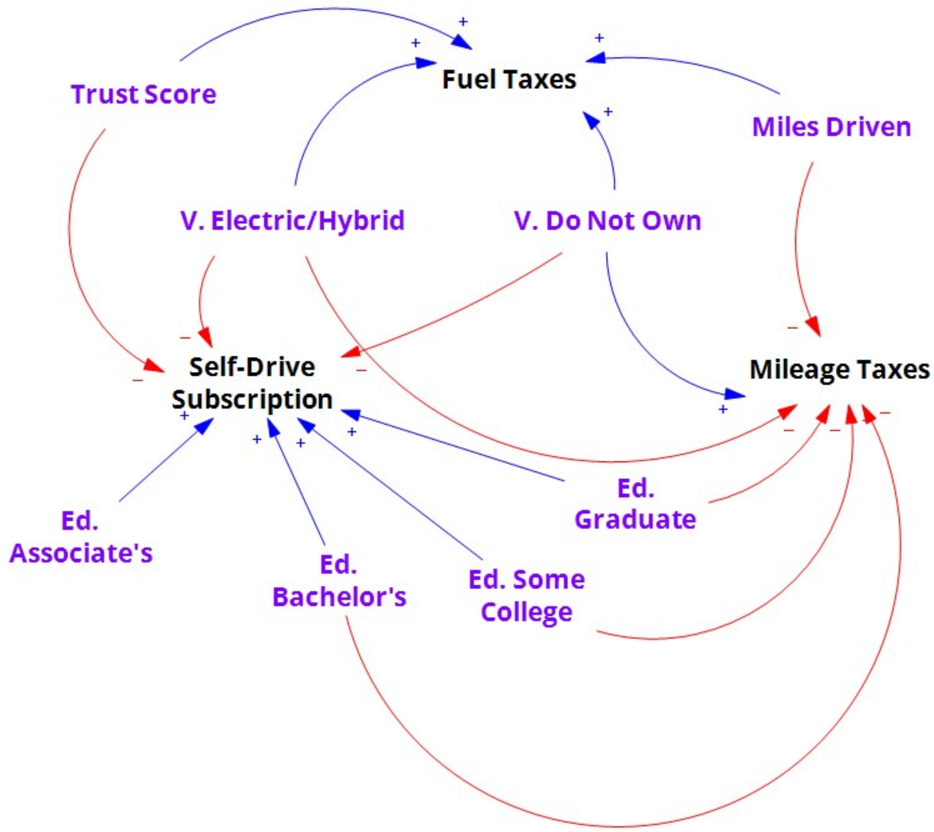


Figure 30. Interaction model for significant predictors on acceptance of taxes and fees

12.4. Discussion

This experiment provides new insight into public preferences for funding mechanisms to support the infrastructure and oversight needs associated with widespread self-driving vehicle (SDV) adoption. By identifying significant predictors of support, and opposition, for different revenue options – including fuel taxes, milage-based taxes, and self-driving subscription feeds – this research highlights the complex interplay between demographic factors, trust in SDVs, and vehicle ownership patterns.

Results indicate a strong preference among the survey population for increased vehicle prices instead of increases in fuel or vehicle taxes to provide revenue to support SDV adoption, along with a preference for funding via self-driving subscriptions versus an increase in vehicle prices. These findings are consistent with previous literature on the topic of improving transportation, though not specific to SDVs, with taxes, where participants preferred a general sales tax increase (55%) versus a gas tax increase (31%) or a mileage tax (24%) (Agrawal et al., 2023). This suggests a general preference for the cost of supporting SDV adoption be funded by those who will use the SDV technology through either the cost of a new, self-driving capable vehicle or through a monthly subscription to be able to use the self-driving technology. Using increased new vehicle prices and subscriptions would also ensure that non-self-driving capable vehicle owners are not required to provide some of the revenue needed to support SDV adoption.

Funding method preferences were influenced by factors such as vehicle ownership, annual miles driven, comfort with self-driving vehicles, and level of education. For example, owners of hybrid or electric vehicles had a greater preference for fuel taxes than owners of standard internal combustion engine vehicles, while at the same time hybrid and electric vehicle owners had greater opposition to mileage taxes versus respondents who drive standard gasoline or diesel vehicles. This result is expected as electric and hybrid vehicle owners are less impacted by increases in fuel taxes versus owners of standard vehicles. For those who do not own a personal vehicle, there was an observed preference for fuel taxes when compared to the preferences of standard vehicle owners. Non-vehicle owners also expressed a stronger opposition to self-drive subscriptions than standard ICE vehicle owners. Opposition to self-driving subscriptions by non-vehicle owners is consistent with previous literature that showed concerns about reduction in public transportation as a result of autonomous vehicle adoption (Wu et al., 2021), and concerns that individuals without access to smart phone technology would not be able to benefit from subscription-based, app controlled autonomous vehicle services (Lee & Kockelman, 2022).

Results also indicated that the average number of miles driven per year influenced funding method preferences, with those who drive more miles each year having higher opposition to mileage taxes and greater acceptance of fuel taxes versus those who drive a lower number of miles per year. This finding contradicts patterns observed in previous studies, where miles driven did not have an impact on tolerance of mileage taxes (Agrawal & Nixon, 2024).While the result regarding opposition to mileage taxes increasing with number of miles driven is intuitive, the higher preference for fuel taxes for respondents who have higher average miles driven per year suggest the result is influenced by responses from drivers of electric and hybrid vehicles who are less impacted by increased fuel taxes than respondents who own conventional gasoline and diesel vehicles.

Education was also a significant predictor for preferences regarding funding sources for SDV adoption. Participants who had completed some college, held an Associate's Degree, held a Bachelor's Degree, or held a Graduate Degree were more opposed to mileage taxes than high school graduates, while those same respondents showed a preference for the self-drive subscription funding mechanism versus increased vehicle prices when compared to high school graduates. This suggests that those with more than a high school education would prefer a funding mechanism where only those who are using self-driving technology are responsible for providing the revenue needed to support the infrastructure improvements and government oversight of the technology. Lack of support for a mileage tax is consistent with previous studies where supporters of a mileage tax were a minority (32%) in the United States (Nelson & Rowangould, 2024).

Trust scores were predictors of preference for both fuel taxes and self-driving subscriptions, with those having a higher comfort score showing stronger preference for increasing the fuel tax while at the same time opposing the imposition of self-driving subscriptions. Given that owners of electric/hybrid vehicles and non-vehicle owners had higher mean trust scores and also favored fuel taxes and disliked self-drive subscriptions, this result is consistent with other findings within the survey.

The findings presented in this experiment address a critical gap in the literature by exploring how public toward funding strategies may affect the feasibility and acceptance of future transportation policies. Understanding these preferences is essential for policymakers seeking to implement sustainable, publicly supported funding models in an evolving mobility landscape. This study suggests that the respondent population has strong preferences for the costs associated with the adoption of SDVs to be borne by those who are planning to utilize self-driving technology, with increased new vehicle prices and self-driving subscriptions being the preferred funding methods for SDV adoption. The exception to this observation is that respondents who do not own a vehicle opposed the self-drive subscription model. Additionally, mileage taxes were generally disliked by respondents, except for those who did not own a vehicle. Fuel taxes are opposed by a majority of respondents, though owners of hybrid or electric vehicles and non-vehicle owners prefer fuel taxes versus increases in vehicle price. Finally, vehicle taxes, while less preferred than increased vehicle prices, were less disliked than fuel taxes or mileage taxes within the sample. Based on these observations, funding for SDV implementation should be raised via increased vehicle prices and self-driving subscriptions, with funds being dispersed to the entities responsible for infrastructure maintenance and SDV oversight.

Chapter 13. Aim 5 Results – Effectiveness of Human Oversight on Autonomous Systems

13.1. Introduction

Self-driving vehicles (SDVs) are often associated with potential benefits related to safety, roadway efficiency, and environmental sustainability. However, recent deployments of SDVs on public roadways have revealed a more complex reality in which automated driving systems can make critical errors, resulting in crashes, injuries, and fatalities. Such incidents raise concerns regarding the reliability of SDV technologies and the roles humans are expected to play when automation fails.

These concerns have extended beyond technical performance to questions of legal responsibility. Vehicle manufacturers such as Tesla, Waymo, and Cruise have faced lawsuits relating to their automated driving systems (Kropka, 2023); Ingram and Pinero, 2025). In response, these companies have often utilized a recurring defense based on the assertion that drivers were informed that SDV systems require active human supervision and that responsibility for crashes should therefore be shared with the driver. This argument rests on the assumption that human occupants can effectively monitor highly automated systems and intervene when necessary. However, it remains unclear whether humans can realistically maintain effective oversight, and how descriptions of SDV capabilities and the frequency of system failures influence the effectiveness of that oversight.

The importance of human oversight within SDV safety architectures creates a need to fully understand how well human oversight can catch automated system failures and the impacts of automated system failure rates and system capability framing on that oversight. This understanding can only be gained through experimental testing of the oversight effectiveness of human participants. The data from this experimental effort can help answer the following research questions:

- **RQ5.1:** What impact, if any, does positive framing have on the effectiveness of driver oversight of a TSR AI on an SDV?
- **RQ5.2:** What impact, if any, does a frequency of errors by a TSR AI have on the effectiveness of driver oversight of that system?
- **RQ5.3:** What impact, if any, does framing of TSR capability and TSR error frequency have on user trust of a TSR system?
- **RQ5.4:** Are Manchester DBQ values, SDV familiarity, SDV trust, or demographic factors significant predictors of oversight effectiveness?

The results of this chapter were submitted to a journal and are under review, paper titled "Human Oversight of Traffic Sign Recognition: Impact of Error Rates and Framing on Effectiveness" (Stewart & Gallegos, 2026).

13.2. Human Oversight and SDV Traffic Safety Liability

Previous studies have raised doubts about the effectiveness of human oversight of automated driving systems, citing factors such as driver distraction and alerting methods that impact oversight performance (Zhang et al., 2019; Boyle et al., 2013). Research has also shown that driver vigilance declines more severely in automated driving scenarios compared to manual driving scenarios (Lin et al., 2025). Additional observed challenges to effective human oversight of self-driving systems include driver complacency and loss of situational awareness (Lu et al., 2016). These findings have prompted researchers to suggest the need for feedback mechanisms within SDVs to help sustain effective human oversight over extended durations (Lin et al., 2025; de Winter et al., 2014). Research also indicates that such feedback mechanisms must be carefully designed to avoid the appearance of inconsistent protocols (Suryana et al., 2025) and excessive oversight requests that could produce "cry wolf" effects (Xu et al., 2022).

Human oversight has also emerged as a central issue in legal discussions surrounding SDV-related crashes. From a legal standpoint, human oversight during automated driving has been identified as a significant factor in emerging case law addressing the extent of manufacturers liability for traffic collisions and moving violations involving their SDVs. Previous literature remains divided on the feasibility of using a human supervision defense strategy to mitigate or shift liability for injuries and damages caused by malfunctioning SDVs. Some studies conclude that manufacturers should have only limited protection under a human supervision argument; however, other cases demonstrate that supervision-based defenses have resulted in shared liability between the manufacturer and the vehicle driver, or even a complete shift of blame to the driver (Marchant and Bazzi, 2020).

Recent legal actions against Cruise and Waymo illustrate how supervision arguments have focused on warnings contained in vehicle user manuals and on accident scenarios involving drivers who were sleeping or otherwise engaged in non-supervisory activities while the vehicle was moving (Kropka, 2023). Tesla has also faced litigation related to its self-driving technology, including a 2025 jury verdict finding Tesla partially responsible for an accident despite Tesla's claims that the driver failed to properly supervise the Autopilot system and did not brake when the autonomous system behaved unsafely (Ingram & Pinero, 2025). Additional research suggests that manufacturer advertising of their product may further influence blame assignment for SDV failures. One study found that a majority of survey respondents increased blame assignment to the manufacturer across four hypothetical scenarios involving SDV traffic sign recognition (TSR) failures when the manufacturer advertised that human supervision was not required (Stewart & Gallegos, 2025a).

13.3. Impact of Framing on Perception of Autonomous Technologies

Framing has been widely used as a predictive variable in studies evaluating trust in self-driving vehicles and the effectiveness of human oversight of automated technologies. Prior work has employed a range of framing approaches, including capability framing through the presentation of trust-promoting or trust-reducing videos of self-driving vehicles (Cegarra et al., 2025), as well as descriptive labels such as "advanced" or "highly automated" to frame the system's capability (Dixon et al., 2023). Other studies have examined how users' mental models of automated systems influence trust, particularly in scenarios where over-trust may lead to system use under conditions that increase the likelihood of a collision (Merriman et al., 2023). Findings from these studies suggest that expectations and perceptions of advanced driver assistance system (ADAS) features are influenced by the names of those features (Harms & den Berghe, 2025), and that information about system reliability can also promote trust in the system Li et al., 2025). In addition, initial expectations of automation reliability often match the explicit reliability and capability framing presented prior to interacting with the system (Barg-Walkow & Rogers, 2015).

Framing has also been shown to directly influence user trust and blame attribution in autonomous systems. One study found that utilitarian framing enhances trust in autonomous systems in accidents with high-severity outcomes in individualist countries (such as the United States), while undermining trust in more collectivist societies (such as China) (Teychenie et al., 2026). This same study also demonstrated that risk-based system descriptions can calibrate user trust and, by extension, oversight performance (Teychenie et al., 2026). In another study, framing SDVs as superior to human drivers in terms of reaction speed and accuracy affected post-accident trust and blame attribution, with more blame assigned to SDVs for unpredictable scenarios and more blame assigned to human drivers for predicable events (Zhang et al., 2024). The authors noted that mismatched framing could both erode trust in the system and foster over- or under-reliance on the automated technology. Additional research has shown that describing an autonomous system as a moral agent rather than a tool increases user trust in the system, with a stronger effect than system performance alone (Hurst & Sintov, 2022).

To further extend this line of research, an experiment was conducted to evaluate driver trust in the system following exposure to a TSR system capability framing statement and a simulated video of SDV TSR performance. The goal of the experiment was to examine how capability framing and perceived system reliability shape trust in automated driving technologies.

13.4. Manchester Driver Behaviour Questionnaire

The Manchester Driver Behaviour Questionnaire (DBQ) was originally developed by Reason et al. (1990) as a research instrument for examining whether the frequency of drivers committing errors or violations was associated with the occurrence of traffic accidents. In this framework, errors are defined as unintended outcomes arising from involuntary actions, while violations refer to deliberate and conscious departures from traffic rules or commonly accepted safe driving practices (Ozkan et al., 2006). The original DBQ consisted of 50 items related to driving behavior and was designed for applicability to drivers in the United Kingdom (Reason et al., 1990). Subsequent revisions reduced the total number of items and updated the language to improve applicability to driver populations outside of the United Kingdom (Parker et al., 1995).

Later versions of the DBQ further refined the classification of errors by distinguishing between slips (resulting from action-based failures) and lapses (stemming from errors of intention) (Ozkan et al., 2006).

Across its various versions, the DBQ has been widely used in studies examining driver behavior and traffic safety occurrences. Driver populations assessed using the DBQ span diverse geographic and demographic contexts, including elderly drivers in France (Gabaude et al., 2010), taxi drivers in Nigeria (Taiwo et al., 2024), and long-haul truck drivers in Spain (Useche et al., 2020). A 2010 meta-analysis by de Winter & Dodou (2010) identified 174 published studies that utilized the DBQ, representing approximately 45,000 respondents that completed the DBQ as part of those studies.

13.5. Methods

An experiment was conducted to understand the impact of SDV system capability framing and frequency of TSR system errors on both respondents' trust in the system and their performance in identifying errors in the TSR system. The experimental design consisted of a 2 (framing: positive, negative) x 2 (error rate: random, concentrated) factorial design.

13.5.1. Experiment Design Elements

A copy of the survey can be found in Appendix B. The online anonymous experiment used in the experiment included the following elements:

1. Capture of consent
2. Screening questions
3. Manchester Driver Behaviour Questionnaire
4. SDV Trust Questions (Section3.3)
5. SDV Familiarity Questions (Section 3.5)

6. Video Experiment Section (Sections 8.1.2, 8.1.3, and 8.1.4)
7. Trust in Automated Systems Questions (Section 13.5.5.1)
8. Demographics Questions (Section 3.2)
9. Amazon Gift Card Raffle Opt-In

13.5.2. Experiment 2 Human Study Approval

Since the survey for Experiment 2 involved the use of human subjects as respondents to the online experiment, the survey went through IRB approval through the Colorado State University Institutional Review Board IRB. Approval was granted under protocol #5825, and followed ethical human subject testing principles.

13.5.3. Experiment 2 Participant Recruiting

Experiment participants were recruited though social media (LinkedIn and Facebook) and announcements to students, faculty, and staff within the Systems Engineering Department at Colorado State University.

13.5.4. Procedures

All study instructions, video links, and questionnaires were embedded within an online experiment administered using Qualtrics. Informed consent was obtained first, followed by screening questions to confirm that participants lived in the US, drove at least once per week, were able to spend approximately 30-minutes completing the study in a single sitting, and could view online videos. Participants then completed a series of questions capturing their general driving behaviors and perceptions of self-driving vehicles.

Participants were then provided instructions for the video tasks, which included the TSR framing prompt and directions to press the space bar on their keyboard whenever they believed the TSR system missed a traffic sign relevant to the vehicle or misidentified a detected traffic sign. A link to the video portion of the experiment was then provided, which opened in a separate browser tab. Participants initiated the video by pressing a “Start” button within the browser tab, which logged a timestamp in the backend data system. Space bar presses were also recorded with timestamps and were later cross-referenced with the seven known TSR errors to determine error detection accuracy.

After completing the videos, participants were instructed to return to the Qualtrics interface, where they completed questionnaires assessing trust in the TSR system, provided demographic information, and provided an email address if they wished to be entered into the gift card raffle.

13.5.5. Experiment Participant Assessments

Survey data was collected using three validated instruments to assess driver behavior and trust-related constructs: (1) the Trust in Automation Scale (de Winter et al., 2010), (2) a general trust in SDV scale (Stewart & Gallegos, 2025a), and (3) the Modified Manchester Driver Behavior Questionnaire (MM-DBQ) (Parker et al., 1995).

13.5.5.1. Trust in TSR System

The Trust in Automation Scale, developed by Jian et al. (2000) is a well-established instrument for assessing trust between humans and automated systems (Yagoda & Gillan, 2012) and has demonstrated reliability and validity for quantifying human trust in AI (McGrath et al., 2025). This scale is widely used in the literature, as demonstrated by Gutzwiller et al. (2019), who identified more than 100 studies employing the scale. The assessment consists of 12 items measured on a 7-point Likert scale. A cumulative trust score is calculated, with possible values ranging from 12 to 84, where higher scores indicate greater trust in the system.

In this experiment, the Trust in Automation Scale was administered immediately following the driving videos, with participants responding in reference to the TSR system they had just experienced. Accordingly, it was used to measure trust in the TSR system.

13.5.5.2. General Trust in SDVs

Baseline (prior) trust in SDVs was assessed at the beginning of the experiment. This measure captured participants' general trust in SDVs across a variety of driving contexts, including willingness to share the road with SDVs and willingness to use SDVs in residential areas, medium traffic, dense traffic, school zones, and parking lots (Stewart & Gallegos, 2025a). The scale consisted of 8 items measured on a 5-point Likert scale. A composite trust score was calculated, with possible values ranging from 8 (low trust) to 40 (high trust).

For Experiment 2, the reduced question set DBQ (Parker et al, 1995) was utilized to evaluate a driver behavior-based risk score as a potential predictor of driver oversight accuracy and TSR trust level. Since the original reduced question-set DBQ was written for drivers in the United Kingdom, some updates were needed to the question text to be more familiar and applicable to drivers in the United States, who were the group being examined in Experiment 2. Examples of changes to question text include replacing the term "overtake" (and its variations) with the term "pass" (and its variations), updating question text to reflect for United States drivers driving on the right-hand side of the road versus the left-hand side, and updating question text to account that automatic transmissions are the most typical transmission type versus than manual transmissions in the original DBQ. These updated questions are documented in Table 61.

Table 61. Modified Manchester Driving Behaviour Questionnaire Questions

Question Text
Manchester – Lapses
Attempt to drive away from traffic lights in the wrong gear.
Forget where you left your car in a parking lot.
Turn on one thing, such as your headlights, when you mean to switch on something else, such as the windshield wipers.
Realize that you have no clear recollection of the road along which you have just been traveling.
Misread the signs and turn the wrong direction on a one-way street.
Hit something when backing up that you had not previously seen.
Intending to drive to destination A, you "wake up" to find yourself on a road to destination B, because destination B is a more common destination.
Get into the wrong lane approaching an intersection.
Manchester – Errors
Attempt to pass someone that you hadn't noticed to be making a left turn.
Fail to notice that pedestrians are crossing when turning onto a side street from a main road.
When turning right, nearly hit a bicyclist who is riding along side of you.
Attempting to turn onto a main road, you pay such close attention to traffic on the road you are entering that you nearly hit the car in front of you that is also waiting to turn.
Drive even though you might be over the legal blood alcohol limit.
Underestimate the speed of an oncoming vehicle when attempting to pass a vehicle in your own lane.
Miss "Yield" signs, and narrowly avoid colliding with traffic having the right of way.
Fail to check your rearview mirror before pulling out, changing lanes, etc.
Brake too quickly on a slippery road or steer the wrong way into a skid.
Manchester – Violations
Become impatient with a slow driver in the fast lane and pass on the right.
Drive especially close to a car in front as a signal to the driver to go faster or get out of the way.
Cross an intersection knowing that the traffic lights have already changed from yellow to red.
Disregard the speed limits late at night or early in the morning.
Angered by another driver's behavior, you catch up to them with the intention of giving him/her "a piece of your mind."
Have an aversion to a particular class of road user, and indicate your hostility by whatever means you can.
Get involved in unofficial "races" with other drivers.

Each of the questions in Table 61 was presented to the respondents for Experiment 2 as a six-point Likert scale question, with options ranging from “Never” to “Nearly All the Time”. Respondents were asked to report how often they engaged in those behaviors based on the Likert scale. Points were assigned to each Likert level as shown in Table 62, with a cumulative score being calculated for each question group (Lapses, Errors, and Violations). Scores could range from 0 – 40 for “Lapses”, 0 – 45 for “Errors”, and 0 – 35 for “Violations”.

Table 62. Likert-Scale Levels and Point Values for Modified Manchester Questions

Likert Level	**Point Value**
Never	0
Hardly Ever	1
Occasionally	2
Quite Often	3
Frequently	4
Nearly All the Time	5

13.5.6. Human Oversight Performance Measures

Two performance measures were derived from the video task based on participants’ spacebar presses to assess human oversight of the TSR system: (1) detection count and (2) detection accuracy.

13.5.6.1. Detection Count

Detection count was calculated based on the total number of spacebar presses made by a participant during the videos. This measured reflects the number of times the participant believed the TSR system made a detection or identification error.

13.5.6.2. Detection Accuracy

Detection accuracy was calculated as a percentage of TSR errors correctly identified by the participant. The timestamps of all seven errors were known to the research team. A spacebar press was considered a correct detection if it occurred while an error was present within the video. Detection accuracy was computed by dividing the number of correctly identified errors by 7.

The start of an error window was defined as the point at which the TSR error became reasonably visible in video stream. The end of the error window was defined as one second after the error was no longer visible. Participant inputs occurring after the error start time and within two seconds following the end of the error window were counted as correct detections of the TSR error.

13.5.7. Assessment of Trust in Automation Scale

The Trust in Automation Scale (TIAS) was developed by Jian et al. (2000) as a way to measure the level of trust a human has in an automated system. The TIAS consists of a total of 12 questions, where seven (7) of the questions are asked with a positive system framing and five (5) questions are asked with a negative system framing (Jian et al, 2000). The questions with the positive system framing are captured in Table 63, while the questions with the negative system framing are captured in Table. The TIAS has been recognized as a well-established checklist for identifying trust between humans and automation (Yagoda & Gillian, 2012), has been found to be a reliable and valid means for quantifying human trust in AI (McGrath et al., 2025), and has been used in previous studies, with Wischnewski et al. (2023) identifying 16 studies that had used TIAS as part of their research.

A TIAS trust score was calculated for each respondent in Experiment 2 based on their responses to the TIAS Likert questions within the survey. For the questions that used positive framing for the questions, Likert responses were worth the point values captured in Table 64. For the questions that used negative framing for the questions, Likert responses were worth the point values captured in Table 66.

Table 63. System Trust Questions – Positive

System Trust Question
I am confident in the system.
The system provides security.
The system has integrity.
The system is dependable.
The system is reliable.
I can trust the system.
I am familiar with the system.

Table 64. Likert-Scale Levels and Point Values for System Trust Questions (Positive)

Likert Level	**Point Value**
Strongly Agree	6
Agree	5
Somewhat Agree	4
Neither Agree or Disagree	3
Somewhat Disagree	2
Disagree	1
Strongly Disagree	0

Table 65. System Trust Questions – Negative

System Trust Question
The system is deceptive.
The system behaves in an underhanded manner.
I am suspicious about the system’s outputs.
I am wary of the system.
The systems’ actions will have a harmful or injurious outcome.

Table 66. Likert-Scale Levels and Point Values for System Trust Questions (Negative)

Likert Level	Point Value
Strongly Agree	0
Agree	1
Somewhat Agree	2
Neither Agree or Disagree	3
Somewhat Disagree	4
Disagree	5
Strongly Disagree	6

13.5.8. Assessment of Aberrant Driving Behaviors

The Modified Manchester Driver Behavior Questionnaire (MM-DBQ) (Parker et al., 1995) was used to measure self-reported aberrant driving behaviors as a proxy measure of driver risk. MM-DBQ consists of 24 items measured on a 6-point Likert scale. A cumulative score was calculated across the 24 items, with a possible range from 0 to 120. Higher scores indicate more frequent engagement in aberrant driving behaviors.

13.5.9. Data Cleaning

Data cleaning and analysis were conducted using Excel and Rstudio (R version 4.4.0). To ensure that only high-quality human respondent data was included in the data analysis, a multi-criteria approach was used to identify likely non-human responses and low-quality responses. This approach included the following:

1. **reCAPTCHA bot detection.** Qualtrics uses the Google invisible reCAPTCHA (v3) technology, which assigns each respondent a score between 0 to 1, with scores greater than 0.5 considered to be likely human. All responses with reCAPTCHA scores below 0.5 were removed.

2. **Video interaction requirement.** The TSR video assessment required respondents to open and interact with a second browser tab to view the videos. Participants were required to select a button within the video tab to initiate playback and generate a "zero" timestamp. Responses lacking this required video interaction were excluded from analysis.
3. **Survey duration reasonability assessment.** The video portion of the experiment lasted approximately 940 seconds. To ensure sufficient time for thoughtful responses, surveys completed in less than 1090 seconds were excluded from analysis, providing at least a 2.5-minute survey completion time.

After removing responses that failed these quality checks, there was a total of 62 participants that fully completed the survey, interacted with the video portion of the survey, and determined to likely be human respondents versus bot respondents.

13.5.10. Data Analysis

Analysis methods included linear regression models for determination of significant predictors of continuous independent variables (i.e., general trust in SDVs and Manchester DBQ scores) and analysis of variance (ANOVA) to evaluate the effects of categorical independent variables (i.e., TSR framing and error concentration). The dependent variables in these models included detection count, detection accuracy, and trust in TSR.

13.6. Results

Results from the human oversight accuracy experiment are captured within this section.

13.6.1. Experiment 2 Participant Demographics

A total of 213 participants took part in the study; however, after data cleaning, there were 62 participants that fully completed the study and were included in analysis.

The final sample comprised of 41 males (66%), 19 females (30%), and 2 (4%) non-binary. Highest level of education completed was distributed as follows: less than high school diploma (N = 1, 1%), high school diploma (N = 4, 6%), some college (N = 8, 13%), associate's degree (N = 7, 11%), bachelor's degree (N = 21, 34%), and post-graduate degree (N = 21, 34%). All participants reported owning a vehicle; self-reported driving frequency was daily (N = 35, 56%), 4-6 times per week (N = 17, 27%), 2-3 times per week (N = 8, 13%), and once per week (N = 2, 3%).

13.6.2. Participant Baseline Profiles

Given that participants were randomly assigned to experimental conditions, baseline individual difference measures were evaluated to assess potential differences across framing and error concentration groups in Manchester DBQ scores and general trust in SDVs scores. As shown in Figure 31, distributions were highly similar across framing and error concentration groups, with overlapping medians and comparable variability, indicating no meaningful baseline differences between conditions.

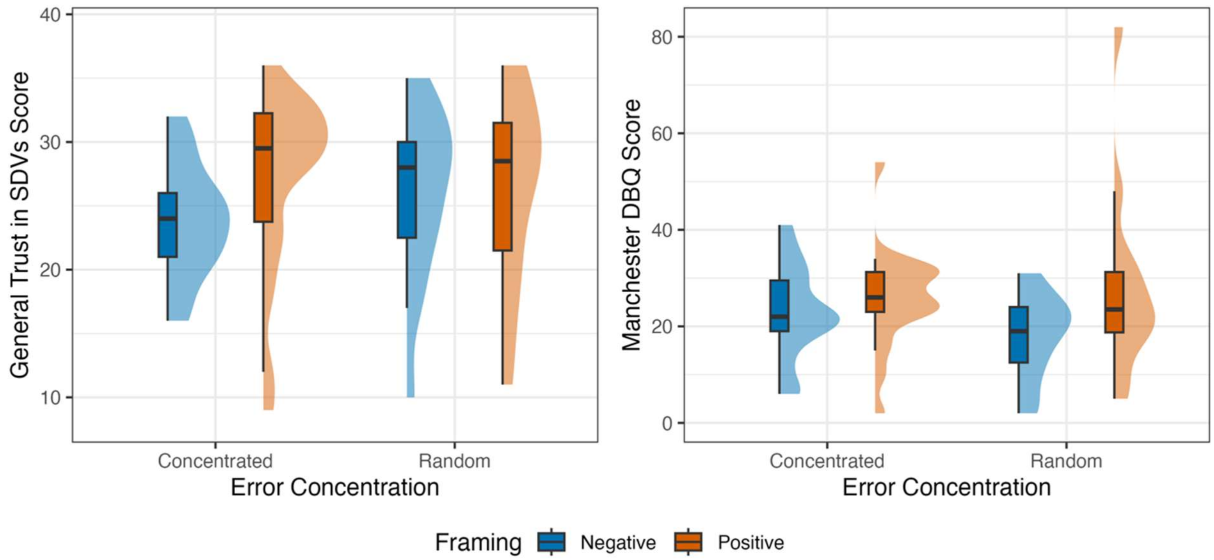


Figure 31. General Trust in SDVs and Manchester DBQ Scores by Experimental Condition

13.6.3. Detection Count

Detection counts (i.e., the number of times participants tagged the TSR as incorrect) were analyzed to evaluate the effects of framing and error concentration. The ANOVA showed a significant main effect of error concentration, $F(1, 58) = 4.61$, $p = 0.036$, where participants in the random condition had more detection events (mean = 23.0) than participants in the concentrated condition (mean = 6.5), see Figure 32. Neither the main effect of framing, $F(1, 58) = 0.17$, $p = 0.685$, nor the framing × error concentration interaction, $F(1, 58) = 0.54$, $p = 0.464$, had statistical significance.

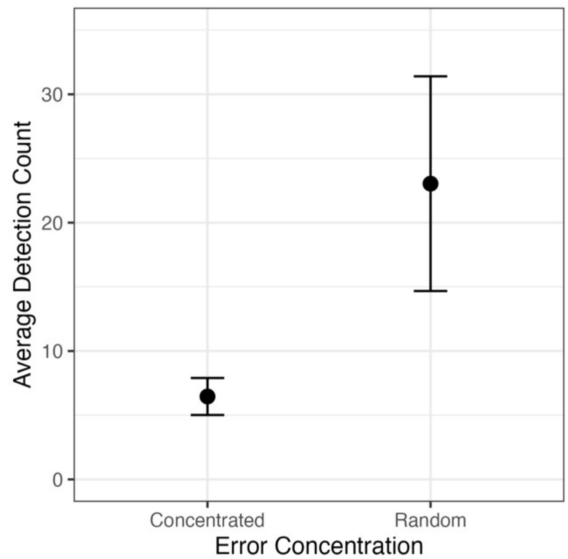


Figure 32. Average Detection Count by Error Concentration Group (with Standard Error)

A linear regression analysis was used to evaluate detection count based on Manchester DBQ scores and general trust in SDV scores, see Table 67. Manchester DBQ score emerged as a significant positive predictor, indicating that participants reporting more aberrant driving behaviors provided more detection inputs during oversight. General trust in SDVs score was not a significant variable.

Table 67. Prediction of Detection Count by DBQ and General SDV Trust Scores

Variable	Estimate	Std Error	t-value	p-value
(Intercept)	-18.93	14.91	-1.27	0.209
Manchester DBQ Score	0.78	0.30	2.61	0.011
General Trust in SDVs Score	0.55	0.57	0.96	0.343
Model Fit: F (2, 59) = 4.969, p = 0.010; R-squared = 0.144				

13.6.4. Detection Accuracy

An ANOVA was conducted on detection accuracy (i.e., correct identification of the seven TSR errors), with framing and error concentration as factors. Results indicate no significant main effects or interaction on detection accuracy. Overall, performance was low, with mean detection accuracy below 15% across conditions, see Figure 33.

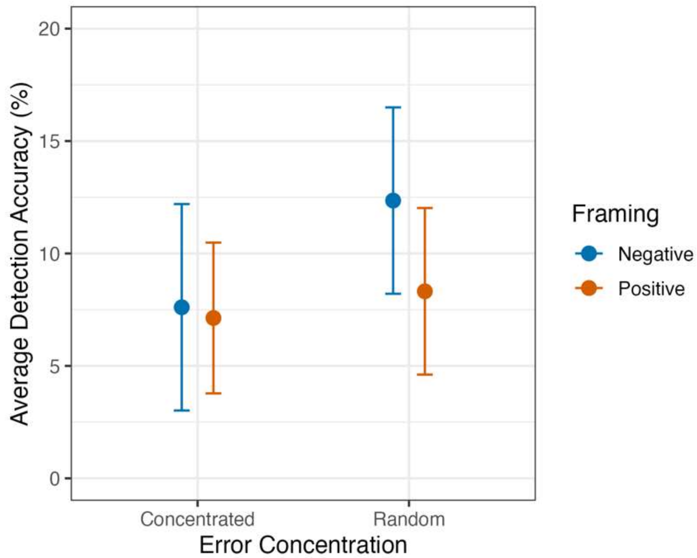


Figure 33. Average Detection Accuracy by Error Concentration and Framing Groups

13.6.5. TSR System Trust

A linear regression analysis was conducted to examine whether framing, error concentration, Manchester DBQ score, and general trust in SDVs predicted TSR system trust, see Table 68. Error concentration was a significant predictor, where participants in the random error concentration condition reported significantly lower trust (5.61 points less) than those in the concentrated condition. Manchester DBQ was also a significant negative predictor, suggesting a tendency for participants reporting more aberrant driving behaviors to exhibit lower trust. General trust in SDVs was a strong positive predictor, indicating that greater prior SDV trust was associated with higher trust in the TSR system. Framing did not significantly predict TSR system trust.

Table 68. Prediction of TSR System Trust

Variable	Estimate (B)	Std Error	t-value	p-value
(Intercept)	40.83	5.18	7.88	< 0.001
Positive Framing *(ref. Negative)*	1.82	2.56	0.71	0.480
Random Error Concentration *(ref. Concentrated)*	-5.61	2.50	-2.24	0.028
Manchester DBQ Score	-0.23	0.10	-2.26	0.027
General Trust in SDVs Score	0.91	0.19	4.64	< 0.001
Model Fit: F (4, 57) = 6.92, p < 0.001; R-squared = 0.327				

13.7. Discussion

This experiment examined whether system capability framing and error concentration influence human oversight performance and trust in a simulated TSR system. Across all four experimental groups, detection accuracy was uniformly low, with mean accuracy below 15%. Most participants failed to detect the majority of simulated TSR errors. This result suggests that arguments asserting that human supervision is sufficient to account for failures in autonomous systems may be overly optimistic. Relying on human intervention to mitigate SDV failures appears to be a high-risk approach given the low detection accuracy observed across conditions. These findings align with prior physiological and on-road studies showing that roadway conditions can influence driver stress, cognitive workload, and overall driving performance (Miller, 2013; Miller & Boyle, 2013).

Additionally, the framing of the TSR system's maturity and capability, and the frequency of TSR errors were not significant predictors of TSR error detection accuracy. The concentration of errors within the TSR videos, however, was predictive of the number of TSR error identifications reported by participants. Those assigned to the random error profile made an average of approximately 16.5 more TSR error reports than respondents in the concentrated error condition. This suggests that temporal distribution of failures influenced reporting behavior, even though it did not improve correct detection performance. Increased reporting in the random condition may reflect heightened uncertainty about system reliability, but it did not translate into improved oversight effectiveness. Prior human-automation research has shown that exposure to and interaction with automated driving systems can alter operator vigilance and cognitive workload without necessarily improving monitoring performance (Miller & Boyle, 2017).

Regarding trust outcomes, TSR system trust was not significantly influenced by capability framing. These findings add to the mixed conclusions reached by previous studies regarding the impact of framing and error frequency on system-level trust. Several studies have reported that negative framing does not necessarily decrease trust in SDVs (Stewart & Gallegos, 2025a; Cegarra et al., 2025; Dixon et al., 2023), with researchers suggesting that brief framing manipulations may not be sufficient to alter established mental models of automation reliability (Cegarra et al., 2025). Other studies have observed contrasting results, including reductions in trust following automation failures or training exposure (Merriman et al., 2023), and trust being influenced by reliability, dependability, and automation failures (Lee et al., 2021; Hancock et al., 2011; Khavas et al., 2020). Recent work further emphasizes that perceived and actual system reliability are central determinants of appropriate trust calibration and effective human-automation interaction in self-driving vehicle applications (Stewart & Gallegos, 2025b).

Chapter 14. Conclusions

14.1. Research Contributions

The experimental methods, data collected, and associated findings from this dissertation provide several research contributions relevant to human factors and self-driving vehicle research. These contributions are described in detail within this section.

14.1.1. Theoretical Contributions

Several new prediction concepts were introduced and successfully utilized within the experiments supporting this research, including the following:

1. **SDV Trust:** This experimental predictor is a unique set of questions generated to capture the level of trust an experiment participant has in self-driving vehicles. Experimental data showed that this measure had a Cronbach Alpha score of α = 0.724, verifying that this new measure has an acceptable level of internal consistency. This metric was found to be a significant predictor of primary blame assignments for SDV-involved traffic collisions and moving violations, a significant predictor of blame assignment shift caused by manufacturer advertising claims, and oversight and infrastructure funding preferences.
2. **SDV Familiarity:** This experimental predictor is a unique set of questions generated to capture the level of familiarity an experiment participant has in self-driving vehicles. Experimental data showed that this measure had a Cronbach Alpha score of α = 0.524, which while considered "Poor" by Geroge and Mallery (2003), is an acceptable initial value for an initial set of Likert questions designed

to assess this metric (Taber, 2018; Nunally, 1967). SDV familiarity was found to be a significant predictor of impact of advertising on primary blame assignment for SDV-involved traffic collisions and traffic regulation violations.

3. **Impact of Manufacturer Advertising:** This unique predictor was utilized to evaluate how capability claims made in SDV advertising could impact primary blame assignment for SDV-involved collisions and violations of traffic regulations. What was unique about this approach is that experiment participants were first asked to assign blame for the scenario, and then asked describe how advertising claims would impact their blame assignment against the SDV manufacturer. Using this approach allowed for the evaluation of the default blame assumptions for the respondent population, and then the evaluation of how environmental factors could shift that blame model. The results of this approach helped fill a gap in existing literature regarding how advertising could influence blame assignment for SDVs, and impact legal risk for SDV manufacturers. A similar approach could be used to evaluate the manufacturer risk profile for other autonomous technologies.

14.1.2. Methodological Contributions

This research involved a novel experimental approach as part of a 2x2 experiment evaluating the effectiveness of human oversight on a TSR system under varied capability framing and error frequency environments. In this approach, the error detection accuracy of the participants was evaluated based on their ability to detect seven artificially generated TSR errors within a sequence of simulated driving test videos versus evaluating their error detection performance for all TSR events within the video. By limiting accuracy calculations to the defined seven errors within the simulated TSR test results, the error detection accuracy of each participant could be evaluated objectively without potential variability caused by the use of real TSR test results where error identification could be subjective. This in turn allowed for the evaluation of the impacts of framing and TSR error frequency on respondent error reporting rates and error identification accuracy.

Utilizing this approach, the findings from this research indicate that human supervision of automated driving systems may be far less reliable than is often assumed. Across all experimental conditions, participants in the experiment demonstrated very low accuracy in identifying simulated traffic sign recognition errors, with most failing to detect the majority of system failures. Neither system capability framing nor the timing of errors improved oversight accuracy, although randomly distributed errors increased the frequency of reported detections. This pattern suggests that greater monitoring activity does not necessarily correspond to more effective oversight.

Another methodological contribution from this research involved a novel modeling approach to visually capture the interconnected influences of various predictors on experiment outcomes and feature preferences. As shown in Figure 34, predictors such as demographic data, risk preference, SDV trust profiles, SDV familiarity profiles, and influence of advertising claims influence not only experiment outcomes and preferred feature levels, but also influence one another in many instances. For example, SDV trust scores serve as predictors of primary blame assignment, how advertising impacts blame assignment in SDV collision and traffic regulation violation scenarios, and oversight funding method preferences, while predictors such as race or ethnic identify and gender identify serve as predictors of SDV trust scores. In another example of predictors influencing predictors, the impact of advertising metric is a significant predictor of

WTP for advanced driver assist technology, which in turn is a significant predictor of preferences for SDV system reliability and resiliency levels. This novel modeling approach allows for the intuitive visualization of second order effects of predictors on SDV human factors, and rapid identification of what predictors have influence on human preferences and decision outcomes within the analyzed human-SDV interaction space.

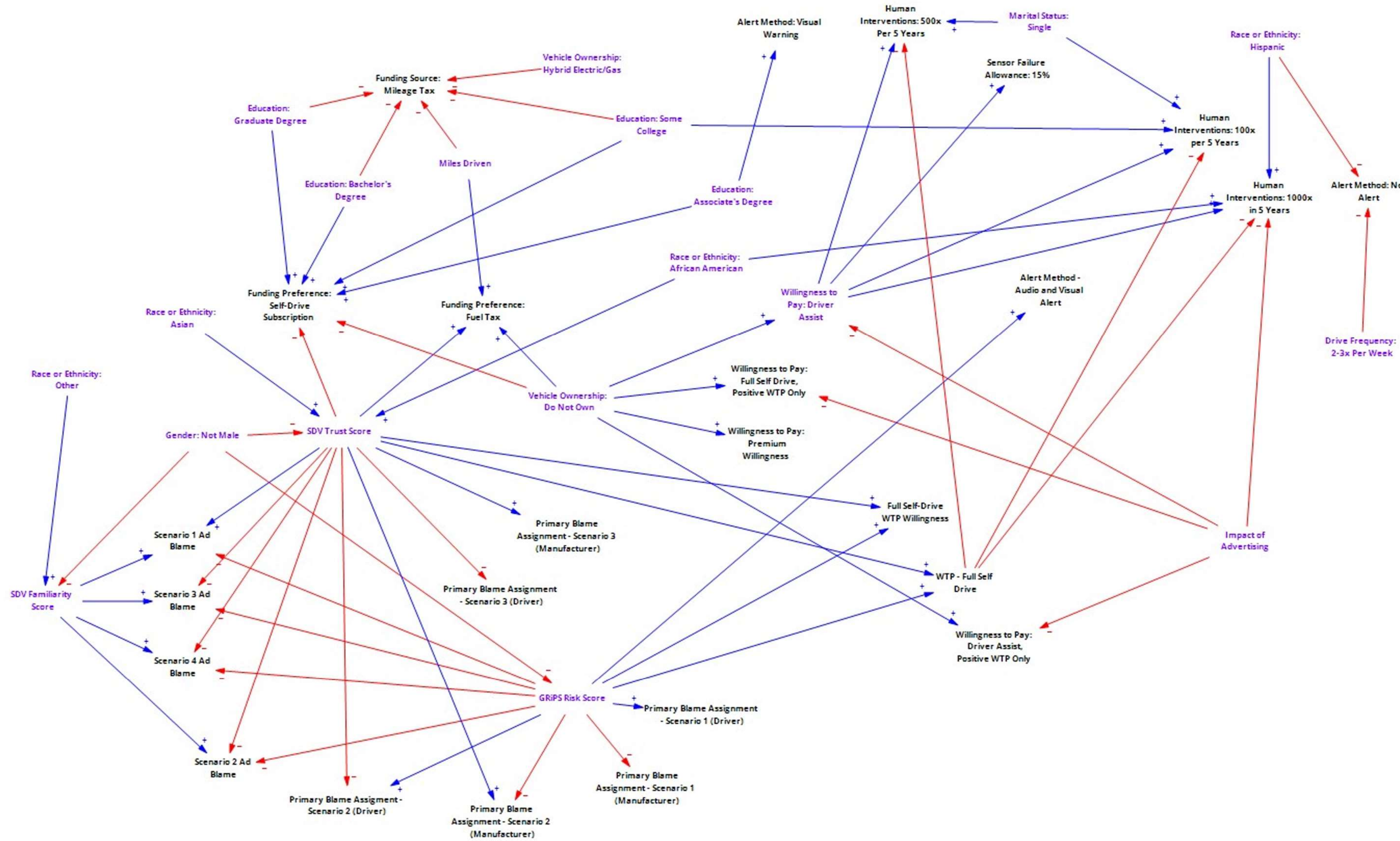


Figure 34. General Model for Predictors and Outcomes (Experiment 1)

14.1.3. Practical Contributions

This research provided a practical contribution regarding design insights into preferred safety and reliability features for current and future SDV designs. Through the results of a Conjoint experiment, it was determined that that consumer preferences for self-driving vehicle safety features are driven primarily by driver alert methods and system reliability, with resilience and failure behavior playing comparatively minor roles. Across the sample, multimodal alerts (audio + visual) emerged as the dominant factor, followed by a strong preference for extremely low rates of required human intervention. In contrast, complex failure behaviors had little influence on choice decisions, suggesting that predictable safe-stop responses are sufficient from a consumer perspective. As for the optimum feature set, consumers preferred a low system failure rate that required only 1 human intervention within a five-year period, preferred a system with sufficient resilience to allow up to 5% of sensors to fail before repairs were required, and preferred a driver alert design that included both visual and audio alert cues for when driver input or intervention is required. Based on these results SDV manufacturers, should prioritize intuitive, multi-modal driver alert systems and dramatic improvements in reliability, while recognizing that investments in redundant sensor systems or sophisticated fallback behaviors may yield limited returns in terms of consumer acceptance. For policymakers and regulators, these results provide insight into the alert methods, system reliability, and system resilience feature levels the consumers are most likely to support as regulatory standards for future SDV designs.

Another practical contribution provided by this research effort is decision support data regarding what framing SDV designers may want to utilize when advertising their products. As the analysis of the data from the first experiment illustrated, the framing of the capability of the

SDV to operate without human supervision has a significant impact on the price SDV manufacturers can demand for their vehicles, with fully self-driving vehicles requiring no human supervision being able to command a premium that is $4,000 more than what a vehicle with advanced driver-assist features can command. At the same time, however, claims that human supervision is not required exposes the manufacturer to a greater blame assignment in the event their product is involved in a traffic collision or traffic regulation infraction than would be assigned in the absence of advertising. This increase in liability risk is present even though the second experiment found that capability framing was not a significant predictor of error detection and that overall error detection accuracy was very low (average < 15%).

One final practical contribution from this research is decision support data that can assist government agencies in determining what types of fees or taxes can be used to fund oversight activities and supporting infrastructure improvements for the SDV transition. Results from this research effort provides additional understanding of funding preferences that can support policymakers seeking to implement sustainable, publicly supported funding models in an evolving mobility landscape. This data suggests that the respondent population has strong preferences for the costs associated with the adoption of SDVs to be borne by those who are planning to utilize self-driving technology, with increased new vehicle prices and self-driving subscriptions being the preferred funding methods for SDV adoption. The exception to this observation is that respondents who do not own a vehicle opposed the self-drive subscription model. Additionally, mileage taxes were generally disliked by respondents, except for those who did not own a vehicle. Fuel taxes are opposed by a majority of respondents, though owners of hybrid or electric vehicles and non-vehicle owners prefer fuel taxes versus increases in vehicle price. Finally, vehicle taxes, while less preferred than increased vehicle prices, were less disliked than fuel taxes or mileage taxes within the sample. Based on these observations, funding for SDV implementation should be raised via increased vehicle prices and self-driving subscriptions, with funds being dispersed to the entities responsible for infrastructure maintenance and SDV oversight.

14.1.4. Empirical Contributions

This research effort provided two empirical contributions to the general body of knowledge regarding SDVs and their general adoption by consumers in the United States. The first of these contributions was an update to the current WTP of consumers in the United States for both full self-driving capability and advanced driver-assist technology. Results showed that a larger portion of the population had a positive WTP for self-driving vehicles, and that the mean WTP value had increased when compared to previous studies. Additionally, consumers in the United States were still willing to pay a higher premium for full-self driving versus vehicles with advanced driver-assist features. It must be noted, however, that the observed increased mean WTP was influenced by several high outlier WTP values and when these values were removed, the median WTP ($5,000) was less than the median observed in previous studies, suggesting that while more consumers have a positive WTP for SDVs and some are willing to pay a high premium for the technology, the average magnitude of the WTP is decreasing.

The second empirical contribution from this research effort was providing a foundation for understanding the potential legal culpability risk SDV manufacturers face, both as a baseline and as influenced by their advertising efforts, when their products are involved in traffic collisions or moving violations. The data collected as part of this research effort indicated that a majority of the respondents defaulted to primarily blaming the driver of the SDV for collisions and traffic regulation violations committed by the SDV while in self-drive mode. At the same time, a majority of respondents would increase the amount of blame they would assign to a vehicle manufacturer if that manufacturer had advertised that human oversight of the SDV was not required. Taken together with the WTP data, these results provide insight on the risk versus reward decision SDV manufacturers will need to make as they balance their business goal of maximizing revenue through increased premium available based on promises of no oversight being required and the enhanced legal risk they would take on based on those claims.

14.2. Summary of Research Findings

14.2.1. Aim 1 – Perceptions of SDV Legal Culpability

RQ 1.1: Who would the average American assign blame to if an SDV was involved in a traffic collision or traffic law violation?

Answer: Primary blame for accidents and moving violations involving SDVs was assigned to the driver of the vehicle by the majority of participants in the experiment, with 156 of 403 respondents assigning primary blame to the driver in all scenarios and 204 additional respondents blaming the driver in a least one of the scenarios. The assignment of blame was influenced by SDV manufacturer advertising messages that suggested human oversight was not required, with 263 respondents being more inclined to blame the manufacturer over the four scenarios, and 127 respondents within that group assigning additional blame to the manufacturer in all scenarios.

RQ1.2: Are risk tolerance, SDV familiarity, SDV comfort, or demographic factors significant predictors of views of legal culpability for SDV-involved traffic incidents?

Answer: Assignment of blame for accidents or moving violations involving SDVs against the SDV manufacturer increased with increasing SDV trust scores, and decreased with increasing risk profile scores.

14.2.2. Aim 2 – Reliability and Safety Expectations

RQ2.1: What are customer expectations for SDV system accuracy and resilience?

Answer: The optimum level of reliability for SDVs was identified as only one human intervention being required within a five-year operating period for the general experiment population. Optimum system resilience was found to be 5% of SDV sensors being allowed to fail before repairs are required, such suggested that sensor number optimization would be acceptable even if such optimization required more frequent maintenance activity. Preferred failure behavior was the vehicle coming to a stop safely, and the preferred system alert method was a combination of audio and visual alerts.

RQ2.2: Are risk tolerance, SDV familiarity, SDV comfort, or demographic factors significant predictors of expectations on system performance and resilience?

Answer: System resilience preference was predicted by driving frequency and willingness to pay for advanced driver-assist technology. System reliability was predicted by education, marital status, race or ethnic identity, and willingness to pay for full self-driving capability and advanced driver-assist technology.

14.2.3. Aim 3 – Willingness to Pay for SDVs

RQ 3.1: How much is a potential SDV buyer in the United States willing to pay for an SDV versus a traditional vehicle?

Answer: Mean WTP for full self-driving capability was found to be $13,842 for the respondent population, with a median WTP of $5,000. When removing respondents with $0 WTP, mean WTP increases to $19,104 (median = $10,000) for the remaining respondent pool of 292 respondents. 32 responses were found to be outliers within the positive WTP respondent pool, and removing these outliers resulted in a mean WTP of $9,650 (median = $5,000).

RQ 3.2: How much does that premium change based on the level of driver supervision required for the SDV?

Answer: WTP for advanced driver-assist technology was lower than the WTP for full self-driving capability, with the mean WTP for driver-assist of $8,292 (median = $1,000). When looking only at respondents who had a positive WTP for driver-assist technology, mean WTP increased to $13,621 (median = $4,500) for 252 respondents. Within this reduced dataset, 45 responses were found to be outliers, and removing these outliers reduced mean WTP to $4,385 (median = $2,500).

RQ 3.3: Are risk tolerance, SDV familiarity, SDV trust, or demographic factors significant predictors of willingness to pay or preferences for funding methods for SDV oversight and infrastructure investment in the United States?

Answer: Full self-drive WTP was predicted by SDV trust score, with higher trust scores having an increase in WTP of $487 for each additional point in the SDV trust category , risk profile, with WTP increasing approximately $528.5 for every point in the risk assessment, vehicle ownership, with those not owning a vehicle being willing to pay $11,358 more than those who owned internal combustion engine vehicles, and impact of advertising score, where those who assigned more blame to manufacturers due to claims made in advertisements willing to pay $2,046 less for each point in their impact of advertising score above 0. Driver-assist WTP was predicted by vehicle ownership, with those not owning a vehicle being willing to pay $9,382 more for driver-assist than owners of internal combustion engine vehicles, and impact of advertising where those who assigned more blame to manufacturers due to claims made in advertisements willing to pay $1,293 less for each point in their impact of advertising score above 0.

14.2.4. Aim 4 – Tax and Fee Preferences for Oversight and Infrastructure Funding

RQ 4.1: What method of funding for the regulatory framework and infrastructure is least opposed by the general population of the United States?

Answer: There was a preference for a self-drive subscription fee to pay for technology oversight and infrastructure improvements versus increased vehicle prices, while increases in vehicle price was preferred to either new mileage or fuel taxes.

RQ 4.2: Are risk tolerance, SDV familiarity, SDV trust, or demographic factors significant predictors of preferences for funding methods for SDV oversight and infrastructure investment in the United States?

Answer: Preferences for funding methods was predicted by the following: 1) Respondents who did not own a vehicle preferred increased fuel taxes over increased vehicle prices, but had a strong preference for increased vehicle prices over self-drive subscription fees; 2) Those who owned hybrid or electric vehicles strongly favored increased vehicle prices over new or increased mileage taxes; 3) Those who drove more miles per year moderately favored increased gasoline taxes over increased vehicle prices, but had stronger preferences for increased vehicle prices over increased fuel taxes; 4) Self-drive subscription fees were strongly favored over increased vehicle prices for those with education levels greater than a high school diploma, while those with some college, Bachelor's degrees, and Graduate degrees had strong preferences increased vehicle prices over new or increased mileage taxes, and 5) Those with higher SDV trust scores had a slight preference for increased fuel taxes over increases in vehicle prices.

14.2.5. Aim 5 –Effectiveness of Human Oversight on Autonomous Vehicles

RQ 5.1: What impact, if any, does positive framing have on the effectiveness of driver oversight of a TSR AI on an SDV?

Answer: Capability framing for the simulated TSR system was not a significant predictor of error detection accuracy. Overall, the error detection accuracy of all experiment participants was low (mean detection accuracy below 15%) across all experiment conditions.

RQ 5.2: What impact, if any, does a frequency of errors by a TSR AI have on the effectiveness of driver oversight of that system?

Answer: The frequency of errors was not a predictor of error detection accuracy, but was a predictor of the number of error reports. Experiment participants exposed to a random error profile having an average of 16.5 more error reports than respondents being exposed to a concentrated set of TSR errors.

RQ 5.3: What impact, if any, does framing of TSR capability and TSR error frequency have on user trust of a TSR system?

Answer: Error frequency was a significant predictor of trust in the simulated TSR system, with experiment participants who were exposed to the random error profile reporting a significantly lower level of trust in the system (5.61 points less) versus participants exposed to the concentrated error profile. TSR system trust was also predicted by Manchester DBQ score, with drivers reporting more aberrant behavior exhibiting a lower trust in the simulated TSR system.

RQ 5.4: Are Manchester DBQ values, SDV familiarity, SDV trust, or demographic factors significant predictors of oversight effectiveness?

Answer: There were no significant predictors of human oversight effectiveness observed within the experiment.

14.3. Limitations

14.3.1. SDV Feature and Capability Preference Limitations

While this dissertation has provided several insights into feature preferences for SDVs, there are limitations with the data collection method that should be noted. First, data for this study was collected via an online experiment, and this method has several inherent limitations. Specifically, not all members of the population are reachable via online experiments, and there are members of the population who are unwilling to respond to online experiment participation requests. Additionally, only registered Prolific survey takers were given the opportunity to participate within the experiment, further limiting the potential participant pool. Future work could benefit from using additional methods to obtain experiment responses, including phone experiment data capture using both mobile and landline numbers or in-person survey data collection. Additionally, future research could also benefit from comparing the stated preferences captured in this experiment with observed preferences. Observed preferences could be measured using driving simulators in which various error rates, methods of alert, and failure behaviors are simulated. Then, respondents could be asked to rank the simulated capabilities according to their preferences or be evaluated objectively through driving performance measures such as takeover time.

14.3.2. WTP Limitations

This study's focus on predictors of willingness to pay provide novel insights into the factors shaping public valuation of self-driving vehicle technology. However, several limitations should be noted.

First, although the experiment population sample was structured to approximate U.S. Census distributions for major demographic variables, it cannot be considered fully representative of the national population. Participation was limited to users of an online survey platform, and self-selection bias cannot be ruled out. Consequently, while statistically significant relationships were identified within this dataset, the findings should be interpreted as reflective of the examined population rather than conclusive for the broader U.S. public.

Second, our use of the term advertising was focused specifically on consumer-directed information delivered through commercials. However, this framing may still risk conflating promotional messaging with other forms of consumer information. Future work could benefit from distinguishing these communication channels more explicitly, examining how different modes of information (e.g., advertising, regulatory disclosures, public safety campaigns) shape perceptions of responsibility in distinct ways.

Additionally, we approached SDV deployment as if it were an eventual outcome, limited mainly by economic feasibility. However, the economic models for SDVs are still evolving, and are dependent on public buy-in. Therefore, public acceptance should not just be seen as a barrier to adoption, but as a key stakeholder with community engagement helping inform SDV deployment and adoption (Stilgoe & Cohen, 2021). Future research could investigate ways to bring the public more directly into these decisions, moving past a simple buyer-seller dynamic, toward more participatory models of technology development.

Lastly, the findings in this experiment assume that SDVs must achieve economic viability through direct consumer purchase, and that SDV manufacturers would not have the ability to influence external approaches to improve their market viability. However, it is also possible that future deployment could be supported through regulatory mandates, subsidies, or insurance-based models. Nevertheless, our analysis centers on consumer acceptance and buy-in, providing insight into the conditions under which individuals are most willing to pay for self-driving capability.

14.3.3. Oversight Funding Limitations

While this dissertation provides additional insight into what methods of funding for the widespread adoption of SDVs would be most tolerated, there are opportunities for additional study into the topic. One such opportunity would be to develop a reasonable estimate of the average annual cost for infrastructure improvements and SDV oversight, and then convert the funding profiles from a percentage of an unknown value to an actual discrete funding amount. As an additional level of detail, an estimate could be made as to the total additional cost a respondent may experience based on the type of vehicle they drive and the number of miles they drive per year. These updated and more detailed funding profiles for the DCE would allow the survey respondents to compare estimated personal financial impacts from each funding profile and potentially change their funding preferences.

A second opportunity for future research would be to examine public perceptions on the idea that all users of the road infrastructure should be equally responsible for a share of the cost of updating infrastructure to accommodate SDVs and providing oversight of SDV technology, or if that cost should instead only be levied on those who purchase self-driving vehicles. This experiment was run under the assumption that all road users would potentially be responsible for some of the cost of the mass adoption of SDVs. A future study on public opinion on who should be paying for the incidental costs of increased SDV use on common roadways could determine if this assumption has public support.

14.3.4. Human Oversight Limitations

Several limitations of this experiment should be noted. First, the final sample size was modest, somewhat unbalanced, and participants were recruited primarily through convenience sampling. As a result, the sample may not be fully representative of the broader population of US drivers, which may limit the generalizability of the findings. Additionally, the experimental task relied on video-based supervision rather than an immersive driving context. While this approach allowed for controlled manipulation of framing and error timing, it did not capture the full range of cognitive demands present during real-world or simulated driving. Future studies conducted in a high-fidelity driving simulator could better represent the mental workload experienced by drivers supervising automated systems and provide additional insight into how cognitive load affects oversight accuracy and trust in automated vehicle systems.

14.4. Future Work

The experimental results generated by this dissertation effort included data that raised additional questions that warrant additional research activities. For some of these questions, subtle changes in results suggested respondent sensitivity to changes in the experiment scenario that were not fully explored in this research effort, and future examination of those sensitivities is warranted. In other cases, research results, when combined with previous literature results, suggested that experimental results potentially had a limited validity duration and that more refined and more frequent data sampling and analysis were needed. This section provides documentation for these observations and makes suggestions on how future experiments could be structured to capture these missed sensitivities or address limitations in previous data collections.

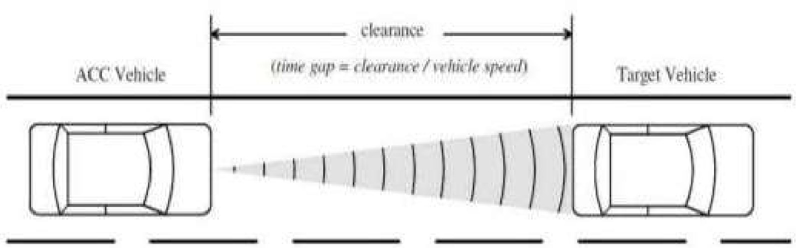
14.4.1. Willingness to Pay Future Work

Several challenges persist when examining consumer WTP data, to include the fact that the previous and current research shows this WTP data has a limited period of validity due to WTP profiles changing over time, and challenges in identifying what survey and experiment respondents were referring to when they were describing their willingness to pay for a “self-driving” or autonomous vehicle. Without a standard definition of what capabilities and technologies are assumed to be a part of a SDV, it becomes challenging to compare data results between studies or generate predictive or parametric models for WTP for future SDVs based on the current and future inclusions of SDV-relevant technologies (such as Adaptive Cruise Control (ACC)) in standard human-driven vehicles.

To address these challenges, future research effort regarding WTP for SDVs should take a more granular approach to measuring WTP. This granular approach would look at WTP for specific SDV-related features and technologies versus a more abstract (and less-defined) respondent definition of an SDV. Additionally, future research should gather response information from respondents that explicitly captures if the respondent believes the technology or feature is something that would exist solely on a self-driving vehicle, or if that technology or feature should be expected on a human-driven vehicle with driver-assist technologies. One possible approach to capturing this data is to include survey questions that identify and describe SDV-relevant technologies such as adaptive cruise control and ask the respondent to identify that technology as one that would only be on an SDV or one that could be on a human vehicle with driver assist (see Figure 35). A follow-on question would then ask the respondent to assign a WTP for that technology, with “0” being an acceptable answer (see Figure 36). Answers to these questions would help researchers identify both the respondent’s WTP for each feature or technology, and identify what features and technologies are expected on an SDV. Candidate technologies that should be evaluated with this survey approach include adaptive cruise control (ACC), traffic sign recognition (TSR) technology, lane keeping technology, waypoint navigation, self-parking technology (including parallel parking), thermal and radar imaging technology for bad weather driving, heads up display (HUD) technology, and any other technologies or features the researchers want to evaluate.

Adaptive Cruise Control (ACC)

This technology uses radar or cameras along with a computer alogrithm to match the speed of a leading vehicle and ensure safe separation distance between the vehicles, regardless of the changes in speed in the leading vehicle.



Source: Hashmi et al (2019); 10.1109/ACCESS.2019.2917652

Do you consider this technology to be a Self-Driving Vehicle (SDV) feature, or an Advanced Driver-Assist feature?

- ○ Self-Driving Vehicle Feature
- ○ Advanced Driver-Assist Feature

Figure 35. Example Survey Question for SDV vs Driver-Assist Feature Identification

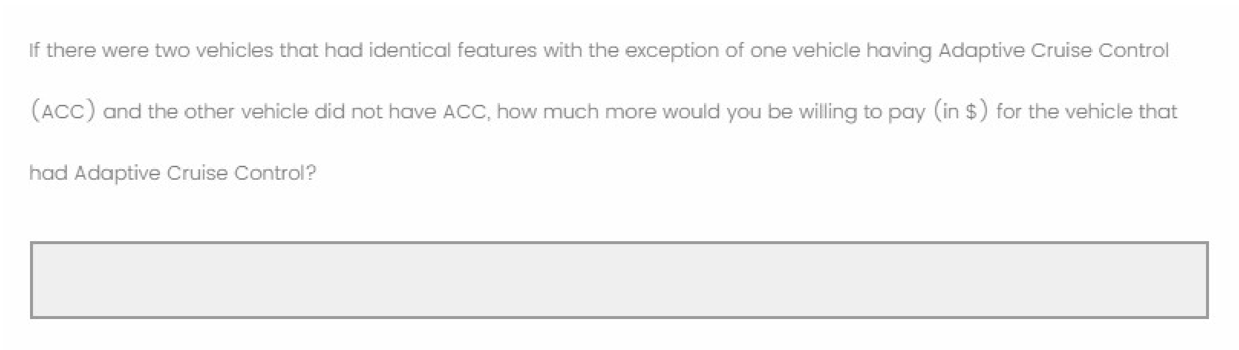

If there were two vehicles that had identical features with the exception of one vehicle having Adaptive Cruise Control (ACC) and the other vehicle did not have ACC, how much more would you be willing to pay (in $) for the vehicle that had Adaptive Cruise Control?

Figure 36. Example Willingness to Pay Capture Question for Feature WTP

Use of this updated experimental approach should yield several advantages of previous methods. First, this approach would allow researchers to generate a list of features and technologies that consumers would expect on what they would consider an SDV. Second, this approach would provide WTP values for specific features and technologies versus a more abstract SDV description. This data would allow for model- or parametric-based estimations of changes in WTP based on the widespread inclusion of an SDV-relevant technology on human-driven vehicles, and allow for the generation of WTP estimates on different SDV trim packages. Third, this approach would allow researchers to identify which features and technologies had the greatest impact on consumer WTP for SDVs, and identify potential predictors of feature-level WTP using respondent demographic and characteristic data.

14.4.2. Human Oversight Effectiveness Future Experiment Method

The experiment results generated as part Research Aim 5 showed a very low human oversight accuracy rate (mean < 15%) when attempting to identify the simulated TSR errors within the video portion of the experiment. This low accuracy rate occurred even with a low-stress, low-cognitive burden experiment where survey respondents were simply viewing a video on their computers or smart phones and providing error reports. Concurrently, the consequences of not detecting the TSR failures within the experiment were benign, with there being no risk of harm to the survey respondent if a missed TSR detection or bad TSR identification was not reported. These observations suggest that extrapolating the results of the human oversight experiment to real-world driving conditions would be challenging.

To address these challenges in future research efforts, future experiments will need to simulate, in a manner that is safe to the experiment participants, the stress and risk of negative outcomes that would exist in a real SDV driving scenario. This would most likely require that experiment participants be in a moving vehicle and be under the impression that they are solely responsible for ensuring the SDV AIs are working properly and intervene when SDV behavior is putting the vehicle and themselves at risk. One possible approach to this experiment would be to have an experiment vehicle where a second set of driver controls (steering wheel, gas pedal, and brake pedal) is available to a hidden safety driver, and that safety driver is mimicking the SDV driving AI during the experiment. During the course of the experiment, the vehicle approaches several experiment-controlled intersections where TSR failures would put the vehicle at risk (such as a bad recognition on a Stop Sign or Yield Sign), and test the respondent's reaction (or non-reaction) to the induced error. The safety driver would be responsible for stopping the vehicle safely if the experiment participant did not react in time, and a safely simulated near-miss on colliding with a vehicle could remind the participant of the dangers they missed. To evaluate possible effects of technology over-trust, these near miss accident scenarios would need to occur after a significant period of fully accurate "AI" detections and identifications.

14.4.3. Legal Culpability Future Experiment Method

The design of the experiment used for Research Aim 1 assumed a series of scenarios where the driver's position of the SDV retained all of the human-driver control elements (steering wheel, brake pedal, and accelerator pedal) that would allow the person in the driver's seat to take over driving responsibility in the event of a TSR failure. This design limits the extensibility of the experiment results to other control configurations for SDVs, such as SDV passengers only having access to brake pedals or emergency stop buttons, or passengers being in locations other than the driver's seat. Additionally, the results from Research Aim 1 showing an increase in primary blame assignment to the driver in Scenario 2 versus Scenario 1 based on the change in placement of the TSR results data suggests there may be sensitivity in primary blame assignment based on data display locations within the vehicle. These observations suggest that additional future research is needed to evaluate potential primary blame assignments for SDV-involved traffic collisions and traffic law violations based on different data display approaches and passenger control architectures.

One potential design approach for these future experiments would be to expand the scenarios shown to experiment participants to account for additional data display and user control configurations. Example permutations that could be considered included where the SDV passenger is located within the vehicle (front seat versus back seat), what types of controls are made available to the passenger (full controls, brake pedal only, manual emergency stop button only, or digital emergency stop button only), and where the system information, such as TSR recognitions and identifications, are being displayed (windshield HUD, center console display, backseat partition display, or driver console display). Table 69 shows a possible set of display, control, and seat location permutations for future experiments. These feature level permutations would be paired with traffic collision or traffic regulation violation descriptions and presented to the experiment participants to determine their primary blame assignments for each scenario.

Table 69. Example Scenario Summary for Future Legal Culpability Experiment

Display Location	**Human Controls**	**Seat Location**
Driver Console	Steering Wheel/Pedals	Front Seat
	Emergency Stop Physical Button	
	Touch Screen Emergency Stop	
Driver Console	Brake Pedal Only	Back Seat
	Emergency Stop Physical Button	
	Touch Screen Emergency Stop	
Center Console Large Display	Steering Wheel/Pedals	Front Seat
	Emergency Stop Physical Button	
	Touch Screen Emergency Stop	
Center Console Large Display	Brake Pedal Only	Back Seat
	Emergency Stop Physical Button	
	Touch Screen Emergency Stop	
Windshield HUD	Steering Wheel/Pedals	Front Seat
	Emergency Stop Physical Button	
	Touch Screen Emergency Stop	
Windshield HUD	Brake Pedal Only	Back Seat
	Emergency Stop Physical Button	
	Touch Screen Emergency Stop	

Artificial Intelligence could be used to generate visual images of the feature level permutations, and these visuals could be combined with the scenario descriptions used in the Research Aim 1 experiment to create the scenario permutations presented to the respondents for primary blame assignment. Previous research has demonstrated improved exploratory capability through augmentation with generative AI images, specifically using Generative Adversarial Networks, to expand the solution space (Alipour & Gallegos, 2025). Figure 37 through Figure 47 show examples of a subset of the feature levels and scenario feature level permutations shown in Table 69. After collection of primary blame assignment data, analysis could be performed to determine the impacts of display location, control feature level, and user seat location on primary blame assignment and manufacturer legal risk.

Figure 37. AI Generated Image of Driver Console System Information Display

Figure 38. AI Generated HUD Display Example

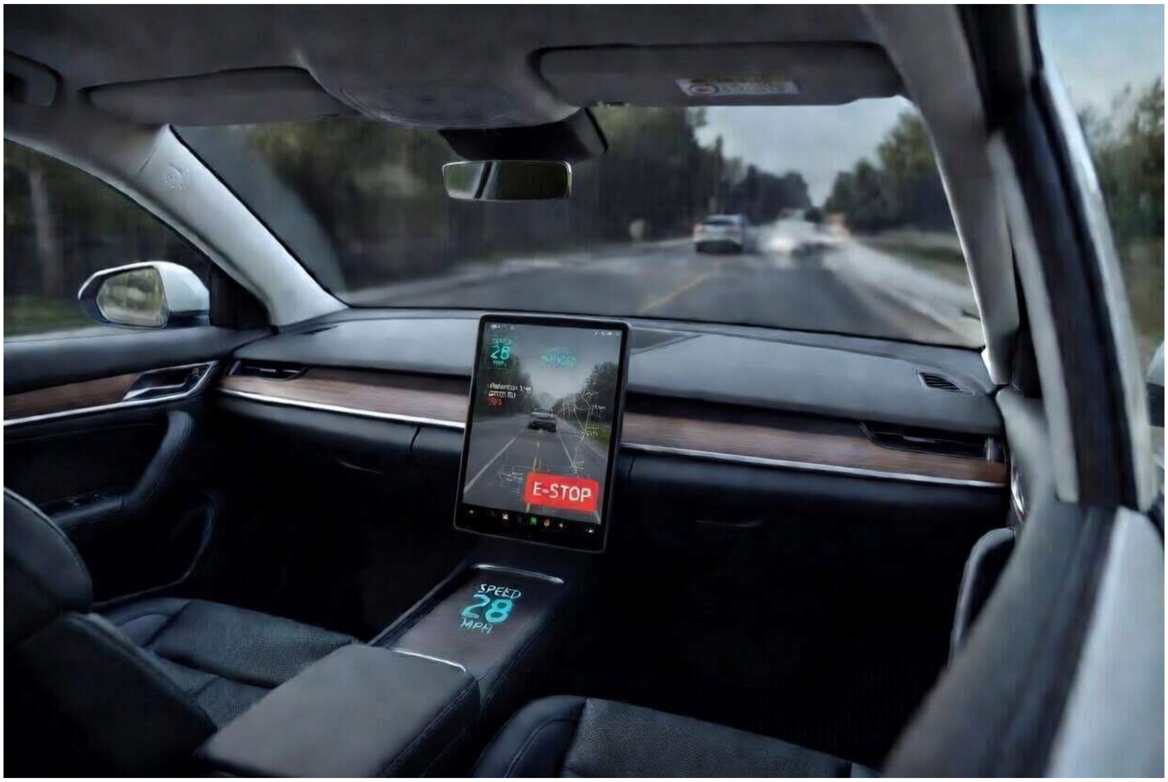


Figure 39. AI Generated Center Console Driving AI Screen

Figure 40. AI Generated SDV HUD Display, Front Seat, Brake Pedals Only

Figure 41. AI Generated SDV HUD Display, Front Seat, Physical E-Stop Only

Figure 42. AI Generated SDV HUD Display, Front Seat, Digital E-Stop Only

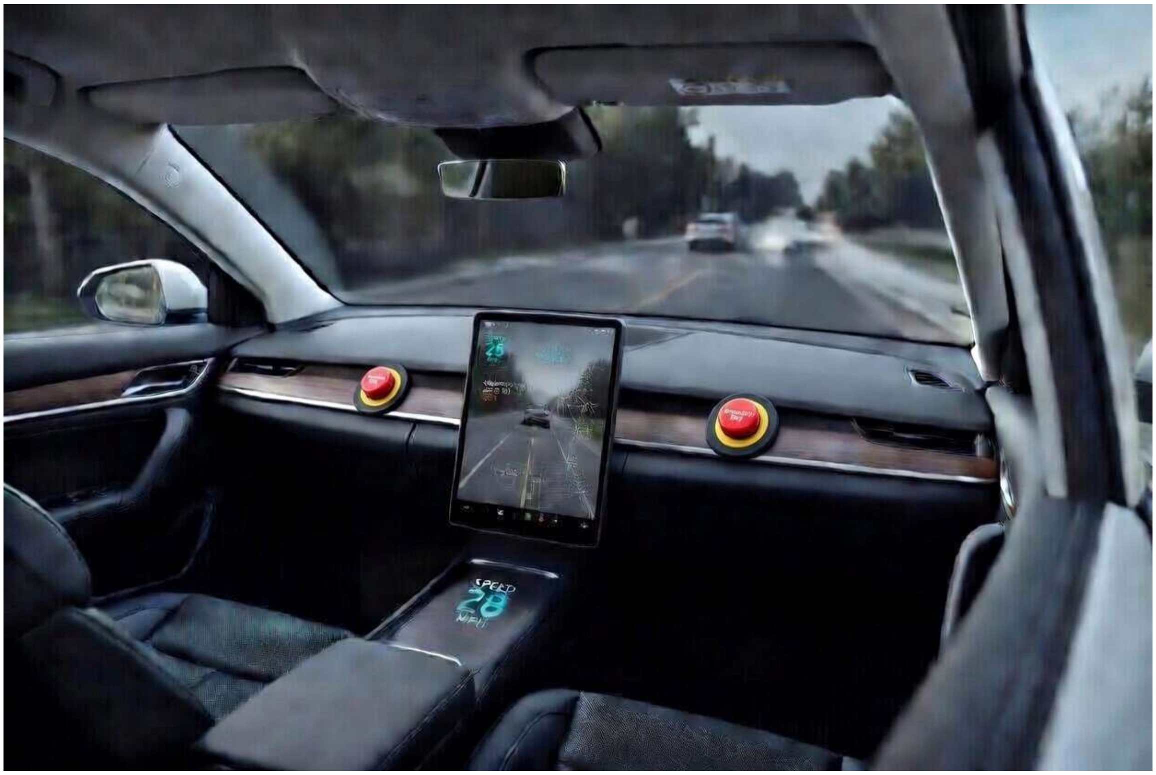


Figure 43. AI Generated SDV Center Console Display, Front Seat, Physical E-Stop Only

Figure 44. AI Generated SDV Center Partition Display, Back Seat, Physical E-Stop Only

Figure 45. AI Generated SDV Center Partition Display, Back Seat, Digital E-Stop Only

Figure 46. AI Generated SDV Center Partition Display, Back Seat, Brake Pedals Only

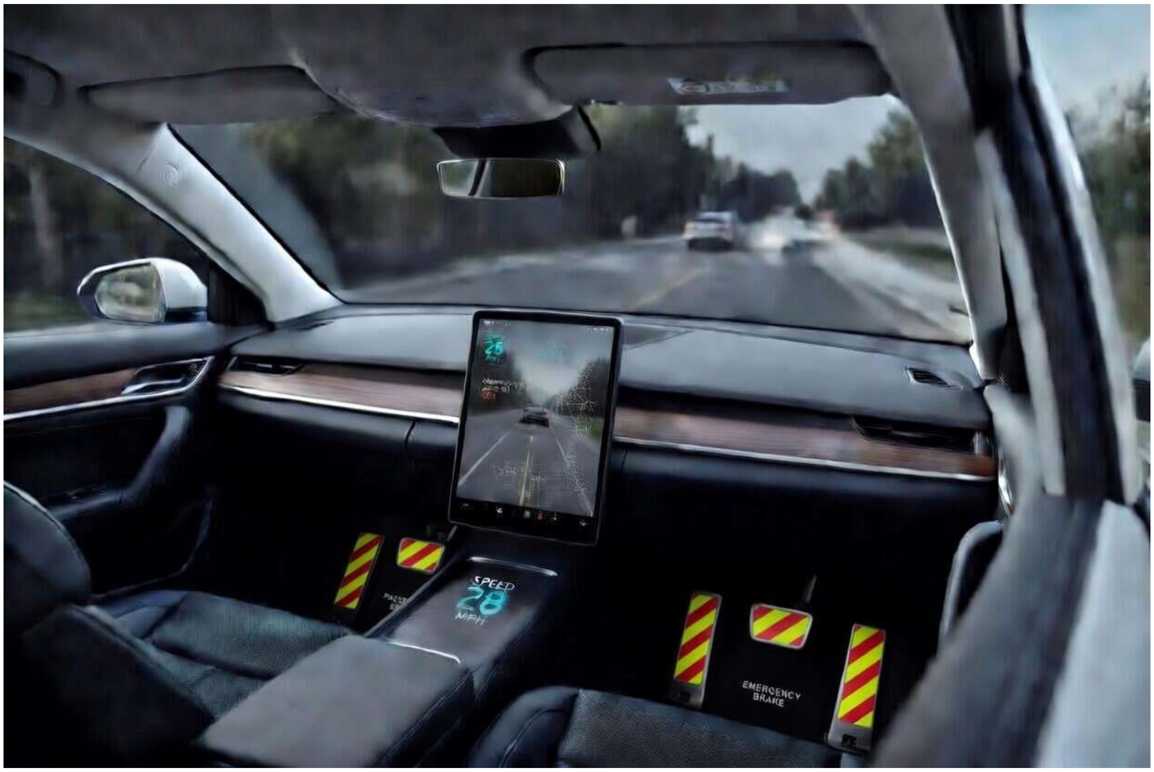


Figure 47. AI Generated SDV Center Console Display, Front Seat, Physical Brakes Only

14.4.4. Expansion of SDV Trust Question Set

The concept of SDV Trust introduced by this research effort focused on the amount of trust a person would have in using an SDV personally in a number of traffic scenarios, and if that person would feel comfortable sharing a roadway with vehicles that were self-driving. This concept proved to be a significant predictor of several independent variables examined within this research effort, and the collected data had an acceptable level of consistency as measured by Cronbach's Alpha. While these initial results were promising, this initial iteration of this SDV Trust measure may have a potential gap in that the measure did not evaluate the level of trust a respondent would have in an SDV when it came to the transport of people whose safety was considered important to the respondent. In other words, there is a possibility that respondents who would trust an SDV with their own safety may not share the same level of trust in the SDV keeping their children safe, as an example.

To address this potential gap, the addition of the following questions to the SDV Trust question matrix is recommend in any future experiments using this measure as a potential predictor:

1. I would be willing to allow my children or someone I care about who is not able to drive a vehicle to ride in a self-driving vehicle if I was also in the vehicle as well and able to take over driving.
2. I would be willing to allow my children or someone I care about who is not able to drive a vehicle to ride in a self-driving vehicle if I was also in the vehicle and able to perform an emergency stop.
3. I would be willing to allow my children or someone I care about who is not able to drive a vehicle to ride in a self-driving vehicle without me if they were able to initiate an emergency stop of the vehicle.
4. I would be willing to allow my children or someone I care about who is not able to drive a vehicle ride in a self-driving vehicle without me even if they were not able to initiate an emergency stop of the vehicle.
5. I would be willing to allow my children or someone I care about who is not able to drive a vehicle ride in a self-driving vehicle without me even if I was unable to track the location of the vehicle in real time.

The addition of these questions will allow researchers to determine if trust in SDVs is limited to scenarios where only the respondent is impacted by SDV behavior, or if that trust also extends to scenarios where important persons who cannot drive a vehicle are asked to ride in an SDV.

14.4.5. Future Experiment Design – Economic Factors

Additional research on the individual economic factors associated with SDVs is warranted based on the results from this experimental effort and the potential questions that remain unanswered following the completion of this research effort. As an example, the results from Research Aim 4 found that there was strong resistance to the general idea of new or increased mileage and fuel taxes, and a general preference for oversight funding and infrastructure improvements to be paid with either self-drive subscription fees or general increases in the cost of a vehicle. The experiment looked at these funding methods abstractly, as the total potential cost to a respondent from the funding method was not defined and the total cost required for infrastructure improvements and oversight was not easily estimated at the time the experiment was conducted. Because of the abstract method used, the research data did not provide guidance on the magnitude of the self-driving subscription fees or vehicle price increases respondents would accept, nor did the data determine if the increase in vehicle prices required to provide oversight funding were in addition to, or to be included within, their overall WTP for self-driving vehicles.

To address this gap, future experiments should adjust the discrete choice experiment to include the features of "Self-Drive Subscription", "SDV vehicle fee", and "General Fees and Taxes", and define levels for each feature that reflect annual cost of that option. For example, levels for "Self-Drive Subscription" could be \$300, \$600, \$900, and \$1200 to represent monthly fees of \$25, \$50, \$75, and \$100, respectively, above and beyond any subscription fees imposed by the SDV manufacturer. For "General Fees and Taxes", respondents would be told that these would be fees applied to everyone to cover the cost of oversight of SDV technology and enforcement of minimum safety standards. This updated discrete choice experiment would provide the data needed to identify what tax and fee levels were least opposed, and allow for extrapolation of oversight and infrastructure improvement revenues based on anticipated SDV adoption rates and fleet growth.

Another element that future consumer SDV economics research efforts should include the expanded WTP experiment that breaks down each SDV technology and feature into its own WTP data point and allows for parametric calculations of WTP based on SDV trim packages and what technologies have been widely adopted as “standard” on human-driven vehicles. Finally, future experiments should attempt to capture the perceived value of time or transport chore avoidance as one of the key economic arguments for SDVs is that the time consumed today by driving activities can be used instead for productive work or leisure activities. Questions designed to capture this information could take the following format:

“What would you be willing to pay, on a yearly basis and in U.S. Dollars ($), for the ability to [description of task taken over by access to an SDV]?”

Tasks to be included in the experiment could include:

1. Access video entertainment during commutes while an SDV takes you to work?
2. Perform work activities during the commute while an SDV takes you to work?
3. Avoid needing to drive children to friends’ houses or after-school activities because an SDV can perform this task?
4. Avoid driving to stores for curbside or parking lot pickup because you can send your SDV?

5. Use your SDV to provide paid rideshare services for Uber, Lyft, or similar ride share program when you are not needing your vehicle?
6. Avoid valet and parking fees as your SDV can drop you off for the event and pick you up afterwards?
7. Travel long distances via road comfortably as you are able to sleep or access entertainment while your SDV drives to the destination (or the next planned stop at a gas station or charging station)?

Capture of WTP values for these SDV vehicle capabilities and features would help provide a more complete understanding of respondent WTP, support development predictive models for WTP, and provide insight on which features and capabilities are the primary value drivers for SDVs.

14.4.6. Future Experiment Design – Consumer SDV Design Feature Expectations

The results from this research effort suggest that additional research is warranted regarding consumer expectations of SDVs, including safety and reliability expectations and what features are assumed to be included in SDV architectures. Specifically, the results from Research Aim 2 could be further investigated and refined to better identify the minimum reliability expectation for the SDV system. The original experiment only provided reliability levels of 1x per 5 years, 100x per 5 years, 500x per 5 years, and 1000x per 5 years, and the optimal package was identified as 1x per 5 years and some acceptance of a reliability rate of 100x per 5 years. Future experiments could focus on reliability ranges between 1x and 100x to further refine the reliability requirement. Additionally, the discrete choice experiment could be expanded to include a cost feature to determine if respondents would be willing to accept lower levels of reliability for reduced SDV cost.

Another potential area of focus for an updated reliability and safety feature experiment would be a more refined sensor subsystem resilience analysis. The results from Research Aim 2 showed a willingness to accept a lower level of sensor subsystem resilience even at the expense of having to perform more frequent maintenance and repair on the SDV. Since there was no cost component included in the Conjoint analysis, there is not a way to utilize the current data to evaluate if there is any cost sensitivity to system resilience stated preference results. In future experiments, a maintenance cost feature and a purchase cost feature should be added to the experiment design to evaluate if there is an inflection point where respondents are willing to pay more upfront to avoid higher maintenance costs over the long term.

Finally, future experiments should also include elements for the updated legal culpability experiment design, where respondents would be queried on their preferences regarding location where system information is displayed, what type of information is presented on those displays, what level of control they have over the SDV as passengers (being able to take over driving, performing an emergency stop only, or other level of control), and preferences on where they would be seated in the vehicle (front seat versus back seat). This stated preference information could be used to inform human factors requirements for future SDV designs.

14.5. Publications of Results

This research effort resulted in the publication of results, or the submission of results for consideration for publication, for all of the research aims. This section provides a summary of the results accepted for publication, and those results currently under consideration of publishing.

14.5.1. Aim 1 – Perceptions of SDV Legal Culpability

Results discussing who Americans would blame for accidents and traffic violations caused by self-driving vehicles (Research Aim 1) were presented at the 2025 INCOSE International Symposium in Ottawa, Canada, and subsequently published in the INCOSE IS 2025 conference proceedings.

Stewart, E., & Gallegos, E. (2025) What would I see in court? A survey analysis of who Americans would blame for self-driving vehicle crashes and traffic violations. *International Council on Systems Engineering International Symposium*, *35*(1), 736-759. https://doi.org/10.1002/iis2.70017

14.5.2. Aim 2 - Reliability and Safety Expectations

Results discussing SDV accuracy and resilience expectations for Americans and predictors for these expectations (Research Aim 2) were published in *Future Transportation*.

Stewart, E., & Gallegos, E.E. (2025). Reliability, resilience, and alerts: Preferences for autonomous vehicles. *Future Transportation, 5*(4), 164. https://doi.org/10.3390/futuretransp5040164

14.5.3. Aim 3 - Willingness to Pay for SDVs

Willingness to Pay (WTP) for full self-driving and advanced driver assist technology, and predictors for WTP (Research Aim 3) were published in the *Journal of Transportation Engineering*.

Stewart, E., & Gallegos, E.E. (Forthcoming). Full Self-Driving in the United States: Willingness to Pay and Its Predictors. *Journal of Transportation Engineering, Part A: Systems*. https://doi.org/10.1061/JTEPBS/TEENG-9304

14.5.4. Aim 4 – Tax and Fee Preferences for Oversight and Infrastructure Funding

Results discussing American preferences for funding methods for oversight of SDV technology and SDV-related infrastructure investments, and predictors for those funding preferences (Research Aim 4) were submitted for publication and currently under review at *Transport Policy*.

Stewart, E., Gallegos, E.E., & Conrad, S. (2026). *Paying for AV infrastructure and effective oversight: Preferences for funding methods and their predictors*. [Unpublished Manuscript]. Colorado State University.

14.5.5. Aim 5 – Effectiveness of Human Oversight on Autonomous Systems

Results discussing the effectiveness of human oversight of self-driving systems and predictors of that effectiveness (Research Aim 5) were submitted for publication and currently under review.

Stewart, E., & Gallegos, E.E. (2026). *Human Oversight of Traffic Sign Recognition: Impact of Error Rates and Framing on Effectiveness*. [Unpublished Manuscript]. Colorado State University.

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APPENDIX A – QUALTRICS ONLINE SURVEY FOR EXPERIMENT 1

Self-Drive: How Public Perceptions Will Shape a Transition to a Self-Driving Future - Prolific

Start of Block: Informed Consent

Q58 Dear Participant, My name is Eric Stewart and I am a researcher from Colorado State University in the Systems Engineering department. We are conducting a research study on perceptions of self-driving vehicles, willingness to use self-driving technology, preference for fee types to fund making self-driving cars more common, preference for certain features on self-driving cars, and perceptions of who is to blame if a self-driving car is involved in an accident to breaks traffic laws. The title of our project is Self-Drive: How Public Perceptions will Shape a Transition to a Self-Driving Future. The principal investigator of this project is Dr. Erika Gallegos and I am a student investigator. We would like you to take an online survey. Participation in this survey should take approximately 20 minutes. Your participation in this research is voluntary. If you decide not to participate in this study, you may withdraw your consent and stop participation at any time without penalty.   We will ask you for some general demographics questions as part of this survey, but we will not be collecting personal information likes names, home address, or email. Any information you provide will not be traceable back to you. The information collected as part of this research will not be used or distributed for future research studies. While there will be no direct benefits to you, we hope to gain more knowledge on potential barriers to the greater adoption of self-driving vehicles in the future. You will be compensated for your participation based on your agreement with the paid survey provider who brought you this survey. It is not possible to identify all potential risks in research procedures, but the researchers have taken reasonable safeguards to minimize any known and potential (but unknown) risks. There is a multiple choice question below. Selecting "Yes" will take you to the survey, while selecting "No" will end the survey. If you have any questions about the research, please contact Dr. Erika Gallegos at erika.miller@colostate.edu or Eric Stewart at redeagle@colostate.edu. If you have any questions regarding your rights as a volunteer in this research, contact the CSU IRB at: CSU_IRB@colostate.edu; 970-491-1553.

Q62 Do you agree to take this survey?

- I AGREE (1)
- I DO NOT AGREE (2)

End of Block: Informed Consent

Start of Block: Prolific ID Capture

Q63 What is your Prolific ID? ***Please note that this response should auto-fill with the correct ID***

____

End of Block: Prolific ID Capture

Start of Block: Screener Validation

Q64 In what country do you currently reside?

- United States (US) (1)
- United Kingdom (UK) (2)
- Other Country (3)

End of Block: Screener Validation

Start of Block: Risk Tolerance Assessment

Q1 This section is intended to find out your risk tolerance level. Please answer each question truthfully, as one of the goals of this survey is to find out if there is a relationship between risk tolerance and attitudes toward Self-Driving capabilities for personal vehicles.

Q2 To what extent do you agree with the following statements about your perception of risk?

	Strongly Agree (1)	Somewhat agree (2)	Neither agree nor disagree (3)	Somewhat disagree (4)	Strongly disagree (5)
Taking risks makes life more fun. (1)	○	○	○	○	○
My friends would say that I'm a risk taker. (2)	○	○	○	○	○
I enjoy taking risks in most aspects of my life. (3)	○	○	○	○	○
I would take a risk even if it meant I might get hurt. (4)	○	○	○	○	○
Taking risks is an important part of my life. (5)	○	○	○	○	○
I commonly make risky decisions. (6)	○	○	○	○	○
I am a firm believer of taking chances. (7)	○	○	○	○	○
I am attracted to, rather than scared by, risk. (8)	○	○	○	○	○

End of Block: Risk Tolerance Assessment

Start of Block: Familiarity with Self-Driving

Q1 This section asks a series of questions to assess your current familiarity and comfort level with Self-Driving vehicles. Please answer these questions truthfully as there are no "wrong" answers.

Q2 To what extent do you agree or disagree with the following statements?

	Strongly Agree (1)	Somewhat agree (2)	Neither agree nor disagree (3)	Somewhat disagree (4)	Strongly disagree (5)
I know about the concept of Self-Driving vehicles. (1)	○	○	○	○	○
I am willing to buy a vehicle that is capable of Self-Driving. (2)	○	○	○	○	○
Limits should be placed on when Self-Driving can be used. (3)	○	○	○	○	○
I would be willing to share the road with Self-Driving vehicles. (4)	○	○	○	○	○
I know of the potential limitations of Self-Driving vehicles. (5)	○	○	○	○	○
I have traveled in a vehicle using Self-Drive, such as Tesla Autopilot or like technology. (6)	○	○	○	○	○

Q3 To what extent do you agree or disagree with the following statement: I would feel safe using Self-Driving capability within the next year in the following locations?

	Strongly Agree (1)	Somewhat agree (2)	Neither agree nor disagree (3)	Somewhat disagree (4)	Strongly disagree (5)
Highway/Freeway with moderate traffic. (1)	○	○	○	○	○
Highway/Freeway with gridlock. (2)	○	○	○	○	○
Residential neighborhood. (3)	○	○	○	○	○
School zone. (4)	○	○	○	○	○
Busy parking lot. (5)	○	○	○	○	○
Urban / city streets. (6)	○	○	○	○	○

End of Block: Familiarity with Self-Driving

Start of Block: Perceived Value of Self-Driving

Q1 To what extent do you agree or disagree with the following statement: I would be willing to pay more money for a vehicle able to self-drive even if I must monitor the self-driving vehicle at all times and take over if the system makes a mistake?

○ Strongly Agree (1)

○ Somewhat agree (2)

○ Neither agree nor disagree (3)

○ Somewhat disagree (4)

○ Strongly disagree (5)

Q2 How much more would you be willing to pay (in dollars), for a vehicle capable of self-driving safely *without you having to keep track of the vehicle's movement* normal vehicle?

____

Q3 How much more would you be willing to pay (in dollars), for a vehicle capable of self-driving technology *but requires you to keep track of the vehicle's movement in order to ensure the safety of the vehicle and passengers*, versus a normal vehicle?

____

End of Block: Perceived Value of Self-Driving

Start of Block: Legal Culpability

Q1 This section talks about several events in which a vehicle using Self-Driving mode is either involved in an accident or is cited for speeding. Please review each event and answer the questions regarding who you believe is most to blame for the accident or traffic law infraction. Please be honest with your answers, as there are no "wrong" answers.

Q2 **Event 1**

Q3 In Scenario 1, the Traffic Sign Recognition (TSR) on the vehicle failed to correctly "see" the Stop sign due to vandalism. The mistake was *shown on the driver's console*, but the driver did not notice and failed to react before the accident in the intersection. In this scenario, who do you believe is most to blame for the accident? (Select One Answer)

○ Driver (Red Car) (1)

○ Vehicle Manufacturer (Red Car) (2)

○ Sign Maintainer (Department of Transportation or Local Government Authority) (3)

Q4 If the vehicle manufacturer for the Red Car had shown commercials that the Self-Drive feature allows the driver to multi-task and not focus on road conditions or on how the self-driving car was driving, how would this information change your opinion on how much the vehicle manufacturer was to blame for this accident?

- ○ Vehicle manufacturer would be more to blame for the accident. (1)
- ○ Vehicle manufacturer would have the same level of blame for the accident. (2)
- ○ Vehicle manufacturer would be less to blame for the accident. (3)

Page Break

Q55 Please review this event and answer the questions regarding who you believe is most to blame for the accident. Please be honest with your answers, as there are no "wrong" answers.

Q5 **Event 2**

Q6 In Event 2, the vehicle failed to correctly "see" the Stop sign due to vandalism. *The mistake was shown on a Heads-Up Display in front of the driver's seat*, but the driver did not notice and failed to react before the accident in the intersection. In this scenario, who do you believe is most to blame for the accident? (Select One Answer)

- ○ Driver (Red Car) (1)
- ○ Vehicle Manufacturer (Red Car) (2)
- ○ Sign Maintainer (Department of Transportation or Local Government Authority) (3)

Q7 If the vehicle manufacturer for the Red Car had shown commercials that the Self-Drive feature allows the driver to multi-task and not focus on road conditions or on how the self-driving car was driving, how would this information change your opinion on how much the vehicle manufacturer was to blame for this accident?

- ○ Vehicle manufacturer would be more to blame for the accident. (1)
- ○ Vehicle manufacturer would have the same amount of blame for the accident. (2)
- ○ Vehicle manufacturer would be less to blame for the accident. (3)

Page Break

Q56 Please review this event and answer the questions regarding who you believe is most to blame for the speeding ticket. Please be honest with your answers, as there are no "wrong" answers.

Q8 **Event 3**

Q9 In this event, the vehicle failed to correctly "see" the correct speed limit due to damage to the sign, and acts like the speed limit is 85 mph. The driver did not notice the mistake, and the vehicle was speeding when a cop pulled over the vehicle. In this scenario, who do you believe is most responsible for speeding? (Select One Answer)

○ Driver (1)

○ Vehicle Manufacturer (2)

○ Sign Maintainer (Department of Transportation or Local Government Authority) (3)

Q10 If the vehicle manufacturer for the vehicle in this event had shown commercials that the Self-Drive feature allows the driver to multi-task and not focus on road conditions or on how the self-driving car was driving, how would this information change your opinion on how much the vehicle manufacturer was to blame for this speeding ticket?

○ Vehicle manufacturer would have more blame for the speeding ticket. (1)

○ Vehicle manufacturer would have the same amount of blame for the speeding ticket. (2)

○ Vehicle manufacturer would have less blame for the speeding ticket. (3)

Page Break

Q57 Please review this event and answer the questions regarding who you believe is most to blame for the speeding ticket. Please be honest with your answers, as there are no "wrong" answers.

Q11 **Event 4**

Q12 In this event, the vehicle did "see" the "Speed Limit 75" sign, but did not "see" the 45 mph sign for when workers are present. The vehicle maintains a speed 75 mph, and the driver did not notice that the vehicle was speeding. The vehicle was speeding when a cop pulled over the vehicle and gave the driver a ticket. In this scenario, who do you believe is most responsible for the speeding ticket? (Select One Answer)

- ○ Driver (1)
- ○ Vehicle Manufacturer (2)

Q13 If the vehicle manufacturer for the vehicle in this event had shown commercials that the Self-Drive feature allows the driver to multi-task and not focus on road conditions or on how the self-driving car was driving, how would this information change your opinion on how much the vehicle manufacturer was to blame for this speeding ticket?

- ○ Vehicle manufacturer would have more blame for the speeding ticket. (1)
- ○ Vehicle manufacturer would have the same amount of blame for the speeding ticket. (2)
- ○ Vehicle manufacturer would have less blame for the speeding ticket. (3)

End of Block: Legal Culpability

Start of Block: Cost Sensitivity

Q1 This section will present you with different ways to pay for the cost of putting into place self-driving vehicles, including the costs for the technology required to meet the public's expectations for safety and reliability. The types of funding being considered are the following: 1. Gas Tax - This will be an added tax on the cost of a gallon of fuel (gasoline, diesel, hydrogen, etc.). This tax is on top of any fuel taxes in place today. 2. Mileage Tax - This would be a tax based on the number of miles the vehicle is driven in a given year, collected when plates are renewed. The cost is per every 100 miles traveled. 3. Self-Driving Subscription Fee - This would be a monthly fee for a service that allows for self-driving. If the service is not paid for by the driver, the driver will not be able to use the self-driving feature. 4. Vehicle Purchase Tax - This would be a one-time tax paid when a new vehicle is purchased. 5. General Increase in Vehicle Price - Vehicle manufacturers increase the cost of vehicles to pay for the costs of putting into place self-driving. For these five options, percentages are shown (which add up to 100%) for what percentage of the total cost will come from each funding source. As an example, if "Gas Tax" is at 80% and "Self-Driving Subscription Fee" is at 20%, then Gas Tax will provide 80% of the money and subscriptions will provide 20% of the money. In this example, the other funding sources would not be used. For each option pair, pick the option that you would prefer if you had to choose one of the options.

End of Block: Cost Sensitivity

Start of Block: Choice Analysis Hard Coding - Set 1

Q1 **Funding Profile 1** **Funding Profile 2** Mileage Tax ${lm://Field/1} ${lm://Field/2} Fuel Tax ${lm://Field/3} ${lm://Field/4} Vehicle Tax ${lm://Field/5} ${lm://Field/6} Increase Vehicle Price ${lm://Field/7} ${lm://Field/8} Self Drive Subscription ${lm://Field/9} ${lm://Field/10}

Q2 Which funding profile do you prefer?

○ Funding Profile 1 (1)

○ Funding Profile 2 (2)

Q54 1. Gas Tax - This will be an added tax on the cost of a gallon of fuel (gasoline, diesel, hydrogen, etc.). This tax is on top of any fuel taxes in place today. 2. Mileage Tax - This would be a tax based on the number of miles the vehicle is driven in a given year, collected when plates are renewed. The cost is per every 100 miles traveled. 3. Self-Driving Subscription Fee - This would be a monthly fee for a service that allows for self-driving. If the service is not paid for by the driver, the driver will not be able to use the self-driving feature. 4. Vehicle Purchase Tax - This would be a one-time tax paid when a new vehicle is purchased. 5. General Increase in Vehicle Price - Vehicle manufacturers increase the cost of vehicles to pay for the costs of putting into place self-driving. For these five options, percentages are shown (which add up to 100%) for what percentage of the total cost will come from each funding source. As an example, if "Gas Tax" is at 80% and "Self-Driving Subscription Fee" is at 20%, then Gas Tax will provide 80% of the money and subscriptions will provide 20% of the money. In this example, the other funding sources would not be used. For each option pair, pick the option that you would prefer if you had to choose one of the options.

End of Block: Choice Analysis Hard Coding - Set 1

Start of Block: Choice Analysis Hard Coding - Set 2

Q1 **Funding Profile 1** **Funding Profile 2** Mileage Tax ${lm://Field/1} ${lm://Field/2} Fuel Tax ${lm://Field/3} ${lm://Field/4} Vehicle Tax ${lm://Field/5} ${lm://Field/6} Increase Vehicle Price ${lm://Field/7} ${lm://Field/8} Self Drive Subscription ${lm://Field/9} ${lm://Field/10}

Q2 Which funding profile do you prefer?

- ○ Funding Profile 1 (1)
- ○ Funding Profile 2 (2)

Q55 1. Gas Tax - This will be an added tax on the cost of a gallon of fuel (gasoline, diesel, hydrogen, etc.). This tax is on top of any fuel taxes in place today. 2. Mileage Tax - This would be a tax based on the number of miles the vehicle is driven in a given year, collected when plates are renewed. The cost is per every 100 miles traveled. 3. Self-Driving Subscription Fee - This would be a monthly fee for a service that allows for self-driving. If the service is not paid for by the driver, the driver will not be able to use the self-driving feature. 4. Vehicle Purchase Tax - This would be a one-time tax paid when a new vehicle is purchased. 5. General Increase in Vehicle Price - Vehicle manufacturers increase the cost of vehicles to pay for the costs of putting into place self-driving. For these five options, percentages are shown (which add up to 100%) for what percentage of the total cost will come from each funding source. As an example, if "Gas Tax" is at 80% and "Self-Driving Subscription Fee" is at 20%, then Gas Tax will provide 80% of the money and subscriptions will provide 20% of the money. In this example, the other funding sources would not be

used. For each option pair, pick the option that you would prefer if you had to choose one of the options.

End of Block: Choice Analysis Hard Coding - Set 2

Start of Block: Choice Analysis Hard Coding - Set 3

Q1 **Funding Profile 1**
Funding Profile 2 Mileage Tax
${lm://Field/1} ${lm://Field/2}
Fuel Tax ${lm://Field/3}
${lm://Field/4} Vehicle Tax
${lm://Field/5} ${lm://Field/6}
Increase Vehicle Price ${lm://Field/7}
${lm://Field/8} Self Drive
Subscription ${lm://Field/9} ${lm://Field/10}

Q2 Which funding profile do you prefer?

- Funding Profile 1 (1)
- Funding Profile 2 (2)

Q56 1. Gas Tax - This will be an added tax on the cost of a gallon of fuel (gasoline, diesel, hydrogen, etc.). This tax is on top of any fuel taxes in place today. 2. Mileage Tax - This would be a tax based on the number of miles the vehicle is driven in a given year, collected when plates are renewed. The cost is per every 100 miles traveled. 3. Self-Driving Subscription Fee - This would be a monthly fee for a service that allows for self-driving. If the service is not paid for by the driver, the driver will not be able to use the self-driving feature. 4. Vehicle Purchase Tax - This would be a one-time tax paid when a new vehicle is purchased. 5. General Increase in Vehicle Price - Vehicle manufacturers increase the cost of vehicles to pay for the costs of putting into place self-driving. For these five options, percentages are shown (which add up to 100%) for what percentage of the total cost will come from each funding source. As an example, if "Gas Tax" is at 80% and "Self-Driving Subscription Fee" is at 20%, then Gas Tax will provide 80% of the money and subscriptions will provide 20% of the money.   In this example, the other funding sources would not be

used. For each option pair, pick the option that you would prefer if you had to choose one of the options.

End of Block: Choice Analysis Hard Coding - Set 3

Start of Block: Choice Analysis Hard Coding - Set 4

Q1 **Funding Profile 1**
Funding Profile 2 Mileage Tax
${lm://Field/1} ${lm://Field/2}
Fuel Tax ${lm://Field/3}
${lm://Field/4} Vehicle Tax
${lm://Field/5} ${lm://Field/6}
Increase Vehicle Price ${lm://Field/7}
${lm://Field/8} Self Drive
Subscription ${lm://Field/9} ${lm://Field/10}

Q2 Which funding profile do you prefer?

- Funding Profile 1 (1)
- Funding Profile 2 (2)

Q57 1. Gas Tax - This will be an added tax on the cost of a gallon of fuel (gasoline, diesel, hydrogen, etc.). This tax is on top of any fuel taxes in place today. 2. Mileage Tax - This would be a tax based on the number of miles the vehicle is driven in a given year, collected when plates are renewed. The cost is per every 100 miles traveled. 3. Self-Driving Subscription Fee - This would be a monthly fee for a service that allows for self-driving. If the service is not paid for by the driver, the driver will not be able to use the self-driving feature. 4. Vehicle Purchase Tax - This would be a one-time tax paid when a new vehicle is purchased. 5. General Increase in Vehicle Price - Vehicle manufacturers increase the cost of vehicles to pay for the costs of putting into place self-driving. For these five options, percentages are shown (which add up to 100%) for what percentage of the total cost will come from each funding source. As an example, if "Gas Tax" is at 80% and "Self-Driving Subscription Fee" is at 20%, then Gas Tax will provide 80% of the money and subscriptions will provide 20% of the money. In this example, the other funding sources would not be

used. For each option pair, pick the option that you would prefer if you had to choose one of the options.

End of Block: Choice Analysis Hard Coding - Set 4

Start of Block: Choice Analysis Hard Coding - Set 5

Q1 **Funding Profile 1** **Funding Profile 2**
Mileage Tax ${lm://Field/1} ${lm://Field/2}
Fuel Tax ${lm://Field/3} ${lm://Field/4}
Vehicle Tax ${lm://Field/5} ${lm://Field/6}
Increase Vehicle Price ${lm://Field/7} ${lm://Field/8}
Self Drive Subscription ${lm://Field/9} ${lm://Field/10}

Q2 Which funding profile do you prefer?

- Funding Profile 1 (1)
- Funding Profile 2 (2)

Q58 1. Gas Tax - This will be an added tax on the cost of a gallon of fuel (gasoline, diesel, hydrogen, etc.). This tax is on top of any fuel taxes in place today. 2. Mileage Tax - This would be a tax based on the number of miles the vehicle is driven in a given year, collected when plates are renewed. The cost is per every 100 miles traveled. 3. Self-Driving Subscription Fee - This would be a monthly fee for a service that allows for self-driving. If the service is not paid for by the driver, the driver will not be able to use the self-driving feature. 4. Vehicle Purchase Tax - This would be a one-time tax paid when a new vehicle is purchased. 5. General Increase in Vehicle Price - Vehicle manufacturers increase the cost of vehicles to pay for the costs of putting into place self-driving. For these five options, percentages are shown (which add up to 100%) for what percentage of the total cost will come from each funding source. As an example, if "Gas Tax" is at 80% and "Self-Driving Subscription Fee" is at 20%, then Gas Tax will provide 80% of the money and subscriptions will provide 20% of the money. In this example, the other funding sources would not be

used. For each option pair, pick the option that you would prefer if you had to choose one of the options.

End of Block: Choice Analysis Hard Coding - Set 5

Start of Block: Choice Analysis Hard Coding - Set 6

Q1 **Funding Profile 1** **Funding Profile 2** Mileage Tax ${lm://Field/1} ${lm://Field/2} Fuel Tax ${lm://Field/3} ${lm://Field/4} Vehicle Tax ${lm://Field/5} ${lm://Field/6} Increase Vehicle Price ${lm://Field/7} ${lm://Field/8} Self Drive Subscription ${lm://Field/9} ${lm://Field/10}

Q2 Which funding profile do you prefer?

◯ Funding Profile 1 (1)

◯ Funding Profile 2 (2)

Q59 1. Gas Tax - This will be an added tax on the cost of a gallon of fuel (gasoline, diesel, hydrogen, etc.). This tax is on top of any fuel taxes in place today. 2. Mileage Tax - This would be a tax based on the number of miles the vehicle is driven in a given year, collected when plates are renewed. The cost is per every 100 miles traveled. 3. Self-Driving Subscription Fee - This would be a monthly fee for a service that allows for self-driving. If the service is not paid for by the driver, the driver will not be able to use the self-driving feature. 4. Vehicle Purchase Tax - This would be a one-time tax paid when a new vehicle is purchased. 5. General Increase in Vehicle Price - Vehicle manufacturers increase the cost of vehicles to pay for the costs of putting into place self-driving. For these five options, percentages are shown (which add up to 100%) for what percentage of the total cost will come from each funding source. As an example, if "Gas Tax" is at 80% and "Self-Driving Subscription Fee" is at 20%, then Gas Tax will provide 80% of the money and subscriptions will provide 20% of the money. In this example, the other funding sources would not be

used. For each option pair, pick the option that you would prefer if you had to choose one of the options.

End of Block: Choice Analysis Hard Coding - Set 6

Start of Block: Feature Selection Opening Statement

Q53 In this section, you will see a series of choices and asked which choice you would prefer if you had to choose one of the two options. Each options will show different choices for the following self-driving features: How Often the Driver Must Take Over: This represents the number of times the driver will need to take over driving the vehicle from the computer during the time the driver owns the vehicle. Sensor Repair Timings: Self driving relies on cameras and other items on the vehicle to "see" the world and allow for safe travel. Sometimes these cameras break and need to be repaired. This feature asks you how many cameras should be allowed to break, as a percentage of the total, before repairing the broken cameras is needed. What the Vehicle Does When Self-Driving Fails: This feature talks about what the vehicle will do if self-driving stops working. The vehicle can safely come to a complete stop, or the vehicle can alert you with a warning you can see and have you take over driving, or alert you with a touch warning (vibration) and have you take over driving. Method of Alerting Driver to Alerts: This feature talks about how the vehicle will let the driver know about messages or alerts from the self-driving computer. Options for how the vehicle can let the driver know about messages or alerts include a visual alert, a sound alert, both a visual alert and a sound alert, or no alert at all.

End of Block: Feature Selection Opening Statement

Start of Block: ConjointBlock

JS

C1 (1/6) Choose your preferred option below: Option 2How Often Driver Must Take Over${e://Field/688b22ff-8b3b-4a19-ab50-1ece865501db.1.1_CBCONJOINT}${e://Field/688b22ff-8b3b-4a19-ab50-1ece865501db.1.2_CBCONJOINT}Amount of Sensors Allowed to Fail Before Repair is Needed${e://Field/2b2705e7-bb7c-4f8b-9382-3e8131b37993.1.1_CBCONJOINT}${e://Field/2b2705e7-bb7c-4f8b-9382-3e8131b37993.1.2_CBCONJOINT}What the Vehicle Does When Self-Driving Fails${e://Field/1f211aae-2dfe-4c49-8180-98e135dc021e.1.1_CBCONJOINT}${e://Field/1f211aae-2dfe-4c49-8180-98e135dc021e.1.2_CBCONJOINT}Method of Alerting Driver to Alerts and Messages${e://Field/3e306bad-44eb-4601-8094-

699d500531bd.1.1_CBCONJOINT}${e://Field/3e306bad-44eb-4601-8094-699d500531bd.1.2_CBCONJOINT}

- (1)
- (2)

Page Break

JS

C2 (2/6) Choose your preferred option below: Option 2How Often Driver Must Take Over${e://Field/688b22ff-8b3b-4a19-ab50-1ece865501db.2.1_CBCONJOINT}${e://Field/688b22ff-8b3b-4a19-ab50-1ece865501db.2.2_CBCONJOINT}Amount of Sensors Allowed to Fail Before Repair is Needed${e://Field/2b2705e7-bb7c-4f8b-9382-3e8131b37993.2.1_CBCONJOINT}${e://Field/2b2705e7-bb7c-4f8b-9382-3e8131b37993.2.2_CBCONJOINT}What the Vehicle Does When Self-Driving Fails${e://Field/1f211aae-2dfe-4c49-8180-98e135dc021e.2.1_CBCONJOINT}${e://Field/1f211aae-2dfe-4c49-8180-98e135dc021e.2.2_CBCONJOINT}Method of Alerting Driver to Alerts and Messages${e://Field/3e306bad-44eb-4601-8094-699d500531bd.2.1_CBCONJOINT}${e://Field/3e306bad-44eb-4601-8094-699d500531bd.2.2_CBCONJOINT}

- (1)
- (2)

Page Break

JS

C3 (3/6) Choose your preferred option below: Option 2How Often Driver Must Take Over${e://Field/688b22ff-8b3b-4a19-ab50-1ece865501db.3.1_CBCONJOINT}${e://Field/688b22ff-8b3b-4a19-ab50-1ece865501db.3.2_CBCONJOINT}Amount of Sensors Allowed to Fail Before Repair is Needed${e://Field/2b2705e7-bb7c-4f8b-9382-3e8131b37993.3.1_CBCONJOINT}${e://Field/2b2705e7-bb7c-4f8b-9382-3e8131b37993.3.2_CBCONJOINT}What the Vehicle Does When Self-Driving Fails${e://Field/1f211aae-2dfe-4c49-8180-98e135dc021e.3.1_CBCONJOINT}${e://Field/1f211aae-2dfe-4c49-8180-98e135dc021e.3.2_CBCONJOINT}Method of Alerting Driver to Alerts and Messages${e://Field/3e306bad-44eb-4601-8094-699d500531bd.3.1_CBCONJOINT}${e://Field/3e306bad-44eb-4601-8094-699d500531bd.3.2_CBCONJOINT}

- (1)
- (2)

Page Break

JS

C4 (4/6) Choose your preferred option below: Option 2How Often Driver Must Take Over${e://Field/688b22ff-8b3b-4a19-ab50-1ece865501db.4.1_CBCONJOINT}${e://Field/688b22ff-8b3b-4a19-ab50-1ece865501db.4.2_CBCONJOINT}Amount of Sensors Allowed to Fail Before Repair is Needed${e://Field/2b2705e7-bb7c-4f8b-9382-3e8131b37993.4.1_CBCONJOINT}${e://Field/2b2705e7-bb7c-4f8b-9382-3e8131b37993.4.2_CBCONJOINT}What the Vehicle Does When Self-Driving Fails${e://Field/1f211aae-2dfe-4c49-8180-98e135dc021e.4.1_CBCONJOINT}${e://Field/1f211aae-2dfe-4c49-8180-98e135dc021e.4.2_CBCONJOINT}Method of Alerting Driver to Alerts and Messages${e://Field/3e306bad-44eb-4601-8094-699d500531bd.4.1_CBCONJOINT}${e://Field/3e306bad-44eb-4601-8094-699d500531bd.4.2_CBCONJOINT}

○ (1)

○ (2)

Page Break

JS

C5 (5/6) Choose your preferred option below: Option 2How Often Driver Must Take Over${e://Field/688b22ff-8b3b-4a19-ab50-1ece865501db.5.1_CBCONJOINT}${e://Field/688b22ff-8b3b-4a19-ab50-1ece865501db.5.2_CBCONJOINT}Amount of Sensors Allowed to Fail Before Repair is Needed${e://Field/2b2705e7-bb7c-4f8b-9382-3e8131b37993.5.1_CBCONJOINT}${e://Field/2b2705e7-bb7c-4f8b-9382-3e8131b37993.5.2_CBCONJOINT}What the Vehicle Does When Self-Driving Fails${e://Field/1f211aae-2dfe-4c49-8180-98e135dc021e.5.1_CBCONJOINT}${e://Field/1f211aae-2dfe-4c49-8180-98e135dc021e.5.2_CBCONJOINT}Method of Alerting Driver to Alerts and Messages${e://Field/3e306bad-44eb-4601-8094-699d500531bd.5.1_CBCONJOINT}${e://Field/3e306bad-44eb-4601-8094-699d500531bd.5.2_CBCONJOINT}

○ (1)

○ (2)

Page Break

JS

C6 (6/6) Choose your preferred option below: Option 2How Often Driver Must Take Over${e://Field/688b22ff-8b3b-4a19-ab50-1ece865501db.6.1_CBCONJOINT}${e://Field/688b22ff-8b3b-4a19-ab50-1ece865501db.6.2_CBCONJOINT}Amount of Sensors Allowed to Fail Before Repair is Needed${e://Field/2b2705e7-bb7c-4f8b-9382-3e8131b37993.6.1_CBCONJOINT}${e://Field/2b2705e7-bb7c-4f8b-9382-3e8131b37993.6.2_CBCONJOINT}What the Vehicle Does When Self-Driving Fails${e://Field/1f211aae-2dfe-4c49-8180-98e135dc021e.6.1_CBCONJOINT}${e://Field/1f211aae-2dfe-4c49-8180-98e135dc021e.6.2_CBCONJOINT}Method of Alerting Driver to Alerts and Messages${e://Field/3e306bad-44eb-4601-8094-699d500531bd.6.1_CBCONJOINT}${e://Field/3e306bad-44eb-4601-8094-699d500531bd.6.2_CBCONJOINT}

- (1)
- (2)

Page Break

End of Block: ConjointBlock

Start of Block: Demographic Information

Q1 What is your current marital status?

- Single (1)
- Married (2)
- Divorced (3)
- Widowed/Widower (4)
- Prefer not to answer (5)

Q2 How do you identify your racial or ethnic background?

- Hispanic (1)
- Latino (2)
- African American (3)
- White / Non-Latino (4)
- Asian (5)
- Pacific Islander (6)
- Native American / Alaskan Native (7)
- Other (8)
- Prefer not to answer (9)

Q3 What is the highest level of education you have completed?

- Less Than High School Diploma (1)
- High School Diploma (2)
- Some College (3)
- Associate's Degree (4)
- Bachelor's Degree (5)
- Master's Degree (6)
- Doctorate Degree (7)
- Professional Degree (8)

Q4 How do you identify your gender?

- Male (1)
- Female (2)
- Non-binary / other gender (3)
- Prefer not to say (4)

Q5 What much money does you household make in a year?

- Less than $10,000 (1)
- $10,000 - $19,999 (2)
- $20,000 - $29,999 (3)
- $30,000 - $39,999 (4)
- $40,000 - $49,999 (5)
- $50,000 - $59,999 (6)
- $60,000 - $69,999 (7)
- $70,000 - $79,999 (8)
- $80,000 - $89,999 (9)
- $90,000 - $99,999 (10)
- $100,000 - $149,999 (11)
- More than $150,000 (12)

Q6 How often do you drive a personal vehicle such as a car, truck, or van (owned, borrowed, rented, etc.)?

- Daily (1)
- 4-6 times a week (2)
- 2-3 times a week (3)
- Once a week (4)
- Never (5)

Q7 What type of vehicle do you personally own and drive most often?

- ◯ Vehicle using gasoline or diesel fuel (Internal Combustion Engines) (1)
- ◯ Vehicle using fuel other than gasoline or diesel (hydrogen, natural gas, etc.) (2)
- ◯ Hybrid electric/gas vehicle (battery + gasoline powered engine) (3)
- ◯ Electric vehicle (battery only) (4)
- ◯ Do Not Own a Vehicle (5)

Q61 How many miles do you drive each year (best guess)?

____

End of Block: Demographic Information

Start of Block: Participant Thank You

Q65 Thank you for taking part in this survey. Please select the "Next" button below to be redirected back to Prolific and record your responses to this survey.

End of Block: Participant Thank You

APPENDIX B – QUALTRICS ONLINE SURVEY FOR EXPERIMENT 2

Driver Oversight Survey

Start of Block: Informed Consent Capture

Q1 Dear Participant, My name is Eric Stewart and I am a researcher from Colorado State University in the Systems Engineering department. We are conducting a research study on perceptions of user interfaces for Self-Driving Vehicles. The title of our project is Preferences in Self-Driving User Interfaces in the United States. The principal investigator of this project is Dr. Erika Gallegos and I am a student investigator. We would like you to take an online survey. Participation in this survey should take approximately 20-30 minutes. Your participation in this research is voluntary. If you decide not to participate in this study, you may withdraw your consent and stop participation at any time without penalty.   We will ask you for some general demographics questions as part of this survey, but we will not be collecting personal information likes names, home address, or phone numbers. Any information you provide will not be traceable back to you. The information collected as part of this research will not be used or distributed for future research studies. We hope to gain more knowledge the effectiveness of human supervision of self-driving technologies. As a form of potential compensation, you are welcome to opt into a raffle drawing for a $50 Amazon gift card by entering your email at the conclusion of the survey. Participation in the raffle is voluntary, and is dependent on a successful and honest completion of this survey. This survey includes a review of a series of driving videos that feature Artificial Intelligence (AI) highlights and attempted identification of traffic signs. These video clips are from normal driving operations of a test vehicle, and while there are not any flashing sequences, the video does show motion, turns, and curves which may be uncomfortable for some respondents with past concerns viewing videos showing motion/movement. Motion-sensitive respondent discretion is advised. It is not possible to identify all potential risks in research procedures, but the researchers have taken reasonable safeguards to minimize any known and potential (but unknown) risks. Clicking "Yes" on the question below, you consent to participate in this study. If you have any questions about the research, please contact Dr. Erika Gallegos at erika.miller@colostate.edu or Eric Stewart at redeagle@colostate.edu. If you have any questions regarding your rights as a volunteer in this research, contact the CSU IRB at: CSU_IRB@colostate.edu; 970-491-1553.

Q10 Do you consent to take this survey?

○ Yes

○ No

End of Block: Informed Consent Capture

Start of Block: Limit Participation to United States residents

Q11 Do you reside in the United States?

○ Yes

○ No

End of Block: Limit Participation to United States residents

Start of Block: Limit Respondent Pool to Potential Drivers

Q28 Do you currently drive a personal vehicle (such as a passenger car, truck, van, or similar vehicle) at least one time every week?

○ Yes

○ No

End of Block: Limit Respondent Pool to Potential Drivers

Start of Block: Time Commitment

Q29 This survey may take up to 30 minutes to complete. Can you commit to completing this survey in a single session?

○ Yes

○ No

End of Block: Time Commitment

Start of Block: Motion Video Warning

Q40 Part of this survey involves you reviewing driving video clips from test drives supporting the development of a traffic sign recognition software. These videos include motion and highlighting of traffic control signs that may trigger motion sickness symptoms. Do you agree to take this survey and review the driving videos?

- ○ Yes
- ○ No

End of Block: Motion Video Warning

Start of Block: Risk Score

Q2 This section is intended to evaluate your driving behavior. Please answer each question truthfully, as one of the goals of this survey is to find out if there is a relationship between driver behavior and attitudes toward the effectiveness of the traffic sign recognition system.

Q3 Please identify the frequency in which you engage in the following driving behaviors:

	Never	Hardly Ever	Occasionally	Quite Often	Frequently	Nearly All The Time
Attempt to drive away from traffic lights in the wrong gear.	○	○	○	○	○	○
Become impatient with a slow driver in the fast lane and pass on the right.	○	○	○	○	○	○
Drive especially close to a car in front as a signal to the driver to go faster or get out of the way.	○	○	○	○	○	○
Attempt to pass someone that you hadn't noticed to be making a left turn.	○	○	○	○	○	○
Forget where you left your car in a parking lot.	○	○	○	○	○	○
Turn on one thing, such as your headlights, when you mean to switch on something else, such as the windshield wipers.	○	○	○	○	○	○

Realize that you have no clear recollection of the road along which you have just been traveling.						
Cross an intersection knowing that the traffic lights have already changed from yellow to red.						
Fail to notice that pedestrians are crossing when turning onto a side street from a main road.						
Angered by another driver's behavior, you catch up to them with the intention of giving him/her "a piece of your mind."						
Misread the signs and turn the wrong direction on a one-way street.						

Disregard the speed limits late a night or early in the morning.	○	○	○	○	○	○
When turning right, nearly hit a bicyclist who is riding along side of you.	○	○	○	○	○	○
Attempting to turn onto a main road, you pay such close attention to traffic on the road you are entering that you nearly hit the car in front of you that is also waiting to turn.	○	○	○	○	○	○
Drive even though you might be over the legal blood alcohol limit.	○	○	○	○	○	○
Have an aversion to a particular class of road user, and indicate your hostility by whatever means you can.	○	○	○	○	○	○

Underestimate the speed of an oncoming vehicle when attempting to pass a vehicle in your own lane.	○	○	○	○	○	○
Hit something when backing up that you had not previously seen.	○	○	○	○	○	○
Intending to drive to destination A, you "wake up" to find yourself on a road to destination B, because destination B is a more common destination.	○	○	○	○	○	○
Get into the wrong lane approaching an intersection.	○	○	○	○	○	○
Miss "Yield" signs, and narrowly avoid colliding with traffic having the right of way.	○	○	○	○	○	○
Fail to check your rearview mirror before pulling out, changing lanes, etc.	○	○	○	○	○	○

Get involved in unofficial "races" with other drivers.	○	○	○	○	○	○
Brake too quickly on a slippery road or steer the wrong way into a skid.	○	○	○	○	○	○

End of Block: Risk Score

Start of Block: Comfort Score

Q4 This section is intended to find out your comfort level regarding Self-Driving Vehicles. Please answer each question truthfully, as one of the goals of this survey is to find out if there is a relationship between Self-Driving Vehicle comfort level and attitudes toward the effectiveness of the traffic sign recognition system.

Q5 To what extent do you agree or disagree with the following statements?

	Strongly Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
Limits should be placed on when Self-Driving can be used.	○	○	○	○	○
I would be willing to share the road with Self-Driving Vehicles.	○	○	○	○	○

Q6 To what extent do you agree or disagree with the following statements: I would fee safe using Self-Driving Vehicles within the next year in the following locations?

	Strongly Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
Highway/Freeway with moderate traffic.	○	○	○	○	○
Highway/Freeway with gridlock.	○	○	○	○	○
Residential neighborhood.	○	○	○	○	○
School zone.	○	○	○	○	○
Busy parking lot.	○	○	○	○	○
Urban / city streets.	○	○	○	○	○

End of Block: Comfort Score

Start of Block: Familiarity Score

Q7 This section is intended to find out your level of familiarity regarding Self-Driving Vehicles. Please answer each question truthfully, as one of the goals of this survey is to find out if there is a relationship between Self-Driving Vehicle familiarity and attitudes toward the effectiveness of the traffic sign recognition system.

Q8 To what extent do you agree or disagree with the following statements?

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree
I know about the concept of Self-Driving Vehicles.	○	○	○	○	○
I am willing to buy a vehicle that is capable of Self-Driving.	○	○	○	○	○
I know of the potential limitations of Self-Driving Vehicles.	○	○	○	○	○
I have traveled in a vehicle using Self-Drive, such as Tesla Autopilot or like technology.	○	○	○	○	○

End of Block: Familiarity Score

Start of Block: Video Group 1 Instructions

Q35 We currently have an Artificial Intelligence (AI) under development that detects road signs within camera video, determines if the traffic sign is relevant to the Self-Driving Vehicle, highlights the sign deemed to be important for the Self-Driving Vehicle, and displays what the AI believes is an equivalent sign. Based on how the self-driving system is programmed, the driving behavior of the vehicle changes when regulatory signs or warning signs are detected and are applicable to the Self-Driving Vehicle. Some examples of regulatory and warning signs are shown below:

Q36 This traffic sign finding AI **has been in development for over a year**, and **recent tests have shown that the system is very reliable and accurately identifies important regulatory and warning signs**, ensuring the safety of the vehicle and its passengers. This AI was put through its final approval tests recently, and a significant amount of test data was collected. A random selection of this data will be shown to you in a video format. Please review the **four (4) videos** for any detection or identification errors. If you see an error, please hit the space bar on your keyboard (if you are viewing this survey on a computer) or tap the screen if you are viewing this survey on a smart device.

End of Block: Video Group 1 Instructions

Start of Block: Video Experiment Redirect Group 1

JS

Q37 Redirecting to traffic sign recognition experiment.

End of Block: Video Experiment Redirect Group 1

Start of Block: Video Group 2 Instructions

Q37 We currently have an Artificial Intelligence (AI) under development that detects road signs within camera video, determines if the traffic sign is relevant to the Self-Driving Vehicle, highlights the sign deemed to be important for the Self-Driving Vehicle, and displays what the AI believes is an equivalent sign. Based on how the self-driving system is programmed, the driving behavior of the vehicle changes when regulatory signs or warning signs are detected and are applicable to the Self-Driving Vehicle. Some examples of regulatory and warning signs are shown below:

Q38 This traffic sign finding AI **has been in development for over a year**, and **recent tests have shown that the system is very reliable and accurately identifies important regulatory and warning signs**, ensuring the safety of the vehicle and its passengers. This AI was put through its final approval tests recently, and a significant amount of test data was collected. A random selection of this data will be shown to you in a video format. Please review the **four (4) videos** for any detection or identification errors. If you see an error, please hit the space bar on your keyboard (if you are viewing this survey on a computer) or tap the screen if you are viewing this survey on a mobile device.

End of Block: Video Group 2 Instructions

Start of Block: Video Experiment Redirect Group 2

JS

Q38 Redirecting to traffic sign recognition experiment.

End of Block: Video Experiment Redirect Group 2

Start of Block: Video Group 3 Instructions

Q39 We currently have an Artificial Intelligence (AI) under development that detects road signs within camera video, determines if the traffic sign is relevant to the Self-Driving Vehicle, highlights the sign deemed to be important for the Self-Driving Vehicle, and displays what the AI believes is an equivalent sign. Based on how the self-driving system is programmed, the driving behavior of the vehicle changes when regulatory signs or warning signs are detected and are applicable to the Self-Driving Vehicle. Some examples of regulatory and warning signs are shown below:

Q40 This traffic sign finding AI is **still in early development**, and the **developers believe there may still be some bugs in the software**. This AI was tested recently using a human-driven vehicle with a camera mounted to the front of the car. The AI processed the video from the camera and attempted to detect road signs, identify the type of road sign, and highlight signs that were relevant to the human-driven car. A random selection of this data will be shown to you in a video format. Please review the **four (4) videos** for any detection or identification errors as this will help the developers further improve the AI. If you see an error, please hit the space bar on your keyboard (if you are viewing this survey on a computer) or tap the screen if you are viewing this survey on a smart device.

End of Block: Video Group 3 Instructions

Start of Block: Transfer to Simulated Drive Group 3

JS

Q39 Redirecting to traffic sign recognition experiment.

End of Block: Transfer to Simulated Drive Group 3

Start of Block: Video Group 4 Instructions

Q41 We currently have an Artificial Intelligence (AI) under development that detects road signs within camera video, determines if the traffic sign is relevant to the Self-Driving

Vehicle, highlights the sign deemed to be important for the Self-Driving Vehicle, and displays what the AI believes is an equivalent sign. Based on how the self-driving system is programmed, the driving behavior of the vehicle changes when regulatory signs or warning signs are detected and are applicable to the Self-Driving Vehicle. Some examples of regulatory and warning signs are shown below:

Q42 This traffic sign finding AI is **still in early development**, and the **developers believe there may still be some bugs in the software**. This AI was tested recently using a human-driven vehicle with a camera mounted to the front of the car. The AI processed the video from the camera and attempted to detect road signs, identify the type of road sign, and highlight signs that were relevant to the human-driven car. A random selection of this data will be shown to you in a video format. Please review the **four (4) videos** for any detection or identification errors as this will help the developers further improve the AI. If you see an error, please hit the space bar on your keyboard (if you are viewing this survey on a computer) or tap the screen if you are viewing this survey on a smart device.

End of Block: Video Group 4 Instructions

Start of Block: Transfer to Simulated Drive Group 4

JS

Q40 Redirecting to traffic sign recognition experiment.

End of Block: Transfer to Simulated Drive Group 4

Start of Block: System Trust Questions

Q1 To what extent do you agree or disagree with the following statements about the Self-Driving system you were just shown?

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
The system is deceptive.	○	○	○	○	○	○	○
The system behaves in an underhanded manner.	○	○	○	○	○	○	○
I am suspicious about the system's outputs.	○	○	○	○	○	○	○
I am wary of the system.	○	○	○	○	○	○	○
The system's actions will have a harmful or injurious outcome.	○	○	○	○	○	○	○
I am confident in the system.	○	○	○	○	○	○	○
The system provides security.	○	○	○	○	○	○	○
The system has integrity.	○	○	○	○	○	○	○
The system is dependable.	○	○	○	○	○	○	○
The system is reliable.	○	○	○	○	○	○	○
I can trust the system.	○	○	○	○	○	○	○

I am familiar with the system.	○	○	○	○	○	○	○

End of Block: System Trust Questions

Start of Block: Demographics

Q1 What is your current marital status?

○ Single

○ Married

○ Divorced

○ Widowed/Widower

○ Prefer not to answer

Q2 How do you identify your racial or ethnic group?

- ○ Hispanic
- ○ Latino
- ○ African American
- ○ White / Non-Latino
- ○ Asian
- ○ Pacific Islander
- ○ Native American / Alaskan Native
- ○ Other
- ○ Prefer not to answer.

Q3 What is the highest level of education you have completed?

- ○ Less Than High School Diploma
- ○ High School Diploma
- ○ Some College
- ○ Associate's Degree
- ○ Bachelor's Degree
- ○ Master's Degree
- ○ Doctorate Degree
- ○ Professional Degree

Q4 How do you identify your gender?

- ◯ Male
- ◯ Female
- ◯ Non-binary / third gender
- ◯ Prefer not to say

Q5 How much money does your household make in a year?

- ◯ $0 - $19,999
- ◯ $20,000 - $39,999
- ◯ $40,000 - $59,999
- ◯ $60,000 - $79,999
- ◯ $80,000 - $99,999
- ◯ $100,000 - $149,999
- ◯ $150,000 or more
- ◯ Prefer not to answer

Q6 How often do you drive a personal vehicle such as a car, truck, or van (owned, borrowed, rented, etc.)?

- Daily
- 4-6 times a week
- 2-3 times a week
- Once a week
- Less than once a week
- Never

Q7 What type of vehicle do you personally own and drive most often?

- Vehicle using gasoline or diesel fuel (Internal Combustion Engine)
- Vehicle using fuel other than gasoline or diesel (hydrogen, natural gas, etc.)
- Hybrid electric/gas vehicle (battery + gasoline powered engine)
- Electric vehicle (battery only)
- Do Not Own a Vehicle

*

Q8 How many miles do you drive each year (best guess)?

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End of Block: Demographics

Start of Block: Participate in Amazon Gift Card Draw

Q38 Thank you for participating in this survey! If you would like to participate in the $50 Amazon gift card drawing, please enter your email in the box below. Otherwise, please select the arrow to end the survey.

Q39 Email

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End of Block: Participate in Amazon Gift Card Draw

LIST OF ABBREVIATIONS

ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance Systems
AI	Artificial Intelligence
ANOVA	Analysis of Variance
AUD	Australian Dollar
CAV	Connected and Autonomous Vehicle
CI	Confidence Interval
DBQ	Driver Behaviour Questionnaire
DCE	Discrete Choice Experiment
DMV	Department of Motor Vehicles
FAA	Federal Aviation Administration (United States)
GLMM	Generalized Linear Mixed Effects Models
GRiPS	General Risk Propensity Scare
HEV	Hybrid Electric Vehicle
HUD	Heads-Up Display
ICE	Internal Combustion Engine
ICEV	Internal Combustion Engine Vehicle
ID	Identification
IQR	Interquartile Range
IRB	Institutional Review Board
LASSO	Least Absolute Shrinkage and Selection Operator

MCAS	Maneuver Characteristics Augmentation System
ML	Machine Learning
MM-DBQ	Modified Manchester Driver Behaviour Questionnaire
MUTCD	Manual on Uniform Traffic Control Devices
NTSB	National Transportation Safety Board
ODA	Outside Designated Authority
SAE	Society of Automotive Engineers
SDV	Self-Driving Vehicle
TIAS	Trust in Automation Scale
TOR	Takeover Request
TSR	Traffic Sign Recognition
UK	United Kingdom
US	United States
VIF	Variance Inflation Factor
WTP	Willingness to Pay