2022

Automation, Take the Wheel: An Examination of Factors Influencing Trust in Automated Driver Assist Technologies

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AUTOMATION, TAKE THE WHEEL: AN EXAMINATION OF FACTORS INFLUENCING TRUST IN AUTOMATED DRIVER ASSIST TECHNOLOGIES

by

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A dissertation submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
in the Department of Psychology
in the College of Sciences
at the University of Central Florida
Orlando, Florida

Fall Term
2022

Major Professor: Mustapha Mouloua

ABSTRACT

Driving technology has progressed significantly since the introduction of anti-lock braking and cruise control decades ago. Current driver assist features can alert drivers of oncoming vehicles and even take control to keep the vehicle centered within its lane. The level of trust that people place in automation can impact how they monitor and accept these automated systems. Previous research has shown several performance outcomes associated with improper calibrations of trust in automation. However, there is still a need to examine trust in the context of advanced driving technologies. Research has yet to sufficiently investigate factors influencing trust in assistive driving features. The current study was designed to examine whether changes to the driving environment might influence levels of trust in various driver assist features. In addition, this study sought to evaluate if individual characteristics might also influence automation trust. A sample of 166 participants completed a series of hypothetical driving vignettes describing both high and low complexity environments using five different driver assist features. It was hypothesized that trust in driving technologies would be related to scenario complexity, and that trust would vary across driving features (forward collision warning, cruise control, lane centering assist, adaptive cruise/traffic jam assist, and fully automated driving). Results showed that trust was significantly higher in low complexity than in high complexity scenarios. Furthermore, trust significantly varied across the five driver assist features. Findings also revealed that propensity to trust technology moderated the relationship between trust and driving feature manipulations. Similarly, dispositional trust in three of the five unique driving feature moderated the relationship between trust and scenario complexity. These findings have implications for the design and acceptance of autonomous systems, especially automated/assistive driving technologies, as well as other remotely operated vehicles.

To my parents and my love, for enduring the many speed bumps alongside me.

ACKNOWLEDGMENTS

I would like to thank my dissertation committee, Dr. Peter Hancock, Dr. James Szalma, Dr. Phillip Mangos, and Dr. Gerald Matthews, for lending their assistance and vast knowledge as this project was completed. I would also like to thank my dissertation and graduate advisor, Dr. Mustapha Mouloua, for the years of guidance that made this achievement possible. Finally, I would like to thank my undergraduate advisor, Dr. Kenneth Walters, whose teaching and continued support I will always be grateful for.

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CHAPTER 1: INTRODUCTION

Problem Statement

Automated driver assist features have become commonplace in modern automobiles, becoming advanced to the point of adapting to the environment around them. The proliferation of driver assist technologies has altered the way drivers interact with their vehicle and the roads they drive on. Once considered a luxury, features such as forward collision avoidance and blind spot warnings are considered common and hardly among the more advanced driver assist features modern vehicles possess. It is for this reason that nearly every vehicle on the road today can be considered partially automated, and perhaps for good reason. Human error is common in driving tasks, with as much as 94% of serious crashing being attributed to some form of error (Singh, 2015). Driver assist features have taken responsibility away from the driver in some tasks that, theoretically, are better performed by automation. Task allocation in complex human-machine systems is an engineering challenge that has persisted for decades (Hancock, 1991). To address this challenge, human factors researchers have studied the capabilities and limitations of human beings in a variety of complex systems, examining how they interact and deciding how to assign tasks between parties to optimize overall system performance. This dates back to the original Fitts' list, outlining tasks that are better performed by humans or machines (Fitts, 1954), and is a task that still burdens researchers and systems designers to this day. However, it is how drivers are able to effectively utilize this technology that determines whether or the allocation of tasks is successful and the intended safety benefits are realized.

The amount of trust a person places in automated systems can influence how they interact with, accept, and actually use the systems (Parasuraman & Riley, 1997; Lee & See, 2004; Mouloua et al., 2019a). Automation is implemented into a system with the intention to relieve the individuals involved of certain duties, lessening their cognitive and physical workload while hopefully optimizing their performance in other tasks. A person that does not trust automation to perform its intended tasks reliably will inevitably underutilize the technology, thus rendering the system ineffective and not receiving any of the intended benefits (Lee & Moray, 1992; Lee & See, 2004). Conversely, by placing too much trust in an automated system operators and others interacting with the system are vulnerable to unexpected failures. Over-trust can result in a kind of complacency, and a lack of awareness of the state of the system and the surrounding conditions. A proper calibration of trust is needed to get the most out of an automated system while maintaining a high level of safety. As driver assist technologies continue to progress toward a full self-driving vehicle, the world has seen examples of how inappropriate estimations of the reliability of these systems can have catastrophic results.

Automated vehicles have begun to increase in popularity, with brands that boast such technologies such as Tesla becoming more recognizable on the street. Public perception of these vehicles is generally positive, but there are a growing number of examples of individuals being reckless in how much they trust the underlying technology to navigate them safely from point A to point B. An example from May of 2021 describes "a San Fransisco man who was arrested for riding in the back seat of his tesla as it drove on the highway," (Levin, 2021). Allowing yourself to be driven entirely by automation, with no opportunity for user intervention, requires a certain amount of trust that nothing will go wrong. In this example, the consequence was two counts of reckless driving and an impounded Tesla. The man even stated he would be willing to purchase another Tesla and repeat the act again, a clear showing of the trust he has in Tesla's self-driving technology. Earlier in 2021 two passengers in a Tesla that appeared to be in self-driving mode were not quite as lucky (Tangermann, 2021). The Tesla Model S crashed into a tree and both occupants were killed in the accident. Accident investigators on the scene were certain that neither of the occupants were in the driver's seat at the time of the accident and believe the vehicle did not make a turn at a high speed before hitting the tree. These represent two clear examples of a miscalibration of trust in the automated vehicle, which put the occupants of the vehicles in a position that would not allow them to compensate for or correct any action on the part of the vehicle.

The incidents described above and the role that drivers' trust may have played in them, considered with the increase in automation in vehicles on the road today, begins to raise the question – what about an individual makes the more or less likely to trust and effectively use driver assist technologies? What information can be used to predict who is susceptible to inappropriate calibrations of trust in driving automation? Does trust in driver assist features vary depending on the driving context? It is important to answer these questions as researchers and engineers continue to try and solve problems related to task allocation and user-centered design in automated vehicles.

Purpose of the Current Study

Improper calibrations of trust in automated vehicles and their capabilities have led to a number of accidents. Researchers, consumers, and manufacturers may benefit from a more complete model of factors that influence driver trust. This knowledge can help inform methods to compensate when a driver's trust does not match the reliability of the vehicle or specific automated feature (e.g., dynamic task allocation, adaptive automation). It can also be used to inform decisions regarding what tasks can be automated with minimal risk of consequences related to user acceptance and trust (e.g., complacency, misuse).

The purpose of this study was to examine how various factors contribute to an individual's level of trust in several automated driver assist features. Manipulations to driving conditions and the level of autonomy in the technology can help provided a clearer picture of the contexts in which automated driving is likely to be trusted. Despite the fact that there is no current fully autonomous vehicle on the road today (SAE 2021), research into automated driving has focused very little on the discrete features that are truly prevalent in most vehicles (Tenhundfeld et al., 2020). Additionally, research investigating interactions between the various factors known to impact operator trust and acceptance of automated systems (Hancock et al., 2011; Hoff & Bashir, 2015; Schaefer et al., 2016) is lacking as it relates to driver assist features. This study will begin to fill this existing gap in the literature by evaluating a range of dispositional, situational, and system-related factors that may influence the level of trust a driver has in various driver assist features. To address questions about how these factors impact driver trust, participants reviewed a series of vignette driving scenarios that described using different driver assist features under different road conditions. It was generally hypothesized that road condition and the level of autonomy associated with the driver assist feature would significantly impact participants' trust in the technology.

CHAPTER 2: REVIEWING THE LITERATURE

Current Driver Assist and Automated Driving Features

Vehicles now possess a potentially full complement of automated elements that are designed to make roads safer and lessen prospects for human error. With advancements in technologies such as computer vision, more sophisticated systems have been incorporated into vehicles that can help drivers maintain overall situation awareness at all times. The timeline of driver assist feature development is provided below (Figure 1; NHTSA, 2022a).

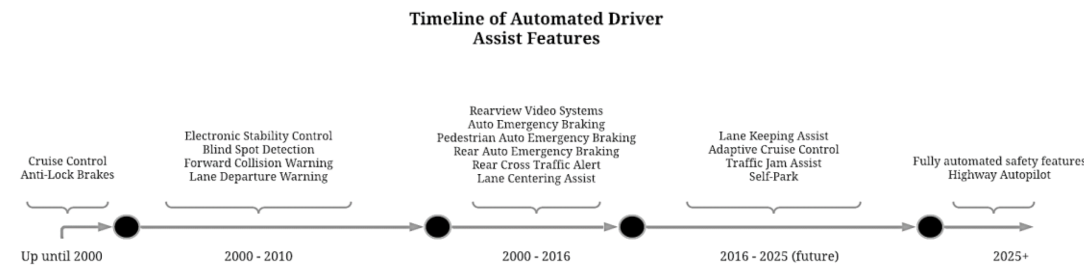

FIGURE 1: TIMELINE OF DRIVER ASSIST TECHNOLOGY DEVELOPMENT

Early driver assist systems include cruise control and anti-lock braking, true accomplishments in driving automation at their conception. However, a vehicle's ability to sense, interpret, and react to the environment has grown and given way to a long list of more dynamic features. This progression began with systems to alert users of sudden or hazardous events surrounding the vehicle (e.g., blind spot detection, forward collision warning). These were rather passive systems that aimed to raise drivers' awareness of their surroundings, while being granted to level of control over whether or not any action was taken in response to an alert. It was not until features such as emergency braking and lane centering assist were made available that the vehicle could supersede the actions of the driver and maneuver the vehicle for the sake of avoiding an accident or dangerous situation. New, advanced sensors were capable of detecting objects and movement around the vehicle, attempting to create a full awareness of the environment beyond what a driver is capable of – one free of a vigilance decrement or risk of distraction. With the introduction of each new feature, the industry moved closer to what some see as an inevitability in the self-driving car. This would represent a drastic shift in the role of the driver, contributing to a trend seen in many human-machine systems and effectively taking the driver's hands off the wheel.

Automated features that are beginning to replace or compliment tasks previously performed by human drivers are one example of the larger change in the responsibilities of humans in complex systems. Modern human-machine systems include some balance of function or tasking between the human and the machine components, and the prevailing position assigned to the human is that of a supervisor in charge of ensuring tasks are accomplished and procedures followed without obstruction or error (Parasuraman et al., 1996; Parasuraman & Riley, 1997; Ebnali et al., 2019; Mouloua et al., 2019b). This position remains essential as there are still notable limitations present in the driver assist features available, even in the more common ones. In fact, despite their popularity and apparent ubiquity across all vehicles produced in recent years, only a handful of the available driver assist features are considered to be recommended safety technology by the National Highway Traffic Safety Administration (NHTSA, 2022b). This includes forward collision warning, lane departure warning, and automatic emergency braking. It is notable that two of these NHTSA recommended safety features only include warnings, taking no responsibility for the movement of the vehicle. There remain questions related to the safety and reliability of the technology underlying each of the features mentioned thus far. For this reason, ensuring drivers are vigilant in monitoring for hazards or automation failures is critical to maximizing the safety benefits of any single automated driving system.

Monitoring Automated Systems

Advancements in driver assist technologies, such as those described above, have transformed pedestrian vehicles into incredibly complex human-machine systems wherein the machine is receiving more and more say in how the system performs. Not only have certain driver assist systems made maintaining situation awareness easier for the driver (i.e., back up camera), but they are now making situation awareness possible for the vehicle itself through artificial intelligence (AI) and computer vision. Sophisticated computer vision systems have made it possible for cars to detect pedestrians in its path or to determine if drivers are straying from the center of their lane using markings on the road. It is certainly an impressive human achievement, granting computers the ability to detect and identify objects and act accordingly to maintain system safety. However, maintaining this desired high level of safety is dependent on various complex systems operating and communicating simultaneously and without error. At Tesla's Artificial Intelligence Day in 2021, company CEO Elon Musk stated that the company was "effectively building a synthetic animal from the ground up," when discussing their full self-driving technology (CNET Highlights, 2021). This is hardly an understatement, as developing reliable driver assist systems is easier said than done.

There does not exist today a truly infallible automated device. It is for this reason that contingency planning and recovery procedures are so necessary for the effective use and handling of tasks that involve automated systems. Therein lies the need for the human operator, occupying the supervisory role and stepping in when needed for what could be any of a number of reasons (Parasuraman & Riley, 1997; Mouloua et al., 2019b). The need of a human monitoring component to the system is essential when using driver assist technologies, as even those at the forefront of autonomous driving state plainly that even a vehicle utilizing an autopilot feature needs constant monitoring by a driver (Tesla, 2022a). Many driver assist features come with certain disclaimers designed to temper expectations and ensure drivers properly use these features to optimize safety. For example, the suite of automated driving features known as Honda Sensing is equipped with a lane keeping assist feature. This feature comes with the following disclaimer:

> "LKAS only assists driver in maintaining proper lane position when lane markings are identified without a turn signal in use and can only apply mild steering torque to assist. LKAS may not detect all lane markings; accuracy will vary based on weather, speed, and road condition. System operation affected by extreme interior heat. Driver remains responsible for safety operating vehicle and avoiding collisions," (Honda, 2021).

This demonstrates the lack of a perfectly reliable system, re-emphasizing the need of an attentive operator. There should not, however, be any misconception that the inclusion of a human to monitor the system provides a truly flawless fail-safe in an otherwise flawed system. Human factors research into human monitoring of automated systems has found it to be a task for which they "are magnificently disqualified," (Hancock, 1991).

Despite the noted limitations in human performance from a supervisory role within a human-machine system, more and more drivers are placed in this supervisory position (De winter & Hancock, 2021). In the description of the Tesla Model S autopilot feature, it insists that autopilot will perform tasks such as steering, acceleration, and braking under driver supervision, claiming these to be "the most burdensome parts of driving," (Tesla, 2022b). However, it may be the supervising that the driver is now expected to do that may be the most burdensome part of driving. Presenting a variety of attentional challenges (distraction, complacency, etc.) monitoring automation and surrounding conditions may actually be as taxing to a driver as manual driving (Stapel et al., 2019). In critical signal detection tasks, operators have been found to struggle monitoring complex environments (Bailey & Scerbo, 2007). Cognitive limitations related to vigilance and fatigue will also impact how effectively a driver can attentively monitor a system and detect errors or anomalies when they inevitably occur (Mouloua et al., 2019b).

Another explanation for the poor monitoring performance of humans within complex human-machine systems is a phenomenon referred to in human factors research as automation-induced complacency (Parasuraman et al., 1993; Wiener, 1981). Complacency occurs when a human operator's focus wanes and they lose awareness of the status of the system and/or surrounding conditions. Researchers have found there is a tendency for operators monitoring static, reliable systems to become complacent (Bagheri & Jamieson, 2004; Bailey & Scerbo, 2007) which can make them vulnerable to automation failures and loss of situation awareness. The low workload that elicited by highly reliable systems requires less effort on the part of the operator, and during extended periods of monitoring for failures the ability to step in and correct an error degrades (Parasuraman, Molloy, & Singh, 1993; Mouloua et al., 2019; Ferraro & Mouloua, 2021).

Complacency has been previously referred to as a "psychological state characterized by a low index of suspicion," (Weiner, 1981, p 117). A likely contributor to complacency exhibited in operators of multiple automated systems is a bias (Bahner et al., 2008; Parasuraman & Manzey, 2010) toward the reliability and misunderstanding of the limitations of the system. The amount of trust an operator places in an automated system is viewed as an indicator of a likelihood to become complacent during period of prolonged monitoring (Parasuraman, Molloy, & Singh, 1993; Lee, 2008; Hergeth et al., 2016; Korber et al., 2018). Similarly, whether or not a person chooses to execute a task manually or allow an automated system to perform the task may be due to how much trust they have in that system (Muir, 1994).

A Matter of Trust

Examinations of human-automation interaction have revealed a multitude of factors that contribute to the success and efficacy of any human-machine system. Much like interpersonal relationships, the relationship between a human and an automated agent is based largely on the construct of trust (Lee & See, 2004). Trust is a concept that influences and drives many of our daily interactions. Commuters' trust in the weather forecast determines when they leave the house and what they wear each day. Consumers' trust in the expiration dates on milk carton influences decisions whether to have cereal each morning. Similar to the trust we place in individuals, we have begun to trust automation (often with some fairly important tasks). Trust in automated systems can often be equated with a likelihood to use and accept a system, impacting a person's reliance on and compliance with actions or recommendations of a system.

Trust shapes the way people treat and interact with technology. A commonplace example of technology that is only effectively utilized with the proper calibration of trust is the Roomba. This is an automated vacuum; a small robot that traverses the floors of your home and gathers up dust and small debris that it can reach. Equipped with a system of sensors that create 360 degrees of awareness, the Roomba is designed to avoid furniture and cliffs (stairs, for example) and return to its charging station when it has finished its job, or its battery is depleted. This is a technology designed to help humans avoid the simple, tedious, and occasionally time-consuming task of vacuuming, allowing the owner of the Roomba to do other things while it takes care of whatever may reach its automated, sweeping bristles. A tool to maximize human productivity in the household. However, this tool is not nearly as effective if not treated with an appropriate level of trust.

In a situation where the owner of a Roomba does not place enough trust in the machine to do its job, the technology becomes less effective in achieving its ultimate purpose. This lack of trust can manifest in multiple ways. A person may decide to follow the Roomba from room to room, ensuring it gets to all the spaces it should. A person may also decide to take a vacuum of their own and do the job themselves after the Roomba has finished, perhaps as a way to ensure the job is done. The ultimate purpose of the Roomba is to vacuum, so the human does not have to. If a person purchases an automated vacuum but chooses to either spend their time monitoring the vacuum or repeating its tasks manually, they are no longer seeing the benefits of automation. Should, however, a person place too much trust in the Roomba to flawlessly perform its job they may find it caught on a rug and out of battery hours later. A failure to attend to the technology, entrusting it to operate flawlessly and without intervention, leaves one unable to recover in case of malfunction. This can result in lost time as automation waits for its correction in order to finish accomplishing the task. The consequences demonstrated here as a result of inappropriate levels of trust are amplified in magnitude and risk when considering more safety-critical features that are implemented into complex systems, such as partially automated vehicles.

In the context of all human-machine systems, a proper calibration of trust is critical when attempting to see the full benefit of automation (Parasuraman & Riley, 1997). A lack of trust, as demonstrated in the example above, can lead to automation misuse (Muir, 1994; Parasuraman & Riley, 1997). This occurs when an operator does not believe in the capabilities of an automated system, providing additional oversight at the potential compromising of their own task performance. This may result in a higher rate of error detection on the part of the operator, as their persistent allocation of attentional resources to the task performed by the automation puts them in position to step in should the automation fail or be compromised in any way. For example, in tasks involving automated driving systems, research has found lower levels of trust to be associated with faster reaction times (Payre et al., 2016) and more time spent monitoring the road (Korber, Baseler, & Bengler, 2018). However, this is likely to compromises the performance of the system as a whole (Lee & Moray, 1992). Misuse, or the underutilization of driver assist features is already an issue for manufacturers. Previous research has found that drivers are inclined to turn their driver assist systems off, and the frequency of use and apparent acceptance of these systems seems to vary depending on the system itself (Eichelberger & McCartt, 2014; 2016; Kidd et al., 2017). A 2016 study found that nearly all Honda vehicles surveyed at service centers had their forward collision warning systems activated (Reagan & McCartt, 2016). That same study found that less than one third of these same vehicles had their lane departure warning system activated. By not activating or underutilizing these systems, they can be rendered unintentionally useless.

There are, however, notable consequences for placing too much trust in an automated system. Similar to interpersonal relationships, more trust does not equate to the correct amount of trust (Ebnali et al., 2019). Automation-induced complacency is often considered a consequence of overtrust in automated systems (Parasuraman et al., 1993; Mouloua et al., 1993; Parasuraman & Manzey, 2010; Mouloua et al., 2019b). Operators that trust automation beyond the capabilities of the system are susceptible to lapses in situation awareness due to complacency. A study examining the role of trust in the operation of autonomous vehicles found that participants appeared to "accept to fall asleep due to high trust in automation," (Kundinger et al., 2019). This study found a positive relationship between trust and levels of drowsiness. There is also an apparent impact on human monitoring performance based on levels of trust in a system (Bailey & Scerbo, 2007; Lee, 2008). A longer reaction time during emergency manual recovery scenarios was associated with higher levels of trust in a study looking at performance and trust in operating fully autonomous vehicles (Payre et al., 2016). The attitude accompanying these behaviors appears to be, ‘if I trust the system to be reliable, I do not need to monitor its behavior.’

Unfortunately, examples of consumers placing an inappropriate amount of trust in automated vehicles have already begun to accumulate. Some, despite the best efforts of the individuals involved, do not end in disaster. In May of 2021, a man in San Francisco was pulled over and arrested while riding alone in the back passenger seat of his Tesla (Levin, 2021). This particular individual placed enough trust in the vehicle and the underlying technology that he did not feel it was necessary to put himself in a position to take the wheel in case of an emergency. Fortunately for this individual, the ticket was the only consequence of his reckless behavior. However, in the month prior to this incident in April of 2021, two individuals were killed in a single-vehicle accident involving a Tesla Model S (Tangermann, 2021). Investigators at the scene were “100 percent certain” that neither of the passengers were in the driver seat at the moment of the accident. The vehicle appeared to have failed to make a turn and impacted a tree not far off the road. This is a tragic example of how placing too much trust in an automated system can have devastating consequences, especially in potentially dangerous tasks such as driving.

Manufacturers should be interested in what factors contribute to these decisions made by drivers. Is it related to the quality of the system in place? The underlying systems and computer vision technologies that support features such as forward collision warning and lane departure warning are far from perfect. Could it be due to the environment these vehicles are driven in? It is possible these features provide an unneeded benefit for this segment of drivers, who may drive in residential neighborhoods with minimal complexity to their environment. Or perhaps it is related to the individuals themselves, being distrusting in nature or feeling more comfortable with the systems they are familiar with. Human factors research has identified a multitude of factors that may contribute to how much trust an individual has in an automated system (Hancock et al., 2011; Schaefer et al., 2014; Hoff & Bashir, 2015). These include dispositional factors, or those related to the individual, environmental factors, or those related to the scenario or context in which the system is being used, and those related to the system itself.

A goal of this current study was to examine these factors and see how they contribute to the amount of trust a person places in automated driving systems.

Factors Influencing Trust in Automation

Dispositional Factors

Dispositional factors are the aspects of an individual that make them more or less likely to trust an automated system. While trust calibration is typically acknowledged as a dynamic process, research has found that certain characteristics and abilities of an individual will significantly impact how likely they are to trust automation. A primary example of this is a person's predisposition to trust in general (Merritt & Ilgen, 2008, Schaefer et al., 2016), a trait that has been shown to make them more likely to trust automation. Trust assessed prior to experience with driving in a driving simulator was found to lead to differences in trust construction in participants (Manchon et al., 2021). It has also been found that those who are less likely to trust automation may be more accurate when it comes to calibrating a proper level of trust. However, findings from Merritt and Ilgen (2008) suggest that, with experience, trust in automation is less impacted by a propensity to trust the system and more by characteristics related to the machine.

Trust calibration may closely follow laws of learning, wherein the more a person learns about a system and its capabilities and limitations, the better they can calibrate an appropriate level of trust (Ebnali et al., 2019). To that end, experience with automated driving systems has shown to strongly effect operator trust (Gold et al., 2015; Azevedo-Sa et al., 2020). Some research has found that more exposure to a system results in increased trust (Kundinger, Wintersberger, & Riener, 2019), but this may also depend on the performance of the system in those experiences (Tenhundfeld et al., 2020). Additional dispositional factors include a person's own confidence in their ability to perform the automated task. If an operator is not confident in their ability to perform the task, they tend to rely more heavily on the automation (De Vrise et al., 2003). There appears to be a relationship between self-efficacy and trust in lower levels of automation in studies of automated driving systems (Miele et al., 2021). Differences in levels of trust in automation between genders and education level, and even based on age (Donmez et al., 2006; Abraham et al., 2016; Hillesheim et al., 2017). Newer drivers might display different levels of trust in driving technologies when compared to older drivers (Shahini et al., 2021). These characteristics, many unique to each individual, may ultimately influence how likely a person is to trust automated driving features and how much trust they initially place in the features.

Environmental Factors

In addition to the dispositional factors that may impact how much trust an individual places in an automated system, the environment in which they system is operating will also play a role in determining trust. Examples of these environmental are represented in the model for environmental conditions that influence the relationship between trust and reliance developed by Hoff and Bashir (2015). They suggest that the strength of the relationship between trust and reliance is determined by:

- Complexity of the automation
- Novelty of the situation
- Operator's ability to compare automated performance to manual
- Operator's degree of decisional freedom

Higher levels of these characteristics are believed to result in a stronger relationship between trust and reliance.

The amount of trust a person places in automation in a particular situation (situational trust; Balfe, Sharples, & Wilson, 2018) can also vary based on the complexity of the situation and the workload imposed on the operator (Hancock et al., 2011; Hoff & Bashir, 2015). Increased in workload have been found to elicit an increase in reliance behaviors (Hillesheim et al., 2017). Additional situational or environmental factors that may impact trust and reliance are the time pressure associated with accomplishing a certain task (Lee & See, 2004) and the amount of risk perceived by the individual (Li et al., 2019).

System Related Factors

A final set of factors that researchers have found can significantly contribute to the calibration of trust in automated systems pertain to the characteristics of the system itself. It appears to be true that user experience with a system will impact their trust in that system, but the behaviors of the system also will influence trust calibration. One characteristic of an automated system that has consistently shaped trust is the reliability or competence of the system

(Miller & Parasuraman, 2007; Balfe et al., 2018). Research has shown that highly reliable systems tend to increase trust (Bailey & Scerbo, 2007). The types of errors committed by an automated system will have unique impacts for how users trust and interact with that technology. For example, in aviation the 'Cry Wolf Effect' was so named as pilots began to ignore alerts that they had learned are not always reliable and were often false alarms (Bliss, 1993). This is a learned response by pilots who experience the incompetence of the automation (some researchers also refer to system-related factors 'learned factors') and choose not to comply with its instructions. A miss, or failure to detect or act upon a stimulus when expected, on the part of automation has shown to uniquely impact reliance behaviors (Rice, 2009). This is demonstrated in studies of human monitoring performance that have found error detection to be far better in conditions of low automation reliability, indicating users of low reliability systems are less likely to rely on that system to perform its job well (Oakley et al., 2003; Ferraro et al., 2018). Related to system reliability, if a user finds they are able to perform an action before the system they are less likely to trust and rely upon that system. Examples of this can be found in research that observed a driver less likely to use an emergency braking system if they noticed themselves hitting the break earlier than the system would engage (Lees & Lee, 2007).

Another aspect of an automated system that has been shown to impact trust and reliance is the amount of transparency and feedback provided by the system (Sheridan, 1999; Beck et al., 2007; Azevedo-Sa et al., 2020). This could be feedback regarding the system's intentions, reasons for previous actions, and overall operational status of its components. Researchers have found that a drivers' trust in automated features within a vehicle is better calibrated when the system communicated its reasoning for making a maneuver or its level of certainty when making a decision (Manchon et al., 2021). During a series of partially automated trials utilizing a Tesla

Model X's automated parking feature, participants reported a greater likelihood to trust the feature once they were able to understand what the system was doing (Tenhundfeld et al., 2020).

Additionally, the level or degree of automation in use can often have an impact on the trust a user places in that system. Levels of automation describe the amount of responsibility the automated system has in performing a task, relative to that of the human (Parasuraman et al., 2000; Kaber & Endsley, 2004; Endsley, 2018). When introduced into a broader system the automation does not have to serve an "all or none" function (Onnasch et al., 2014), and can be assigned to performing part of a task or components of a task only at certain times. While there are a variety of models for levels of automation, they follow a general pattern with lower levels involving more human participation and higher levels delegating more work to the automation. Below is one example, developed by Parasuraman, Sheridan, and Wickens (2000), of a model for levels of automation of decision action and selection.

*TABLE 1: LEVELS OF AUTOMATION OF DECISION ACTION AND SELECTION (*PARASURAMAN ET AL., *2000)*

HIGH	10	The computer decides everything, acts autonomously, ignoring the human
	9	…informs the human only if it, the computer, decides to
	8	…informs the human only if asked, or
	7	…executes automatically, then necessarily informs the human and
	6	…allows the human a restricted time to veto before automatic execution, or
	5	…executes that suggestion if the human approves, or
	4	…suggests one alternative
	3	…narrows the selection down to a few, or
	2	The computer offers a complete set of decision/action alternatives, or
LOW	1	The computer offers no assistance, human must take all decisions and actions

Higher levels of automation are implemented with the goal of lessening the burden on the operator, while lower levels allow the operator to maintain more manual control over the system's performance. It is believed the routine task performance can be optimized at lower levels of automation (Onnasch et al., 2014). Among the multiple models for levels of automation is the Society of Automotive Engineers (SAE) Levels of Driving Automation (SAE, 2021), which refers to the level of responsibility a driver and automated driver assist technologies have in modern vehicles. The SAE levels have been iterated on multiple times, refined as advanced driving technologies increase in their overall capabilities.

TABLE 2: SAE LEVELS OF DRIVING AUTOMATION (SAE, 2021)

SAE Level	Description	Example Features
Level 0	Provide warnings and brief support	Blindspot Warning
Level 1	Handle steering OR brake/acceleration assistance	Lane Centering OR Adaptive Cruise Control
Level 2	Handle steering AND brake/acceleration assistance	Lane Centering AND Adaptive Cruise Control
Level 3	Drive vehicle in certain conditions but driver must drive when the feature requests	Traffic Jam Chauffeur
Level 4	Drive vehicle in certain conditions	Local driverless taxi
Level 5	Drive vehicle regardless of conditions	Same as Lvl 4 but in call conditions

While each model is different and no model is perfect (see Hancock, 2020), each highlights the utility of such a measurement for a level of autonomy within a human-machine system. There is currently no consistently established relationship between levels of automation and operator trust in a system (Rani et al., 2000; Schaefer et al., 2016). Much research in the driving domain have been limited to vehicles at a single level of automation (Kundinger et al. 2019; Cardenas et al., 2020). Additional research has produced conflicting results, with some believing that autonomous vehicles with higher levels of capability are trusted less than lower-level automation (Miele et al., 2021).

CHAPTER 3: CURRENT STUDY RATIONALE

Addressing Gaps in the Literature

The current study intended to address current gaps in human factors literature related to factors that influence trust in driver assist technologies. More specifically, it aimed to resolve previously unanswered questions related to how environmental and system-related factors may interact to effect driver trust, and how individual differences may impact the strength or direction these effects. While it is clear that trust can be a driving factor in the human-automation relationship, having strong implications for system effectiveness, the impact of different levels of trust on human behavior must be understood. Proper calibrations of trust have been identified as those that correspond accurately with the capabilities and limitations of the system they are applied to (Lee & Moray 1994; Muir, 1994). It has been demonstrated throughout the literature that human monitoring performance, the task that, as mentioned above, is becoming essential in human-machine systems, is especially impacted by overtrust and undertrust (Bailey & Scerbo, 2007; Lee, 2008). By placing too much trust in automation, operators are more likely to experience automation-induced complacency (Parasuraman et al., 1993; Mouloua et al., 1993) and a lack of trust fails to see the full benefits of the automation. This is of particular concern when considering the expanding role of driver assist technologies.

Trust and acceptance of automotive technologies represents only a small percentage of driving research (Ayoub et al., 2019), despite the evidence supporting its impact. A review of papers from the International ACM Conference on Automotive User Interface and Interactive Vehicular Applications (AutoUI) dated from 2009 to 2018 found trust and acceptance to be a topic in 4.3% of all articles. While this sample represents but a small segment of all driving research, it helps to highlight a need and a gap in the literature related to automated driving.

Previous research has suggested that there may be a tendency for drivers to show increased reliance in simple, lower-level automated features while reducing reliance for highly complex automated features (Hoff & Bashir, 2015). However, these researchers suggested that “research is needed to confirm [this] trend.” Additionally, more data is needed to determine how features related to the automation, such as degree/level of automation, interact with situational factors such as task complexity or risk to influence how trust is formed.

The goal of this project was to empirically examine factors (e.g., dispositional, situational, system) that may influence the amount of trust a driver places in automated driver assist technologies. This project set out to answer questions related to the use of automated driver assist features performing different functions and in different types of driving scenarios. This project also helped address questions related to interactions between situational and system related factors that impact driver trust in automated driving features.

Hypotheses

The specific anticipated results, based on prior research and theory, are described in the hypotheses below.

H_1: It was expected that participant trust would vary based on the level of autonomy given to the driver assist feature.

H_2: It was expected that participant trust in the driver assist features would be impacted by the complexity of the driving scenario, defined based on traffic density and driving environment.

H_3: It was expected that individual differences in driving (self-confidence, years of experience, etc.) and demographics would influence the effect of our independent variables (scenario complexity, driver assist feature) on participants’ trust in driver assist features.

H_4: It was expected that a propensity to trust in technology would influence the effect of our independent variables on participants' trust in driver assist features.

H_5: It was expected that individual differences (age, etc.) would influence the effect of our independent variables on participants' trust in driver assist features.

H_6: It was expected that participants predisposition to trust certain automated driving features would influence the effect of the driving scenario complexity on participants' trust in that particular feature.

CHAPTER 4: METHODOLOGY

Participants

A total of 259 participants were recruited to participate in the study. Following data cleaning, which included the removal of outliers, those who failed the attention check, those missing data, the final sample was reduced to 166 participants. This included a total of 76 males, 89 females, and 1 who did not identify their gender. Participants were recruited through the University of Central Florida's SONA System. Through this system students were given course credit for participating in a research study. Additionally, in an effort to gather a broader sample from different populations, participants were recruited via social media (e.g., Facebook, LinkedIn) to participate. Participants in the final sample were aged between 18 and 60 years old (*M*= 22.87, *SD*= 10.64). All participants were briefed on the goals of the research prior to beginning the study and were told they were free to withdraw from the study at any time. Upon reading the briefing information, participants provided their consent by advancing to the experimental portion of the study.

Study Design

The study consisted of a 5x2 within-subjects design, wherein all participants experienced the same automated driving features (5) and the same driving scenarios (2) across 10 total vignette driving situations. The automated driving features described in the vignette driving scenarios included Forward Collision Warning, Cruise Control, Lane Centering Assist, Adaptive Cruise Control/Traffic Jam Assist, and Fully Autonomous Driving. Additionally, the driving scenarios described in the study vary between two levels of driving task complexity. Complexity was operationalized based on the traffic density and maneuvering requirements of the driver (Paxion et al., 2014; Fastenmeier & Gstalter, 2007; Teh et al., 2013; Stapel et al., 2019). In a ‘high complexity’ situation, participants were asked to imagine they were operating in a high-density traffic situation in a city setting with many turns. In a ‘low complexity’ situation, participants were asked to imagine they were operating in a low-density traffic situation on a straight country road.

Materials

Driving Vignettes

A series of vignette driving scenarios were provided to participants (see Appendix E). The driving scenarios described the purpose and use of the automated driving features at the five levels of automation before asking participants to imagine using each of these features in two unique driving contexts. In one scenario participants were in the ‘high complexity’ situation described previously, and in the other they are in the ‘low complexity’ situation. The sum of the five driving features in each driving context created a total of 10 vignette driving scenarios for participants.

Questionnaires

Demographics

A demographic survey was provided to gather general information about participants. This included information such as age, gender, and level of education.

Trust in Technology

A questionnaire was provided to participants in order to assess their general trust in technology and automated systems. The Propensity to Trust Technology Scale (Schneider et al., 2017) was used for this purpose. This is a six-item scale used to assess how likely a person is to trust technology based on their attitudes toward it and tendencies to use technology for a variety of purposes. The scale contains six statements, and participants are asked to rate on a five-point scale how much they agree with the statement. Options range from Completely Agree to Completely Disagree, with a single reverse-scored item.

Driver Experience Questionnaire

A questionnaire was created to gather background information on participants history of driving in their lifetime. A total of 16 items asked participants about experiences both as a driver and a passenger on the road. Examples of these items included ‘How long have you had your driver’s license?’, ‘Does the vehicle you currently drive have any automated driving assist features?’, and ‘How many major/minor car accidents have you been in as a passenger?’

Adelaide Driving Self-Efficacy Scale (ADSES)

The ADSES (George et al., 2007) is a scale designed to assess participants’ confidence in their ability to perform several driving maneuvers or drive in certain scenarios. Examples of these scenarios include ‘Driving in heavy traffic’ and ‘Responding to road signs/traffic signals’. The scale includes a total of 12 items, with participants rating their confidence on a scale of 0 to 10 where 0 is no confidence and 10 is completely confident.

Checklist for Trust between People and Automation (Jian et al., 2000)

The Checklist for Trust between People and Automation is an assessment of how much trust an individual places in a particular automated system. It presents 12 items that are comprised of short statements about the system in question. Examples include, “I am wary of the system,” or “The system is dependable.” These items are scored on a Likert scale from 1 to 7 as participants indicate how much they agree with the statement. A 1 would mean “Not at all” while a 7 would mean “Extremely.”

Situational Trust Scale for Automated Driving (STS-AD)

The STS-AD (Holthausen, 2020) was created to assess an individual's trust in automated driving systems following exposure to a certain driving scenario. The scale was adapted for each of the unique driving features described in the vignettes used in this study. Example items for some of the driving features include, 'I trust the forward collision warning system in this situation' and 'The lane centering assist system is likely to make an unsafe judgment in this situation'. There are a total of six items, scored on Likert scale of 1 to 7 where 1 is strongly disagree and 7 is strongly agree. Two items from the scale were reverse scored.

Within the STS-AD, multiple attention checks were included as a means to assess whether or not participants were reading the materials throughout or answering without consideration (Berinsky et al., 2014). First, a single vignette scenario was presented that asked participants to provide a specific answer. The vignette began as the others did, describing a driving scenario, but then asked participants to answer 'Strongly Agree' to all the STS-AD questions that followed. With many believing that a single attention check may be insufficient to achieve its goal of revealing inattentive participants, an additional item was included with the STS-AD for one scenario as a means to determine if participants were properly reading through the items. This item simply stated, 'The scenario describes driving on a country road,' placed within the STS-AD scale for one of the vignette scenarios that did take place on a country road. Participants were expected to respond '7 – Strongly Agree' to this statement to indicate they read the items properly.

Procedure

Participants were first provided with a brief overview of the study in the form of an Informed Consent document. This document described the goal of the study, assured participants that they were free to withdraw at any time and informed them that compensation would only be provided in cases of university students seeking extra course credit. By advancing to the pages beyond this document, participants were providing their consent to participate in the study.

Participants began the study by completing the Demographics survey, followed by the Driver Experience survey. After these surveys were completed, participants were asked to complete the ADSES as a means to assess their confidence in their driving abilities. All participants completed these initial surveys in this manner.

Once the initial three surveys were completed, participants advanced to the experimental portion of the study. The 10 vignette scenarios and 1 attentional check scenario were presented to participants at random. At the beginning of each vignette scenario was a brief description of the function and proper use of the automated driving feature described in the vignette. Following each vignette scenario, participants completed a modified version of the STS-AD. The STS-AD was modified to specifically describe the use of each unique driving feature. After answering all questions for each of the 11 vignette driving scenarios, participants were thanked for their participation and the survey concluded. The total duration of the surveys was, on average under 30 minutes.

CHAPTER 5: RESULTS

Primary Manipulations

The initial analysis performed was a 5x2 repeated measures ANOVA, intending to assess main effects and interactions in trust between automated driver assist features (5) and driving scenario complexity (2). Results indicated a significant main effect for driver assist feature, $F(4, 660)= 28.56$, $p< .01$, $\eta_p^2= .15$. The forward collision warning ($M= 3.91$, $SD= 0.76$) and lane centering assist ($M= 3.92$, $SD= 0.75$) were rated the highest we nearly identical mean trust scores. The fully automated driving feature was rated the lowest ($M= 3.38$, $SD= 0.95$). An examination of pairwise comparisons found that trust in the forward collision warning system, on average, was higher than that of the cruise control, adaptive cruise/traffic jam assist, and fully automated driving features ($p< .01$). Trust in the cruise control feature was also significantly lower than trust in the lane centering assist and adaptive cruise/traffic jam assist features ($p< .01$. Cruise control was rated significantly higher than the fully automated driving feature ($p< .05$). The lane centering assist feature's trust score, while not significantly different from the forward collision warning system, was significantly higher than the cruise control, adaptive cruise/traffic jam assist, and fully automated driving feature ($p< .01$). Trust in the adaptive cruise/traffic jam assist feature was rated significantly higher than the fully automated driving feature and cruise control ($p< .01$). However, this same feature was rated lower than the forward collision warning and the lane centering assist ($p< .01$).

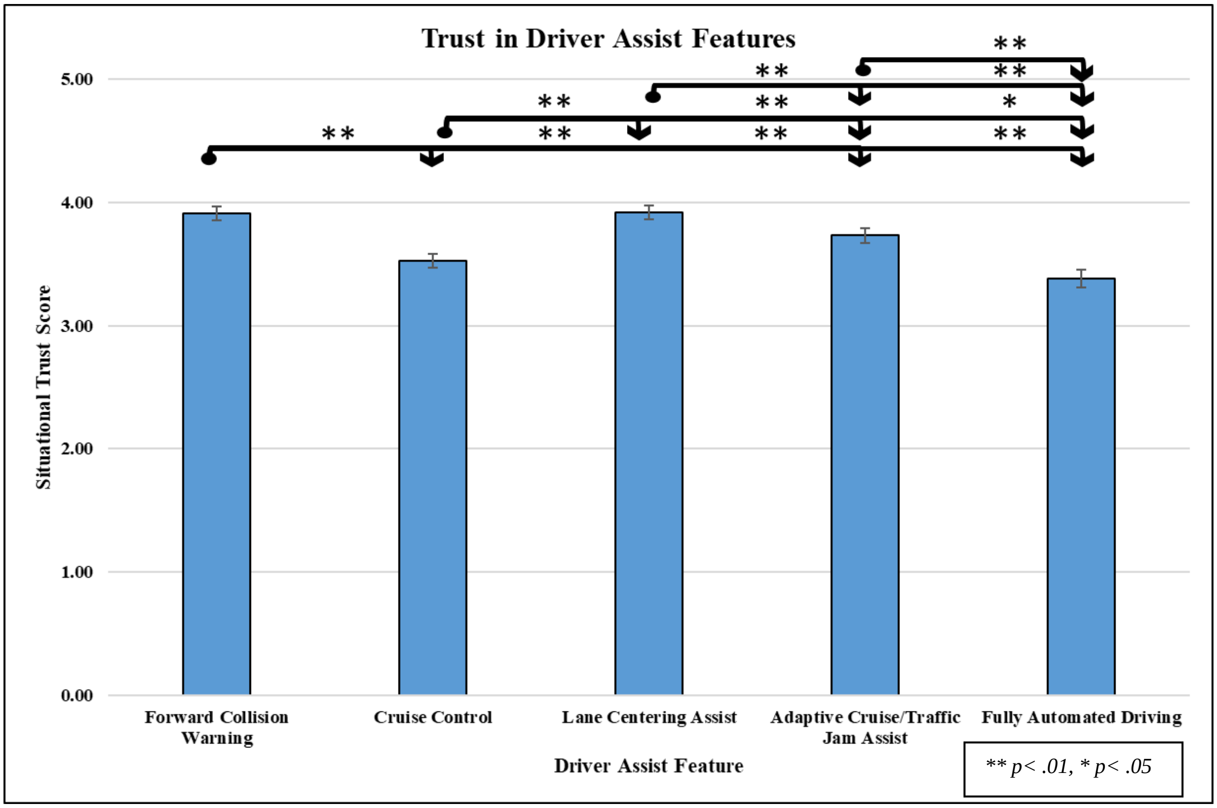

FIGURE 2: SITUATIONAL TRUST BETWEEN DIFFERENT DRIVER ASSIST FEATURES

There was also a very strong main effect for driving scenario complexity, $F(1, 165)= 216.32$, $p< .01$, $\eta_p^2= .57$. Participants generally reported lower levels of trust in driver assist features under in high complexity driving scenarios ($M= 3.25$, $SD= 0.12$) compared to the low complexity scenarios ($M= 4.14$, $SD= 0.14$).

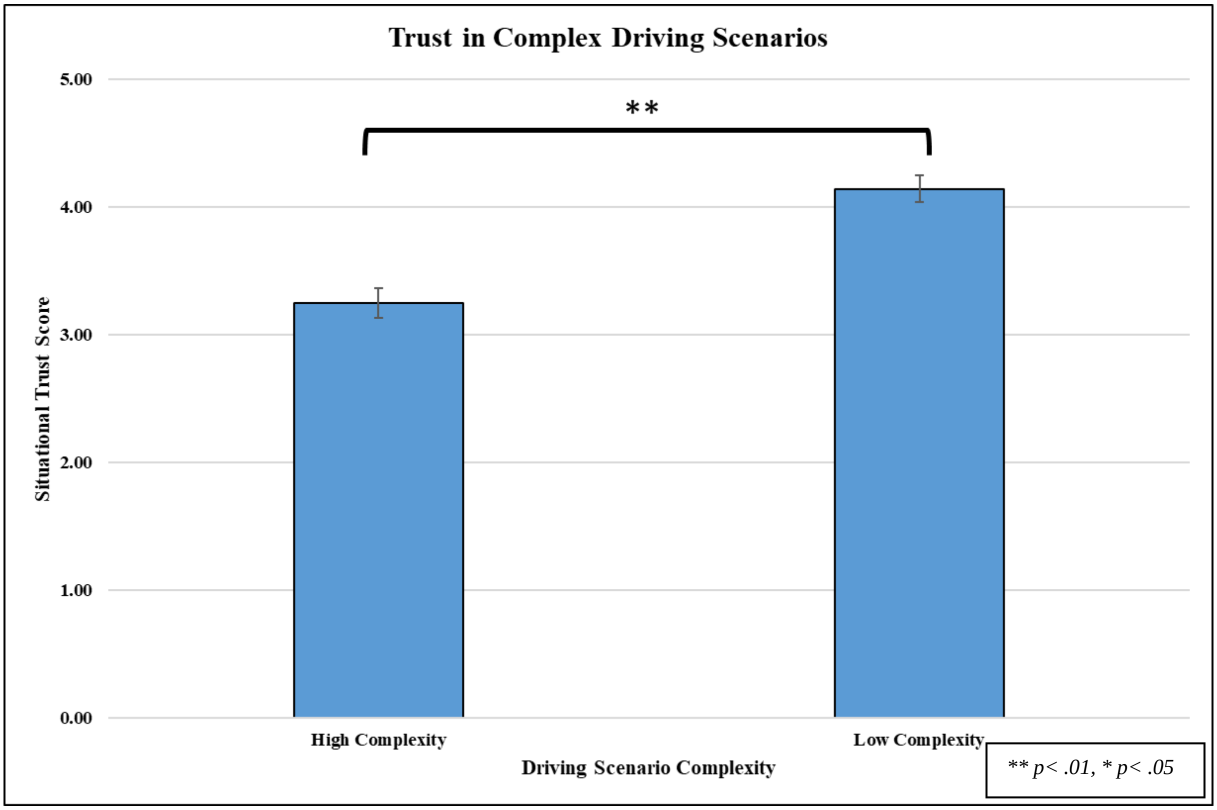

FIGURE 3: SITUATIONAL TRUST BETWEEN HIGH AND LOW COMPLEXITY DRIVING SCENARIOS

Finally, there was a significant interaction effect as well, $F(4, 660) = 54.21$, $p < .01$, $\eta_p^2 = .25$. This effect was most pronounced in the features exhibiting lower levels of automation control. Reported levels of trust seemed to demonstrate a clear pattern among features under higher levels of automation (i.e., lane centering assist, adaptive cruise/traffic jam control, fully automated). Participants' trust in these systems was consistently lower in the high complexity ($M = 3.25$, $SD = 0.74$) driving scenarios compared to the low complexity scenarios ($M = 4.14$, $SD = 0.68$). Additionally, trust in these systems appeared to decrease with an increase in the autonomy of the system. That is, trust was highest in the lane centering assist feature ($M = 3.92$, $SD = 0.87$) and lowest in the fully automated driving feature ($M = 3.38$, $SD = 1.13$). However, trust in the first two driver assist features did not follow this pattern. Participants' trust in the forward collision warning system appeared to be lower in the low complexity scenario (*M*= 4.10, *SD*= 0.84) compared to the cruise control system in the low complexity scenario (*M*= 4.34, *SD*= 0.82). In the high complexity driving scenarios, trust in the forward collision warning system was higher (*M*= 3.72, *SD*= 0.89) than that of the cruise control system (*M*= 2.71, *SD*= 1.12). The main effects and interaction described here can be seen in Figure 3 below.

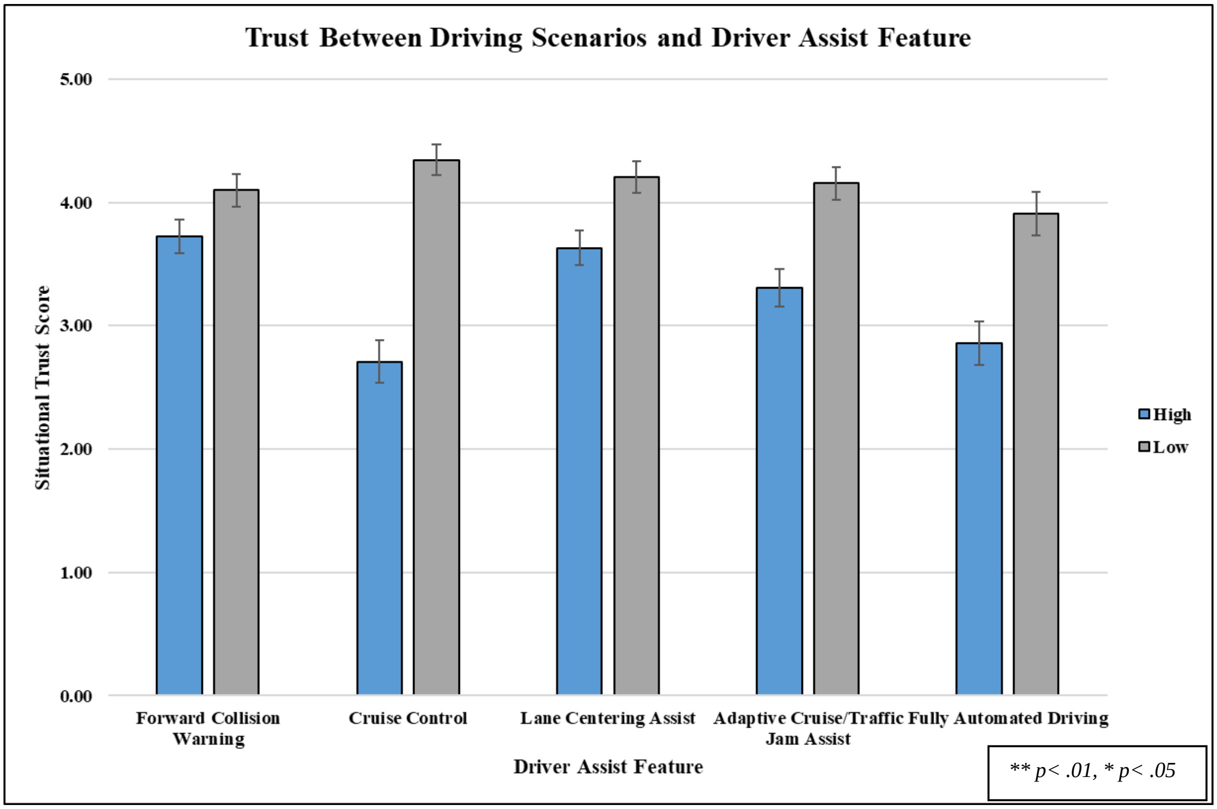

FIGURE 4: SITUATIONAL TRUST SCORES ACROSS DRIVING SCENARIOS AND DRIVER ASSIST FEATURES

Covariate Analyses

A series of 5x2 repeated measures analysis of covariance (ANCOVA) were performed to test the influence of multiple variables on the previously observed effects on trust in the driver assist features. ANCOVA was chosen as it would effectively reveal any interactions between continuous covariates and independent variables on situational trust. Significant interaction effects between the covariate and the independent variables would suggest the covariate moderates the relationship between trust and that manipulation, impacting the direction or strength of that relationship. Should the significant effects observed in the previous repeated measures ANOVA be found non-significant in the presence of a covariate, this would indicate that covariate shares some variance with the dependent variable across levels of the independent variable.

Driving Self-Efficacy

The first ANCOVA included participants' driving self-efficacy as a covariate. The previously observed main effect for situation complexity was still present, $F(1, 164) = 15.35$, $p < .01$, $\eta_p^2 = .09$. However, the main effect for the driver assist features was no longer there, $F(4, 656) = 1.52$, $p = .20$, $\eta_p^2 = .01$. Additionally, the significant interaction between the independent variables found in the prior ANOVA was not present with the covariate, $F(4, 656) = 1.25$, $p = .29$, $\eta_p^2 = .01$.

Moderating effects of the covariate were assessed by examining the interaction between the covariate and the independent variables. No significant interaction between the situation complexity and driving self-efficacy was found, $F(1, 164) = .21$, $p = .65$, $\eta_p^2 = .001$, or with the driver assist features and driving self-efficacy, $F(4, 656) = 1.10$, $p = .35$, $\eta_p^2 = .01$. No interaction effects were found.

Propensity to Trust Technology

The next ANCOVA used participants' scores on the Propensity to Trust Technology scale as a covariate. The main effect of driver assist feature was still significant, despite the covariate, $F(4, 656) = 6.23$, $p < .01$, $\eta_p^2 = .04$. There was, however, only a moderately significant main effect for situation complexity, $F(1, 164)= 3.21$, $p= .08$, $\eta_p^2= .02$. Also, there was no significant interaction between the independent variables in the ANCOVA, $F(4, 656)= 0.90$, $p= .45$, $\eta_p^2= .01$.

Interaction effects between the propensity to trust technology score and the IVs were again assessed in this analysis. No significant interaction was found between the situation complexity manipulation and the propensity to trust technology score, $F(1, 164)= .99$, $p= .32$, $\eta_p^2= .01$. However, a significant interaction between the driver assist features and the covariate was found, $F(4, 656)= 3.31$, $p< .05$, $\eta_p^2= .02$. This result suggested a moderating effect of the covariate on situational trust between the driver assistance features.

To model this interaction, linear regression was performed on each of the five different driver assist features with the Propensity to Trust Technology score as the sole predictor. Regression models were not significant for the forward collision warning system, $F(1, 164)= 2.69$, $p= .10$, $R^2= 0.02$, $\beta= .12$, or for the cruise control feature, $F(1, 164)= 1.56$, $p= .23$, $R^2= 0.01$, $\beta= .09$. The model for the lane centering feature was significant, $F(1, 164)= 4.71$, $p< .05$, $R^2= 0.03$, $\beta= .15$, as were those for the adaptive cruise control/traffic jam assist feature, $F(1, 164)= 9.29$, $p< .01$, $R^2= 0.05$, $\beta= .21$, and the fully automated driving, $F(1, 164)= 14.50$, $p< .01$, $R^2= 0.08$, $\beta= .34$. Regression equations are provided in the table below and graphed in Figure 4.

TABLE 3: REGRESSION EQUATIONS PREDICTING AVERAGE SITUATIONAL TRUST IN DRIVER ASSIST FEATURES AS A FUNCTION OF PARTICIPANTS' PROPENSITY TO TRUST TECHNOLOGY SCORE

Forward Collision Warning	3.41 + 0.12*(Propensity to Trust Tech)
Cruise Control	3.17 + 0.09*(Propensity to Trust Tech)
Lane Centering Assist	3.30 + 0.15*(Propensity to Trust Tech)
Adaptive Cruise/Traffic Jam Assist	2.83 + 0.21*(Propensity to Trust Tech)
Fully Automated Driving	1.97 + 0.34*(Propensity to Trust Tech)

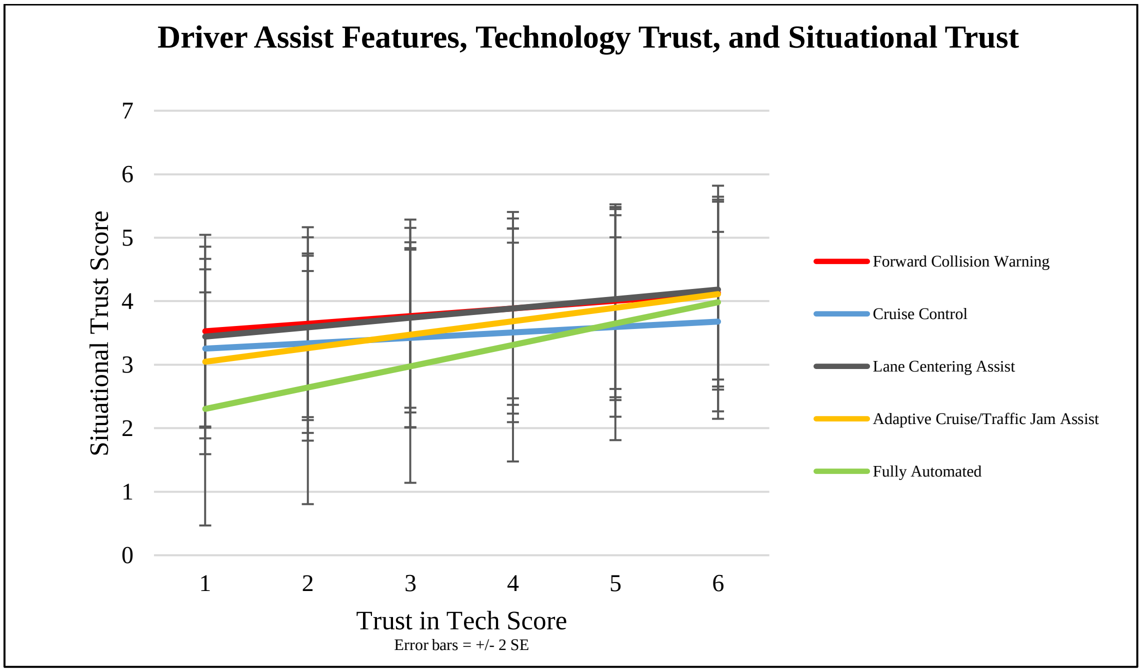

FIGURE 5: INTERACTION OF DRIVER ASSIST FEATURE AND PROPENSITY TO TRUST TECHNOLOGY ON SITUATIONAL TRUST

Age

Both age and driving experience were considered as covariates that might impact trust between high and low complexity and between driver assist features. However, due to the highly significant correlation between the age and driving experience variables ($p < .01$), only driving experience was used as a covariate in the analysis.

Driving Experience

The next covariate included in the analyses was driving experience, measured as the length of time participants reported possessing a valid driver's license. Both main effects found for situation complexity, $F(1, 164) = 104.06$, $p < .01$, $\eta_p^2 = .39$, and for driving feature, $F(4, 656) = 7.63$, $p < .01$, $\eta_p^2 = .04$, in the initial ANOVA were still present when license duration was included as a covariate. The interaction effect was also still present, $F(4, 656) = 20.59$, $p < .01$, $\eta_p^2 = .11$. These results suggest that, even when the amount of time a person has been driving is statistically controlled for, the main effects for scenario complexity and driver assist features still exist and the interaction between these two factors still exists.

Interaction effects between the independent variables and driving experienced were also assessed in the ANCOVA. No significant interaction was found between the driver assist technologies and driving experience, $F(4, 656) = .58$, $p = .65$, $\eta_p^2 = .004$. Interestingly, there was a marginally significant interaction, trending toward significance, between the scenario complexity and driving experience, $F(1, 164) = 3.20$, $p < .10$, $\eta_p^2 = .02$. This result indicates there may be a moderating effect for driving experience on trust between high and low complexity driving scenarios. Linear regression was performed on the two levels of the scenario complexity variable with driving experience as the predictor. The regression model was not significant for the high complexity scenario, $F(1, 164) = .07$, $p = .79$, $R^2 = 0.01$, $\beta = -.01$. The resulting model was significant for the low complexity scenario, $F(1, 164) = 5.70$, $p < .05$, $R^2 = 0.03$, $\beta = -.08$. Regression equations for the two models are provided in the table below and graphed in Figure 5.

TABLE 4: REGRESSION EQUATIONS PREDICTING SITUATIONAL TRUST AS A FUNCTION OF DRIVING EXPERIENCE

High Complexity	3.27 - 0.01*(Driving Experience)
Low Complexity	4.31 - 0.08*(Driving Experience)

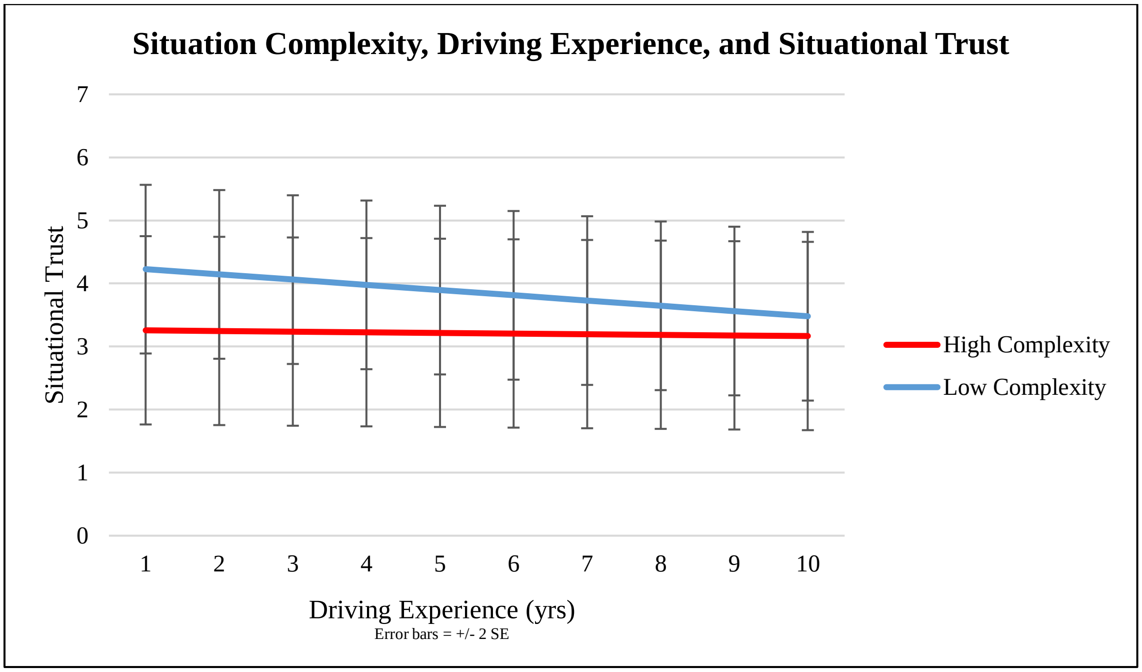

FIGURE 6: INTERACTION OF SITUATION COMPLEXITY AND DRIVING EXPERIENCE ON SITUATIONAL TRUST

Accident History

The next covariate included was the accident history of participants, defined as the total number of minor and major accidents they reported having experienced as either a passenger or a driver in a motor vehicle. The main effect for situation complexity, $F(1, 164) = 115.86$, $p < .01$, $\eta_p^2 = .41$, and for driver assist feature, $F(4, 656) = 10.36$, $p < .01$, $\eta_p^2 = .06$, found in the initial ANOVA were still present when accident history was included as a covariate. The interaction effect was also still significant, $F(4, 656) = 23.96$, $p < .01$, $\eta_p^2 = .13$.

Dispositional Trust in Individual Features

A series of one-way repeated measures ANCOVAs were run to assess the influence of dispositional trust, or participants' initial levels of trust free of any context, in each of the driver assist features on differences in situational trust between high and low complexity scenarios. Scores from the Checklist for Trust between Humans and Automation was used as a covariate in these analyses. There was no interaction between scenario complexity and dispositional trust in the forward collision warning system, $F(1, 164)= 2.23$, $p= .14$, $\eta_p^2= .01$, or between complexity and dispositional trust in cruise control, $F(1, 164)= .55$, $p= .46$, $\eta_p^2= .003$. However, there was a significant interaction between situation complexity and dispositional trust in the lane centering assist feature, $F(1, 164)= 14.21$, $p< .01$, $\eta_p^2= .08$. This same interaction was found for the adaptive cruise control/traffic jam assist feature, $F(1, 164)= 4.76$, $p< .05$, $\eta_p^2= .03$, as well as the fully automated driving feature, $F(1, 164)= 13.35$, $p< .01$, $\eta_p^2= .08$.

Linear regression was then performed on each level of the scenario complexity variable for the lane centering assist, adaptive cruise control/traffic jam assist, and fully automated driving features. The initial regression model, for the lane centering assist feature in the high complexity scenario, was significant, $F(1, 164)= 19.92$, $p< .01$, $R^2= .11$, $\beta= .45$, while the model was not significant for the same feature in the low complexity scenario, $F(1, 164)= .23$, $p= .63$, $R^2= .001$, $\beta= .05$. This indicated that dispositional trust predicted situational trust in the high complexity scenario, but not in the low complexity scenario. The regression equations for these two models are presented and graphed below.

TABLE 5: REGRESSION EQUATIONS PREDICTING SITUATIONAL TRUST AS A FUNCTION OF DISPOSITIONAL TRUST IN LANE CENTERING ASSIST FEATURES

Lane Centering Assist - High Complexity	1.70 + 0.45*(Dispositional Trust in LCA)
Lane Centering Assist - Low Complexity	4.00 + 0.05*(Dispositional Trust in LCA)

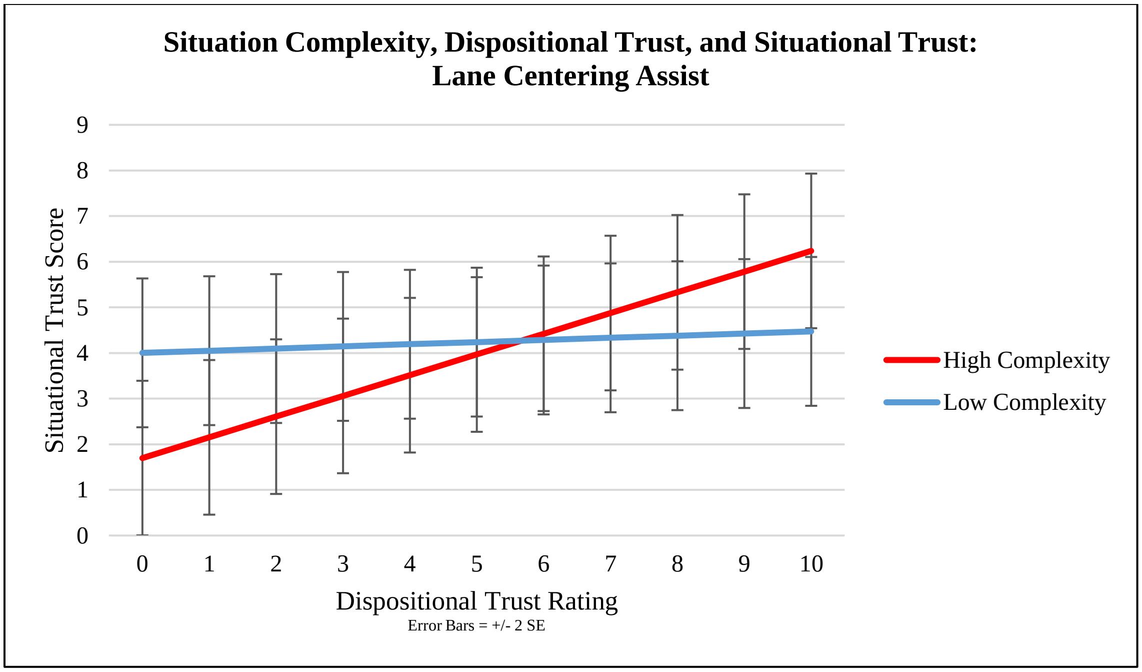

FIGURE 7: INTERACTION OF SITUATION COMPLEXITY AND DISPOSITIONAL TRUST IN LANE CENTERING ASSIST ON SITUATIONAL TRUST

The regression model for the adaptive cruise control/traffic jam assist feature in the high complexity condition was significant, $F(1, 164) = 25.01$, $p < .01$, $R^2 = .13$, $\beta = .52$. The model for the adaptive cruise control/traffic jam assist feature was also significant in the low complexity scenario, $F(1, 164) = 6.62$, $p < .01$, $R^2 = .04$, $\beta = .26$, indicating dispositional trust in the feature significantly predicted situational trust in both driving scenarios.

TABLE 6: REGRESSION EQUATIONS PREDICTING SITUATIONAL TRUST AS A FUNCTION OF DISPOSITIONAL TRUST IN ADAPTIVE CRUISE CONTROL/TRAFFIC JAM ASSIST FEATURES

ACC/TJA - High Complexity	1.15 + 0.52*(Dispositional Trust in ACC/TJA)
ACC/TJA - Low Complexity	3.10 + 0.26*(Dispositional Trust in ACC/TJA)

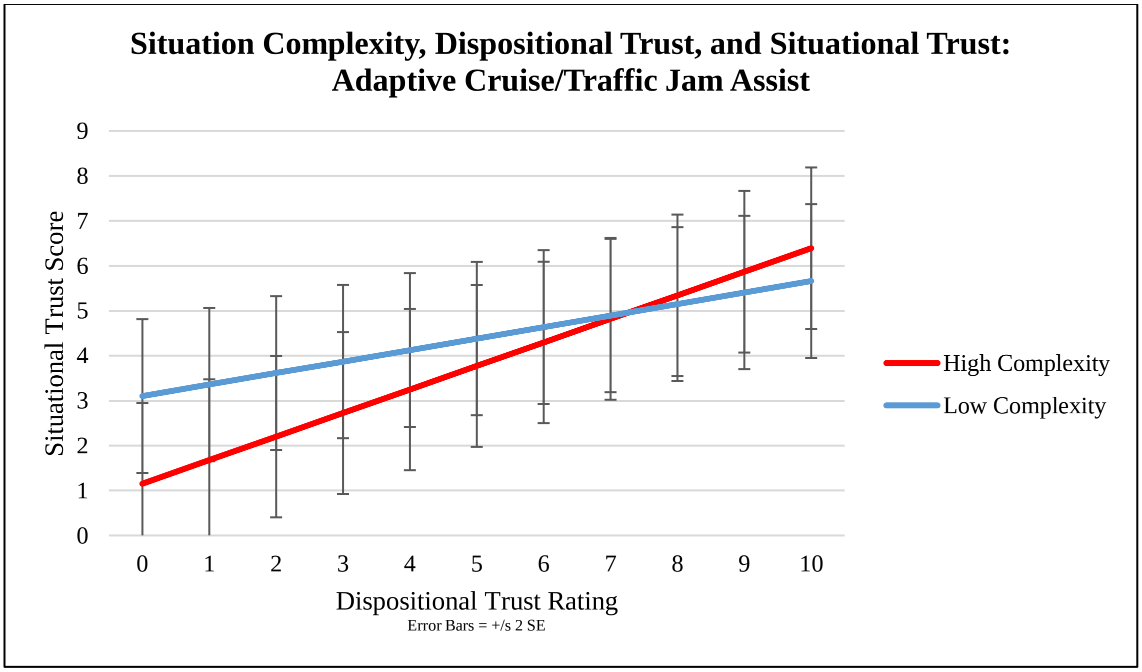

FIGURE 8: INTERACTION OF SITUATION COMPLEXITY AND DISPOSITIONAL TRUST IN ADAPTIVE CRUISE/TRAFFIC JAM ASSIST ON SITUATIONAL TRUST

Finally, the regression models for the fully automated driving feature were calculated. The model in the high complexity condition was significant, $F(1, 164) = 48.82$, $p < .01$, $R^2 = .23$, $\beta = .78$. Additionally, the model for the low complexity condition was also significant, $F(1, 164) = 5.59$, $p < .01$, $R^2 = .03$, $\beta = .30$.

TABLE 7: REGRESSION EQUATIONS PREDICTING SITUATIONAL TRUST AS A FUNCTION OF DISPOSITIONAL TRUST IN FULLY AUTOMATED DRIVING SYSTEMS

Fully Automated Driving - High Complexity	-0.17 + 0.78*(Dispositional Trust in FAD)
Fully Automated Driving - Low Complexity	2.74 + 0.30*(Dispositional Trust in FAD)

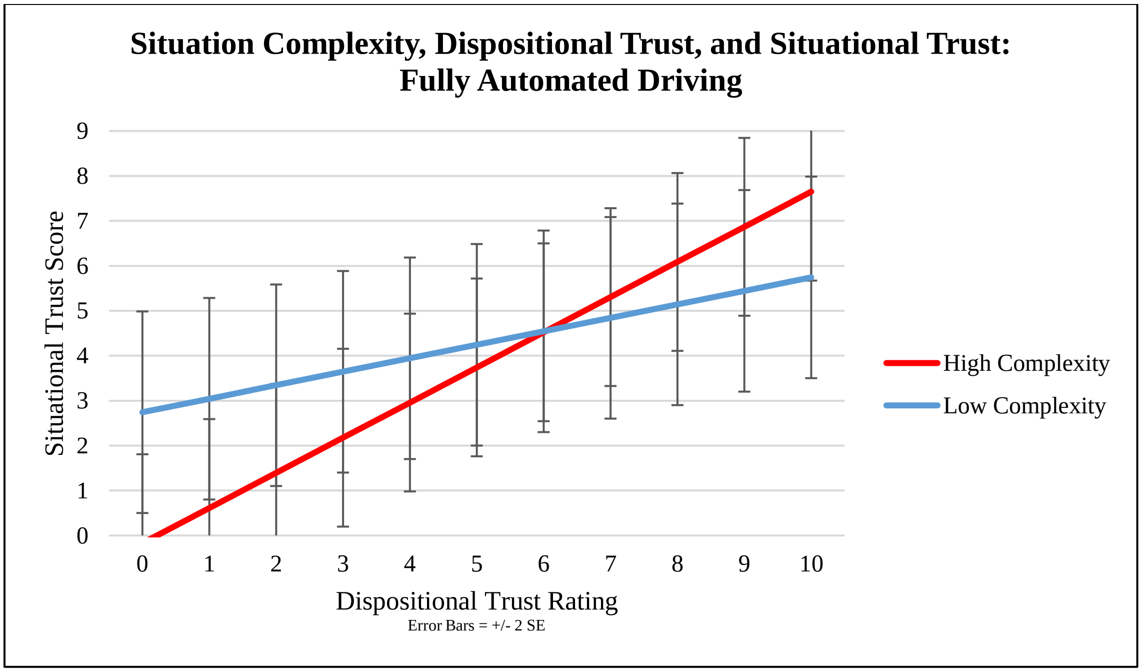

FIGURE 9: INTERACTION OF SITUATION COMPLEXITY AND DISPOSITIONAL TRUST IN FULLY AUTOMATED DRIVING ON SITUATIONAL TRUST

Group Differences

The final analyses performed included a series of mixed ANOVA to assess differences between subsets of the overall sample in their trust across the driver assist features. The first of these ANOVAs was a 5x2x2 mixed ANOVA involving driver assist features, situation complexity, and gender to assess differences across all experimental conditions. Results showed the significant main effect of situation complexity on situational trust, $F(1, 163) = 211.33$, $p < .01$,

η_p^2= .57 and of driver assist features, $F(4, 652)$= 28.27, p< .01, η_p^2= .15, were again found. The interaction effect between these variables was also found, $F(4, 652)$= 53.97, p< .01, η_p^2= .25. There was also a significant difference found between genders, $F(4, 652)$= 12.06, p< .01, η_p^2= .07. Males reported higher levels of trust overall, (M= 3.85, SD= 0.65) than females (M= 3.54, SD= 0.50). Differences can be seen in Figure 8 below.

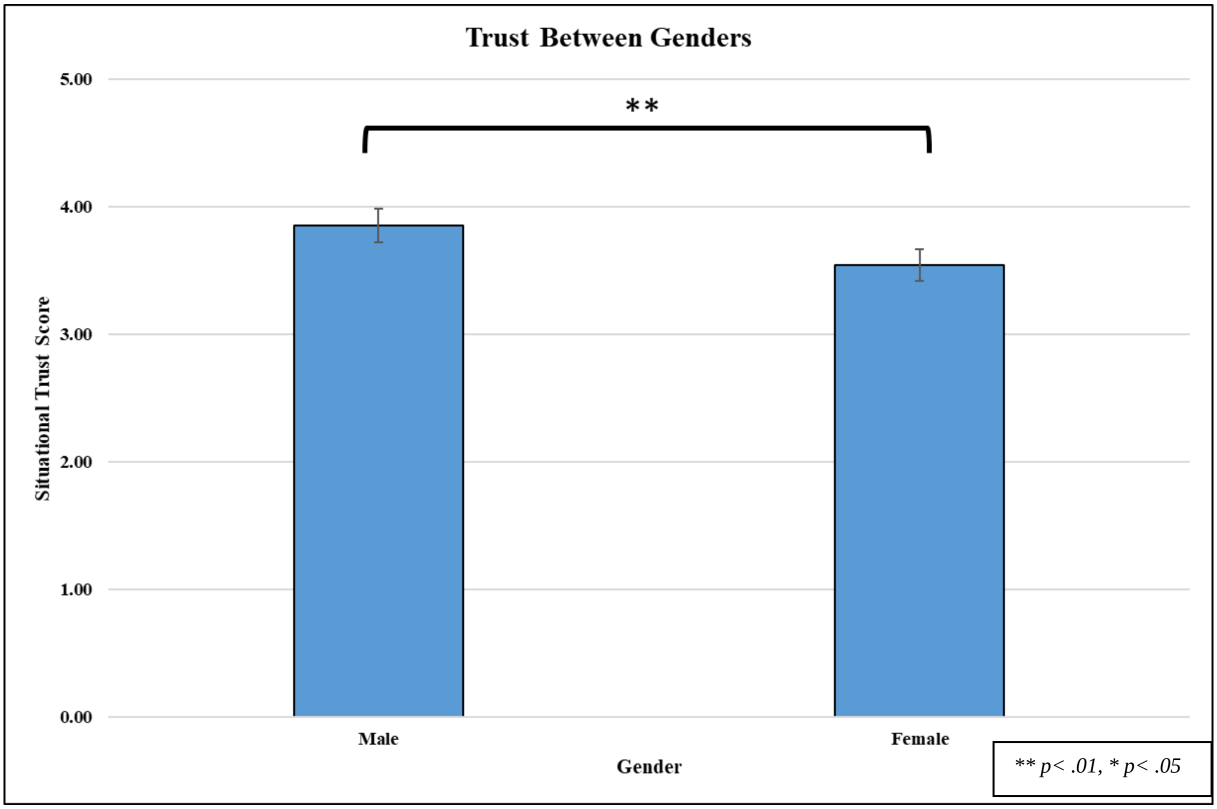

FIGURE 10: DIFFERENCES IN TRUST FOUND BETWEEN MALES AND FEMALES

There was also a significant interaction between gender and the driver assist features, $F(4, 652)$= 4.57, p< .05, η_p^2= .03. Means and standard deviations are displayed in the table below.

TABLE 8: MEAN SITUATIONAL TRUST SCORES BETWEEN GENDERS, STANDARD DEVIATIONS IN PARENTHESES

	Male	**Female**
Forward Collision Warning	3.97 (0.86)	3.84 (0.66)
Cruise Control*	3.65 (0.78)	3.43 (0.63)
Lane Centering Assist	4.01 (0.78)	3.83 (0.65)
Adaptive Cruise/Traffic Jam Assist**	3.97 (0.80)	3.52 (0.63)
Fully Automated Driving**	3.67 (0.92)	3.11 (0.88)

Tests of simple effects indicated that males reported significantly higher levels of trust in the cruise control feature ($p < .05$) compared to females, as well as the adaptive cruise control/traffic jam assist and the fully automated driving ($p < .01$). However, there were no significant differences between genders in the forward collision warning and the lane centering assist features. No significant three-way interaction between scenario complexity, driver assist feature, and gender was found, $F(4, 652) = .86$, $p = .48$, $\eta_p^2 = .01$.

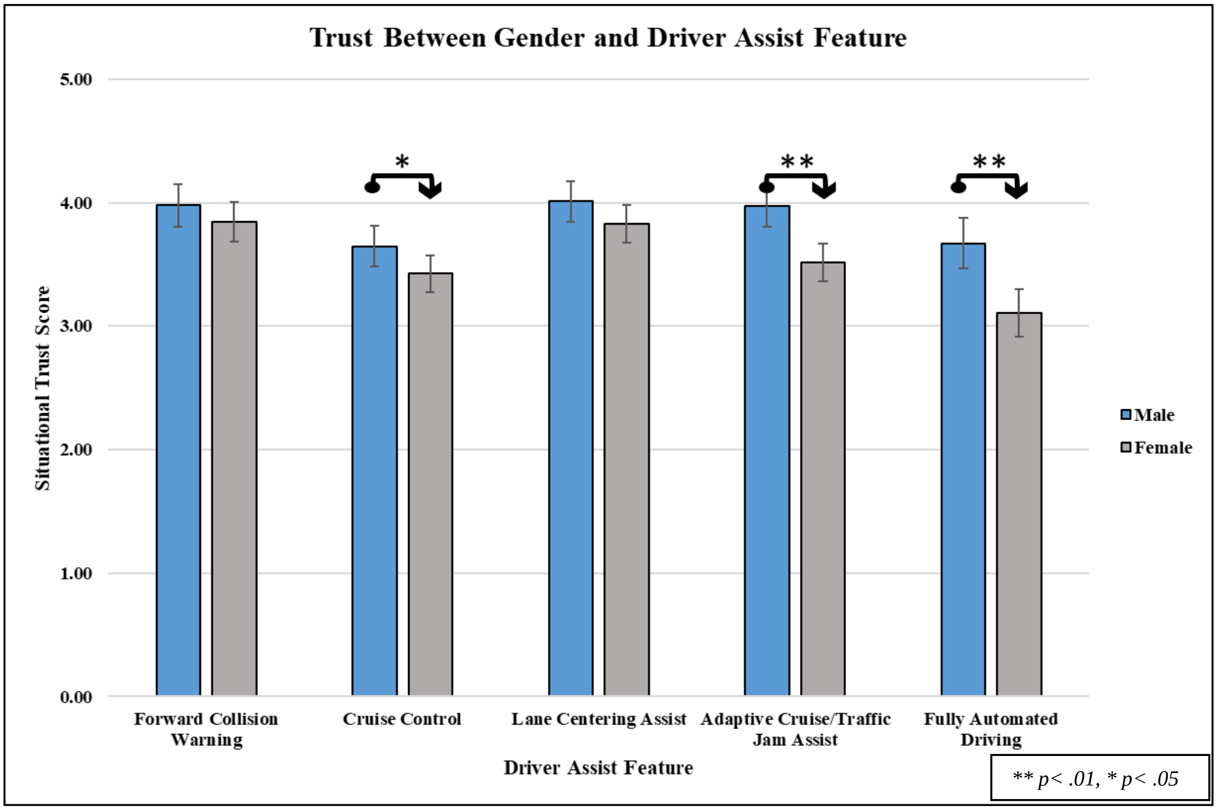

FIGURE 11: INTERACTION OF DRIVER ASSIST FEATURES AND GENDER ON SITUATIONAL TRUST

The next mixed ANOVA performed was a 5x2x5 repeated measures ANOVA with level of education as the grouping variable. Level of education was measured over five levels: high school diploma, some college no degree, associate degree, bachelor's degree, and graduate degree. Main effects for situation complexity, $F(1, 161)= 89.20$, $p< .01$, $\eta_p^2= .36$, and for driver assist feature, $F(4, 644)= 16.03$, $p< .01$, $\eta_p^2= .09$, were significant. There was also a main effect for level of education, $F(4, 161)= 6.88$, $p< .01$, $\eta_p^2= .15$. Post hoc comparisons indicated that the group with a bachelor's degree provided the highest overall trust score ($M= 4.05$, $SD= 0.64$), significantly higher than those with some college experience but no degree, an associate degree, or a graduate degree ($p< .01$) The lowest scores came from those with a graduate degree ($M= 2.82$, $SD= 0.80$), which was significantly lower than all other scores ($p< .01$). None of the other comparisons were significant at .05 level. Examinations of interaction effects found the same interaction between situation complexity and driver assist feature, $F(4, 644)= 54.21$, $p< .01$, $\eta_p^2= .25$. However, there were no interactions found between the independent variables and level of education. There was also no significant three-way interaction between situation complexity, driver assist features, and level of education, $F(16, 644)= 1.18$, $p= .29$, $\eta_p^2= .03$.

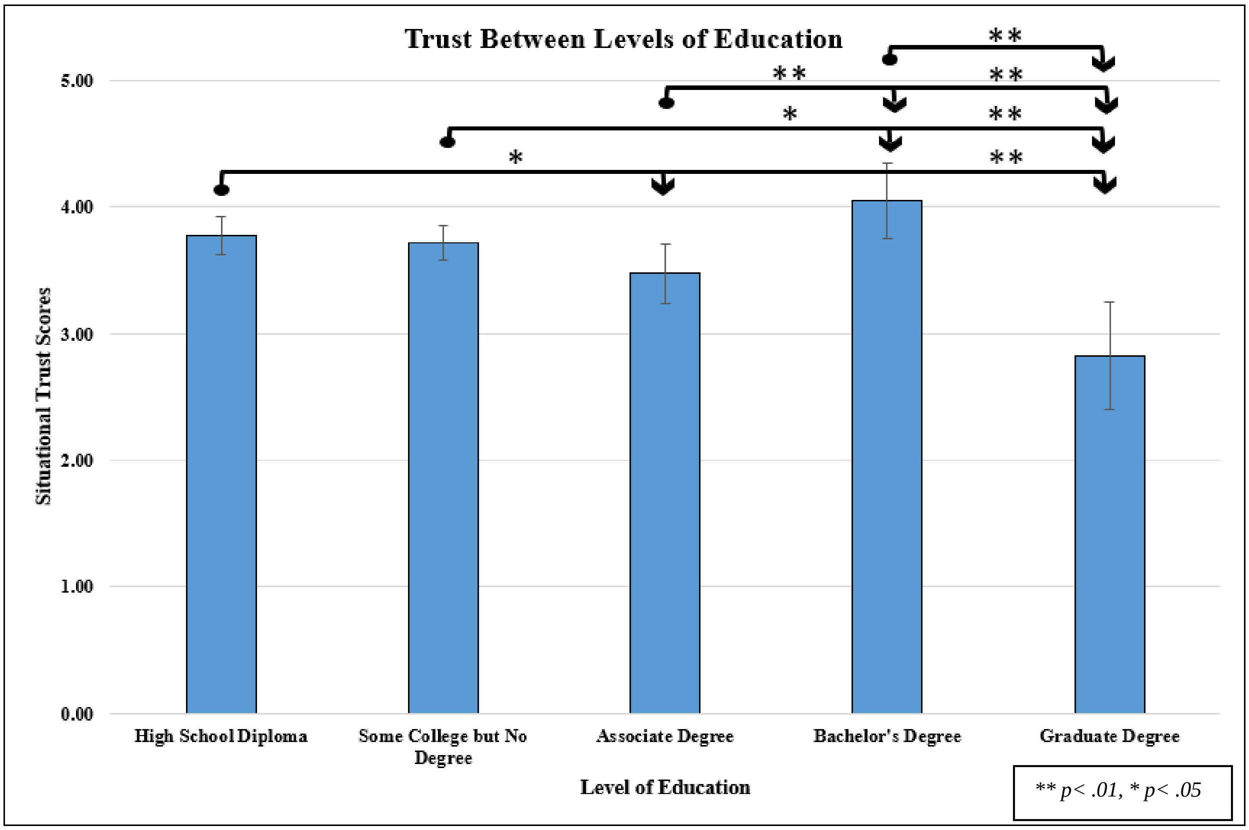

FIGURE 12: AVERAGE SITUATIONAL TRUST SCORES BETWEEN GROUPS BASED ON LEVEL OF EDUCATION

TABLE 9: AVERAGE SITUATIONAL TRUST SCORES BETWEEN PARTICIPANTS AT DIFFERENT LEVELS OF EDUCATION

Education Level	Total N	Mean (SD)
High School Diploma	56	3.77 (0.54)
Some College but No Degree	67	3.71 (0.54)
Associate Degree	22	3.47 (0.48)
Bachelor's Degree	14	4.05 (0.64)
Graduate Degree	7	2.82 (0.59)

The final ANOVA performed was a 5x2x4 repeated measures ANOVA, this time using participants' reported most common driving environment as a grouping variable. Different environments were identified as cities, highways, rural areas, or suburban areas, while those that do not drive were excluded from the analyses. There were again main effects for the situation complexity, $F(1, 158)= 79.91$, $p< .01$, $\eta_p^2= .33$, and for the driver assist features, $F(4, 632)= 9.14$, $p< .01$, $\eta_p^2= .05$. There was no significant main effect, however, for the participants' common driving environment, $F(3, 158)= 1.41$, $p= .24$, $\eta_p^2= .03$.

TABLE 10: AVERAGE SITUATIONAL TRUST SCORES BETWEEN PARTICIPANTS THAT TYPICALLY DRIVE IN DIFFERENT ENVIRONMENTS

Driving Environment	Total N	M (SD)
Cities	21	3.80 (0.59)
Rural Areas	56	3.64 (0.64)
Highways	39	3.57 (0.48)
Suburban Areas	46	3.80 (0.61)
Don't Drive	4	--

There was similarly not any significant interaction between any of the independent variables and the grouping variable. The significant interaction for complexity and driver assist feature was again present, $F(4, 632) = 17.77$, $p < .01$, $\eta_p^2 = .10$.

CHAPTER 6: DISCUSSION

General Discussion

The goal of this study was to examine how different factors related to the environment and an automated system would impact how much trust a person places in automated driver assist technologies. Additionally, it sought to answer questions related to individual differences that may influence the strength or direction of the effect these environmental and system-related factors have on trust. The study empirically examined the impact that driving scenario complexity and level of automation have on trust, while considering a moderating effect of a series of demographic and experience-related variables. It was expected that both environmental and system-related factors would significantly impact participants' trust in driver assist features. It was also expected that individual differences would impact these relationships.

Results strongly support the hypothesis that scenario complexity would impact participants' trust. Participants, on average, reported significantly greater trust in the driver assist features when they were placed in a low complexity driving scenario. Under conditions of low traffic density on a straight, country road participants indicated a willingness to trust and use all driver assist features far greater than in the high complexity scenario. The noted strength of this relationship supports research suggesting that the complexity of the environment or task will play a significant role in how users trust certain types of technology. This relationship was consistent across all driver assist features, with more trust being placed in each individual feature in the low complexity scenario. The greatest difference between high and low complexity score was found with the cruise control feature.

A strong main effect for the different driver assist feature was also found, supporting the hypothesis about differences in automation impacting trust and indicating that participants' trust differed between the five features mentioned in the vignette driving scenarios. Trust, overall, was highest for the forward collision warning and lane centering assist features, with average situational trust scores being nearly equal between the two features. Trust was lowest for the fully automated driving feature, described as handling all driving tasks without driver intervention. In addition to these main effects, a significant interaction was found between the situation complexity and the driver assist feature in use. This interaction was most apparent when examining differences in the cruise control feature. In the low complexity scenario, the cruise control feature received the highest score on the situational trust scale, rated even higher than the forward collision warning and lane centering assists that received the highest average trust score. However, the same cruise control feature received the lowest overall situational trust score in the high complexity scenario. This feature received a trust score even lower than the fully automated driving feature in the high complexity scenario.

Analyses also revealed several variables that may interact with the independent variables and situational trust scores, supporting the hypothesis that trust between conditions may be influenced by individual differences. One covariate, accident history, was not related in any way to the dependent variable. Interactions with the independent variables were both found to not be statistically significant, while controlling for accident history did not change any relationships between the independent variables and the dependent variable. Participants' self-efficacy when driving was considered as a variable that may influence these relationships and was used as a covariate when running the same repeated measures ANOVA as was performed to assess main effects and interactions of the independent variables. No significant interactions were found between the primary manipulations and self-efficacy. However, the main effect for the driver assist features was no longer present with the self-efficacy covariate included in the analysis.

This result suggests that, while self-efficacy may not moderate the effect of the independent variables, it shares some variance with the driver assist feature manipulation on the dependent variable of situational trust. It is possible this is due to the individual tasks delegated to the driver assist features, and how differences in self-efficacy performing those tasks influenced that main effect. Participants higher in their confidence to handle emergency braking tasks, for example, may trust the forward collision warning less than other features. This may have contributed to differences in trust between different driver assist features.

An additional variable considered as a covariate in the series of ANCOVAs was participants' propensity to trust technology and automation. This analysis found an interaction between the propensity to trust technology and the automated driver assist feature manipulation. Regression models showed that the propensity to trust technology score was able to predict situational trust in the lane centering assist, adaptive cruise/traffic jam assist, and fully automated driving features. A propensity to trust technology was not predictive of situational trust in the cruise control or forward collision warning systems.

An examination of beta weights indicates that there is a stronger relationship between the propensity to trust technology and situational trust in driver assist features as the level of control the feature has over driving increases. Beta weights for the propensity to trust technology score were highest for fully automated driving and adaptive cruise control/traffic jam assist features, demonstrated in Figure 4. They were the lowest for the cruise control and forward collision warning features. This relationship indicates that, the higher a person's likelihood to trust technology in general, the more likely they are to trust certain driver assist features. A possible explanation for this relationship is the advancement of driver assist technologies over time. The forward collision warning and cruise control features debuted prior to the lane centering assist and other, more advanced features. A propensity to trust technology would indicate a willingness to accept and adopt new or emerging technologies. More specifically, increases in propensity to trust technology are most strongly related to higher-level automation rather than lower-level automation.

The next ANCOVA included driving experience, measured as the total number of years a person has had their driver's license, as a covariate. A moderately significant interaction was found between participants' driving experience and the complexity of the driving scenario, . This indicates that driving experience may moderate any differences in trust between high and low complexity driving scenarios. Though this effect was not particularly strong, the relationship can be seen in Figure 5. Driving experience was able to effectively predict situational trust only in the low complexity scenario. Regression models for the high and low complexity trust scores produced negative beta weights, indicating a decrease in trust as driving experience increased across both driving scenarios. Trust in the high complexity scenario did not vary much as years of driving experience increased, declining only slightly. However, trust in the low complexity scenario saw a moderately strong decline as years of driving experience increased. The situational trust scores in the low complexity scenario approached that of the high complexity as driving experience increased, an indication of the interaction between driving experience and situation complexity. This relationship may be attributable to the nature of trust as it relates to suspicion and vulnerability (Hoff & Bashir, 2015; Deutsch, 1960). Lee and See (2004) define trust as "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability," (p. 54). Low complexity scenarios are inherently low in uncertainty and vulnerability, particularly as described in this study. Early on in a person's time as a licensed driver, they may be more likely to trust driving technologies in low complexity situations because of this low level of uncertainty and perceived vulnerability relative to the high complexity scenario. In time, drivers may learn that the complexity of the environment may not be influencing the reliability of the system, and the lane centering assist feature is just as likely to make a mistake on the straight country road as it is in the city. With experience comes the realization that, even in low complexity driving scenarios, driver assist features are not infallible.

A series of ANCOVA aimed to determine if participants initial, dispositional trust toward the individual driving features would influence the effect of situation complexity on their situational trust scores. Significant interactions were found primarily in the higher levels of automation, the lane centering assist, adaptive cruise control/traffic jam assist, and the fully automated driving. These relationships again indicate a moderating effect for dispositional trust on situational trust in high and low complexity scenarios for these features. The other features, forward collision warning and cruise control, did not see significant interactions between dispositional trust and situation complexity. A closer look at the regression models, wherein dispositional trust scores predicted situational trust in high and low complexity, showed stronger beta weights in high complexity scenarios than in low complexity. Interactions consistently showed situational trust increasing at a higher rate with increases in dispositional trust within the high complexity scenario, starting lower than the scores in the low complexity and overtaking them with time. The relationship between dispositional trust and situational trust, in both the high and low complexity scenarios, was strongest for the fully automated driving feature.

The final series of analyses examined differences between different groups, beginning with an assessment of gender differences. Results supported the initial hypothesis predicting differences between genders and indicated that males, on average, placed more trust in driver assist features across all conditions than females. The interaction between gender and the different driver assist features can be seen in the trust scores of the fully automated driving and cruise control features. Cruise control provided the lowest trust rating among males between all other driver assist features. However, females rated the fully automated driving feature the lowest by a wide margin. As expected, there was also a noted main effect for level of education. Differences in levels of education saw participants that reported having a bachelor's degree reporting the highest level of trust overall, while those with a graduate degree reported the lowest levels of trust. Trust appeared to progressively decline with each increase in level of education, with the group with a bachelor's degree going against this trend. Interestingly, the driving environment in which participants reported driving in most frequently was not a significant factor. No differences were found between groups of participants driving most frequently in different driving environments. Overall, results supported the hypothesis that driving environment complexity and differences in driver assist features would impact differences in situational trust. Results also support the hypothesis that there are multiple factors related to the participant and their driving experience that may moderate these relationships.

Theoretical Implications

This study and its results have implications for the way trust in automation is formed and influenced by factors related to the environment, the system, and the individual. These are each broad categories of factors that previous research has identified as impactful when determining how likely a person is to trust, rely upon, or comply with automated systems and technology (Schaefer et al., 2016; Hoff & Bashir, 2015). The results of this study help to establish potential predictors of trust in automation, and in driving technology in particular. Researchers suggest that the ability to identify key factors impacting trust in automation is an essential step in finding and creating optimal methods of designing trusted systems (Perkins et al., 2010). The main effect of situation complexity is consistent with previous research that suggests task complexity or workload may impact likelihood to trust technology (Hillesheim et al., 2017; Hancock et al., 2011). High complexity scenarios and those that increase workload for the operator tend to decrease trust in the automated system, as was the case for participants when responding to the high complexity driving scenarios above. The strength and consistency of this effect, in spite of the lack of a physical driving environment to test experimental manipulations, provides support for the use of verbal, vignette scenarios for driving research. It is believed that, particularly in driving research, that putting drivers behind the wheel is the most effective way to assess behavioral tendencies (such as reliance or compliance with automated driving technologies) and performance (Tenhundfeld et al., 2020). However, if results previously found in applied driving research is replicated using descriptive or even visual representations of driving tasks, it presents opportunities for researchers and those aiming to predict how a person may interact with the environment while driving.

Additionally, the main effect for driver assist features further supports research finding that factors related to the automation in question will influence trust (Bailey & Scerbo, 2007; Manchon et al., 2021; Schaefer et al., 2016). To further break down this effect, the differences in the driver assist features must be considered. For example, the forward collision warning system provides just that, a warning. The other features either take momentary control of the vehicle (lane centering assist) or constant control of the vehicle (cruise control, fully automated driving). The SAE level of automation for each feature differs as well (SAE, 2021). The forward collision warning would be considered SAE Level 0, as the SAE lists features such as lane departure warning and blind spot warning in that level. The lane centering and adaptive cruise control features are classified, when considered independently, as SAE Level 1. The full automated driving, as described in this study, would be SAE Level 5 (the SAE does not classify the cruise control feature). Another difference, perhaps a factor considered in the SAE levels of automation classifications, is that the fully automated driving claims full awareness of the environment and the ability to consistently act within it without driver intervention. Conversely, the cruise control feature claims no awareness or ability to adapt to the environment, and the forward collision warning system maintains awareness but acts only under specific conditions (i.e., a forward collision is imminent). Previous research into driver assist technologies has found a similar relationship with trust (Miele, et al., 2021).

The significant interaction between manipulations provides support for previous findings suggesting that trust is uniquely influenced by a multitude of different factors (Schaefer et al., 2016; Hoff & Bashir, 2015). Trust, on average, appeared to be highest for features with conditional awareness of the environment, such as the forward collision warning system and lane centering assist feature. This trend was particularly apparent in the high complexity scenario, however, as a closer examination of the interaction between the variables revealed. Cruise control received the lowest trust rating in the high complexity scenario, while the fully automated driving was also much lower than the other three features. Figure 10 shows this relationship as a generalized model for how trust in driving technology is trusted in high complexity situations is related to the level of awareness the system claims to have of the environment.

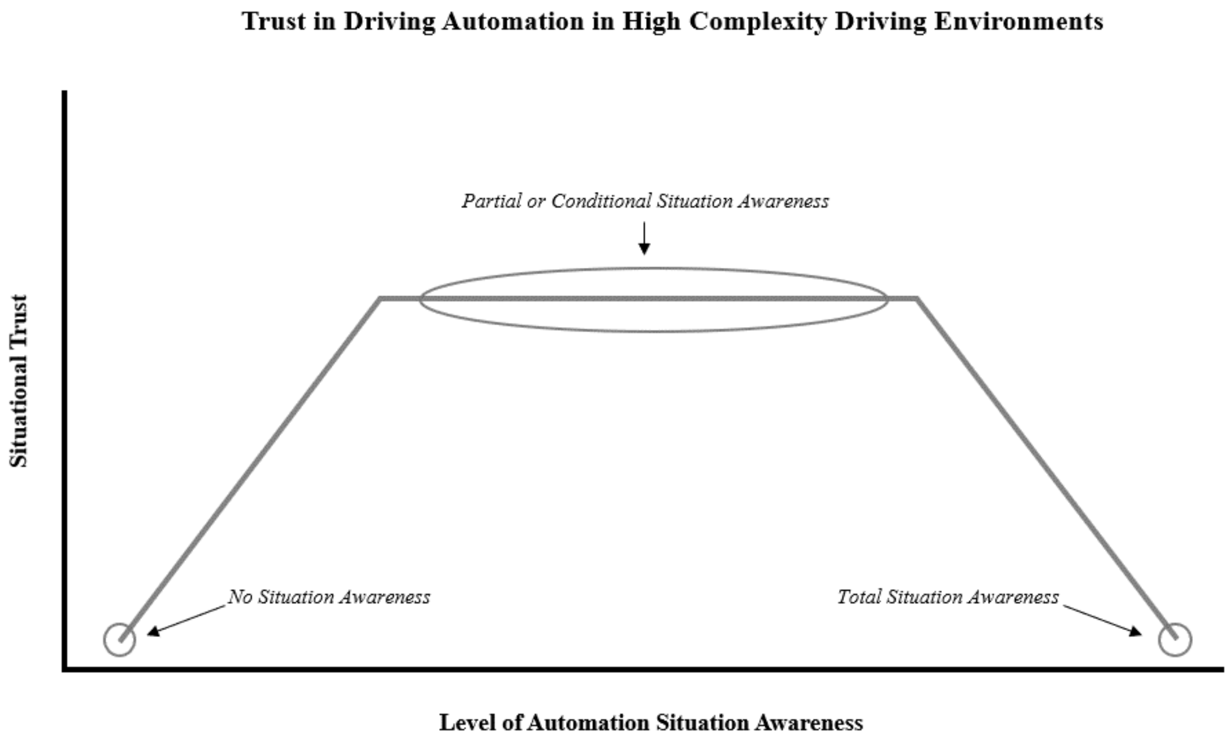

FIGURE 13: A PROPOSED MODEL REPRESENTING THE RELATIONSHIP BETWEEN TRUST IN A DRIVING SYSTEM AND THAT SYSTEM'S AWARENESS OF THE ENVIRONMENT IN HIGH COMPLEXITY DRIVING SCENARIOS

In this model, trust in a high complexity scenario is very low for a driver assist feature that claims no awareness of the environment, and thus has no adaptive capabilities. This includes features such as cruise control. Driving features that have limited or partial awareness of the environment are seemingly trusted the most, with features such as lane centering assist and forward collision warning being rated fairly equally in this study. These features assist in only one aspect of driving (e.g., braking, steering) and act only when certain conditions are met (e.g., lane deviation, oncoming obstruction in the road). Fully automated driving received similarly low scores compared to the cruise control feature in the high complexity scenario, suggesting that the implication of total situation awareness on the part of the driver assist feature would also not be as trusted in this environment. This model closely aligns with the belief that performance consequences of automation are most likely to occur when the automation advances from information analysis to action selection (Onnasch et al., 2014).

Trends in the low complexity scenarios followed a similar pattern, however the cruise control feature was the highest rated of all features rather than the lowest. Each of the remaining features appeared to rate similarly relative to the others. A closer look at other participant data shed light on why this relationship may exist. The cruise control feature was reported by the most participants as a feature they currently have in their vehicle (62%), and this was likely an underestimation as the cruise control feature was introduced decades ago as a feature expected in all vehicles on the road. Interestingly, the forward collision warning feature (24%) and lane centering assist (18%) were the next two most common of the five features used in this study. Adaptive cruise control/traffic jam assist was next (10%), and no participants reported having access to fully automated driving. Trust ratings between the five features in the low complexity scenario appeared to decrease as fewer participants had access to the feature. This would indicate that trust in the feature is closely related to the amount of experience the person has with the technology (Gold et al., 2015; Azevedo-Sa et al., 2020). Differences found in the interaction between situation complexity and driver assist feature indicate that trust in driving features in high complexity scenarios may be dependent on the level of awareness the feature has of the environment, while in low complexity scenarios it may be more dependent on driver experience with the feature.

The analyses that included a covariate were able to identify a few characteristics of the driver that might influence the relationships found through the primary manipulations of scenario complexity and driver assist feature. Each ANCOVA would help to reveal any possible existing relationships between variables that would impact the strength or the direction of the relationships. A propensity to trust technology in general appeared to moderate any relationships between the average situational trust score and the different driver assist features examined. This is consistent with previous research that suggests that individuals that differences in the tendency to trust technology in general will contribute to how likely an individual is to trust specific kinds of technology or automation (Merritt & Ilgen, 2008). The 2008 article from Merritt and Ilgen proposes that differences in trust in automation with which a person may have some experience (in the article, this was considered post-task trust) "may be related to the interaction between propensity to trust machines and machine characteristics," (p. 198). Our results suggest this may be the case.

A propensity to trust technology was highly predictive of trust in three of the five driver assist features. These included the features that take some part reacting to the environment, such as the lane centering assist and fully automated driving. As stated previously, this may suggest that a propensity to trust technology in general makes an individual more likely to trust and accept newer technologies. The interaction between the propensity to trust technology score and the driver assist features suggest that, at lower levels of propensity to trust technology, the cruise control and forward collision warning features are more trusted than the adaptive cruise control/traffic jam assist and fully automated driving features. However, as the propensity to trust technology score increases, the average situational trust in fully automated driving overtakes that of the cruise control and the adaptive cruise/traffic jam assist feature reaches the level of the forward collision warning. This is due to the steep slope associated with the model for those two features. Looking at Figure 4, it appears that an increase in the propensity to trust technology will eventually indicate a similar level of trust for all driving features, while a lower propensity to trust technology would indicate lower situational trust for adaptive and reactive driving features.

As stated earlier, a portion of participants reported having four of the five driver assist features included in the study in their current vehicle. Additionally, this sample included a large number of college students, who likely learned to drive using vehicles equipped with many of these features. With driving being such an essential task for the transportation of goods and services, it is highly likely that all participants began the study with some level of familiarity with each of the driver assist features. However, each feature will be perceived differently by drivers, creating a dispositional trust level based on their perceptions and experiences that will impact how different features are trusted (Merritt & Ilgen, 2008; Balfe et al., 2018). Dispositional trust, or trust in the system outside of any given context, was measured using the Checklist for Trust Between Humans and Automation (Jian et al., 2000) and used in the ANCOVA to assess how it might interact with differences between high and low complexity driving scenarios across each unique driving assist feature. The results support the hypothesis that dispositional trust in a specific driving technology may influence the relationship between trust and situation complexity (Merritts & Ilgen, 2008; Manchon et al., 2021). Dispositional trust scores interacted with the manipulations in scenario complexity for the lane centering assist, adaptive cruise/traffic jam assist, and fully automated driving features. The ability of dispositional trust to predict situational trust in both high and low complexity scenarios for the adaptive cruise/traffic jam assist and fully automated driving Higher dispositional trust scores appear related to higher situational trust scores in both high and low complexity driving environments. However, regression models show the low complexity scores increasing at a much slower rate than the high complexity trust scores. This trend was strongest for the fully automated driving, though high complexity trust scores became higher than low complexity trust scores as dispositional trust increased for the lane centering assist, adaptive cruise control/traffic jam assist, and fully automated driving features.

Driving experience did not have quite the strong effect that was expected, though it did appear to moderate the relationship between trust in high and low complexity scenarios. This effect was not particularly strong, and regression models show no true significant interaction between driving experience and scenario complexity. However, this effect did approach significance ($p< .10$), and Figure 5 shows a clear trend in the low complexity scores. This would be consistent with previous research suggesting that experience with an automated system may impact trust (Gold et al., 2015; Azevedo-Sa et al., 2020). Trust did not appear to change in the high complexity scenario as a function of driving experience, measured in terms of years having a valid driver's license. However, trust appeared to decline in the low complexity scenario as driving experienced increase. While this never reached the level of the high complexity scenario, results suggest that as a person gains more experience with a driving system or the task of driving, they may be less likely to trust it. This would appear to contradict some previous research that has found increased exposure to an automated system tends to increase overall trust (Kundinger et al., 2019; Tenhundfeld et al., 2020). A variable expected to result in lower trust was participants' driving self-efficacy (De Vrise et al., 2003; Miele et al., 2021). However, there was no significant interaction between the level of confidence participants had in their driving abilities and the primary manipulations. The overall results of the series of ANCOVA suggest that there are, indeed, factors related to the individual that could influence how much trust they place in different driving technologies in different driving environments.

This study also as implications for the way different groups of individuals accept and trust automated driving systems. A few of the group differences found were consistent with the hypothesis that individual differences, such as gender and level of education, would result in differences in situational trust. Differences between males and females were also consistent with previous research (Hillesheim et al., 2017). Males, on average, reported higher levels of situational trust. This difference appear to have been replicated multiple times, and while no clear explanation has been provided for this difference, the repeated effect must be noted for future research. Males appeared to report consistent levels of trust for the forward collision warning, lane centering assist, and adaptive cruise control/traffic jam assist features, while also reporting similar scores for the cruise control and fully automated driving features. Females also reported the lowest situational trust scores for the cruise control and fully automated driving features, however the trend in the results suggest a clear loss of trust in higher-level automation, with the fully automated driving receiving the lowest average trust score. The driving features that females appeared to rate higher than the others were those that did not claim responsibility for controlling speed of the vehicle (e.g., forward collision warning and lane centering assist). It is possible that certain populations may be more trusting of a feature that is designed to manage a specific aspect of driving, such as acceleration/braking or control within lanes.

The results of this study and others intending to assess how driver assist features are trusted and used are particularly important as highly automated driving becomes more readily available. Currently, companies such as Tesla are working on fully autonomous driving systems that include each of the driving features used in this study working in tandem to transport an operator (because they are no longer driving) to their destination. The trust a person places in the single driver assist features included in this study has implications for system-wide trust (SWT).

SWT theory suggests that when trust in a single automated device within a grander system degrades, trust in the system as a whole is reduced (Geels-Blair et al., 2013; Rice et al., 2016). In hypothetical scenarios such as those described in this study, participants have reported lower trust in transportation systems when a single component of the system fails. For example, Winter and colleagues (2014) found trust in all aircraft systems (autopilot, landing gear, etc.) was significantly reduced in a condition where participants were told that the oxygen mask deployment mechanism was unreliable. A lack of trust in a particular component of autonomous driving technology could have implications for overall system-wide trust. The information obtained through this study can assist in the development of future autonomous vehicles and systems that are designed to optimize trust at an appropriate level.

Practical Implications

Results from this study suggest that there may be a means to predict how likely a person is to trust, and by extension accept and use, driving technologies. Specifically, these results provide insight into how driver assist features are likely to be trusted in different driving environments. Vehicles absent of any advanced driving technology are becoming increasingly scarce on the market today, and drivers are now working in tandem with these systems in an effort to increase traffic safety and reduce accidents. The real-world applications of this research and projects like it extend to the design, development, and implementation of current and future driver assistance technologies.

This has a litany of applications as driver assistance technologies continue to proliferate modern vehicles, and companies progress toward a fully realized self-driving car. Individuals who may report significantly higher levels of trust might become targets for manufacturing companies who aim to get their advanced driving technologies on the road. Increasing trust is a way to increase acceptance of new technologies (Manchon et al., 2021), so car companies can learn from this research and make decisions about how they will expose potential customers to driver assist features. For example, test driving these features in a low complexity environment may be an opportunity to increase consumer trust and acceptance. It may also be effective in identifying segments of the population likely to be receptive to purchasing a vehicle equipped with these features. This includes those of a certain gender, education level, or age. Driving experience appeared to moderate differences in trust between high and low complexity scenarios, and additional research has suggested that age may be a factor in how likely a person is to trust and use certain driving features (Donmez et al., 2006). Surveys from 2016 suggest that 61% of drivers aged 25 to 34 indicated they would be willing to use driver assist features that temporarily and periodically take control of the vehicle (Abraham et al., 2016). That number dropped to 38.1% for drivers aged 65 to 74. The ability to predict trust based on situational factors or individual differences can change the way the automated vehicle industry approaches marketing and system design.

This approach would certainly benefit those who wish to profit off of the development of these advanced driver assist features, though it may ultimately result in a population of automated vehicle operators who would report very high levels of trust in the system. Thus, this would mean creating a population of drivers highly susceptible to automation-induced complacency (Parasuraman et al., 1993). A more responsible application of these results would be to develop a means of assessing who has the proper level of trust in the driver assist features, not the highest level of trust. More trust does not equate to the right amount of trust, and it is reasonable to propose that the most advanced driving technologies be afforded to those who will use it responsibly rather than those who believe in its infallibility. This relates to the full self-driving feature that Tesla released in recent years. It was reported that, upon initial release of the feature in 2021, that the FSD beta would only be released to drivers who have been deemed "good" drivers based on Tesla telemetry data (Lambert, 2021). This was to be the company's indicator of who might use the technology properly. However, driver performance data may not be sufficient in predicting all reliance and compliance behaviors, particularly with novel technologies that are still imperfect in their own unique ways (see example from Chapter 1).

The results of this study suggest that other information related to the driver may be effective in predicting their likelihood to trust different driver assist features across different driving environments. Identifying a level of trust using self-report measures that corresponds to responsible use of the driving technology could be the most sensible way of releasing advanced driving features to consumers. This method can also be used to create a personalized suite of driver assist features when consumers purchase vehicles. Car companies, provided with some quantifiable indication of a customer's level of trust in the available driver assist features, can make informed recommendations about which features might be used effectively by the driver. Exposing driver's to the driving technology that they place more trust in will create an effective method for avoiding what is referred to as 'future shock' (Townsend, 2020). Future shock can occur when there is too much change or advancement, particularly in technology, in a short period of time (p. 120). If researchers or car companies can identify driving features that are commonly trusted or accepted, as compared to those that are not, it can create opportunities to introduce features to consumers in a more effective way. The information and methods derived from this project could be used to introduce consumers to automated vehicle technology (Payre et al., 2016).

This study can also inform the way automated driving features are designed. The strength of the effect observed between high and low complexity driving scenarios as it related to trust can inform adaptive assistance that accounts for the complexity of the environment. Adaptive automation is designed to account for the capabilities and limitations of the user, providing timely assistance in otherwise manually performed tasks (Parasuraman et al., 1996). This can be based on real-time assessments of the user's performance, noting when thresholds for effective performance have been achieved or not. This can also be model-based, using previous knowledge and research on human performance to make informed decisions about when to allocate tasks to automation. The specific results from this study that show the differences in trust between high and low complexity situations can inform adaptive automation that accounts for the traffic density surrounding the vehicle. Using knowledge obtained from prior research into how inappropriate levels of trust manifest in driving behaviors, automakers can create adaptive systems that compensate for negative behaviors. Current advanced driving systems have adaptive measures in place, likely informed by human factors research, that is intended to keep the driver engaged. For example, in many vehicles that possess driving features that allow the driver to take their hands off the wheel, there is a system in place that calls on the driver to make contact with the steering wheel. This is a form of feedback from the driver to the automated system to let them know that they are attentive and engaged.

Ultimately, this study is practically relevant because the past, present, and future of the field of human factors as a principle of engineering lies largely in determining, in any human-machine system, who does what task and when (Hancock, 2009). This research is one step toward answering these questions with empirical data that also provide answers to the question of why we automate certain tasks. Certain additional, practical questions should be asked as automated vehicles continue to progress toward full autonomy. There should be many additional steps between now and then, with automation slowly beginning to take control of a vehicle away from the driver. For example, research suggests that trust in an automated support system, such as driver assistance technologies, decreases when the level of control the automation has in a task crosses over from providing decision support to making the decision on behalf of the operator (Onnasch et al., 2014). Which driving tasks are drivers willing to delegate to automation? For which tasks would they prefer or trust automation to only help them make decisions for themselves? These are the questions that should be answered before any fully self-driving vehicle is made widely available.

CHAPTER 7: LIMITATIONS AND CONCLUSIONS

Limitations and Directions for Future Research

Several challenges created limitations for this research and the methods through which the data were collected. The largest limitation facing this project was that the experiment was designed, and data were collected during the COVID-19 pandemic. This was at a time when the University was shut down for all human subjects research. Human factors is an applied field of psychology, and transportation research is largely dependent on bringing participants into a controlled setting to conduct human performance research with the use of driving or flight simulators. With this limitation, the study lacks a real-world setting in which to test participants' trust in the driver assist features. The results are reliant on participants' reporting of their levels of trust, and self-report measures can be subject to biases and consequences of attention. Attention checks were included in the surveys to allow the filtering of data from participants that were not truly reading the questions. However, the issue of lacking any objective, behavioral indicator of trust remained. This also made it impossible to assess how seriously participants were taking each question as they were removed from any supervised lab setting.

Putting participants behind the wheel in a real or simulated environment could provide an indication of reliance and compliance behaviors, considered to be behavioral signs of trust (Lee & See, 2004). The self-report measures in particular are unable to assess levels of trust in real time (Azevedo-Sa et al., 2020) and separate the individual even further from the actual driving environment than a simulator would, making it difficult to see how these results might translate to driver performance (Tenhundfeld et al., 2020). Future research should aim to replicate the study in a practical environment. Certain interactions with the vehicle and driving technologies can be indicators of trust and reliance. Levels of operator trust in these features can be assessed using gaze behaviors and recovery time during manual takeover scenarios (Abe et al., 2017; Hergeth et al., 2016). A slower reaction during manual take over scenarios would suggest higher levels of distraction or complacency, likely corresponding to the level of trust placed in the vehicle. The examples described previously, including the individual pulled over for riding the back seat of his Tesla, represent behaviors indicative of high levels of trust in the self-driving technology in the vehicle. These behaviors show levels of trust that do not correspond to the capabilities of the system. It is critical that researchers continue to explore how trust in driving technologies manifests in an applied setting, putting this technology in the hands of the drivers, so to speak. Adding these behavioral indicators of trust to a study that also has participants self-report their levels of trust might be a step toward predicting the proper level of trust using survey scores that correspond to behaviors.

An additional limiting factor was the sample population surveyed for this study. While attempts were made to create a diverse sample with a broad range of ages, much of the sample consisted of undergraduate college students. This presents multiple limitations that should be mentioned as these results are considered for future research. Much of the sample was recruited from a university, and therefore are rather inexperienced when it comes to driving relative to much of the drivers on the road. Additionally, there is existing literature that suggest different generations may have different attitudes toward technology in general (Schaefer et al., 2016; Hoff & Bashir, 2015). The younger demographics have been brought up using technology and To potentially provide further support for those results it would be beneficial to have a more age-diverse sample for future studies investigating trust in driving technologies. Of course, with the limitation related to age comes one related to overall driving experience. Age was not included as a covariate due to its strong, positive correlation with driving experience. Much of the sample that completed this study had been driving for fewer than 5 years. This meant that they likely began driving using vehicles that have multiple assistive driving features. Older drivers would have learned to drive without the use of driver assist features such as those described in this study. A sample with a wider range of driving experiences could also benefit future research. The ANCOVA involving driving experience as a covariate was only marginally significant, but it is possible that a sample with a wider range of ages would strengthen that effect. To further expand the sample population and explore more specialized groups, a comparison of commercial and non-commercial drivers would be practically relevant as autonomous, commercial vehicles responsible for shipping goods are already on the road. This is only one group that could be examined in comparison to other drivers.

Future areas of research can aim to not only fill in the gaps that remain in the literature, build on the results obtained through this study. For example, the strength of the effect found when looking at differences in trust between high and low complexity driving scenarios likely warrants further investigation. A simulated or on-road experiment, placing drivers in the environments described above, could provide further evidence for this manipulation as a predictor of trust in automated driving. The trend observed in the high complexity scenario also should be investigated further. The model presented in Figure 10, based on patterns in the data, shows that trust in driving technologies in high complexity scenarios may be a function of the awareness the vehicle or feature claims to have of the surrounding environment. Additional driving features should be explored to test this theory, looking specifically at features performing the same driving task (e.g., braking, accelerating, steering) at different levels of responsiveness to the environment. Considering the implications these results have for how current and future driver assist systems are likely to be used, this relationship merits more research.

The results of this study strongly suggest that various individual differences related to the driver may impact the way they trust driving technologies in different environments. Future research may expand the factors explored in this study and incorporate additional traits or skills that could have a similar impact. Differences in key personality traits has been shown to impact how different individuals interact with automation (Szalma & Taylor, 2011; Hoff & Bashir, 2015). This includes examinations of the Big Five (McCrae & Costa, 2008), agreeableness, conscientiousness, extraversion, neuroticism, and openness that have found traits effectively associated with performance and workload. Conscientiousness and neuroticism have been associated with performance outcomes in unmanned vehicle operations, while openness and agreeableness predictive of subjective workload. These traits, among others that may be contextualized to the task of operating a motor vehicle (Matthews, 2018), should be examined in a similar context to the variables used in this study (e.g., driving experience, self-efficacy).

An additional trait of interest in the study of autonomous vehicles is locus of control, or a tendency to believe outcomes of a situation are within their own control (You et al., 2013; Rotter, 1954). Locus of control has been a character trait of interest in human factors research as it relates to the safe operations of motor vehicles and aircraft (You et al., 2013). Locus of control has been tied to risk perception and risk-taking behaviors, with internal locus of control scores being linked to specific hazardous actions by pilots (Hunter, 2002). This is of particular interest in the context of an increasingly autonomous system, which creates opportunities where manual takeover from the pilot/operator is required at a moment's notice. Relationships between locus of control and distraction and the management of multiple tasks lead to questions related to how internal or external locus of control might impact compliance and reliance behaviors tied to trust in automated vehicles. These areas of research represent only a few examples of how this study can be expanded. Continuing this research will be critical to answering questions related to the use of automation in driving, both those that are currently available and those that could be in the near future.

Conclusions and Recommendations

The present study was designed to assess the impact of manipulations to the complexity of a driving environment on trust in various driver assist features. Conclusions can be drawn from this study regarding how situational trust in driving technologies varies based on the driving environment and several factors related to the individual driving the car. Several significant effects that have been found in simulated driving research was also found in this study, despite the lack of any practical driving task (Hillesheim et al., 2017). Overlap in the results from self-report studies such as this one and research conducted in a lab setting could help inform a model of predicting driving reliance and compliance behaviors as they related to driving technologies using self-report assessments of trust. If we are able to find strong enough relationship between scores on certain measurements of trust (dispositional, situational, etc.) and certain dangerous driving behaviors, we may be able to effectively predict who is likely to properly use both old and novel driver assist features.

Measurements of trust, such as those used in this study, can give insight into how likely a person is to accept and use technology. This study and its results show how certain environmental or individual differences might predict differences in trust. However, what these results do not do is make any claim about what a proper level of trust in the driver assist features might be. In order to make any practical recommendations about how to leverage trust scores into predictions of driver behavior, it will be critical to establish what an appropriate level of trust is. This value will likely vary between the different driving features.

Truly unmanned vehicles have been a target of transportation engineers for decades. So, while there is not currently an automated car that satisfies the criteria of full self-driving (SAE, 2021), there is hope that we may soon be able to reliably, and comfortably, let automation take the wheel. Unmanned systems provide significant benefits as they can compensate for many human physical limitations (Hancock, 2009). However, the results of this study show that there is still significant variation between who trusts advanced driving technologies and in what context they are most likely to be trusted, suggesting significant variance in how the technology will be used. The future of automated vehicles is largely dependent on the consumers' willingness to trust and accept this highly advanced form of driving technology. As the research and technology moves forward, this study helps answer whether or not these efforts are going to be worth the time and effort. Results show that even the more common driver assist features are not trusted at the same level by all individuals and understanding why these differences exist will help reveal how, and if, the automated driving future that has been dreamt of will become reality any time soon. In light of the results in this study, the following recommendations are proposed for researchers, engineers, and unmanned vehicle operators as they consider the way automation is implemented in future automobiles.

1. Increase transparency for how automated driving systems make decisions, finding intuitive and creative ways to generate this transparency. Proper forms of feedback are essential to safety-critical human-machine systems.
2. Research behavioral indicators of trust in automated driving technology that may correlate with quantifiable measures of trust.

3. Develop adaptive technology to keep operators attentive during automated driving by effectively reducing underload, complacency, and distraction while still providing benefits to cognitive and physical workload.
4. Create systems for dynamic task allocation based on driving scenario complexity defined by traffic density and setting.
5. Provide more education on AI in driver assist features and how other driving technologies work.
6. Identify differences in driving technology (level of automated control, driving task, etc.) that contribute to behaviors related to trust, such as compliance and reliance.

These recommendations provide a way forward toward answering critical questions related to human performance in conjunction with highly advanced automated systems. By following the results of this study and the recommendations provided above, researchers and those leading the charge toward autonomous driving can begin to account for individual differences related to trust. A final, perhaps most critical recommendation would be to human factors researchers, encouraging them to continue empirical research that can answer questions about how trust is formed and how it manifests in potentially detrimental driving behaviors. The goal of applied research in transportation systems is to improve the safety and efficiency of current and future vehicles, and it is important that this research continues as these vehicles become increasingly complex human-machine systems.

APPENDIX A: INTERNAL REVIEW BOARD APPROVAL DOCUMENTATION

UNIVERSITY OF CENTRAL FLORIDA

Institutional Review Board
FWA00000351
IRB00001138, IRB00012110
Office of Research
12201 Research Parkway
Orlando, FL 32826-3246

EXEMPTION DETERMINATION

June 2, 2021

Dear James Ferraro:

On 6/2/2021, the IRB determined the following submission to be human subjects research that is exempt from regulation:

Type of Review:	Initial Study, Initial Study
Title:	Examining Factors Predicting Trust in Automated Driving Features
Investigator:	James Ferraro
IRB ID:	STUDY00003091
Funding:	None
Grant ID:	None
Documents Reviewed:	• Trust in Driving HRP-251- Faculty Advisor Form.pdf, Category: Faculty Research Approval; • Demographics Survey.docx, Category: Survey / Questionnaire; • DM Vignette Questions Modified.docx, Category: Survey / Questionnaire; • Driver Experience Questions.docx, Category: Survey / Questionnaire; • Driving Self-Efficacy Scale.docx, Category: Survey / Questionnaire; • Driving Vignettes.docx, Category: Survey / Questionnaire; • HRP-254-FORM Explanation of Research v2.pdf, Category: Consent Form; • HRP-255-FORM - Request for Exemption v2.docx, Category: IRB Protocol; • Modified Situational Trust Scale for Automated Driving.docx, Category: Survey / Questionnaire; • Trust in Driving Flyer v2.docx, Category: Recruitment Materials;

This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made, and there are questions about whether these changes affect the exempt status of the human research, please submit a modification request to the IRB. Guidance on submitting Modifications and Administrative Check-in are detailed in the Investigator Manual (HRP-103), which can be found by navigating to the IRB Library within the IRB system. When you have completed your research, please submit a Study Closure request so that IRB records will be accurate.

If you have any questions, please contact the UCF IRB at 407-823-2901 or irb@ucf.edu. Please include your project title and IRB number in all correspondence with this office.

Sincerely,

Gillian Bernal
Designated Reviewer

APPENDIX B: DEMOGRAPHICS SURVEY

1. What is your age?
    a. 18-25
    b. 26-35
    c. 36-45
    d. 46-55
    e. 56-65
    f. 65+
2. What is your gender?
    a. Male
    b. Female
    c. Other
    d. Prefer not to say
3. What is the highest level of education you have achieved?
    a. High School Diploma
    b. Some college but no degree
    c. Associate Degree
    d. Bachelor’s Degree
    e. Graduate Degree
4. Are you currently employed?
    a. Yes
    b. No
    c. Retired
    d. Disabled, unable to work

5. How much total combined money did all members of your household earn in 2020?
    a. $0 - $9,999
    b. $10,000 – $19,999
    c. $20,000 - $29,999
    d. $30,000 - $39,999
    e. $40,000 - $49,999
    f. $50,000 - $59,999
    g. $60,000 - $69,999
    h. $70,000 - $79,999
    i. $80,000 - $89,999
    j. $90,000 - $99,999
    k. $100,000 or more
6. Have you served or are you currently serving in the United States military?
    a. Yes
    b. No
7. If you are a student at the University of Central Florida, please provide your SONA Number to receive credit for your participation.

APPENDIX C: DRIVER EXPERIENCE QUESTIONNAIRE

1. Do you currently have a valid US driver's license?
    a. Yes
    b. No
2. If yes, for how long have you had your driver's license?
    a. 0-2 years
    b. 2-5 years
    c. 6-10 years
    d. 11-20 years
    e. 21-30 years
    f. 31+ years
    g. N/A
3. How long have you been driving your current vehicle?
    a. Less than 1 year
    b. 1-2 years
    c. 3-5 years
    d. 6-10 years
    e. 11+ years
    f. I don't own a vehicle
4. Does the vehicle you currently drive have any automated driving assist features?
    a. Yes
    b. No
    c. Not sure
    d. N/A

5. If yes, select all that apply:
    a. Forward collision warning
    b. Cruise control
    c. Adaptive cruise/traffic jam control
    d. Auto-brake/Forward collision avoidance
    e. Auto-lane change
    f. Lane centering assist
    g. Blindspot detector
    h. Back-up camera
    i. Auto-park
    j. Sign recognition
    k. Full autopilot
    l. N/A
6. In what type of environment would you say you most often drive?
    a. Cities
    b. Rural areas
    c. Highways
    d. I don’t drive
7. How many miles would you estimate you drive on the highway in a usual week?
    a. 0-10 miles
    b. 11-20 miles
    c. 21-40 miles
    d. 41-60 miles

    e. 61-100 miles
    f. 100+ miles

8. How many miles would you estimate you drive NOT on the highway in a usual week?
    a. 0-10 miles
    b. 11-20 miles
    c. 21-40 miles
    d. 41-60 miles
    e. 61-100 miles
    f. 100+ miles
9. Do you commute for work/school (or did you prior to the COVID-19 pandemic)?
    a. Yes
    b. No
10. If yes, how far would you estimate is/was your commute? (if no, answer N/A)
    a. 0-5 miles
    b. 6-10 miles
    c. 11-20 miles
    d. 21+ miles
    e. N/A
11. How many minor car accidents (small amount of damage to the vehicle that does not prevent the vehicle from running or cause significant injuries) have you been in as the driver?
12. How many minor car accidents have you been in as a passenger?

13. How many major (large amount of damage to the vehicle that prevents it from running and/or causes significant injuries) car accidents have you been in as the driver?
14. How many major car accidents have you been in as a passenger?
15. Have you ever received a traffic citation for speeding?
    a. Yes
    b. No
16. How often are you driving with a passenger in the car?
    a. Never
    b. Rarely
    c. Sometimes
    d. Usually
    e. Always

APPENDIX D: ADELAIDE DRIVING SELF-EFFICACY SCALE (ADSES)

How confident do you feel doing the following activities?

Please allocate a number from 0-10, where 0 is not confident and 10 is completely confident, for

the

12 questions below.

1) Driving in your local area

2) Driving in heavy traffic

3) Driving in unfamiliar areas

4) Driving at night

5) Driving with people in the car

6) Responding to road signs/traffic signals

7) Driving around a roundabout

8) Attempting to merge with traffic

9) Turning right across oncoming traffic

10) Planning travel to a new destination

11) Driving in high-speed areas

12) Parallel parking

APPENDIX E: MODIFIED SITUATIONAL TRUST SCALE FOR AUTOMATED DRIVING (STS-AD)

To use the STS-AD, present the items in the table below in the order that is presented here after participants experience an automated driving system.

Items should be collected with a 7-point Likert scale ranging from (1 –strongly disagree; 2 – disagree; 3 – somewhat disagree; 4 – neither agree or disagree; 5 – somewhat agree; 6 – agree; 7 – strongly agree).

After the data is collected, reverse score items 2, 4, and 5 (1 = 7; 2 = 6; 3 = 5; 5 = 3; 6 = 2; 7 = 1). Then, compute an average agreement score for the six items. This average score is then the total for the STS-AD

Vignettes 1 and 2: each scored 1 (strongly disagree) to 7 (strongly agree).

1. I trust the forward collision warning system in this situation.
2. I would perform better than the forward collision warning system in this situation. (Reverse scored)
3. In this situation, the forward collision warning system performs good enough for me to engage in other activities (such as reading).
4. The situation is risky.
5. The forward collision warning system is likely to make an unsafe judgement in this situation. (Reverse scored.)
6. The forward collision warning system is likely to react appropriately to the environment.

Vignettes 3 and 4: each scored 1 (strongly disagree) to 7 (strongly agree).

1. I trust the cruise control system in this situation.
2. I would perform better than the cruise control system in this situation. (Reverse scored)

3. In this situation, the cruise control system performs good enough for me to engage in other activities (such as reading).
4. The situation is risky.
5. The scenario describes driving on a country road
    a. *This question will only be used for Vignette 4, with the correct answer being Strongly Agree*
6. The cruise control system is likely to make an unsafe judgement in this situation. (Reverse scored.)
7. The cruise control system is likely to react appropriately to the environment.

Vignettes 5 and 6: each scored 1 (strongly disagree) to 7 (strongly agree).

1. I trust the lane centering assist system in this situation.
2. I would perform better than the lane centering assist system in this situation. (Reverse scored)
3. In this situation, the lane centering assist system performs good enough for me to engage in other activities (such as reading).
4. The situation is risky.
5. The lane centering assist system is likely to make an unsafe judgement in this situation. (Reverse scored.)
6. The lane centering assist system is likely to react appropriately to the environment.

Vignettes 7 and 8: each scored 1 (strongly disagree) to 7 (strongly agree).

1. I trust the adaptive cruise/traffic jam control system in this situation.

2. I would perform better than the adaptive cruise/traffic jam control system in this situation. (Reverse scored)
3. In this situation, the adaptive cruise/traffic jam control system performs good enough for me to engage in other activities (such as reading).
4. The situation is risky.
5. The adaptive cruise/traffic jam control system is likely to make an unsafe judgement in this situation. (Reverse scored.)
6. The adaptive cruise/traffic jam control system is likely to react appropriately to the environment.

Vignettes 9 and 10: each scored 1 (strongly disagree) to 7 (strongly agree).

1. I trust the fully automated driving system in this situation.
2. I would perform better than the fully automated driving system in this situation. (Reverse scored)
3. In this situation, the fully automated driving system performs good enough for me to engage in other activities (such as reading).
4. The situation is risky.
5. The fully automated driving system is likely to make an unsafe judgement in this situation. (Reverse scored.)
6. The fully automated driving system is likely to react appropriately to the environment.

APPENDIX F: CHECKLIST FOR TRUST BETWEEN PEOPLE AND AUTOMATION

Presented five times in relation to each of the five automated driving features. That is, the ‘system’ in each item was referred to as Forward Collision Warning, Cruise Control, Lane Centering Assist, Adaptive Cruise/Traffic Jam Control, and Fully Autonomous driving.

Items rated 1-7 from ‘Not at All’ to ‘Extremely’

1. The system is deceptive.
2. The system behaves in an underhanded manner.
3. I am suspicious of the system’s intent, actions, or outputs.
4. I am wary of the system.
5. The system’s actions will have a harmful or injurious outcome.
6. I am confident in the system.
7. The system provides security.
8. The system has integrity.
9. The system is dependable.
10. The system is reliable.
11. I can trust the system.
12. I am familiar with the system.

APPENDIX G: DRIVING VIGNETTES

Level 1 – Forward Collision Warning Description

You recently purchased a new vehicle equipped with some automated driver-assist features. This particular vehicle possesses a Forward Collision Warning function. The purpose of the Forward Collision Warning is to notify a driver when a collision is imminent with an object in front of the vehicle. Based on the scenario described here, please answer the following questions about your perception and use of the Forward Collision Warning feature.

Scenario 1: Level 1 – High – Forward Collision Warning

Imagine you are driving in a high-density traffic situation on city streets with many turns. Your Forward Collision Warning feature is present in the vehicle to alert you if you are about to collide with a vehicle or pedestrian in front of you. Based on the scenario described here, please answer the following questions about your perception and use of the Forward Collision Warning feature.

Scenario 2: Level 1 – Low – Forward Collision Warning

Imagine you are driving in a low-density traffic situation on a straight country road. Your Forward Collision Warning feature is present in the vehicle to alert you if you are about to collide with a vehicle or pedestrian in front of you. Based on the scenario described here, please answer the following questions about your perception and use of the Forward Collision Warning feature.

Level 2 – Cruise Control Description

You recently purchased a new vehicle equipped with some automated driver-assist features. This particular vehicle possesses a Cruise Control function. The purpose of Cruise Control is to keep the vehicle traveling at a consistent speed without the assistance of the driver.

Scenario 3: Level 2 – High – Cruise Control

Imagine you are driving in a high-density traffic situation on city streets with many turns. Your Cruise Control feature is present in the vehicle to help keep your vehicle at a constant speed and relieving the need to accelerate. Based on the scenario described here, please answer the following questions about your perception and use of the Cruise Control feature.

Scenario 4: Level 2 – Low – Cruise Control

Imagine you are driving in a low-density traffic situation on a straight country road. Your Cruise Control feature is present in the vehicle to help keep your vehicle at a constant speed and relieving the need to accelerate. Based on the scenario described here, please answer the following questions about your perception and use of the Cruise Control feature.

Level 3 – Lane Centering Assist Description

You recently purchased a new vehicle equipped with some automated driver-assist features. This particular vehicle possesses a Lane Centering Assist function. The purpose of the Lane Centering Assist is to recognize when the vehicle is deviating from the center of the lane and automatically adjust steering to direct the vehicle back to the center of the lane.

Scenario 5: Level 3 – High – Lane Centering Assist

Imagine you are driving in a high-density traffic situation on city streets with many turns. Your Lane Centering Assist feature is present in the vehicle to help keep your vehicle centered within its current lane. Based on the scenario described here, please answer the following questions about your perception and use of the Lane Centering Assist feature.

Scenario 6: Level 3 – Low – Lane Centering Assist

Imagine you are driving in a low-density traffic situation on a straight country road. Your Lane Centering Assist feature is present in the vehicle to help keep your vehicle centered within its current lane. Based on the scenario described here, please answer the following questions about your perception and use of the Lane Centering Assist feature.

Level 4 – Adaptive Cruise/Traffic Jam Control Description

You recently purchased a new vehicle equipped with some automated driver-assist features. This particular vehicle possesses an Adaptive Cruise/Traffic Jam Control function. The purpose of the Adaptive Cruise/Traffic Jam Control function is to keep your vehicle moving forward at your desired speed when possible but adjust speed to maintain a safe distance from any vehicle in front of you.

Scenario 7: Level 4 – High – Adaptive Cruise/Traffic Jam Control

Imagine you are driving in a high-density traffic situation on city streets with many turns. Your Adaptive Cruise/Traffic Jam Control feature is present in the vehicle to help keep your vehicle traveling ahead at your desired speed while maintaining a safe distance from vehicles in front of you. Based on the scenario described here, please answer the following questions about your perception and use of the Adaptive Cruise/Traffic Jam Control feature.

Scenario 8: Level 4 – Low – Adaptive Cruise/Traffic Jam Control

Imagine you are driving in a low-density traffic situation on a straight country road. Your Adaptive Cruise/Traffic Jam Control feature is present in the vehicle to help keep your vehicle traveling ahead at your desired speed while maintaining a safe distance from vehicles in front of you. Based on the scenario described here, please answer the following questions about your perception and use of the Adaptive Cruise/Traffic Jam Control feature.

Level 5 – Fully Automated Driving

You recently purchased a new vehicle equipped with some automated driver-assist features. This particular vehicle possesses a Fully Automated Driving function. The purpose of the Fully Automated Driving function is to take the responsibility of operating the vehicle away from the individual in the vehicle, transporting them to their destination with no effort or intervention.

Scenario 9: Level 5 – High – Fully Automated Driving

Imagine you are driving in a high-density traffic situation on city streets with many turns. Your Fully Automated Driving feature is present in the vehicle to transport you to your chosen destination without your assistance. Based on the scenario described here, please answer the following questions about your perception and use of the Fully Automated Driving feature.

Scenario 10: Level 5 – Low – Fully Automated Driving

Imagine you are driving in a low-density traffic situation on a straight country road. Your Fully Automated Driving feature is present in the vehicle to transport you to your chosen destination without your assistance. Based on the scenario described here, please answer the following questions about your perception and use of the Fully Automated Driving feature.

Scenario 11: Attention Check – Level 3 – Low – Lane Centering Assist

Imagine you are driving in a low-density traffic situation on a straight country road. Your Lane Centering Assist feature is present in the vehicle to help keep your vehicle centered within its current lane. Based on the scenario described here, please answer 'Strongly Agree' for all the questions listed below.

APPENDIX H: VARIABLE MEANS AND STANDARD DEVIATIONS

Variable	M	SD	N
License Duration	2.04	1.50	166
Total Accidents	1.83	1.90	166
Forward Collision Warning Dispositional Trust	4.37	0.66	166
Cruise Control Dispositional Trust	4.35	0.75	166
Lane Centering Assist Dispositional Trust	4.26	0.65	166
Adaptive Cruise/Traffic Jam Assist Dispositional Trust	4.11	0.67	166
Fully Automated Driving Dispositional Trust	3.87	0.69	166
Driving Self-Efficacy	7.11	1.74	166
Propensity to Trust Technology	4.21	0.81	166
Sit Trust in High Complexity	3.25	0.74	166
Sit Trust in Low Complexity	4.14	0.68	166
Forward Collision Warning Situational Trust	3.91	0.76	166
Cruise Control Situational Trust	3.53	0.71	166

Lane Centering Assist Situational Trust	3.92	0.72	166
Adaptive Cruise/Traffic Jam Assist Situational Trust	3.73	0.75	166
Fully Automated Driving Situational Trust	3.38	0.95	166
Average Situational Trust	3.69	0.59	166

APPENDIX I: CONTINUOUS VARIABLE CORRELATION TABLE

		Age	License Duration	Total Accidents	Forward Collision Warning Dispositional Trust	Cruise Control Dispositional Trust	Lane Centering Assist Dispositional Trust	Adaptive Cruise/Traffic Jam Assist Dispositional Trust	Fully Automated Driving Dispositional Trust	Driving Self-Efficacy	Propensity to Trust Technology	Sit Trust in High Complexity	Sit Trust in Low Complexity	Forward Collision Warning Situational Trust	Cruise Control Situational Trust	Lane Centering Assist Situational Trust	Adaptive Cruise/Traffic Jam Assist Situational Trust	Fully Automated Driving Situational Trust
Age	Pearson Correlation	1	.915**	.370**	-0.105	-0.138	-0.046	-0.083	0.009	.192*	-0.097	-0.061	-.205**	-0.109	-0.088	-0.138	-0.107	-0.143
	Sig. (2-tailed)		<.001	<.001	0.178	0.075	0.558	0.286	0.908	0.013	0.214	0.437	0.008	0.162	0.258	0.076	0.172	0.066
	N	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166
License Duration	Pearson Correlation	.915**	1	.412**	-0.042	-0.1	0.035	-0.054	0.011	.296**	-0.05	-0.021	-.183*	-0.072	-0.089	-0.091	-0.052	-0.134
	Sig. (2-tailed)	<.001		<.001	0.587	0.202	0.659	0.489	0.893	<.001	0.519	0.787	0.018	0.357	0.252	0.244	0.504	0.086
	N	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166
Total Accidents	Pearson Correlation	.370**	.412**	1	0.015	-0.05	0.016	-0.059	0.053	.291**	0.013	0.076	0.056	.181*	0.009	0.103	0.006	0.013
	Sig. (2-tailed)	<.001	<.001		0.844	0.521	0.835	0.453	0.497	<.001	0.871	0.332	0.477	0.019	0.905	0.188	0.941	0.869
	N	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166
Forward Collision Warning Dispositional Trust	Pearson Correlation	-0.105	-0.042	0.015	1	.424**	.550**	.461**	.265**	0.016	.411**	.307**	0.076	.272**	0.113	0.146	.176*	.184*
	Sig. (2-tailed)	0.178	0.587	0.844		<.001	<.001	<.001	<.001	0.836	<.001	<.001	0.33	<.001	0.146	0.06	0.023	0.018
	N	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166
Cruise Control Dispositional Trust	Pearson Correlation	-0.138	-0.1	-0.05	.424**	1	.477**	.555**	.261**	0.075	.497**	.183*	.210**	0.135	.222**	0.148	.223**	.172*
	Sig. (2-tailed)	0.075	0.202	0.521	<.001		<.001	<.001	<.001	0.339	<.001	0.019	0.007	0.082	0.004	0.057	0.004	0.027
	N	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166
Lane Centering Assist Dispositional Trust	Pearson Correlation	-0.046	0.035	0.016	.550**	.477**	1	.653**	.403**	0.077	.348**	.320**	0.037	0.101	0.11	.227**	.226**	.181*
	Sig. (2-tailed)	0.558	0.659	0.835	<.001	<.001		<.001	<.001	0.327	<.001	<.001	0.635	0.196	0.16	0.003	0.003	0.02
	N	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166
Adaptive Cruise/Traffic Jam Assist Dispositional Trust	Pearson Correlation	-0.083	-0.054	-0.059	.461**	.555**	.653**	1	.508**	-0.009	.286**	.376**	0.133	0.142	.217**	.232**	.349**	.248**
	Sig. (2-tailed)	0.286	0.489	0.453	<.001	<.001	<.001		<.001	0.913	<.001	<.001	0.088	0.068	0.005	0.003	<.001	0.001
	N	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166
Fully Automated Driving Dispositional Trust	Pearson Correlation	0.009	0.011	0.053	.265**	.261**	.403**	.508**	1	-0.004	0.075	.373**	0.097	.159*	0.131	0.152	.217**	.390**
	Sig. (2-tailed)	0.908	0.893	0.497	<.001	<.001	<.001	<.001		0.955	0.338	<.001	0.214	0.04	0.092	0.051	0.005	<.001
	N	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166
Driving Self-Efficacy	Pearson Correlation	.192*	.296**	.291**	0.016	0.075	0.077	-0.009	-0.004	1	0.109	-0.004	-0.045	-0.005	-0.081	-0.044	0.078	-0.051
	Sig. (2-tailed)	0.013	<.001	<.001	0.836	0.339	0.327	0.913	0.955		0.163	0.963	0.564	0.952	0.298	0.573	0.321	0.515
	N	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166
Propensity to Trust Technology	Pearson Correlation	-0.097	-0.05	0.013	.411**	.497**	.348**	.286**	0.075	0.109	1	.155*	.260**	0.127	0.097	.167*	.231**	.285**
	Sig. (2-tailed)	0.214	0.519	0.871	<.001	<.001	<.001	<.001	0.338	0.163		0.046	<.001	0.103	0.213	0.031	0.003	<.001
	N	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166
Sit Trust in High Complexity	Pearson Correlation	-0.061	-0.021	0.076	.307**	.183*	.320**	.376**	.373**	-0.004	.155*	1	.394**	.616**	.642**	.625**	.741**	.634**
	Sig. (2-tailed)	0.437	0.787	0.332	<.001	0.019	<.001	<.001	<.001	0.963	0.046		<.001	<.001	<.001	<.001	<.001	<.001
	N	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166
Sit Trust in Low Complexity	Pearson Correlation	-.205**	-.183*	0.056	0.076	.210**	0.037	0.133	0.097	-0.045	.260**	.394**	1	.653**	.429**	.674**	.683**	.666**
	Sig. (2-tailed)	0.008	0.018	0.477	0.33	0.007	0.635	0.088	0.214	0.564	<.001	<.001		<.001	<.001	<.001	<.001	<.001
	N	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166
Forward Collision Warning Situational Trust	Pearson Correlation	-0.109	-0.072	.181*	.272**	0.135	0.101	0.142	.159*	-0.005	0.127	.616**	.653**	1	.369**	.561**	.595**	.402**
	Sig. (2-tailed)	0.162	0.357	0.019	<.001	0.082	0.196	0.068	0.04	0.952	0.103	<.001	<.001		<.001	<.001	<.001	<.001
	N	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166
Cruise Control Situational Trust	Pearson Correlation	-0.088	-0.089	0.009	0.113	.222**	0.11	.217**	0.131	-0.081	0.097	.642**	.429**	.369**	1	.298**	.450**	.402**
	Sig. (2-tailed)	0.258	0.252	0.905	0.146	0.004	0.16	0.005	0.092	0.298	0.213	<.001	<.001	<.001		<.001	<.001	<.001
	N	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166
Lane Centering Assist Situational Trust	Pearson Correlation	-0.138	-0.091	0.103	0.146	0.148	.227**	.232**	0.152	-0.044	.167*	.625**	.674**	.561**	.298**	1	.666**	.475**
	Sig. (2-tailed)	0.076	0.244	0.188	0.06	0.057	0.003	0.003	0.051	0.573	0.031	<.001	<.001	<.001	<.001		<.001	<.001
	N	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166
Adaptive Cruise/Traffic Jam Assist Situational Trust	Pearson Correlation	-0.107	-0.052	0.006	.176*	.223**	.226**	.349**	.217**	0.078	.231**	.741**	.683**	.595**	.450**	.666**	1	.567**
	Sig. (2-tailed)	0.172	0.504	0.941	0.023	0.004	0.003	<.001	0.005	0.321	0.003	<.001	<.001	<.001	<.001	<.001		<.001
	N	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166
Fully Automated Driving Situational Trust	Pearson Correlation	-0.143	-0.134	0.013	.184*	.172*	.181*	.248**	.390**	-0.051	.285**	.634**	.666**	.402**	.402**	.475**	.567**	1
	Sig. (2-tailed)	0.066	0.086	0.869	0.018	0.027	0.02	0.001	<.001	0.515	<.001	<.001	<.001	<.001	<.001	<.001	<.001	
	N	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166	166
** Correlation is significant at the 0.01 level (2-tailed).																		
* Correlation is significant at the 0.05 level (2-tailed).																		

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