D-STOP

Technical Report 122

Travel Modeling in an Era of Connected and Automated Transportation Systems: An Investigation in the Dallas-Fort Worth Area

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16. Abstract

The North Central Texas Council of Governments (NCTCOG) engaged D-STOP to conduct a planned four-year study to analyze the status and progress of connected/autonomous vehicle (CAV) development, determine what the wide-ranging effects of the technology's adoption in North Central Texas, and, ultimately, begin constructing scenarios and methods to account for these effects in long range planning.

Part I begins by examining the state of technology for both AVs and CVs and provides evidence that the discrete technologies to enable both vehicle capabilities are nearing market readiness. The paper also draws a contrast between the two technologies as they are each being developed in response to distinct factors. Finally, Part I examines certain policy, privacy, and security questions. Part II looks at CAV adoption and finds that there will likely be decades of mixed use between AVs and human-driven vehicles. In addition, this section discusses existing adoption predictions from private consultants and academics, provides adoption estimates of CAVs based on adoption rates of similar technologies in the past, and proposes assumptions for three planning scenarios. Although the implementation timeline is highly uncertain, the market is susceptible to certain disruptors (such as ridesharing) that could significantly affect AV adoption. Finally, Part III describes the approach followed in order to propose 112 potential planning scenarios to reflect the wide range of potential CAV impacts. The proposed scenarios are built based on the analysis of possible adoption timelines for vehicle automation and connectivity, and consider the impact of additional behavioral and technological factors, using existent regional planning methodologies. The limitations of traditional modeling tools may limit the observed impacts of CAVs, which can motivate the exploration of more advanced tools such as activity-based models and dynamic traffic assignment.

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North Central Texas
Council of Governments

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1 Executive Summary

The North Central Texas Council of Governments (NCTCOG) engaged the Center for Transportation Research (CTR) at The University of Texas to conduct a planned four-year study to analyze the status and progress of connected/autonomous vehicle (CAV) development, to determine what the wide ranging effects of adoption of the technology might be on society and economics in North Central Texas, and, ultimately, to begin constructing scenarios and methods to account for these effects in long-range planning. Part I begins by examining the state of technology for both autonomous and connected vehicles and provides evidence that the discrete technologies to enable both vehicle capabilities are nearing market readiness. The paper also draws a contrast between the two technologies as they are each being developed in response to distinct factors. Finally, Part I examines certain policy, privacy and security questions.

In regard to autonomous vehicles, private automakers seeking to affect commercial markets are leading the way. With mass production, the components needed for autonomous vehicles, such as a LIDAR units, will become exponentially more affordable. Alternatively, a select group of automakers is relying on developing advanced artificial intelligence to read camera images and enable autonomous driving. Projections by automakers indicate that this technology will be commercially available by 2020 and these developments should minimize the end-cost of autonomous systems.

The implementation of connected vehicle systems is being spurred by a proposed federal mandate for the inclusion of vehicle-to-vehicle (V2V) communications in all new vehicles by 2023. The mandate, which is being reviewed by the Federal Office of Management and Budget, is expected to be decided on by the second quarter of 2017. Upon implementation of a mature V2V system, in conjunction with a vehicle-to-infrastructure (V2I) communication, more than 80 percent of light vehicle crashes could be avoided.

Part II of this report looks at CAV adoption and finds that there will likely be decades of mixed use between autonomous and human-driven vehicles. In addition, this section discusses existing adoption predictions from private consultants and academics, provides adoption estimates of CAVs based on adoption rates of similar technologies in the past, and proposes assumptions for three planning scenarios. Although the implementation timeline is highly uncertain due to the complexity of factors used, the market is susceptible to certain disruptor entities and occurrences that could have significant effects on adoption of autonomous vehicles. In particular, ridesharing—which is increasingly becoming a larger part of the portfolio of traditional auto manufacturers—is growing rapidly and could potentially disrupt adoption models.

Finally, Part III describes the approach followed in order to propose 112 potential planning scenarios that are expected to reflect the wide range of potential CAV impacts. The proposed scenarios are built based on the analysis of possible adoption timelines for vehicle automation and connectivity, and consider the impact of additional behavioral and technological factors. The combinations of assumptions proposed in this section lead to scenarios that may be modeled in a simplified manner using existent regional planning methodologies. The limitations of traditional modeling tools may limit the observed impacts of CAVs, which can motivate the exploration of more advanced tools such as activity-based models and dynamic traffic assignment.

Part I: The State of CAV Technology

2 Introduction

There is substantial anticipation and excitement in the area of connected/automated vehicles (CAVs) and their potential to change mobility. Given that metropolitan planning organizations (MPOs) incorporate a multi-decade planning horizon, the North Central Texas Council of Governments (NCTCOG) has begun to consider the implications of CAVs now, before their widespread implementation. To this end, NCTCOG has engaged the Center for Transportation Research (CTR) at The University of Texas to conduct a planned four-year study to analyze the status and progress of CAV development, what the wide ranging effects of adoption of the technology might be on society and economics in North Central Texas and, ultimately, to begin constructing scenarios and methods for long-range planning accounting for these effects. In year one, CTR was asked to:

- Survey and categorize existing information concerning CAVs, ranging from existing technologies to anticipated policy issues.
- Explore the potential impacts of CAVs across the entire socio-economic spectrum.
- Develop potential near-future transportation system scenarios, taking into consideration various. CAVs market shares, levels of infrastructure deployment, and assumptions regarding human behavior and decision making, while focusing on scenarios appropriate for the characteristics of the NCTCOG region.
- Study appropriate methodologies to quantify and eventually model the impact of CAVs.
- Investigate changes needed to the transportation planning process to account for the effects of CAVs on both travel demand and transportation network performance.

This report presents the results of the CTR investigation. Part I, presented here, will explore the state of technology in-depth, both of autonomous vehicles and connected vehicles, and draw conclusions about development timelines. It will then explore private, public, and academic research that has been done to develop adoption timelines in an effort to draw conclusions as to when the effects of implementation of the new technology will begin to influence mobility. Finally, Part I will offer a brief overview of law, policy, security, privacy, and liability issues that surround the development of the CAV technology and will present the current state of action taken by governments at all levels. Part II explores adoption timelines and Part III examines how this adoption may affect traditional planning models.

2.1 Background: Connected Vs. Autonomous Vehicles

CTR researchers found that there are two discernable areas of development in CAV technology: one of autonomous vehicle (AV) development and one of connected vehicle (CV) development. While a complete system should benefit from vehicles with both autonomous and connected capabilities, the motivation to produce the two types is driven by a split between public and private interests. Private automakers (sometimes referred to as Original Equipment Manufacturers or OEMs) are competitively developing CVs at a very rapid pace. Due to significant market competition and the need to protect business secrets, OEMs are not sharing their first-hand information. Instead, the researchers found themselves relying on news articles and information from product suppliers that do not have such tight competition for their goods. In parallel, CV development has been a goal of the federal government since the bandwidth needed to support them, the dedicated short-range communication (DSRC) channel, was first reserved in 1999. In the years since, the National Highway Transportation Safety Administration (NHTSA) and the United States Department of Transportation (USDOT) have been methodically working toward evaluation of CV effects—culminating in early 2016 with the submission of a notice of proposed rulemaking to the Office of Budget *(1)*. NHTSA and other USDOT entities have produced numerous informative reports that provide detailed information about the state of CV technology.

2.2 Background: NHTSA Levels of Automation

As an ongoing reference throughout this report, the general levels of automation referred to are based on standards set by the Society of Automotive Engineers (SAE) as described in Figure 1. Importantly, the researchers note that SAE Level 4 is considered an automobile that still has a steering wheel and pedals and that might need human control in conditions that are non-conducive to driving (heavy snow, certain mountainous areas, etc.) However, at Level 4, in the majority of situations, vehicles will be able to safely navigate to their destination without any reliance on a human driver. SAE Level 5 is the instance in which steering wheels and pedals are completely removed from the vehicle and the AV will be able to navigate in all conditions and locations autonomously. The importance of this distinction is seen in the projections of automakers, where it appears that Level 4 vehicles will be commercially available as soon as 2020, while Level 5 vehicles may take significantly longer to develop.

Level 1

"The driver has overall control, and is solely responsible for safe operation, but can choose to cede limited authority over a primary control (as in adaptive cruise control), the vehicle can automatically assume limited authority over a primary control (as in electronic stability control), or the automated system can provide added control to aid the driver in certain normal driving or crash-imminent situations (e.g., dynamic brake support in emergencies)."

Level 2

"This level involves automation of at least two primary control functions designed to work in unison to relieve the driver of control of those functions. Vehicles at this level of automation can utilize shared authority when the driver cedes active primary control in certain limited driving situations. The driver is still responsible for monitoring the roadway and safe operation and is expected to be available for control at all times and on short notice."

Level 3

"Vehicles at this level of automation enable the driver to cede full control of all safety-critical functions under certain traffic or environmental conditions and in those conditions to rely heavily on the vehicle to monitor for changes in those conditions requiring transition back to driver control."

Level 4

"The vehicle is designed to perform all safety-critical driving functions and monitor roadway conditions for an entire trip"

Level 5

Cars have no steering controls and are expected to go from point to point with absolutely no assistance from the driver.

Figure 1: SAE Levels of Automation (2).

3 Autonomous Vehicle Technology

CV and AV development is following two distinct but parallel paths. As such they will be analyzed in discrete sections of this paper. Beginning with AVs, this section moves through every component that may be added to a traditional vehicle to enable semi-autonomous and autonomous driving functions. Then the commercial availability of the combinations of these technologies to produce semi-autonomous and AVs is evaluated, resulting in a predictive conclusion of commercial availability of Level 4 AVs by 2020. In addition, the paper predicts that there will be significant increases in roadway safety through the addition of semi-autonomous and autonomous features.

3.1 Sensors

AV systems receive input from a myriad of information gathering sensors that process the received data and ultimately produce two parameters: a longitudinal control that manages the direction in which the car travels and a directed rate of speed. Common sensors found in AVs include Light Detection and Ranging (LIDAR), video cameras, radar, and ultrasonic sensors that take in information from the perception of the physical world, and sensors that obtain their data through signal processing, such as through global positioning systems (GPS), vehicle-to-vehicle (V2V), and vehicle-to-infrastructure (V2I) communication. In addition, the modern vehicle contains a host of mechanical sensors, such as odometry and pressure sensors, that provide intrinsic data about the activity and performance of the vehicle itself. Figure 2 shows the combination of these sensors as described in one of the Google patents for its AV:

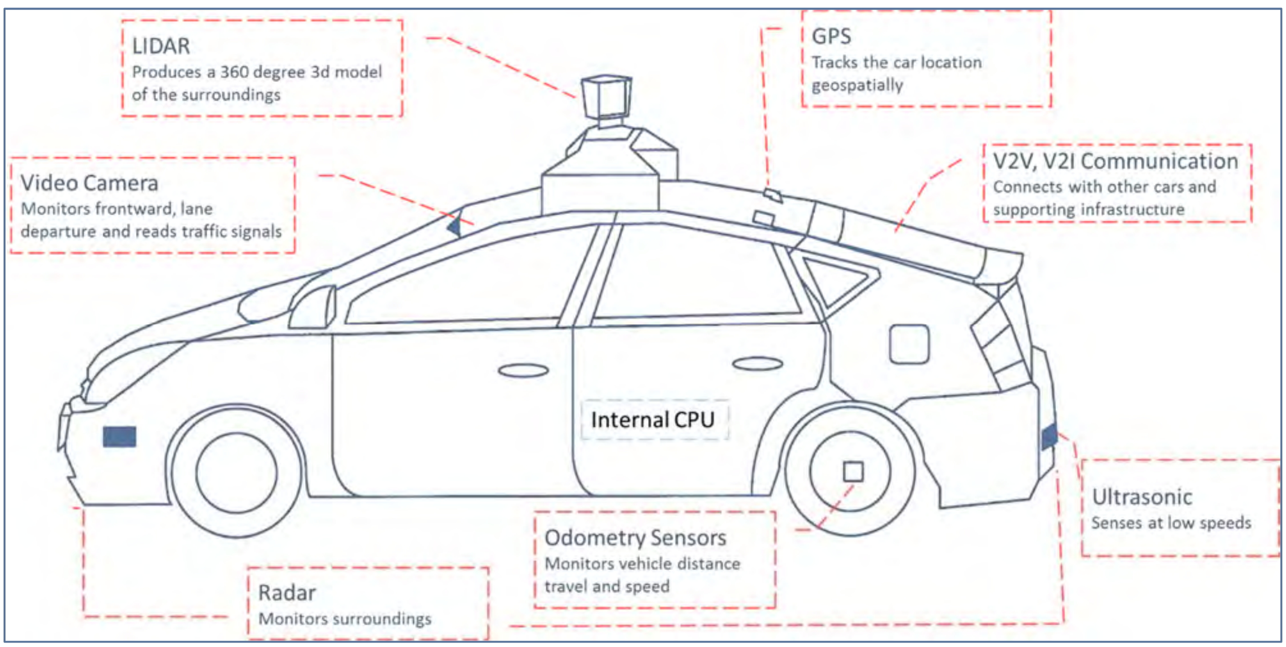

Figure 2: Autonomous Vehicle Sensor Suite (3).

Automated vehicles do not work like the human brain. Humans draw in information via their five senses and perceive one three-dimensional world in which they move, generally seeking obstacle avoidance. In contrast, AVs take a more piecemeal approach: each sensor is assigned a discrete task, such as detecting the color of a traffic light or determining the probable path of a surrounding object (for a potential list of tasks, see Figure 3). Upon every performance iteration of its discrete task, the sensors, usually in conjunction with an individual graphical processing unit (GPU), relay their findings to a central processing unit (CPU). The CPU then stacks the various findings, like building blocks, in complex algorithms to chart a path for the vehicle. Since there is no ascertainable universal truth as to how many building blocks are needed for a "close enough" or "better than" approximation of human driving, every unique entity working on developing a functioning AV appears to have a different view of the necessary combination and placement of sensors required for safe autonomous driving. Usually these combinations are driven by cost, available technology, and varying capabilities of proprietary hardware and software *(3)*. For instance, there is one group of automakers seeking to work without LIDAR, while another group relies on it as their key sensor (to be explored further below). Figure 4 provides a menu of each sensor and a corresponding potential functionality. The research team analyzed several private industry car formulas: Google, the Singapore-MIT Alliance for Research and Technology (SMART), and Mercedes Benz, particularly in regard to their Level 3 autonomous truck. This information is available in Appendix A.

- Traffic-Sign Recognition
- Obstacle Detection
- Lane Detection
- Terrain Mapping
- Vehicle Detection
- Oncoming-Vehicle Detection
- Blind-Spot Monitor
- Parking-Lot Detection
- Scene Classification and Tunnel Detection
- Pedestrian Detection

Figure 3: Potential discrete sensor tasks (4).

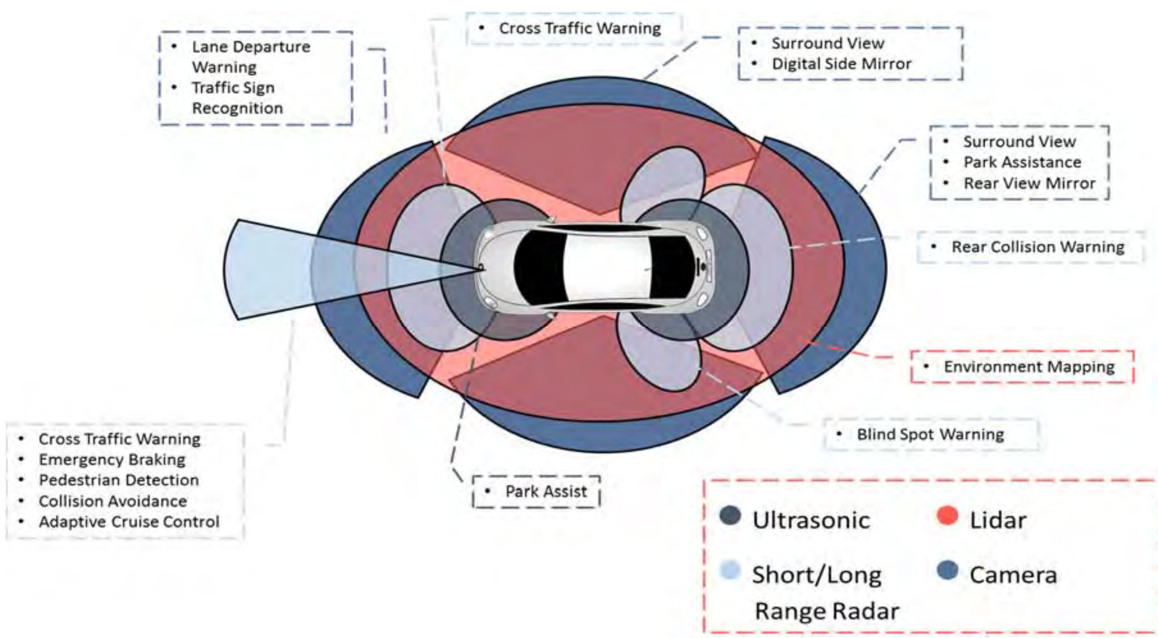

Figure 4: Menu of discrete sensor roles (4).

Common sensors utilized in AV development and their limiting elements are itemized in Figure 5, and explored in greater detail in the sections that follow.

Sensor	Range	Costs	Limiting Elements
LIDAR	200 miles	$8,000-$75,000	Snow and rain
GPS	Unlimited	$100-$2,000	Precision, blocking structures
Cameras	Miles	<$100	Processing artificial intelligence
Radar	200 miles	<$100	Vertical angle
Ultrasonic	6 miles	<$100	Range
Odometry	N/A	<$100	Inaccurate data collection

Figure 5: Summary of Common Sensors.

3.1.1 LIDAR

Most familiar as the rotating piece of equipment mounted on the roofs of AVs, LIDAR sensors can be used for obstacle detection and environmental mapping. By emitting pulses of ultraviolet, visible, or near infrared light (using lasers) and then recording the amount of time to read a reflection of the pulse, LIDAR can calculate, based on the speed of light, the distance to the reflective point. Through rotating light emission and multiple lasers refracting at different angles, the returned readings can be processed to create a three-dimensional point cloud of the sensor's surroundings (Figure 6) *(4)*. By matching up the point cloud with high resolution map, the system can derive information about location and dynamic objects in the environment.

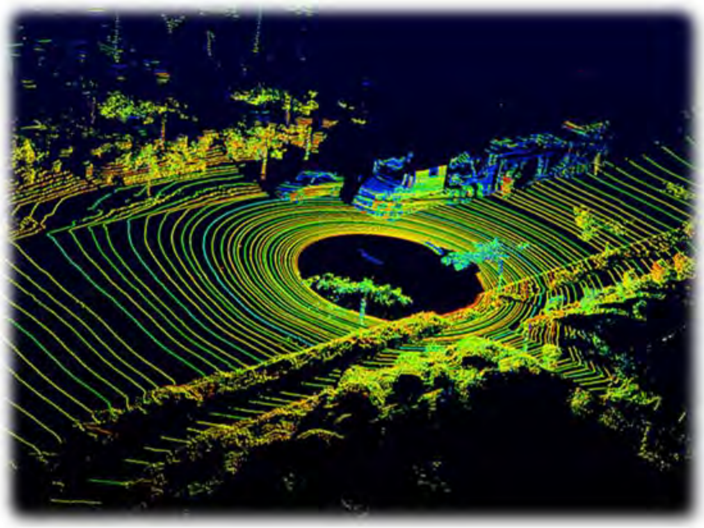

Figure 6: 64-laser LIDAR point cloud (5).

Capabilities and limitations

- High-precision pre-mapping is required to geolocate the vehicle and delineate dynamic and static objects in the environment.
- LIDAR is currently effective to a range of 200 meters.
- Because each laser remains in one plane at a fixed angle in relation to the ground, vertical accuracy is heavily dependent on the number of lasers emitted from the sensor—common LIDAR is available from four lasers to sixty-four lasers (see Figure 7 and Figure 8) *(5)*.
- Costs for LIDAR range from $8,000 for a four-laser unit to $75,000 for a 64-laser unit.
- Because the system produces its own light, LIDAR works well at night.
- Reflection from falling snow and rain can distort the LIDAR point clouds and have a negative effect on the sensor's capabilities

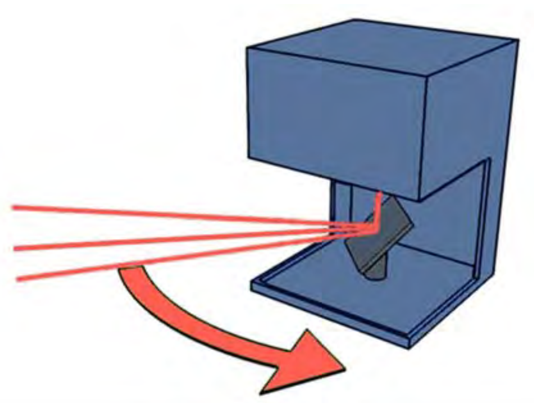

Figure 7: Multiple laser LIDAR representation (6).

Technological challenges

The accuracy of LIDAR is heavily dependent on the number of lasers emitted from the LIDAR sensor. Common commercially available LIDAR ranges from four- to 64-laser systems. The advanced system used by Google costs around \$75,000 *(6)*. Ford uses four 32-laser systems *(7)*, with a cost of \$30,000 per unit *(8)*. For an autonomous solution that utilizes LIDAR, low cost units must be developed. To this end, there are several market developments that are worth noting:

Figure 8: Velodyne 64-laser LIDAR: \$75,000 (7) , Velodyne 16-laser Puck: \$8,000 (11), Quanergy solid state: \$250, estimate (14). Not to scale.

- Market leader Velodyne anticipates that when demand reaches one million units a year, the per-unit production cost will decrease from \$75,000 to \$500 for a solid-state 32-laser unit. They see this reduction occurring as soon as 2018 *(9)*. Velodyne has already developed a 16-channel system that costs only \$8,000, effectively halving the cost of the early LIDAR systems *(10)*. In August 2016, Velodyne received a \$150 million investment from Ford to further develop their technology *(11)*.
- Google has begun developing their own LIDAR system in-house to find a competitive solution *(12)*.
- Quanergy has developed 120-degree solid-state LIDAR which, when in full production, is projected to cost \$250 or less *(13)*.
- Tesla believes LIDAR is not necessary for a vehicle, instead relying on radar and cameras *(14)*.

3.1.2 Global Position Systems (GPS)

The US Department of Defense operates thirty-one satellites in space that broadcast microwave signals to Earth, which contain the coordinates, heading, velocity, and timestamp of the respective satellite. The orbits of these satellites are coordinated so that, at any given time, four are visible in the sky from any point on earth. With the collective data from these microwave signals, a GPS unit triangulates its position on earth *(15)*. Through utilization of GPS technology, AVs are able to define a key reference for their positioning on high accuracy maps *(16)*.

Capabilities and limitations

- GPS is accurate to eleven feet, and is even less accurate when moving *(15)*.
- GPS units are very cost effective (\$100–\$2000).
- Accuracy is heavily dependent on the ability to see sky. Operation in tunnels and dense urban corridors with blocking structures is suspect.
- GPS works well at night, in rain, and in snow, as these conditions have no effect on the microwave signals used by the system.

Technological challenges

Due to the lack of accuracy, GPS can only be used as an indication for locating a vehicle. GPS data must be combined with sensor data and matched to high accuracy maps (tolerances <1cm) to inform the car as to appropriate paths to take (see Figure 9) *(16)*. To further advance GPS accuracy, researchers at The University of Texas are testing technology that would utilize a principle known as “differential GPS.” Through the combination of adding another signal from a known terrestrial position and sensing additional carrier waves from the GPS satellites, differential GPS can produce readings accurate to one centimeter. Further, the cost of producing the units needed to broadcast from known terrestrial positions hovers around $100/unit and researchers believe only sixteen are needed to serve an area of 270 square miles (the metro area of Austin) *(17)*. Advances in this technology could materially increase the role of GPS in AVs.

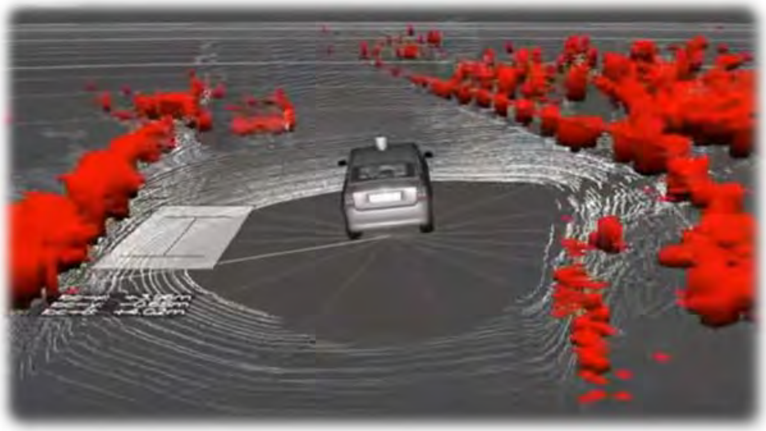

Figure 9: Google Car actual location vs. GPS location (17).

Another challenge to GPS use is ineffectiveness in tunnels or mountainous areas, where there is not a clear channel to the orbital satellites. An AV will simply rely on all of its other sensors to locate itself on a preloaded high accuracy map and continue its path when GPS is inaccessible. However, it is feasible that by using differential GPS (as shown in Figure 10), or the known data from the car’s direction and rate of speed, an extra data point can be manufactured to offset the absence of a satellite and make this technology funcational in all conditions *(18)*.

Figure 10: A stationary differential GPS unit deployed by researchers at the University of Texas (18).

3.1.3 Cameras

Camera systems produce live video output, which is then analyzed by a computer system to determine obstacles and provide roadway information, such as the vehicle’s relation to lane striping and signal interpretation (Figure 11). Currently, most automakers appear to be relying on cameras for obstacle detection, lane departure, and signal reading, while leaving navigation up to data produced from LIDAR and high accuracy maps. However some automakers—Tesla in particular—are seeking autonomy through reliance on video cameras and radars in conjunction with low resolution mapping. This approach is discussed further in the Software Systems section.

Capabilities and limitations

- A camera’s ability to look far down the road provides ample visual information. If fully processed, this information could negate the need for precompiled high-accuracy maps.
- Issues working at night, and in limited visibility, can be overcome by high-sensitivity cameras.
- Because they are heavily software driven, once an advanced artificial intelligence (AI) system is developed, implementation of a camera-based system should be a very cost effective sensor method.

- There is an unknown timeline for development of the requisite AI.

Figure 11: Camera-based object and sign detection and clear space detection (20).

Technological challenges

A camera's ability to assess visual data and look far down the road provides ample information for autonomous driving. However, the ability to fully process this data is currently limited. In particular, "strong AI" is needed to extract depth information from video—and development of this AI is currently proceeding along an unknown timeline. Until strong AI is developed, video cameras can still be used for semi-autonomous and particular autonomous driving situations when supplemented with low-resolution mapping *(19)*.

3.1.4 Radar

Radar emits radio waves and listens for an echo to determine distance and location of surrounding objects.

3.1.4.1 Capabilities and limitations

- Radar wavelengths can penetrate dust and other visual obstacles, allowing the car to "see" in poor visibility *(20)*.
- Radar works well in snow, rain, low light, and fog *(20)*.
- Radar works very well along a two-dimensional plane. Higher angular resolution needed for 3D images can be obtained only with inconveniently large antenna apertures *(21)*.
- Radar—effective at sensing the distance to an object—can be combined with cameras, which are strong at sensing the lateral movement of an object, to determine an object's path vector *(22)*.
- Radar provides both short- and long-range detection capabilities (Figure 12).

Figure 12: Radar systems in AVs (24).

3.1.4.2 Technological challenges

Radar is a compact, efficient sensor system. However, it only functions along a single plane, thus limiting its effectiveness in a three coordinate system. As such, it can serve a strong role in detecting proximity of objects for obstacle avoidance, but it must be combined with other sensor data to enable autonomous navigation.

3.1.5 Ultrasonic Sensors

Ultrasonic sensors are near-range sensors that utilize high frequency sound waves to detect nearby objects. These sensors are currently used in slow-speed operations, such as backing up. Additionally, they may be used to track vehicles in adjacent lanes *(23)*.

3.1.5.1 Capabilities and limitations

- Ultrasonic sensors have a very limited sensor range of six meters on average.
- They are very energy efficient and cost effective.
- They are generally very reliable.

3.1.6 Odometry Sensors

Odometry sensors are motion sensors that estimate the change of position over time, sometimes by counting the revolutions of a wheel.

3.1.6.1 Capabilities and limitations

- Odometry sensors are low cost.
- Readings are often inaccurate; errors build with every rotation.
- They can be calibrated over time and combined with other sensors to provide more accurate readings.

3.1.7 Hardware Computer Systems

Computers with specially designed chipsets process all the sensor information and produce driving instructions for the vehicle.

Capabilities and limitations

- Chip maker NVIDIA's current premier system offers 2.3 teraflops of processing power (roughly 20 percent more computing power than a PlayStation 4) and can handle twelve sensor feeds *(24)*. NVIDIA recently began showcasing its Drive PX 2 (Figure 13), with an eight teraflop processor (equivalent to roughly 150 MacBook Pro computers) *(25)*.
- Chip maker Mobileye, in conjunction with STMicrolectonics, is anticipating making available a twelve teraflop platform by 2020 that will be able to handle twenty sensor feeds *(26)*.
- These more advanced CPUs will need water cooling.
- These units are currently very expensive, around $10,000/unit *(27)*.

Figure 13: NVIDIA Drive PX 2 (27)

3.1.7.1 Technological challenges

Processing hardware is a significant cost to the AV and continued AV development will benefit from an expected drop in the price of computational power. The research team could not find a specific projection of cost-over-time for these specific systems. However, following Moore's law, processing speed should double every two years. Following the trend of the iPad2: Considering a corresponding drop in price, in five years, these systems should cost in the hundreds of dollars *(28)*. Already, through parallel processing, AV computer systems have been physically scaled down in size from filling the trunk of a vehicle to the size of a lunchbox.

3.2 Software Systems

Software requires hardware to translate input from the sensor array and process data to provide driving directions to the vehicle. Currently two schools of thought have developed as to how autonomous driving should be achieved.

The first group, championed by Google, relies on high-accuracy maps and LIDAR readings. Through matching up LIDAR data with precompiled high-accuracy maps, the LIDAR-dependent group can precisely locate its vehicle and pick exact (down to a centimeter) paths for its car to follow *(29)*. Additionally, it can identify dynamic objects around the vehicle by simply subtracting everything that has already been predetermined to be static on its map (Figure 14). The LIDAR-dependent group is hindered by the availability of constantly updated high-resolution maps needed for its system to work. To solve this mapping need, companies such as Google send out pilot cars with very high resolution LIDAR mapping systems to pre-map the areas in which vehicles will be operating. In the future, this mapping issue may be solved by crowd sourcing data collected from AVs.

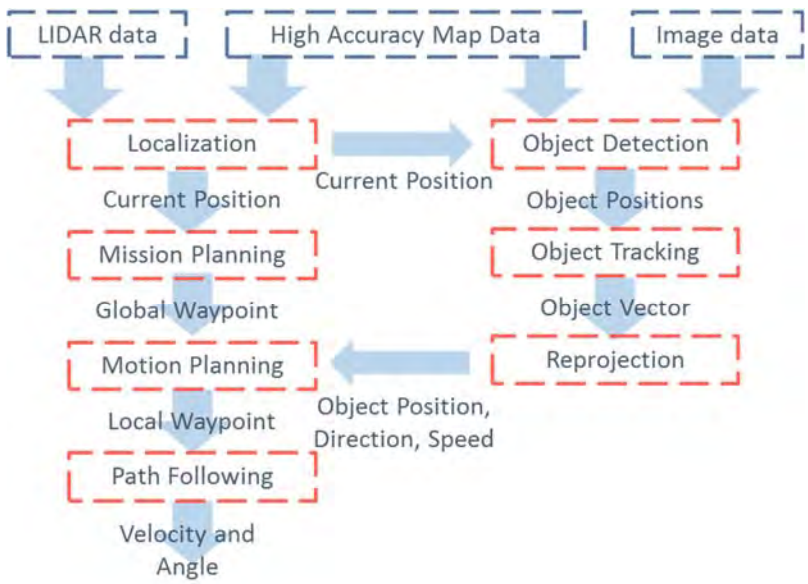

Figure 14: LIDAR Dependent Software Process(31)

The second group, championed by Tesla, relies on high-resolution sensing through the use of video cameras and radar and utilizes advanced artificial intelligence to interpret video images. Ultimately, the goal of this camera-dependent group is to create a system that is comparable in capability to the human brain at processing visual cues and responding as a human driver would. However, as this level of AI is currently unattainable and with an uncertain development timeline, camera-dependent group has supplemented currently available advanced AI with radar and low resolution maps to achieve a level of autonomous driving *(19)*. Still, the camera-dependent group has faced criticism from proponents of LIDAR-based systems, who believe that AI is not currently at an advanced enough level to support safe autonomous functions *(30)*.

Regardless of the methodology, safe autonomous driving software is focused on choosing the right path and obstacle avoidance. The sections below explain these two principles in more detail.

3.2.1 Obstacle Identification and Avoidance

No matter which practice is being used, the AV must identify and avoid obstacles. The software, via the suite of available sensors, identifies dynamic objects around the vehicle (Figure 15). In the LIDAR-dependent model, dynamic objects are those that remain when the static objects on the high-accuracy map are subtracted. In the video-dependent model they are identified as moving by artificial intelligence interpreting video images. The dynamic objects are cataloged and classified as a type of object, with a direction vector and a rate of speed *(31)*. Object identification directs the AVs to avoid obstacles and predict where they will be in the near future, allowing AVs to pick a path that will not conflict with other objects' paths.

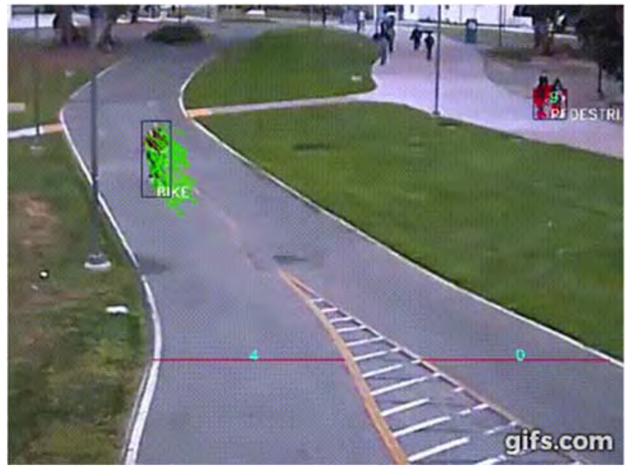

Figure 15: Obstacle Identification and Vectoring (33).

3.2.2 Geolocation and Path Determination

Until the development of Strong AI, both schools will make use of maps and landmark matching to geolocate their vehicles on a roadway. In the first school of thought, through LIDAR readings matched against a high accuracy map, the software can determine path based on the driver's preferred destination. However, in the second school of thought, camera data is analyzed to create a virtual grid that demarcates the areas in which the car can travel (Figure 16) *(32)*. This, combined with landmark identification and low resolution maps, allows the vehicle to pick an appropriate path.

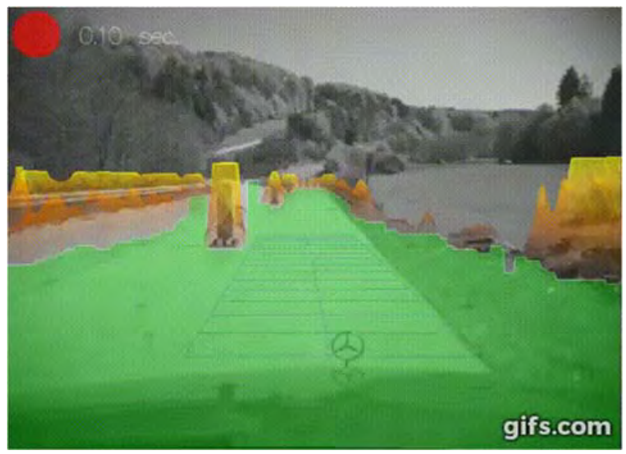

Figure 16: Grid-based Occupancy Mapping (34).

3.3 Commercial Path to Autonomy

As described above, there are still some facets of autonomy that have not yet fully matured. As such, the actual date of commercially available AVs is unknown. Some proponents, such as Tesla founder Elon Musk are very optimistic that autonomous systems are just around the corner—fewer than two years away *(33)*. Notably, American automakers, spurred by Google and Tesla, seem to have made a shift in recent years toward an accelerated timeline to make Level 4 vehicles commercially available. In recent months, high ranking officials for both Ford and GM have declared that 2020 will likely see the first commercially available AVs *(34, 35)*. In addition, Ford has put a potential date for Level 5 autonomy by 2021 *(36)*. However, globally, Volvo seems to be leading the industry. Volvo has announced a partnership with Uber to use self-driving cars in Pittsburg in August of 2016 *(37)*. Additionally, in 2017, it will be providing 100 AVs to local families to use in select corridors around Gothenburg, Sweden—with similar plans for London in 2018 *(38)*. Through media releases and statements by car officials, the research team put together Figure 17, which displays the general trend towards commercial availability early next decade.

	US Market Share	Level 2	Level 3	Level 4
GM	20%	2016		2020
Ford	16%	2016		2020
TOYOTA	13%	2016	2020	
DAIMLER	12%			
HONDA	9%	2016	2020	
NISSAN	7%	2016	2018	2020
HYUNDAI	7%	2016	2020	2030
SUBARU	3%	2016	2020	
	2%	2016	2017	2020

	Level 2	Level 3	Level 4
Volkswagen	2016		2025
BMW	2016		2021
Audi	2016		2030
VOLVO	2016	2017	2018
TESLA	2016	2016	2018
Google			2020

Figure 17: Private automaker projections for commercial availability of their AVs (blank spaces indicate no found public data on projections).

3.4 Semi-autonomous Systems

Semi-autonomous features are already being offered by automakers in their current lines. While most automakers appear to be utilizing their high-end models for their semi-autonomous features, Honda is offering a host of features (Figure 18) as part of a $1000 package on most of their vehicles—including a Honda Civic that will cost around $20,000 *(39)*. Looking market-wide, common semi-autonomous features currently available are described in Figure 19. Notably, in March of 2016, twenty auto makers agreed to voluntarily make automatic braking standard on all new light vehicles by September 2022 *(40)*. As a result, the Insurance Institute of America projects, with full market penetration, a 40 percent reduction in rear-end crashes. While the research team was unable to find any studies on the impact of semi-autonomous features to the overall efficiency of transportation systems as a whole, what is manifest is that most or all of these features will have an impact on vehicle safety and lead to reduced accidents *(41)*.

- Adaptive Cruise Control w/low-speed follow
- Collision Mitigating Braking System
- Lane Departure Warning
- Forward Collision Warning
- Lane Keeping Assist
- Road Departure Mitigation

Figure 18: Honda Sensing Package (39).

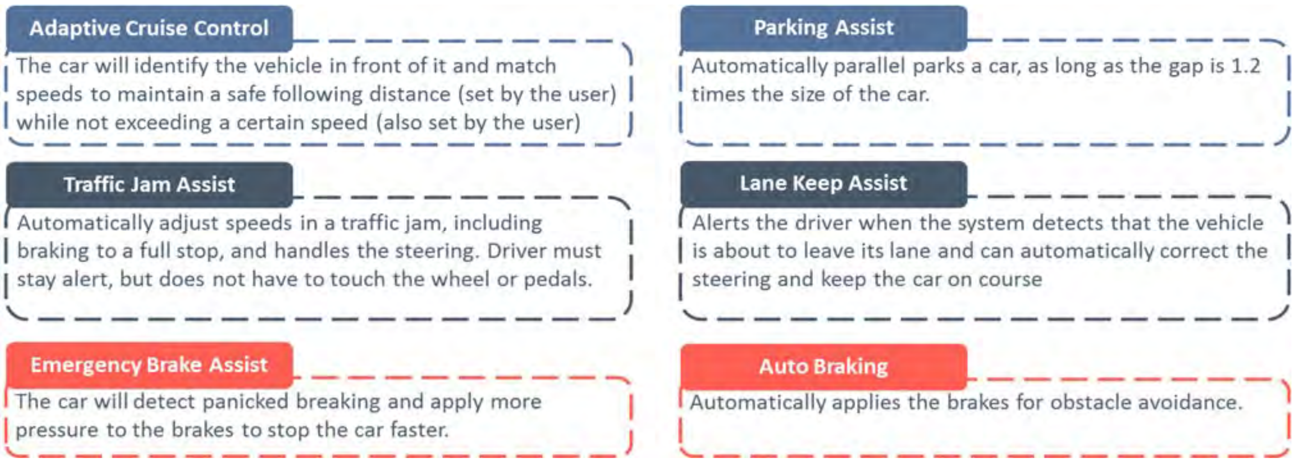

Figure 19: Commercially available autonomous features already in the market.

3.5 Aftermarket Opportunities

While most of the focus is on automakers and new vehicles due to the apparent holistic complexity of autonomous systems, there are some companies in the market that are seeking to offer aftermarket solutions. Led by a prodigy hacker, the start-up Comma.ai promises to offer a semi-autonomous aftermarket system with lane keep and adaptive cruise control commercially available by the end of 2016, for a cost less than $1000 *(42, 43)*. Comma.ai's system is designed to work on any vehicle with electronic braking and steering (generally model year 2012 or later). Otto, a recent start-up founded by former Google employees, is developing a $30,000 kit that would make semi-trucks built after 2013 semi-autonomous (with lane keep and adaptive cruise control) *(44)*. Both start-ups have created working prototypes of their systems. The research team believes that while there is not enough information to fully evaluate the efficacy of these market claims, they reveal two key considerations: 1) although aftermarket systems could lead to a bump in semi-AVs on the road, the additional penetration may be limited due to aftermarket ineffectiveness on vehicles without electronic braking and steering (pre-2012 models), and 2) both systems only reach Level 3 autonomy (although both companies intend to keep progressing) which, while it may help transportation safety, will make less of an impact on network behavior.

4 Vehicle and Infrastructure Communication

In parallel to the development of AVs, there is an ongoing push for CVs employing V2V, V2I, and vehicle-to-other (V2X) communications. In essence, V2X technology connects vehicles, infrastructure, and any other communicating devices. By sending and receiving short communications, known as Basic Safety Messages (BSMs), vehicles will receive key information about their surroundings that can be relayed to their drivers to aid safe operations. The potential for safety applications under a mature V2X system is tremendous: through use of a system with just V2V communications, NHTSA studies indicate that up to 76 percent of unimpaired crashes could be avoided. Using just a mature V2I communication system, NHTSA estimates that 26 percent of unimpaired crashes could be avoided. And, using both systems together, NHTSA studies indicate that 81 percent of all unimpaired crashes could be avoided *(45)*. See Figure 20.

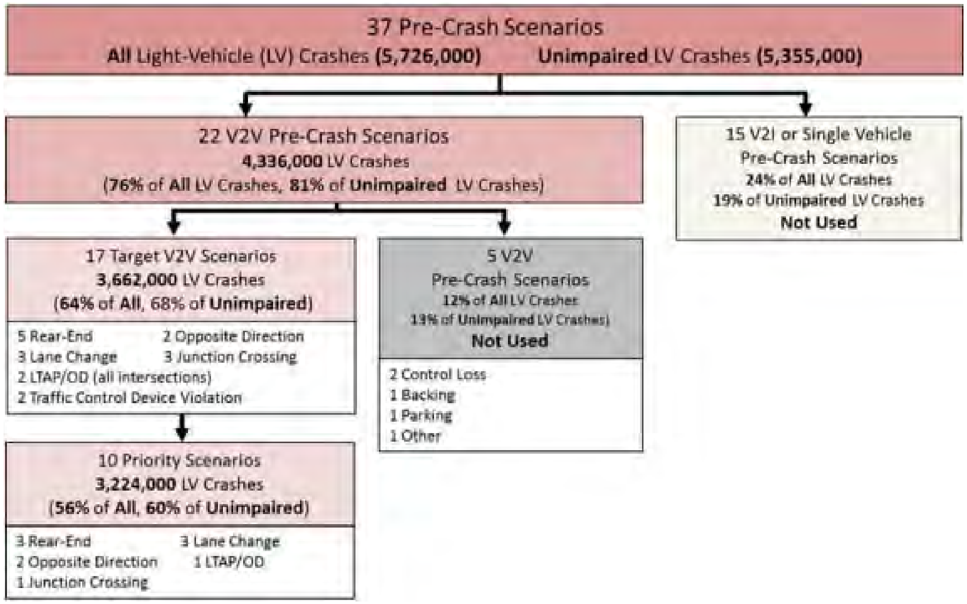

Figure 20: NHTSA V2V Light Vehicle Crash Reduction Scenarios (45).

The Society of Automotive Engineers (SAE) has established messaging standards for CVs (compiled in SAE J2735) *(46)*. At the most basic communication level, V2X communications rely on the broadcast of BSMs from individual vehicles within a vehicular ad-hoc network (VANET) *(47)*. Messages are broadcasted by each vehicle at an adjustable rate of up to ten per second *(46)(48)*. BSMs contain a standard data set about the vehicle, known as BSM I, and optional data, known as BSM II, which reflects specified car behavior at time of broadcast (see Figure 21) *(49)*. Through sending and receiving BSMs, V2V communication can enable in-car warnings via an alarm or view screen (see Figure 22, Figure 23) *(49, 50)*. In an advanced configuration the communications could even direct semi-autonomous or autonomous maneuvers.

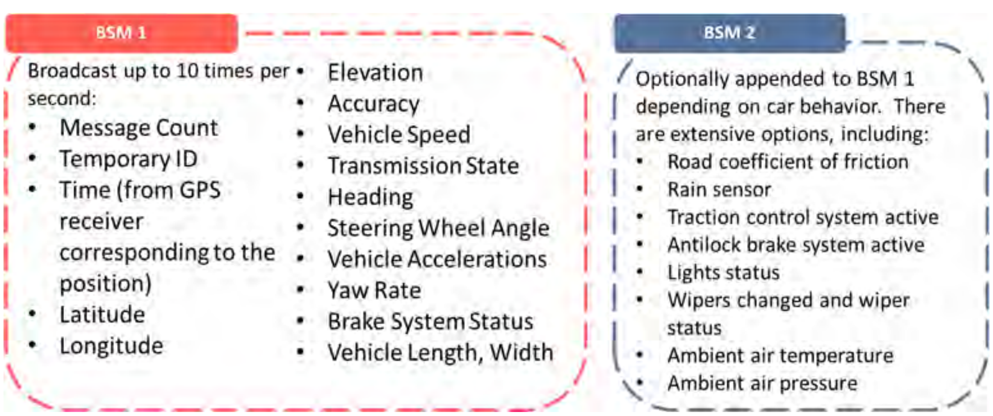

Figure 21: BSM Contents (49).

Figure 22: V2V Dashboard Warning (50).

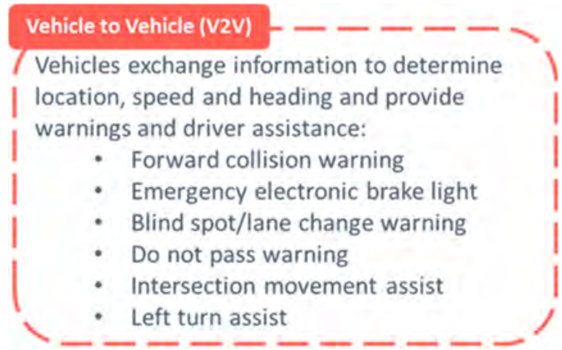

Figure 23: V2V warnings (49).

The information communicated across the VANET can be supplemented with data broadcasted by the infrastructure. Broadcasts of this type are currently contemplated to include Signal Phasing and Timing (SPaT), Intersection Geometry (MAP Data), position correction, and traveler information messages (TIM) *(51)*. Through use of broadcast information, there is opportunity for increased safety applications (Figure 24) and for information gathering applications (Figure 25) *(49)*.

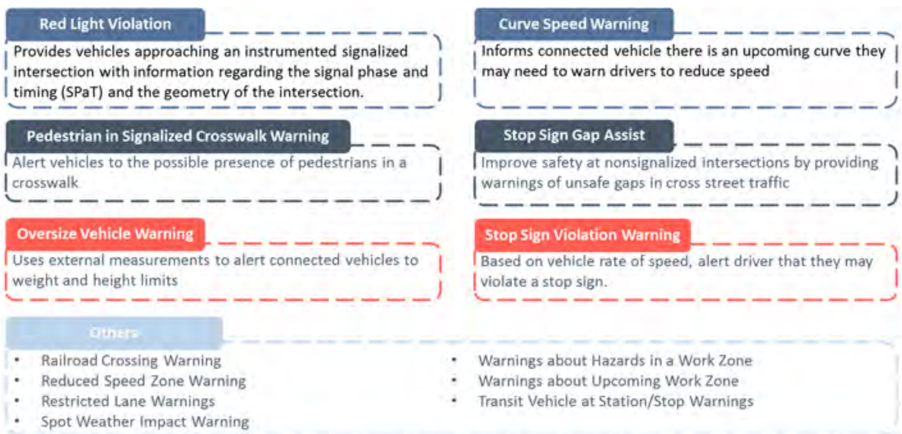

Figure 24: Potential V2I Safety Applications (51).

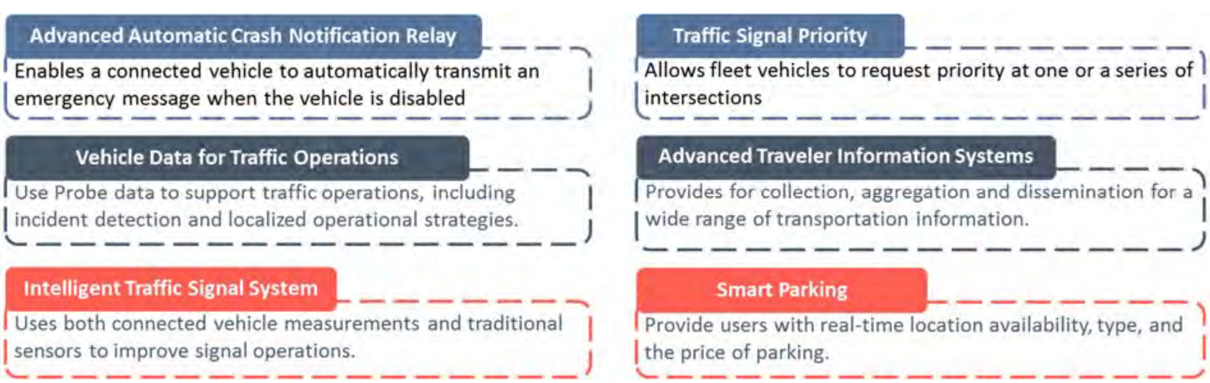

Figure 25: Potential V2I Mobility Applications (51).

4.1 Dedicated Short-Range Communication (DSRC)

To enable the wireless transmission of BSMs and other messages in VANETs, the Federal Communications Commission (FCC) reserved the range between 5850 and 5925 MHz for DSRC for intelligent transportation systems *(52)* (Figure 26). Dedicated bandwidth is necessary to handle the volume of transmissions that will likely be sent in V2X systems—congested bandwidth can be ineffective at conveying data. Already, there is anticipation that the allotted bandwidth will not be able to handle high density vehicle corridors without certain message aggregation and coordination *(53)*. The dedicated range, which sits on top of the highest frequency used by cell phones and Wi-Fi devices, has recently come under legislative scrutiny because Wi-Fi device makers are seeking to relax federal regulations that prohibit their use of the range *(54)*.

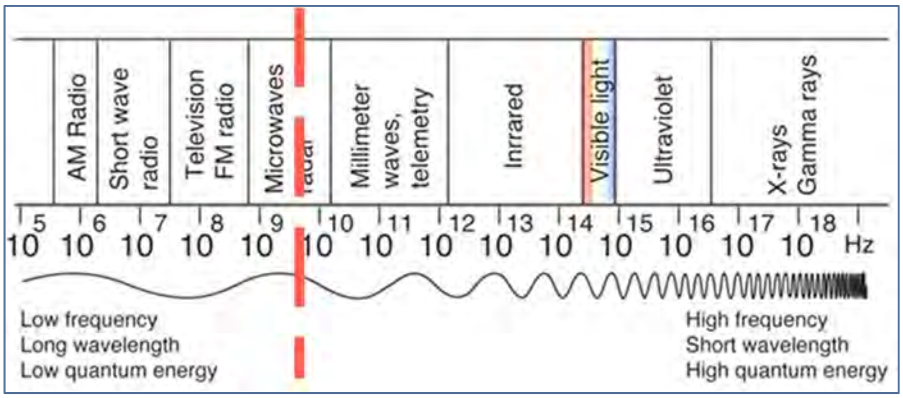

Figure 26: DSRC Frequency (53).

DSRC is expected to be the primary channel for BSM broadcasting but, due to its limited range, it will be insufficient to enable more advanced mobile applications such as those listed in Figure 27 that will still require the information found in the BSMs, but will also demand advanced processing and analysis. For this, the data produced in the VANETs must be cached, bundled and transmitted over long distances to a central processing warehouse. For these advanced applications, cellular transmissions or 5G protocols may offer future communication solutions *(49)*. However, this remains a point of research.

- FRATIS (Freight Advanced Traveler Information Systems)
- M-ISIG (Multimodal Intelligent Traffic Signal System)
- ICM (Next Generation Integrated Corridor Management)
- R.E.S.C.U.M.E. (Response, Emergency Staging and Communications, Uniform Management, and Evacuation)
- IDTO (Integrated Dynamic Transit Operations)
- Road Weather Applications

Figure 27: Advanced V2X Applications (52).

4.1.1 Considerations for Cellular Technology

Given DSRC's limited bandwidth to handle large amounts of data, especially in high density vehicle corridors, fifth-generation ("5G") cellular networks offer a promising alternative. Although 5G technology is still under development, researchers comment that the ultra-reliable, low-latency connection is well-suited for automotive applications *(55)*. In addition to transmitting data at more than 10 gigabits per second, 5G also has the ability to function with existing networks, thus reducing the relatively high capital expenditures that telecommunication companies generally spend on new cellular infrastructure. Many private firms have already demonstrated the power of 5G networks and have commissioned research to test the compatibility of 5G with V2I. One of the most relevant scenarios revolves around automated vehicles, which are connected to the cloud via a 5G connection, receiving detailed maps with up-to-update information on road conditions including traffic, weather, and lane closures. Compared to DSRC, 5G will provide automated vehicles with greater and more reliable access to the cloud to pull information that will ultimately improve driving and mobility. Today, Tesla has been using cellular technology in their cars with active first generation Autopilot hardware to collect and transmit more than 300 million miles of data*(56)*. As more CVs are deployed on roads, the use of 5G networks will become vital in improving the overall autonomous experience.

4.1.2 Equipment

To create the VANETs, technical hardware must be networked using communication equipment and standards, known as Wireless Access in Vehicular Environment (WAVE). WAVE standards mandate the operational parameters of the equipment within the network, such as defining frequencies and security protocols *(57)*. The equipment that works within the VANET can generally be divided into onboard units (OBUs) inside the car and roadside units (RSUs) that are exterior to the vehicle. Figure 28 provides an overview of RSUs. Generally onboard unit design and specification has been left to the private sector; however, the federal government has released guidance on hardware specifications for RSUs *(51)*. The latest version of these specifications (Version 4) was released in April of 2014 and is expected to receive an update in summer 2016 *(58)*. These specifications mandate that RSUs weigh less than fifteen pounds and be capable of being installed on a mast arm or traffic pole or installed in an adjacent cabinet. Generally, RSUs should have a range of 300 meters with a maximum packet error rate of 10 percent *(59)*.

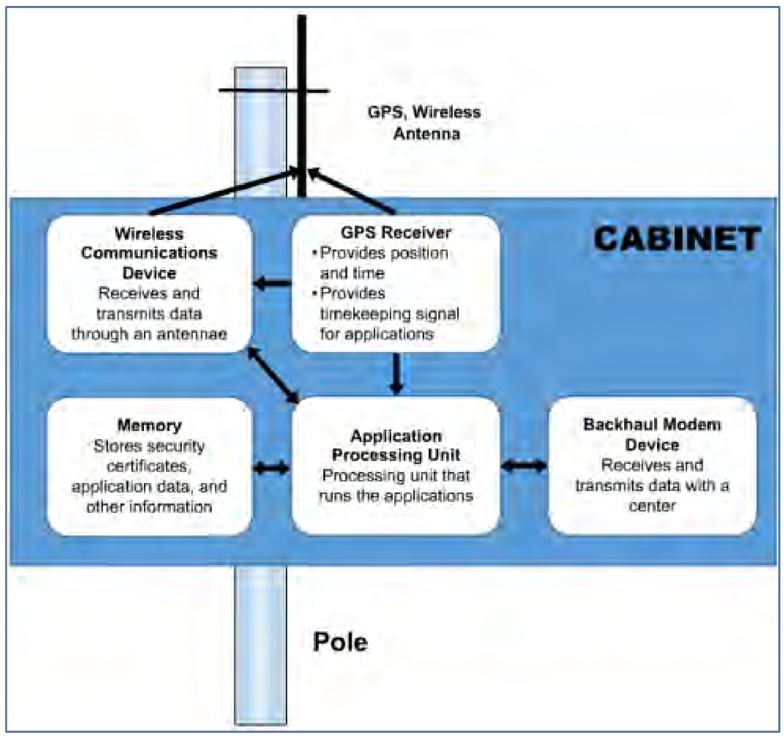

Figure 28: Overview of RSU Functions (51).

4.1.3 Security and Privacy

In a report to congress, the USDOT included appropriate privacy protection and credential security as requirements of the V2V system design. For instance, system requirements include the splitting of system functionalities so that no one entity has the ability to match records that would lead to identification of a specific driver or vehicle, digital credentialing using frequently changing random identifiers, and an element to obscure location coordinates, among other measures *(54)*. Importantly, representatives at FHWA believe that their entire credential management security system will be completed by 2020—necessitating an RSU specification that might lead to the need for installation of new communication hardware *(58)*. Further issues related to security and privacy are addressed in the Policy section below.

4.1.4 System Costs

USDOT has sponsored several V2I installations across the country to begin real world testing of DRSC systems. Further, it have begun a subsequent phase by selecting and funding three more test sites, as covered in the next session. Based on USDOT tests, RSU costs—including the hardware systems, installation labor, design, and planning—can be approximated as follows *(60)*:

- The average direct DRSC RSU equipment and installation cost per site is estimated to be **$17,600.**
- The cost to upgrade backhaul (connection to a TMC) to a DSRC RSU is estimated to vary between $3,000 and $40,000 depending on an agency's existing investments, at an estimated national average of **$30,800.**
- The typical cost of signal controller upgrades for interfacing with a DSRC RSU is estimated to be **$3,200.**
- The annual operations and maintenance cost for a DSRC RSU site is estimated to be **$3,050.**

Regarding vehicles, NHTSA estimates that new vehicle installation of a DSRC system with a view screen to provide driver information would cost around $350 to consumers in 2020 *(45)*. This number is a markup on an original equipment manufacturer (OEM) installation cost of around $220. For aftermarket installations, NHTSA estimates a range of $160 to $390 for a commercially installed system, depending on the underlying technology of the vehicle *(45)*.

4.2 Path to V2X

In 2014, NHTSA submitted advanced notice of proposed rulemaking concerning V2V implementation. In January 2017, it offered *Federal Motor Vehicle Safety Standard (FMVSS) 150—Vehicle to Vehicle (V2V) Communication* in draft form. This proposed rule is expected to become a federal rule in the second quarter of 2017 *(61)*. As the rule is currently constructed, phase in of V2V on all new models would begin in 2021 and all new vehicles would be expected to be in compliance by 2023 *(61)*. This mandate is discussed in further detail in Part II below.

Regarding infrastructure and V2I, there is not anticipated to be any federal mandate to install V2I systems, however, the AASHTO Connected Vehicle Deployment Coalition has set goals as shown in Figure 29.

V2I Intersection Deployment	Objective	Number of Sites	Year (projected)
20%	High volume intersections, corresponding up to 50% of intersection crashes	62,200	2025
50%	Deploy to cover 80% of intersection crashes	155,500	TBD
80%	Blanket deployment where warranted	248,800	2040

Figure 29: AASHTO Connected Vehicle Deployment Coalition V2I implementation goals (61).

4.3 Pilot Programs

Currently, USDOT provides funding to implement real-world testing of V2V systems in three test corridors, which each have unique qualities that will allow for V2X systems to be widely tested among various use cases:

- Wyoming DOT – I-80, a heavy freight corridor subject to heavy snow and ice conditions
- New York City – a heavy pedestrian area with numerous traffic signals
- Tampa, Florida (Figure 30) – a heavy urban corridor with a freeway, a trolley, and a bus system operating in the area *(62)*

As of the date of this writing, each project is developing their comprehensive implementation plans. Actual deployment of their systems appears to be around the middle to end of 2017. USDOT anticipates selecting another round of pilot cities, with application opportunities beginning in 2017 *(62)*. Close following of the development of these projects will inform future decisions about V2X infrastructure implementation in the NCTCOG region.

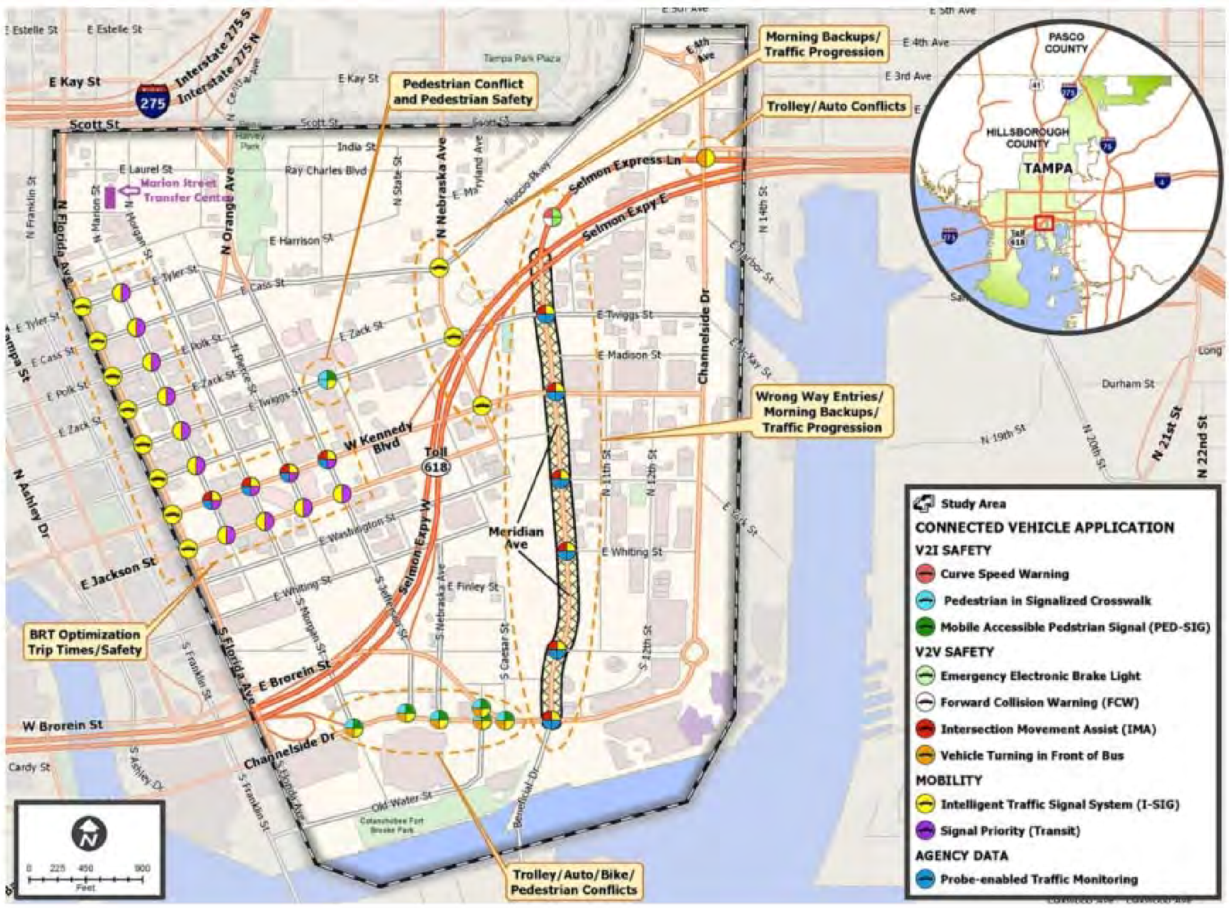

Figure 30: Tampa V2X Pilot Deployment (62).

4.4 Big Data Opportunity

The implementation of CVs also affords the opportunity for new sources of data to provide information on the transportation system as a whole, and to perhaps provide better insights on how to model human behavior. Figure 31 provides a roadmap for handling data produced by a CV system *(63)*. With early CV data sets becoming available, and the additional data that will be added through the three new pilot projects, the ability to handle and translate data into meaningful information that can provide insights and influence long-range transportation planning is an enticing research field that may warrant further exploration. As part of this study, the researchers analyzed CV data released from a pilot study in Michigan and developed a computing framework for processing and visualizing this data (see *107*).

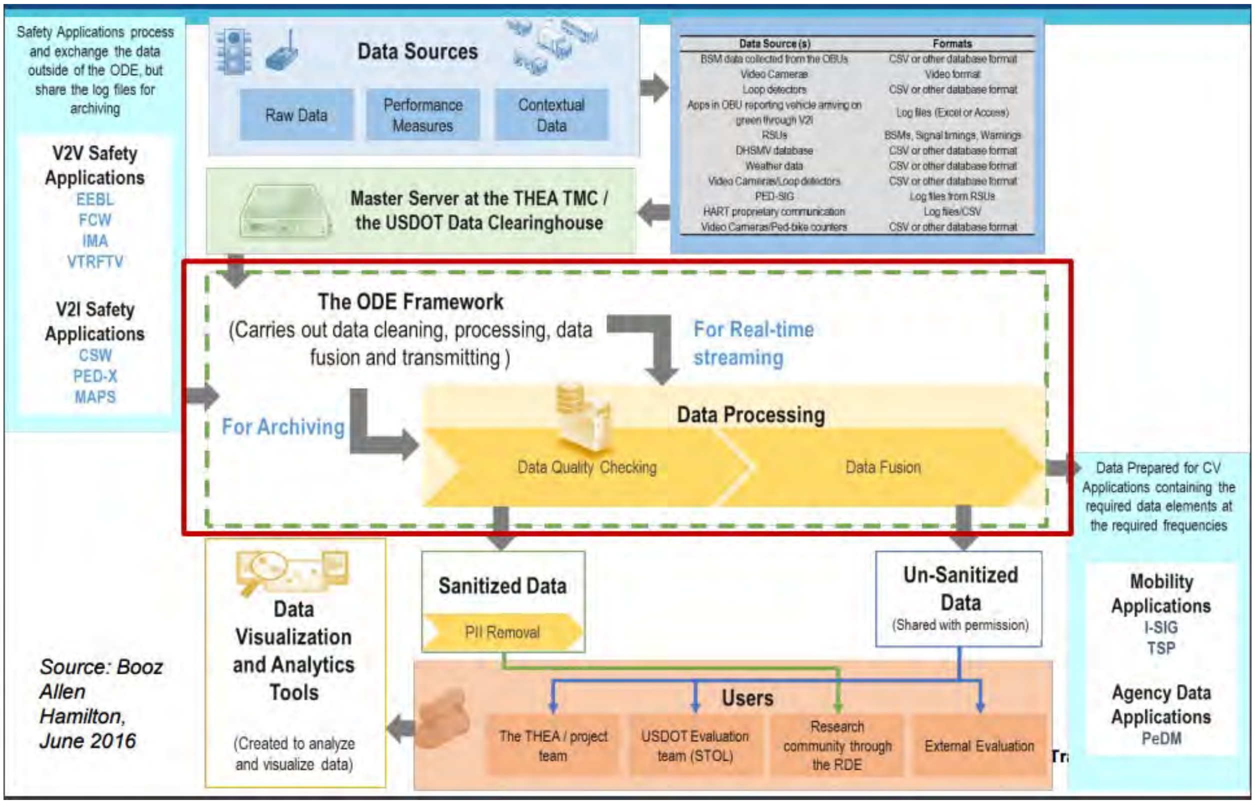

Figure 31: Big data framework (63).

To fully maximize CV data, there must be a certain number of CVs working within the transportation system. Various studies have analyzed the level of penetration that might be needed to realize meaningful analysis. In a 2016 study, Day and Bullock found that more than 20 percent of CVs on the road would be required for real-time operational strategies. However, they also found that this could be reduced to below 10 percent through inclusions of estimates of the non CV states. Going even further, through data aggregation over an extended period of time they found that they could potentially produce tangible results with as little as 1 percent penetration. Using this data aggregation they also found that with just 5 percent penetration they could offer "rudimentary elements" needed for adaptive signal control *(64)*. Another study by Argote et al., found that accuracy of Measures of Effectiveness (MOEs) were dependent on saturation, with over saturated conditions providing more reliable statistical analysis of the transportation system. Still, the study concluded that penetration rates of less than 15 percent would produce reliable (within 1 percent) analysis of multiple MOEs such as average acceleration noise, average rate of speed, and average delay per distance *(65)*.

5 Policy and Societal Concerns

Currently policy and legislation regarding CAVs is in a nascent stage. As these technologies move closer to commercial availability, federal, state, and local governments are beginning to investigate legislation to address accompanying concerns. The following provides a brief overview of national and state efforts, and examines the challenges in security, privacy, and liability that must be addressed.

5.1 National Guidelines on Autonomous Vehicles

In September of 2016, FHWA released its federal guideline on AVs *(66)*. These new guidelines include a model legislative policy for state regulation *(67)*. However, states still have full discretion to adopt or ignore the guidance. In addition to the model guidelines, the release includes a 15-point safety assessment to be utilized in the design, manufacture and deployment of HAVs Additionally it reiterates the opportunity to use existing tools NHTSA can employ concerning HAVs: (1) letters of interpretation; (2) exemptions; (3) rulemaking; and (4) enforcement of safety standards. Finally, it also lists off potential new tools for NHTSA, including (1) safety assurance; (2) pre-market approval of new technologies; (3) cease and desist; (4) expanded exemptions to safety standards; and (5) post-sale regulation of software changes *(66)*. Performance standards will likely come in the form of a modification to the Federal Motor Vehicle Safety Standards (FMVSS) *(68)*. Notably, NHTSA has signaled a willingness to accommodate AVs through current rule interpretation. The most publicized case was NHTSA's decision to interpret the word "driver" in the FMVSS to include self-driving software *(68)*.

5.2 Texas Law

Currently, Texas law is silent on the use of AVs. Google interpreted this silence to indicate that AV use is not restricted and is currently operating a pilot program for AVs in Austin *(69)*. In the 2015 Texas Legislature, three bills related to autonomous driving were offered for consideration, all containing very similar language to that shown in Figure 32.

Texas Proposed Autonomous Vehicle Legislation, Filed 2015 Legislative Session – 84 (R) SB 1167

- TxDPS to license autonomous vehicle drivers.
- Prohibits use of AV without a license and 1) employment by DPS, TxDOT or 2) an autonomous vehicle manufacturer with permission to operate in Texas or 3) someone who has installed aftermarket autonomous capabilities on a car and has permission from TxDOT.
- Requires DPS to establish minimum requirements for autonomous motor vehicles.
- TxDOT must establish insurance requirements.
- TxDOT must establish rules governing safe operation of AVs.
- Establish minimum AV requirements and registration program for testers.
- TxDOT can restrict operations to geographic regions of the state.
- Authorizes TxDOT to establish an autonomous freight transportation pilot program.
- Requires TxDOT to establish a plan to install or deploy roadside infrastructure for a statewide wireless communication system to support V2I that are essential to the performance of autonomous vehicles.

Figure 32: Proposed 2015 Texas Legislation.

5.3 Other States

In mid-2016, Florida House Bill 7027 changed Florida law to allow for consumer use of AVs *(70)*. This legislation appears to put them at the forefront of legalization of AVs, joining Washington D.C. in allowing AV use by consumers. Four other states have implemented some sort of testing policy, and three have commissioned studies on the issue. Additionally, in 2015, sixteen states introduced legislation related to AVs. The National Conference of State Legislatures provides an overview of state-enacted regulations of AVs and Figure 33 summarizes their findings *(71)*.

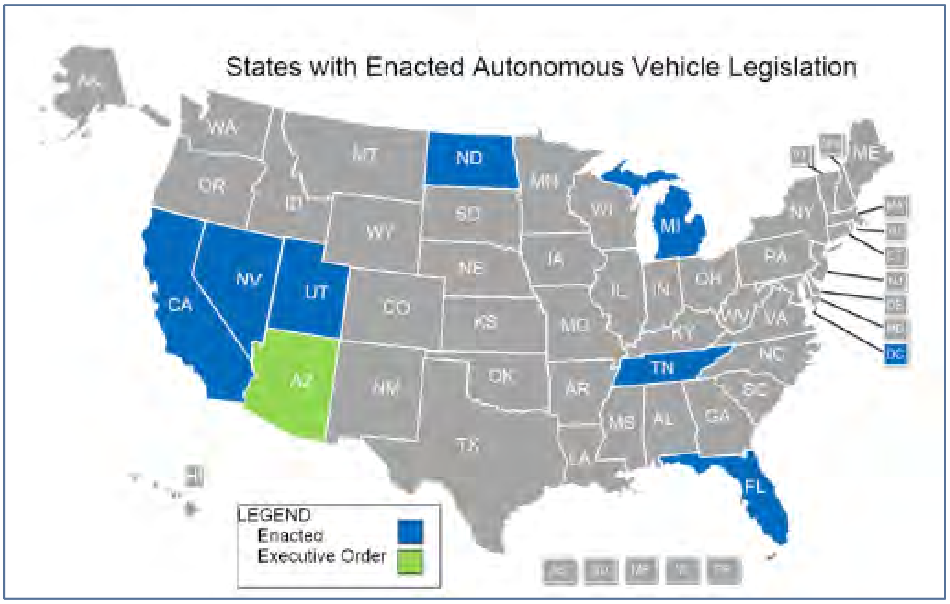

Figure 33: National Conference of State Legislatures (71).

5.4 Privacy

Data generated by CAVs contains information on origin of trip, destination of trip, and location throughout the trip. This data, if accessed by a third party with malicious intent, could be used to track system users and inform criminal activity. As such, private groups such as the Electronic Privacy Information Center (EPIC) are calling for complete anonymity and assurances that data will not be stored *(72)*. In response, NHTSA guidelines proposed to scrub the data, ensuring that vehicles are not identified nor tracked *(45)*. However, since V2X systems will be operated by state and local agencies, there is a limit on how much Federal Privacy Protection will have to be adopted *(73)*. The extent to which Texas enforces privacy protection will have a significant impact on the use of the data for real time operations and planning. At an extreme, such as the privacy settings implemented by New York for their DOT pilot program, the utility of the data could be nearly eliminated *(74)*. There, the data will be stripped of all geo-locating information including longitude and latitude, time of day, and street identifiers. Figure 34 displays the level of scrubbing to be used by New York to protect user privacy.

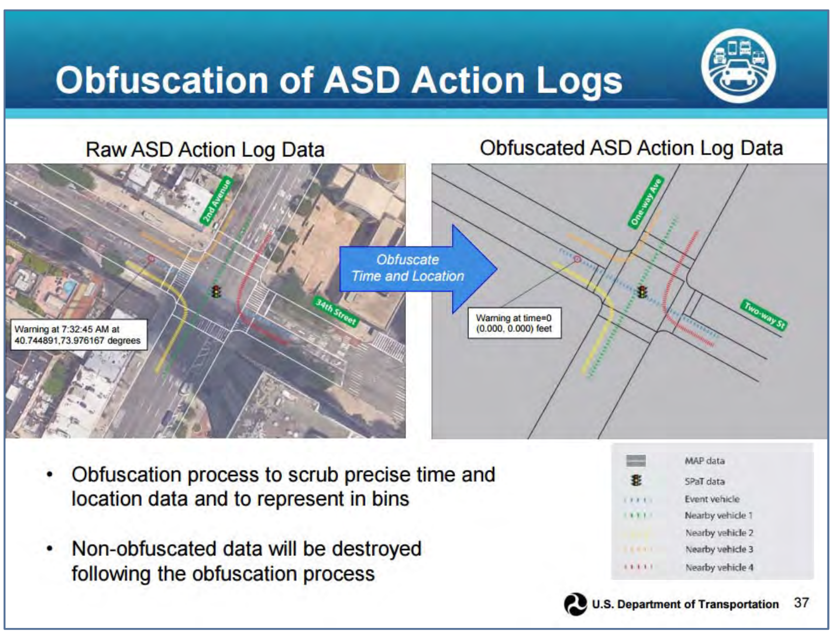

Figure 34: New York Obfuscation (74)

5.5 Data Ownership

Currently no rules regulate the ownership of data produced by vehicles driven by consumers. In a survey of twenty of the United States' largest automakers, conducted by the office of Senator Edward Markey (D-MA), 50 percent admitted to actively transmitting and storing data off-board from their in-use vehicles *(75)*. In response to concerns over this unadulterated access, Global Automakers and Auto Alliance, two consortiums collectively representing the largest automakers in the United States, publicly committed to a set of "Consumer Privacy Protection Principles" in 2014 *(76)*. However, as described by Senator Markey, these principles leave many privacy matters to the discretion of the manufacturers *(75)*. As such, Senator Markey proposed the "Security and Privacy in Your Car Act of 2015," to mandate NHTSA oversight of both data ownership and use and cybersecurity (discussed below) *(77)*. Although Markey's bill did not make it out of committee it may provide some insight into future regulations. Regarding data collection, the bill proposed conspicuous notice of data collection and the ability for drivers to opt out of the collection of their personal data. However, the bill did not touch on government collection of data, and currently there is no federal legislation that explicitly enables collecting data from V2X communication.

5.6 Security

Another significant issue highlight by Senator Markey revolved around cybersecurity protections for CAVs. In a 2014 survey of the twenty largest automakers in America, Senator Markey's office found huge gaps in the cybersecurity protocols for automobiles. Major findings of his study related to cyber security are included in Figure 35.

- Nearly 100 percent of cars on the market include wireless technologies that could pose vulnerabilities to hacking or privacy intrusions.
- Most automobile manufacturers were unaware of or unable to report on past hacking incidents.
- Security measures to prevent remote access to vehicle electronics are inconsistent and haphazard across all automobile manufacturers, and many manufacturers did not seem to understand the questions posed by Senator Markey.
- Only two automobile manufacturers were able to describe any capabilities to diagnose or meaningfully respond to an infiltration in real-time, and most say they rely on technologies that cannot be used for this purpose at all.

Figure 35: Cybersecurity Concerns (78).

Researchers at the University of Texas verify that many of security issues remain today, two years after Senator Markey's survey *(78)*. Everything from ODB-II diagnostic ports wireless access to vehicle computers could provide an entry point for hackers. Additionally, V2X communications provide another risk, not only in providing access to vehicles, but also in potential issues that could arise via spoofing of V2X signals that would effectively misinform traveling vehicles. In response to these concerns, NHTSA is working on cybersecurity protocols for V2X, expected in 2020. Automakers, however, do not appear to be focused on establishing cybersecurity protocols *(58)*.

5.7 Liability

In states in which there are regimented programs for testing of AVs, it appears that automakers generally retain liability for accidents caused by their AVs. California, Nevada, and Florida all require $5 million in coverage for these automakers *(79)*. In addition, in 2015, Google, Volvo and Mercedes-Benz all stated that they would accept liability for car wrecks while their vehicles are in autonomous driving mode *(80)*. While this seems logical, ownership of liability becomes more complex in semi-AVs, AVs owned by private parties, or vehicles with aftermarket installations. As such, many of these liability issues will probably be left up to the courts applying well established principles of tort law and product liability.

In Texas, there is a well-defined product liability statute and well settled tort law that would likely be extended or reaffirmed to cover issues with autonomous systems *(81)*. This statute provides a rebuttable presumption of non-negligence if a product meets a federal safety regulation. In addition, Texas is a modified comparative negligence state, which means that if someone is more than 50 percent responsible for a tort, they cannot recover damages for their injuries *(82)*. For instance, in a semi-autonomous situation, if the auto manufacturer can show that the driver should not have enabled semi-autonomous control due to inappropriate conditions, there is a chance that the negligence of the driver will rise above this threshold and preclude any recovery from the automaker. However, if the driver of the vehicle can prove that his fault did not rise to more than 50 percent of the total fault and that there was a safer alternative design and that the defect caused the injury, the driver should be able to recover against the auto manufacturer. If a third party is involved, they too will have to undergo a similar process. If they can prove that, in total, their responsibility for any accident is 50 percent or less they will be able to recover against the driver and/or the automaker. While there are already existing applicable laws, the exact lines of liability in these instances may develop over several years of rulings in various courts and jurisdictions in Texas.

5.8 Summary

The federal government will provide guidance on AVs.

On a state level as to implementation of AV regulations. States are free to choose what they would like to follow or ignore, but these guidelines will likely be highly persuasive.

Liability will be solved by the courts.

Over time, the judiciary will apply established Texas law to new situations that arise in AV driving. Likely this will be an ever-evolving process

Privacy will be determined by the states.

Privacy is a true concern for many and the federal government will suggest guidelines. However, each state will have to determine their own set of rules regarding privacy with the understanding that too many protections could make data gathered by the government unusable for planning or traffic operations.

Cybersecurity is a real problem.

Cybersecurity will have to be well developed over the next four years to keep up with the rest of autonomous technology. This may necessitate limited communications to the car or independent critical system architecture or mechanical overrides—whatever the solution, there will be attacks against the system and they will need to be addressed by auto manufacturers.

6 Overall Conclusions

The findings of this section indicate three major implications for NCTCOG. The first is that, as a whole, roadways will become much safer, beginning in the short term because the likelihood of government mandated V2V implementation plus the growth of the semi-autonomous and, eventually, AV production (beginning in 2019) will result in fewer accidents. Relying on V2V alone, by 2030 or 2035, there should be almost full market penetration, which will lead to a 76 percent reduction in accidents. If NCTCOG is proactive and implements V2I communications, this could increase to an 81 percent reduction. However, due to unsettled regulations and policies, NCTCOG should plan for a roll out of V2I technologies beginning in 2020. Until then, NCTCOG should pursue federal funding opportunities to implement pilot V2I programs.

The second major implication of these findings is that there will be decades of mixed roadway traffic, comprised of autonomous, semi-autonomous, and human drivers, likely extending beyond NCTCOG planning horizons (40+ years). Unfortunately, the network effects of this mixed environment are unknown, and require more research, but NCTCOG should not scrap long-term planning for new roadways and facilities. Further, traditional structures needed for human drivers, such as parking lots, will be necessary for the foreseeable planning future.

The third major implication of this study is that CAVs provide a boundless resource for system data, however cybersecurity and privacy protections will play a significant role in how useful this data ultimately becomes. With powerful data, a smart city transportation grid becomes a viable prospect, with potentially significant mobility ramifications—however, citizen concerns could prevent this system.

As CAV technology reaches final maturation over the next few years, it will continue to make headlines and spark the interest, or alarm, of citizens of North Texas. NCTCOG should continue to serve as a resource to its member organizations to provide updates and information on the effects to mobility that these changes will bring. Part II of this report will begin to look at effects that will affect the wider society through implementation of the AV—such as socioeconomic ramifications—and begin to construct a foundation on which to plan future scenarios.

Part II: Adoption Scenarios

7 Introduction

Part II discusses potential adoption timelines for both CAVs, as the first step toward identifying relevant scenarios to be considered in planning models. Such scenarios, which are the main deliverable for the first year of this research effort, will describe possible combinations of multiple factors that are expected to shape the actual impact of CAVs. Relevant factors include the number of CAVs in the market, the pervasiveness of ride-share systems, residential and car-ownership choices, trip making, route choice behavior, and the impact of CAVs on capacity. While ideally all these factors would be accounted for endogenously in an integrated modeling framework, further research is required in order to design appropriate methodologies. The proposed scenarios will serve two purposes: to provide a framework to estimate the range of potential impacts of CAV technologies with existing modeling tools, and to support the development of methodologies to explicitly capture the behaviors that ultimately determine the impact of CAVs.

The adoption rate of CAVs in the short, medium, and long range is central to the study of their impacts on mobility, and a key component of planning scenarios. For AVs, adoption is expected to be the result of a complex combination of interdependent factors, such as vehicle ownership decisions, availability of alternative transportation modes, and prevalent traffic conditions. Part II provides simple AV adoption estimates based on the adoption rates of similar technologies in the past *(6)*, and discusses existing methodologies to model CAV adoption based on behavioral considerations *(7)*.

Additionally, Part II will look at deploying vehicle connectivity capabilities, which is less complex than implementing automation, and significantly less expensive. The adoption of CVs is largely dependent on a federal mandate from the National Highway Transportation Safety Administration (NHTSA) which will mandate that all new vehicles are V2V enabled by 2023. The mandate was proposed by NHTSA in January 2017 and is expected to become a federal rule in the second quarter of 2017. From the support of this mandate, a federally researched adoption prediction is readily available.

The following sections briefly summarize some of the challenges involved in estimating the adoption of CAVs, and the approach taken by CTR in providing estimates for the short, medium, and long range (2025, 2035, and 2045, respectively) and provides proposed criteria for modeling assumptions.

8 Adoption of Connected Vehicles

The expected adoption of CVs in the United States relies heavily on the implementation of a federal mandate which was proposed in draft form in January of 2017 and is expected to become a federal rule in the second quarter of 2017 *(61)*. As the rule is currently constructed, phase in of V2V on all new models would begin in 2021 and all new vehicles would be expected to be in compliance by 2023 *(61)*. Within the proposed rule-making, NHTSA notes that they are mandating connectivity, either by DSRC or any other means that meets the protocol standards, but not safety application installation *(61)*. As discussed in Part I, safety applications are the individual programs that utilize DSRC to improve driving safety. As such, while

NHTSA indicated it may consider mandating safety applications in the future, currently NHTSA offers a split predicted adoption table, as shown in Table 1.

Table 1: V2V Connectivity Deployment for Proposed Planning Horizons (1).

Year	Calendar	With DSRC Radios		With Apps	
	Year	Number of Vehicles (Million)	Percent	Number of Vehicles (Million)	Percent
1	2021	8.1	3.3%	0.0	0.0%
5	2025	68.13	27.4%	6.3	5.2%
10	2030	144.3	55.8%	87.2	33.7%
15	2035	208.4	77.6%	163.7	61.0%
20	2040	253.0	90.8%	226.1	81.2%
25	2045	276.6	96.2%	265.3	92.3%
30	2050	291.3	98.6%	286.9	96.8%
35	2055	300.6	99.7%	298.1	98.9%
40	2060	305.2	100.0%	304.6	99.8%

While this timeline for adoption seems to be more certain than that of AVs, potential regulatory challenges remain. The proposed rule has to make it through a 90 day comment period and has to be enacted by the new presidential administration. Still, there is a very high likelihood that this mandate will be enacted as proposed *(61)*, and the proposed rates of adoption for the selected planning years will be adopted for the purpose of this study.

While the main expected impact of connectivity surrounds safety, the availability of data from CVs may allow for the deployment of more efficient ITS technologies, and support the development of more advanced planning models. In order to fully capture the impacts of connectivity on the performance of transportation systems, assumptions must be made concerning the availability of both real-time and historical data. Section 8.1 discusses potential data availability scenarios.

8.1 Availability of Connected Data

Under the currently proposed rulemaking, the data produced and recorded by a vehicle cannot be stored on the vehicle "except for a limited time needed to maintain awareness of nearby vehicles for safety purposes or in case of equipment malfunction" *(61)*. However, beyond this limitation, any public or private entity can collect the basic safety messages through roadside installations *(61)*. Additionally, drivers may be able to voluntarily participate in data collection efforts, similar to those conducted for pilot CV deployments *(83)*. While the data must not be "directly identifying or 'reasonably linkable' data" regarding driver identification, the transmission of Basic Safety Messages (BSMs) could still produce substantial data regarding current traffic conditions and performance, and could be integrated with smart infrastructure on varying levels to improve traffic operations *(61)*. Depending on the availability of V2I capabilities, improvement can be deployed at the intersection, corridor, or system level. The latter may require backhauling data to a centralized Traffic Management Center (TMC) that could coordinate infrastructure system wide. AASHTO proposed V2I installation goals, which are used in this study to develop assumptions concerning the availability of CV data, compared to the dates of DSRC Application penetration in Table 2 *(60)*.

Table 2: Infrastructure Connectivity Timeline.

Year	Percent of CVs	Percent of System Connected to Infrastructure
2025	27.4%	20%
2035	77.6%	65%
2045	96.2%	95%

The connectivity for each of these years will be assumed for model input when considering the ability of the infrastructure to adapt to changing traffic conditions and perhaps provide higher performance related to capacity.

9 Adoption of Autonomous Vehicles

Thanks to innovations from companies such as Google and Tesla, what was once thought to be a timeline that would introduce AVs by 2035 *(35)* has turned into a race to produce AVs as fast as possible. AVs in the United States are expected to be commercially available at the beginning of the next decade *(36)*. With stated timelines that include Level 4 autonomy within the next five years common across the private sector, the public sector must begin to prepare for a future with CVs and AVs.

To date, there have been various studies conducted in academia focusing on predicting the timeline for AV adoption in the coming decades, some of which are summarized in Section 9.1 *(84–90)*. Generally researchers have determined that there is a high likelihood that there will be a prolonged mix of human-piloted, semi-autonomous, and AVs sharing the roadways. Potentially, this mix could last decades. Considering that there are approximately 260 million vehicles in the United States *(91)* and that just over 17.5 million light passenger and commercial vehicles were sold in 2015 *(92)*, if every new car sold was an AV, it would take nearly 15 years for all existing vehicles on the road to be replaced. However, supply is not the only factor determining the future adoption rates of AVs: the actual number of AVs on the roads will also depend on consumer acceptance and use of these technologies, which at this point is highly uncertain. Further, there is the real possibility of a disruptor influence in the market that could drastically affect adoption timelines. Among such influences, ridesourcing services are envisioned by many to become the preferred mobility alternative in the future, which may result in a reduction of the vehicle fleet size and a considerably higher fraction of AVs *(93)*.

Given the complexity of the factors that will ultimately determine the adoption of AVs, and the significant uncertainty concerning the data and parameters that ultimately determine the results of adoption models, a relatively general approach has been selected for this project. The methodology, described in Section 9.3, is based on the use of adoption curves from past technologies, and informed by a recent worldwide expert survey *(94)*. The outcomes of this analysis will be used to define AV adoption assumptions for the purpose of generating alternative planning scenarios. The process may be revisited in latter project stages. Ridesourcing plays a critical role in understanding the number of trips and AVs on the road, and is discussed in Section 9.4.

9.1 Adoption of Autonomous Vehicles: Existing Predictions

Although the variables for adoption of AVs remain nebulous in nature, a number of qualitative and quantitative estimates have been provided by experts, consultants and researchers. Private sector consultants have released various reports in support of business decisions, which are discussed in Section

9.1.1. The literature presents several examples of relatively systematic methodologies to estimate AV adoption, including surveys, macro-economic models, and discrete-choice models, some of which are described in Section 9.1.2.

9.1.1 Adoption Estimates by Private Consultants

A number of private-sector consultants have provided qualitative timelines for the adoption of AVs. Excepting Morgan Stanley, consultants from private industry are generally more pessimistic or in line with academic predictions. While many consultants do not freely release their detailed findings or methodologies, key graphics available on the Internet provide some insight into their projections. Ticoll, from the University of Toronto, cataloged several consultants' predictions, and these predictions were updated or added to create Table 3 *(95)*. From this table, the great variability of consultant predictions is evident. As such, since the consultant methodologies are private, the value of the consultants' work for this research lies perhaps not in their predictions, but in the confirmation of the great uncertainty that surrounds the adoption of AVs.

Table 3: Consultant Predictions.

2015	Morgan Stanley: Limited driver substitution begins to roll out
2018	Morgan Stanley: Complete autonomous capability begins to roll out
2020	Price Waterhouse Cooper (PwC): semi- and full-AVs have 9-10% global share in basic scenario; 12-13% in disruptive scenario
2025	PwC: Semi- and full-AVs have 14-16% global share in basic scenario; 19-22% in disruptive scenario Goldman Sachs: Full AVs will be "commonplace" Boston Consulting Group (BCG): Fully autonomous are commercially available
2028	McKinsey: Consumers begin to adopt AVs
2030	PwC: Semi- and full-AVs have 15-18% global share in basic scenario; 28-30% in disruptive scenario Gartner: AVs are 25% of passenger vehicle population in use in mature markets IHS: 17-27% of new light vehicles sales will be AVs
2035	Morgan Stanley: 100% autonomous penetration BCG: Combined, semi and full autonomous vehicles make up 25% of new car sales
2040–2050	Morgan Stanley: 100% autonomous penetration BCG: Combined, semi and full autonomous vehicles make up 25% of new car sales

9.1.2 Prediction of AV Adoption through Modeling

Researchers have used surveys to estimate AV adoption *(85, 86, 88)*. These survey results show a high variability in possible outcomes based on assumptions of future influences. For instance, one research team at the University of Texas conducted a survey involving more than 2,100 people from a wide representation of socioeconomic status, producing a long term choice model based on their collected responses *(85)*. The survey (and subsequently the model) considered factors such as price decreases at different rates, willingness to pay over time at different rates, and the addition, or lack thereof, of regulations to mandate technology use. From the study, the research team found that the wide variety of influencing factors led to a wide range of adoption curve possibilities, with potential curves ranging from a conservative case of 25 percent penetration to an optimistic case of 87 percent penetration by 2045.

Discrete choice models based on current vehicle ownership, use of car-sharing and ride-sourcing services, and residential location have also been proposed to estimate AV adoption *(88, 89)*. These models, when combined with local data, could provide insight into local adoption trends of ridesourcing and AVs. Behavioral models also provide a better understanding of the relative importance of the multiple factors affecting ridesourcing and AV adoption, ultimately supporting the design of appropriate strategies to promote beneficial behaviors. Lavieri et al. suggests that AV adoption via ridesourcing is more likely to occur in dense neighborhoods *(88)*. Their work also found a relatively high opposition to sharing of AVs, as shown in Figure 36. Discrete choice models are likely to be important components of comprehensive methodologies to assess the impact of CAVs. While they will not be implemented at the current stage of this project, given the higher-level-approach used to define general scenarios, they will be revisited for prototype implementation at later stages.

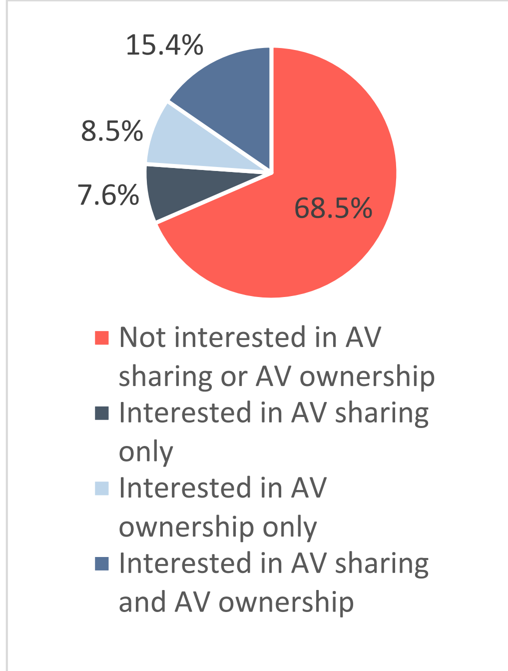

Figure 36: Lavieri et al. Attitudes on AV Sharing (88)

Another option available to researchers is to use diffusion models to predict the propagation of new goods into the market. The Bass Diffusion Model, first published by Frank Bass in 1969 *(96)*, is widely accepted in the economics community, and has been used in at least one study to estimate the adoption of AV technologies using historic data from high tech devices such as cell phones, internet adoption, and hybrid vehicle adoption (21). The Bass Model predicts the market penetration curve of a new technology by considering two types of consumers: Innovators, who would buy a product due to effective marketing or a belief in the potential of the product; and, Imitators, who adopt the product after observing its use by others (Figure 37). Using this model, the above-mentioned study predicts that there will be, cumulatively, more than 87 million AVs sold in the United States by year 2060, which signifies a saturated market of 75 percent AV use *(21)*. However, researchers in another study found that the wide range of Bass Model coefficients may lead to widely disparate numbers and cautioned against reliance on this model before the initial data points are established *(97)*. In an effort to study the feasibility of implementing the Bass Model in the context of this project, CTR created a web-based tool to visualize the results of the Bass Model under various assumptions. The application may be used to develop insights as to what would happen if AVs and/or ridesourcing were to be diffused through the general market at the same rate as various established technology. Table 4 provides an overview of some select adoption curves, showcasing the great variability in model results depending on the selected comparable technology (with a beginning year assumption of 2021).

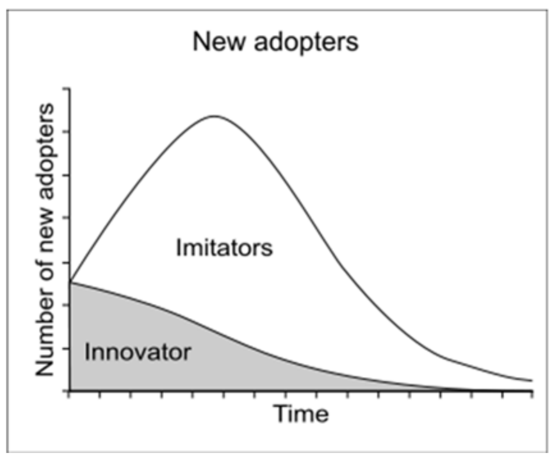

Figure 37: Bass Diffusion Model (21)

Table 4: Computed Bass Diffusion Comparisons.

Scenario	Percent Penetration in Year		
	2025	2035	2045
At the Rate of Automobiles	0%	3%	9%
At the Rate of Electric Vehicles	2%	16%	66%
At the Rate of Mobile Phones	2%	20%	78%
At the Rate of HEVs	10%	88%	100%
At the Rate of the Internet	12%	80%	100%
At the Rate of Air Conditioners	10%	92%	100%
At the Rate of Color TV	11%	100%	100%
At the Rate of Smartphones	16%	100%	100%
At the Rate of the Home PC	67%	100%	100%

Since the above table provides such a wide range of predictions for the adoption of AV, choosing any one such comparative technology to predict future penetration of AVs is very much a guessing game. As such, in an attempt to still utilize a Bass curve in our final proposed scenarios offered below, we chose to match a Bass adoption curve to the results of a survey of world-wide experts that revealed their collective judgment as to the availability and commercial penetration of AVs. This survey, process and results are detailed below.

9.2 Autonomous Vehicle Adoption Scenarios

Given the wide variability of results for behavioral studies, the research team chose to use the Bass Diffusion Model to predict adoption scenarios of AVs. The selection of model parameters was guided by the outcomes of a Delphi survey conducted in August of 2016. A Delphi consists of rounds of surveys among acknowledged experts in a field until a consensus is reached. The study used in this work was conducted by Kineo Analytics and included 33 professionals from around the world, with about two-thirds of the respondents residing in North America and Europe *(94)*. The results are displayed in Table 5. Notably, the world outside of the United States and Canada was much more pessimistic on their prediction paradigms. For this effort, the world's combined responses will be used to generate a conservative case; while the results of the United States and Canada are the basis for an aggressive adoption scenario.

Table 5: Results from the Delphi Analysis.

Question	Respondents			
	World (33)		US & Canada (9)	
	Average	Standard Dev	Average	Standard Dev
Year AV's will be available	2023	2.9	2021	2.0
AVs will be 10% of the car fleet	2032	7.0	2028	5.7
AVs will be 20% of the car fleet	2037	8.5	2033	8.0

Using the year of AV availability in Table 5 as the start date, researchers identified Bass model parameters that led to 10 percent and 20 percent adoption rates for the corresponding group (World or US & Canada) in the years cited. For the "World" group, used to develop a conservative scenario, the innovator and imitator coefficients were found to be 0.008 and 0.09, respectively. For the aggressive scenario the values are 0.01 ad 0.09. The resulting curves are the basis for the adoption estimates presented in Table 6.

Table 6: AV Adoption Assumptions for Conservative and Aggressive Scenarios.

Year	Adoption	
	Conservative	Aggressive
2025	5%	6%
2035	20%	25%
2045	45%	51%

The above predictions seem reasonable in light of the collected material currently available on the subject. However, the researchers caution that there is ample opportunity for variance in these predictions. As such, further research should be done to refine and explore the prediction methodology, and there should be updates on an annual or biannual basis to check the status of the market. As adoption occurs and starts to inform the beginning of the curve, long-range prediction paradigms should become more realistic.

9.3 The Impact of Ridesourcing

Ridesourcing services allow users to contact and utilize third party ride providers to complete their trips. Some researchers envision that, in post-2020 scenarios, such third parties will be AVs. An estimated 5.8 million people globally are already using ridesourcing services, a number expected to grow to 15 million by 2020 *(98)*. The popularity of these services is also evident in the impressive growth of the ridesourcing providers. The largest, Uber, is the most valuable venture-capital-backed private company in the world after just seven years of operations *(99)*. Valued around $50 billion, the service is conceptually worth more than GM. Uber has more than one million active drivers and is working in more than 300 cities worldwide. Uber also has a purported goal of replacing its human driven fleet with AVs as soon as possible *(37)*. While still just a small portion of total global mobility portfolio, the conceptual impact of ridesourcing is profound, and the traditional automotive companies are noticing. Besides Ford's bold claim of a 2021 Level 5 ridesourcing vehicle *(36)*, other traditional car manufacturers are making meaningful investments in ridesourcing companies as displayed in Table 7 *(100)*.

Table 7: Investments in Ridesourcing (23).

Investor	Investee	Investment
GM	Lyft	$500 M
Volkswagen	Gett	$300 M
Toyota	Uber	Undisclosed
Apple	Didi Chuxing (China)	$1 B

While the total reach of ridesourcing as a primary means of transportation is yet to be determined, the effects of such a system could be significant. The fraction of drivers choosing to use ridesourcing for their trips may be estimated through behavioral choice modeling *(88, 89, 93)*. While some currently available models *(88)* suggest a fairly negative attitude towards ridesharing (77 percent), attitudes may change a these technologies evolve. As more data becomes available, the research team may be able to better estimate the change of attitude towards ridesharing over time. For the purpose of this study, the assumptions concerning the fraction of travelers choosing ridesourcing will be based on Lui et al.'s findings *(93)*. The authors estimate that ridesourcing has the potential to capture between 13 percent and 50 percent of the trips depending on the cost per mile. The previous estimates correspond to $0.5 and $0.75 per mile, respectively. Industry experts such as Larry Burns, a former head of research at GM and a professor of engineering practice at the University of Michigan, predicts that AV costs could be brought to as low as $0.25 per mile—which would likely expand the influence of ridesourcing even beyond the 50 percent predicted above *(101)*.

Based on the previous discussion, three ridesourcing assumptions will be considered when developing planning scenarios, as shown in Table 8.

Table 8: Ridesourcing Influence Scenarios.

Conservative case	Middle Case	Aggressive Case
10% mode share, same fraction of AV as in General fleet (Table 6).	23% mode share, all AV	50% mode share, all AV

10 Current Applications of Autonomous Vehicle Technology

While widespread adoption is probably a decade away, the technology is being introduced now. As such, public entities should begin working with the new transportation paradigms to ensure that these technologies are responsibly introduced into their respective areas. For instance, several current real world uses of AVs are summarized below:

- **USDOT AV Proving Grounds:** In January 2017, the U.S. Department of Transportation designated ten regions across the U.S. as "Proving Grounds" where CV and automated vehicle technologies can be tested. The Texas AV Proving Grounds Partnership, which includes CTR, was selected as one of the ten regions and offers a wide range of testing environments including the University of Texas at Austin, the city of Austin, and the Austin-Bergstrom International Airport *(102)*.
- **Uber's Pittsburgh Pilot Program:** Launched in September 2016, Uber's pilot program allows customers to hail an AV, either a Ford Fusion or a Volvo XC90 SUV, in the downtown Pittsburgh area. Per state regulation, there must be a safety driver in the driver's seat that can take over control of the vehicle in the case of an emergency. Although the vehicles are limited to predetermined routes that have been extensively mapped, the fact that customers are riding AVs in a commercial setting represents a major milestone *(103)*.

- **Otto's First Self-Driving Truck Delivery:** Otto, which was acquired by Uber in August 2016, completed the first autonomous truck commercial delivery in the U.S. in October 2016. Otto partnered with Anheuser-Busch to deliver over 50,000 cans of Budweiser from Fort Collins to Colorado Springs in Colorado. Otto's technology allowed the driver to monitor the system from the back seat of the truck for the 120-mile trek on the freeway *(104)*.
- **Self-Driving Public Buses in Helsinki:** Helsinki's Metropolia University of Applied Sciences, in partnership with the city of Helsinki, tested a fleet of autonomous buses late last year. The buses, which can carry up to 12 passengers each on public roads, were previously tested on closed roads in the Netherlands. Finland has become a testing ground of AV technology because Finnish law does not require drivers in vehicles on public roads. Helsinki hopes to convert its entire public bus system to a fully autonomous fleet by 2025 *(105)*.

11 Summary

The implementation timeline for CVs and AVs is highly uncertain. This section proposes assumptions for the rate of adoption of AVs and CVs at three planning horizons, based on existing knowledge. Assumptions concerning the adoption of CVs are based on a Federal Mandate *(61)* to requires V2V connectivity in all vehicles starting in 2023. For autonomous technologies, optimistic and pessimistic assumptions are provided based on a simple model used in economics *(96)*, and the outcomes of a world-wide Delphi study *(94)*. Assumptions concerning the potential role of ridesourcing are also provided, given the major role that this mod can play in determining the ultimate impact of CAV technologies.

The assumptions proposed in this section will be combined with an analysis of several behavioral and technological factors that may affect the ultimate impact of CAV technologies on travel. These will include activity and residential location choice, vehicle ownership, trip making behavior, mode choice, and route selection paradigms. The analysis, which will be presented in the third part of this report, will lead to the identification of a number of planning scenarios that may be used to assess the range of potential impacts of CAVs in future research efforts. It will also provide a better understanding of the type of methodological research that may be required in order to explicitly capture the complex impacts of CAVs.

Part III: Development of Planning Scenarios to Assess the Impacts of Autonomous and Connected Vehicles

12 Introduction

This section of the report proposes an approach to generate a comprehensive list of planning scenarios to estimate the impacts of CAVs. Such scenarios combine assumptions about the availability and adoption of CAV technologies, presented in Part II, with the analysis of behavioral and other technological factors which are ultimately expected to shape the system-wide impact of CAVs.

Understanding the impact of CAVs over time requires integrative modeling approaches that can capture the complex processes that determine travel demand and the corresponding transportation system performance. Among others, travel demand estimation in such models should consider the impact of CAVs on individual choices, such as vehicle ownership, residential choice, activity patterns, and mode choice. The system performance estimation needs to be sensitive to the impacts of CAVs by capturing the multiple mechanisms through which these may affect traffic flow, such as increased efficiency at intersections, reduced headways, and increased availability of network-wide information, among many others.

Developing an integrated model such as the one described above is challenging for a number of reasons, foremost of which is the considerable uncertainty that characterizes both the availability of CAV technology and the response of travelers to such availability. The goal of this section is to identify the most critical factors to be considered when assessing the impacts of CAVs, and to describe existing hypotheses of how these may change in response to CAV technologies. This section also proposes a number of scenarios that result from combining assumptions regarding the behavior of all the considered factors. Such assumptions may be incorporated into existing modeling methodologies to assess the potential range of impacts of CAVs.

As more data becomes available from pilot projects and surveys, researchers will be able to develop methodologies to integrate critical behavioral and technological factors within a modeling framework *(88, 106)*, progressively replacing assumptions with endogenous estimates. Data analysis will be critical in the development of new methodologies, and CAVs have the potential to dramatically increase the availability of information. Preliminary work conducted by CTR and partially funded through this effort discusses the potential impact of data availability on the planning process*(107)* based on data from Michigan's pilot CV deployment *(83)*, and the use of new computational technologies which are expected to facilitate the manipulation and use of complex datasets *(108)*.

The following sections describe the multiple factors considered relevant in the definition of planning scenarios and propose combinations of assumptions concerning their behavior, which are expected to exemplify the range of potential CAV impacts (Section 2). These assumptions may be used in future project stages to build simple models to quantify CAV impacts in the NCTCOG region.

13 Relevant Factors to be Considered in a Comprehensive Assessment of CAVs' Impact

Potentially disruptive technologies, such as CAVs, are likely to have complex impacts that may not be assessed without appropriate modeling techniques.

Planning models are intended to capture the complex interactions between travel demand and transportation supply (provided by the roadway infrastructure and transit systems), and are expected to provide an adequate framework to evaluate the potential impacts of CAVs. In planning models, traffic conditions emerge from the supply-demand interaction, which in turn shapes activity and travel patterns. In order to describe supply-demand interactions, the transportation planning process includes two broad categories of models: travel demand estimation and traffic assignment. The latter models estimate system performance for a given travel demand pattern, and their outputs may be used in a feedback loop to adjust travel demand estimates. In order to successfully study CAV impacts using existing frameworks, it is crucial to understand how these technologies may affect behavioral assumptions, as well as other modeling inputs and parameters. In light of the CAV research done to date, the research team established Figure 38 as a list of the most relevant components of planning methodologies for the purposes of this section.

Travel Demand

- Trip Making Behavior - Understanding the propensity of individuals to make trips is central to determining travel demand.
- Location choice/Residential choice – This ultimately determines the travel patterns that may place more or less stress on existing transportation systems.
- Mode choice - The number of personal vehicles on the roadway is also affected by the choice of travel mode, which in turn is related to individual preferences, vehicle ownership, and the characteristic and availability of alternative modes.
- Vehicle Ownership – A key factor affecting mode choice.
- Parking Demand – A special consideration in light of the CAV paradigm (see below).

Travel Behavior

- Route choice - Another behavioral factor to be considered in the assessment of CAV, while this does not affect the number of trips directly, it has an impact on system performance, which ultimately impacts travel patterns, as well as mode and residential choices.

System Performance

- Capacity - Currently, vehicles are designed to account for human drivers. However, the transition towards machine conductors, and away from human error, affords ample opportunity for the transformation of the automobile and driving behavior.
- Safety – Another special consideration in light of the CAV paradigm (see below).

Figure 38: Modeling Inputs and Parameters

13.1 Possible CAV Impacts

Building from Figure 1, the research team established a lengthy list of some of the possible CAV impacts that could be classified into each of the above components, available in this section. Understanding the magnitude and positive or negative influence of each possible effect of CAVs is important in order to define scenarios to explore the complete range of potential CAV effects. The availability of CAV technologies, described in Part I of this report, and the behavioral acceptance and adoption of CAVs, described in Part II, are expected to determine the magnitude of the observed impacts, and are also considered in the definition of planning scenarios.

13.1.1 Travel Demand

13.1.1.1 Trip Making Behavior

- **Wider access to transportation:** With AVs, a class of people that do not currently have access to car transportation will be suddenly receive this access. These groups include the elderly, disabled and youth that are not yet old enough to drive. In addition, inanimate objects and animals can be moved around without direct supervision by a human *(109, 110)*. For instance, if someone travels to work and forgets something at home, they can send a car to retrieve the missing item with great ease. All of this could lead to more trips in the system.
- **Fewer barriers to making trips:** Some researchers *(109, 111)* hypothesize that AVs will increase the number of trips taken by individuals by increasing comfort and reducing the perceived burden of travel. When a traveler decides to travel for any given purpose, they might factor in the value of the trip itself: usually considering factors such as cost of time, gas and emotional stress that might come through travel. With AVs, travelers might find that the barrier to making trips is reduced or eliminated; as such, they may be more likely to judge trips worthwhile—leading to more trips. Also included in this consideration is the effect of AVs on transportation of low value items, particularly revolving around delivery services. Whereas in the past, the cost of the trip itself would make the transportation of the item undesirable, the reduction or elimination of this cost might precipitate more trips of low value items.
- **A lower burden of travel:** This consideration relates to the decision tied to the distance of any given trip. If an AV provides a low enough burden of travel, populations may be inclined to accept longer trips. This would influence the distance of trips such as daily commutes, inter-community trips or even those trips seeking out education, entertainment or other social options.
- **Reliable service:** On a daily basis, some proportion of the traveling public is limited by mechanical problems of their vehicles. However, in a robust ridesharing paradigm, these travelers will simply turn to AV/ridesharing services to complete their desired trips.
- **Empty trips:** Passenger-less trips may become common, as AVs with no passengers may still move from place to place to retrieve a person or thing *(112)*.

13.1.1.2 Location/Residential Choice

- **Sprawl:** As the burden to travel becomes lower, residential decisions may change. More cost effective land, usually found further away from the city center, will become more palatable to buyers as commute burden is decreased. This may accelerate residential sprawl.

13.1.1.3 Mode Choice

- **Opportunities for trip-sharing:** Ridesharing or transit services that experience expanded capacity due to autonomy may increase shared ridership opportunities. This expanded opportunity would influence traveler decisions to ride in a vehicle alone, or otherwise utilize a shared vehicle (via a transit service or otherwise).
- **Ridesharing effects on transit:** In transit, there is a problematic concept known as First Mile / Last Mile. This concept revolves around the idea that transit does not generally pick up or drop off at a user's origination point or final destination. As such, the uncertain segments of travel between these points and the transit stop deter transit use. AVs could potentially solve this through a floating fleet of ridesharing vehicles that offer cost effective service to move travelers from their origin and/or final destination to the appointed transit stops. Under this scenario transit may become more reliable, eliminating the uncertain segments of travel and less burdensome *(113)*. However, also under this scenario, the issue of transfer to a transit stop becomes the focal point of the traveler decision. Perhaps the user of the ridesharing service would be more content to simply pay for a ride directly from their

origin to their final destination and cut out the middle transit ride. Depending on costs and ease of use, a fleet of ridesharing vehicles could severely undercut transit ridership *(114)*.

- **Sprawl effects on transit:** As contemplated above, AVs may lead to residential sprawl. This spread of people may make transit lines/gathering points infeasible in terms of distance from origination points. On the other hand, it may make the gathering points feasible for smaller transit vehicles (vans instead of buses at more locations).
- **Intermodal cooperation:** Through CVs, there may be increased coordination between all modes of transportation. This could make intermodal transportation more attractive as wait times are decreased through precise and/or adaptive schedules of arrivals and departures.
- **A reduction in walking and bicycle traffic:** AVs may reduce the barriers and burden of travel so much that they may materially affect walking and bicycling activities for non-recreational transportation. If small intercity shuttles can move passengers a few blocks at a time, walking and/or biking may become less necessary for local transportation—instead being replaced by autonomous transport. Additionally, AVs may lead towards autonomous intersections. These intersections, with their regular flow, would seemingly not allow crosswalk opportunities for foot traffic, further discouraging foot/bicycle traffic.

13.1.1.4 Vehicle Ownership

- **CAV adoption/use:** There are many Human Decision Factors (for example: number of kids, propensity to share vehicles, distrust of the technology, enjoyment of driving, etc.) that will influence the adoption and use of AVs versus other forms of transportation. If travelers own their own vehicle, or rely on ridesharing, or rely on transit or rely on a mix of any of these factors, the potential for significant change in this paradigm as compared to current factors is significant *(88, 89)*.

13.1.1.5 Parking Demand

- **A reduction in parking needs:** Both AVs and ridesharing scenarios would seem to lead to a reduced demand in parking. Instead of being parked in a high value local space, vehicles could be sent to park away from urban cores, or, in a ridesharing scenario they could simply continue in pursuit of their next passenger. However, there is also a scenario in which individual ownership of CAVs could increase the demand for parking if more people have access to vehicles (such as the elderly, blind, young, etc.) and these groups all begin to visit higher density urban cores with more frequency.

13.1.2 Travel Behavior

13.1.2.1 Route Choice

- **Sensitivity to travel times:** Travelers may become less sensitive to travel times as a result of a decrease in the perceived burden of travel, which may lead to a desire to select a route for different reasons. For instance, perhaps someone would like to take the "scenic route," or perhaps they are watching the nightly news in the vehicle and they would like to time their arrival to coincide with the completion of the program. All of this could lead to new routing decisions.
- **Alternative routing paradigms:** AVs and CVs open up the opportunity for adaptive route selection based on system-wide real-time information. This informed route selection could be made on a user by user basis or could be coordinated through a centralized system designed to create optimal routing across the system as a whole. Most existing modeling approaches assume that drivers selfishly minimize their travel cost based on their perception of travel times across the system. Such approaches typically ignore the availability of real-time information, which can change travel and congestion patterns. The information expected to be collected and shared by CAVs *(115)* may require new modeling paradigms which explicitly account for the availability such data. Still, even the effects of the availability of this information opens potential assumptions along a spectrum; for instance, ubiquitous real-time

information provision may not lead to improved system performance, particularly if all drivers behave in a purely reactive fashion without considering the reaction of other drivers. However, in a fully connected system, CAVs may enable the deployment of new routing strategies that optimize system performance, such as cooperative routing strategies, in which some drivers may be assigned to slightly longer routes in order to avoid congestion and promote system-wide travel time savings.

- **Departure times:** AVs in a coordinated and controlled system could lead to reliable travel times, which could eliminate the need to plan for contingency time. For example, if system wide optimization virtually guarantees your travel time to be a certain amount, you would be less likely to leave your origin early, which you might normally do to afford time for traffic or other unforeseen slow-downs in the route. This could have a widespread effect on departure times. Additionally, highly coordinated ridesharing during heavy traffic hours could optimize trip distribution over the period to help avoid congestion. Finally, departure times for the delivery of goods or inanimate objects could be shifted to periods of low traffic.

13.1.3 System Performance

13.1.3.1 Capacity

- **Vehicle performance:** Roadways could see an increase in capacity due to the elimination of human error, the optimization of driving behavior *(116)*, and the influence of CVs *(115)*. Notably, while the benefits of connectivity may be attained at relatively low penetration rates, some of the benefits of automation are only possible if the entire fleet is automated *(117)*. Assumptions concerning the market penetration of these technologies (provided in Part II) are important in order to assess their impact. These system advancements include:
    - Platooning
    - Weaving/Movement Coordination
    - Reduced Headways *(117)*
    - Faster Speeds
    - String stability in mixed traffic (smoother vehicle spacing that leads to system gains)*(118)*
- **Roadway performance:** Additionally, potential reconstruction of existing infrastructure could lead to further capacity gains, potentially through:
    - Precise lateral control allowing for reduced lane widths and removal of shoulders, which should allow for the addition of more lane miles in the existing right of way
    - Removal of on-street parking that could also provide additional space for new lanes.
- **Intersection performance:** AVs and CVs could potentially produce optimized movement at intersections. Lag time between vehicle acceleration could be minimized, allowing more vehicles to pass through each light phase. Additionally, in an advanced system, traffic signals could be entirely eliminated, with the coordinated crossing of vehicles serving to allow changes in direction *(109)*.
- **Vehicle size:** Vehicle size could be affected, as vehicles that currently carry many in-built safety measures could be reduced in size due to the decrease in collisions *(119)*. Alternatively, size could increase as travelers could opt for larger cars with amenities to pass the time during long trips or to handle multiple passengers *(109)*.
- **Reliability due to fewer collisions**: The prevention of accident-caused traffic disruptions could greatly increase roadway efficiencies and help maintain free flowing traffic.

13.1.3.2 Safety

- **Vehicle accident reductions:** Safety could increase significantly with fewer wrecks on the roadway. Estimates of up to 80% of unimpaired roadway accidents could be avoided through V2V communication

(115), and with the addition of AVs, this could likely go higher.

- **Vehicle/Pedestrian accident reduction:** In the same mode as vehicle accident reduction, vehicle pedestrian accidents should also decrease.
- **Evacuation system:** Vehicle coordination in evacuation situations could help save lives after natural disasters or terrorist events and aid transportation of populations away from any disaster area.
- **High-speed chases/fugitive searches:** These could be safer through automated alerts to other vehicles along the route to move away from the activity.
- **Transportation of hazardous materials:** Hazardous cargo could alert other vehicles to maintain a buffer space around transports.

Since there is extensive variability in the potential impacts listed above, the research team selected the key factors that they believed would have the most influence on planning methodologies. To this end, Table 9 summarizes the aspects of planning methodologies that may be affected as a result of changes in human behavior as a response to CAVs, while Table 10 describes changes required to account for the impact of the technologies on the operations and design of the transportation system. The team believes that these factors should be either modeled explicitly, or clearly captured by simplified modeling assumptions when assessing CAV impacts.

Table 9: Behavioral factors to be considered in the modeling of CAVs impacts.

Category	Factor	Response to CAV deployment	Impact
Travel Demand	Trip Making Rates	• Remain unchanged. • Increase.	• Total number of trips.
	Vehicle ownership	• Remains unchanged. • Decreases. • Increases.	• Modal split • Trip making rates
	Residential Choice	• Remain unchanged. • Increased sprawl.	• Location of home-based-trip origins.
	Activity Location Choice	• Remains Unchanged. • Less sensitive to travel time.	• Location of trip destinations.
	Modal Split	• Remains unchanged. • Increased use of ridesourcing (Part II)	• Trips by mode. • Number of vehicles on the road.
Traffic Assignment	Route selection paradigms for CAVs	• Remains unchanged. • User optimal w/ real-time and/or historical information. • System optimal or other.	• Path choice & resulting travel times. • Modal split (indirectly).

Table 10: Technological factors to be considered in the assessment of CAVs impacts.

Category	Factor	Possible Assumptions	Impact
System Performance	Vehicle fleet characteristics	• Remains unchanged. • Decrease in vehicle size • Increase in vehicle size	• Arterial and freeway performance. • Residential location choice (Indirect).
System Performance	Automation	• Optimistic adoption rate for personal vehicles (Part II). • Pessimistic adoption rate for personal vehicles (Part II). • Automation of transit fleet. • Automation of freight fleet.	• Headways. • Traffic control strategies. • Safety. • Indirect: Arterial and highway performance. • Indirect: Modal Split
System Performance	Communications	• Technology adoption. timeline dictated by DSRC deployment. • Technology adoption timeline accelerated through cellular technologies. • V2V. • V2V+V2I. • V2X+Backhaul (enabling centralized data collection and traffic management).	

The following section combines assumptions for the factors described in Tables 9 and 10 in order to define planning scenarios for preliminary modeling exercises.

14 Proposed Planning Scenarios

Different combinations of assumptions regarding the behavior of the factors described lead to distinct planning scenarios. In order to select a representative range of scenarios, researchers distinguish between assumptions that are likely to result in a worse performance of the transportation system, mostly through an increase in vehicle miles traveled (VMT), and those that may lead to predicting improved system performance as a result of operational efficiencies. In Table 11 we have broken out these factors; for simplicity, vehicle ownership decisions are assumed to be reflected by the trip making rates.

Table 11: Classification of modeling assumptions based on expected impact on transportation system

Increase VMT or Reduce Capacity	Improve System Performance
• Increase in sprawl • Decrease in travel-time sensitivity • Increase in trip making rates • Increase in ridesourcing • Increase in vehicle size	• Automation in personal vehicles • Automation in transit • Improved routing paradigms • Vehicle connectivity • Decrease in vehicle size

Optimistic scenarios may be constructed by assuming that all the factors that can potentially lead to worsening the transportation system will remain unchanged, and that all the benefits of vehicle automation are realized. Conversely, pessimistic scenarios will include assumptions that lead to increased VMT and/or reduced capacity. Otherwise, mid-level scenarios can be constructed by combining assumptions for each of the specified factors. Table 12 proposes a list of basic scenarios considered meaningful for the next phases of this project. The table considers four possible combinations of automation and connectivity adoption (corresponding rates are provided in Part II). Scenarios 1-4 represent an optimistic case, or the early-stage impacts of CAVs during which trip making behavior is not significantly affected. Scenarios 5-8, 9-12, and 13-16 progressively incorporate changes in trip making behavior which may be expected as individuals become more comfortable with the new technologies. Additionally, due to potential disruptor influences, Table 13 is included to highlight several more independent variables that may affect the model.

Table 12: Basic Planning Scenarios

	Automation	Connectivity	Route Choice (VMT)	Trip making behavior (VMT)	Capacity
Scenario 1	Optimistic	Optimistic	Same	Same	Same
Scenario 2	Optimistic	Pessimistic	Same	Same	Same
Scenario 3	Pessimistic	Optimistic	Same	Same	Same
Scenario 4	Pessimistic	Pessimistic	Same	Same	Same
Scenario 5	Optimistic	Optimistic	Decrease	Same	Same
Scenario 6	Optimistic	Pessimistic	Decrease	Same	Same
Scenario 7	Pessimistic	Optimistic	Decrease	Same	Same
Scenario 8	Pessimistic	Pessimistic	Decrease	Same	Same
Scenario 9	Optimistic	Optimistic	Decrease	Increase	Same
Scenario 10	Optimistic	Pessimistic	Decrease	Increase	Same
Scenario 11	Pessimistic	Optimistic	Decrease	Increase	Same
Scenario 12	Pessimistic	Pessimistic	Decrease	Increase	Same
Scenario 13	Optimistic	Optimistic	Decrease	Increase	Increase
Scenario 14	Optimistic	Pessimistic	Decrease	Increase	Increase
Scenario 15	Pessimistic	Optimistic	Decrease	Increase	Increase
Scenario 16	Pessimistic	Pessimistic	Decrease	Increase	Increase

More likely as time passes

Table 13: Scenario Variations

Ridesourcing (Part II)	Low/Very High/High
Freight & Transit	No change/Automated
Vehicle size	No change/Increase
Routing Paradigm*	User Equilibrium/User Equilibrium with information/System optimum/other

*These variations are not expected to be considered in the near term due to the modeling complexities.

Different variations of the 16 basic scenarios may be considered depending on assumptions concerning ridesourcing, vehicle size, and the automation of the transit and freight fleets (Table 13), which lead to a total of 112 scenarios. The change in routing paradigms is not included in the final list of scenarios at this point because of the significant research required to meaningfully incorporate it in regional modeling approaches. It may be considered in the latest stages of this project. Using the constructs above, one such plausible planning scenario is shown in Figure 39.

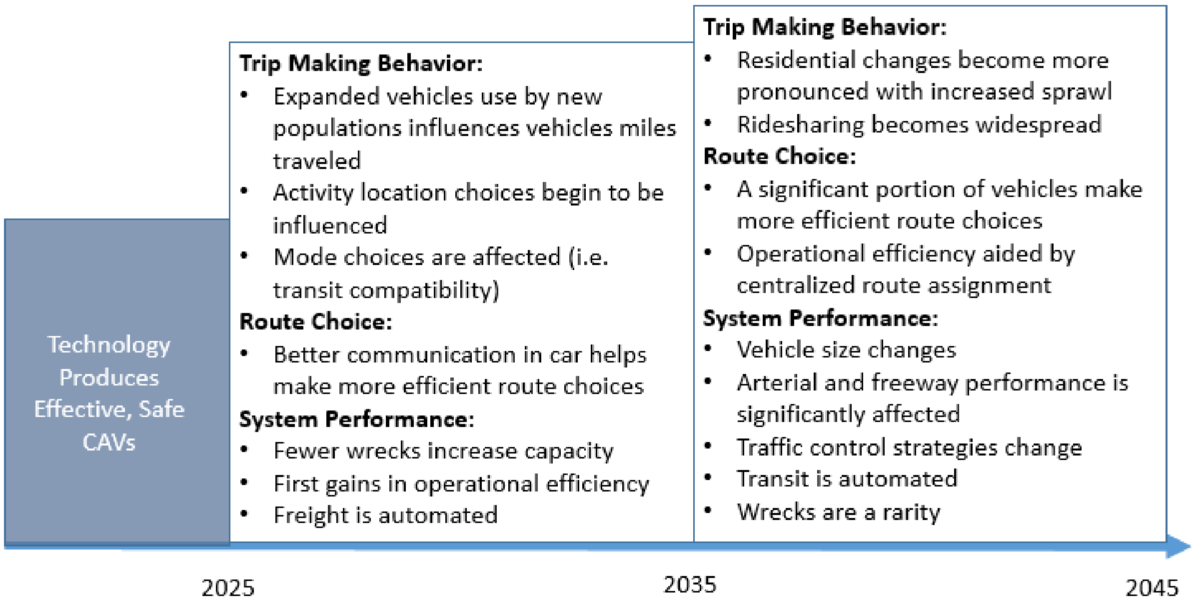

Figure 39: A plausible timeline for evolution of the transportation system under CAVs

Evaluating the proposed scenarios requires mapping assumptions into a meaningful adjustment of modeling inputs or parameters. Given the limitations of existing modeling tools, particular those appropriate for regional-level analysis, significant simplifications will be necessary to represent desired assumptions in early project stages. Table 14 suggests possible modeling approaches when using a traditional four-step model, which may be an appropriate tool for initial assessments.

Table 14: Potential modeling approach using a traditional 4-step model

Automation	• Capacity increase in freeways proportional to the adoption rate • Delay decrease in arterials proportional to adoption rate
Connectivity	• Delay decrease in arterials proportional to adoption rate
Travel Time Sensitivity	• Trip distribution parameters
Trip Making Rates	• Trip generation parameters
Sprawl	• Land use assumptions
Ridesourcing	• Mode choice—may not be able to capture additional VMT due to ridesourcing.
Vehicle size	• Capacity reduction
Freight & transit automation	• To be determined

15 Future Research

Future research includes:

- Specify the details of the methodology to be used to conduct the simplified modeling of the proposed scenarios.
- Provide appropriate values for all required parameters. Study the sensitivity of the model to the value of the parameters, and increase the number of scenarios if considered appropriate.
- Through further modeling, refine the analysis of the range of potential CAV impacts in the NCTCOG region.
- Identify mode limitations and prioritize further research directions to address the issues considered most relevant.

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Appendix A: Industry Car Formulas

Google • Level 4 • Electric Hybrid • 2 people capacity

Market View

Google expects to launch commercially available autonomous vehicles in Spring 2019. However, they are seeking to license their technology to other auto companies. They recently signed an agreement with Chrysler to automate 100 Chrysler minivans. Google see full adoption in 10 years and they predict a ridesharing model.

Cost Projections

Current Total Cost:
$150,000
Projected cost in 5 years:
$10,000

Limitations

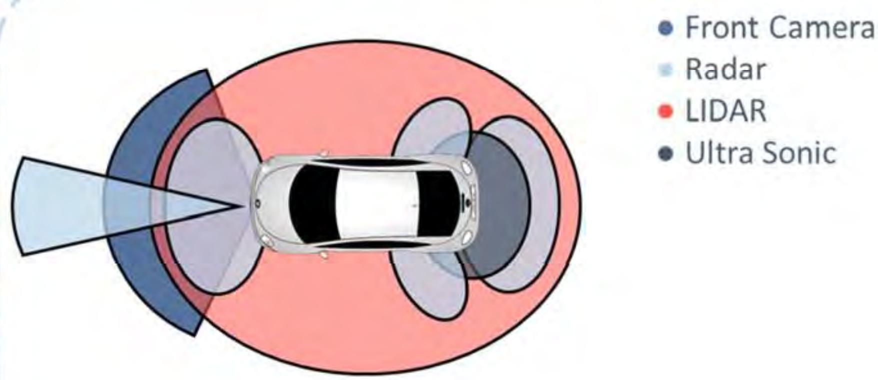
- High accuracy GPS maps must be made before the car can go through an area, changes in actual conditions could have unexpected consequences
- Hasn't driven in cold weather like snow
- Pedestrians are detected as moving, column-shaped blurs of pixels, so what if a police officer is waving for traffic to stop – Google is working on being able to identify this as well

Technology

Communications: 5G
Software: Proprietary system based on grid based occupancy
Sensors:

- LIDAR – 64 lasers beams, camera creates a 3D image of objects helping the car see hazards. Laser can calculate distance and create images for objects in a 200m range
- Two front cameras for lane delineation and traffic sign/landmark identification.
- Bumper Mounted Radar – 4 radars mounted on car's front and rear bumper
- Rear ultrasonic sensors– helps keep track of the movements of the car and alert the car about the obstacles in the rear.
- Inside car – Altimeters (instrument for determining altitude attained), Gyroscopes (), and tachymeters (measuring speed)
- Aerial that reads precise geo-location – car receives information about the precise location of the car aka GPS satellites. GPS data is compared with sensor map data previously collected from same location.

Sensors



SMART
Singapore-MIT Alliance for Research and Technology

• Level 4 • Electric • 4 people capacity

Market View

A team of 25 researchers from the National University of Singapore (NUS) and the Singapore-MIT Alliance for Research and Technology (SMART), which has now received $16 m in venture funding, plan to have a fleet of Level 4 Taxis on the road in Singapore by 2018. This project is backed by the government of Singapore who wants to have the first fleet of self-driving vehicles in the world.

Cost Projections

Current Total Cost:
$23,500
Projected cost in 5 years:
$7,800

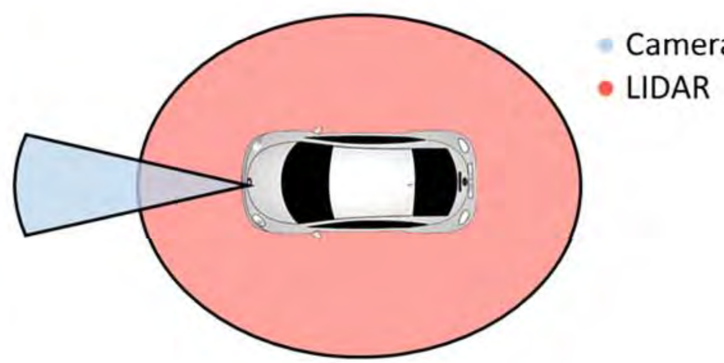
Limitations

- Electric car can only go 62-80 miles on a charge, and a full charge takes 6-8 hours
- Current autonomous mode maxes out at 18 mph

Technology

Communication: V2V enabled
Sensors: SMART relies solely on low cost Lidar and one camer – it is not dependent on GPS
Mobility on Demand: Mobility-on-Demand (MoD) Transportation Model, SMART is building a mobile app that will exemplify the ridesharing model. Users will be able to call for a Taxi and be ferried to their destination without a human ever touching the controls.

Sensors



Mercedes-Benz • Level 3 • Electric Power • 2 people capacity

Market View

Mercedes Benz is test driving Level 3 trucks in European highways, Daimler, their parent company, is testing autonomous trucks in Nevada. In early 2016 Mercedes platooned 3 trucks across Europe, with no drivers in the two following trucks. Currently, these trucks are being tested on public German highways.

Limitations

- Level 3 automation keeps the need for a human driver when not on the highway
- Level 3 has to give ample warning for the driver to safely resume control.
- Public perception may hinder adoption

Technology

Communications: V2V
Software: "Highway Pilot"
Sensors: Radar and Camera sensors
Technology:

- LED Lights go from white to blue when the truck's driving itself and replace the headlights.
- The truck uses platooning and an aerodynamic trailer designed to limit wind resistance and cut fuel consumption by as much as 5 – 15 percent. When platooning, vehicles are separated by only 50 feet (as opposed to the 164 normal separation)
- Doesn't need to check google maps, the truck has a navigation system to independently find the best route.
- The system does not make decisions simply bases on information from its own sensors. Instead, the truck acquires a significant amount of information by exchanging data with other vehicles, infrastructures stationary communication network, and by satellite navigation