University Transportation Research Center - Region 2

Final Report

Risk Analysis of Autonomous Vehicles in Mixed Traffic Streams

Performing Organization: Rowan University

May 2017

Sponsor:
University Transportation Research Center - Region 2

University Transportation Research Center - Region 2

The Region 2 University Transportation Research Center (UTRC) is one of ten original University Transportation Centers established in 1987 by the U.S. Congress. These Centers were established with the recognition that transportation plays a key role in the nation's economy and the quality of life of its citizens. University faculty members provide a critical link in resolving our national and regional transportation problems while training the professionals who address our transportation systems and their customers on a daily basis.

The UTRC was established in order to support research, education and the transfer of technology in the field of transportation. The theme of the Center is "Planning and Managing Regional Transportation Systems in a Changing World." Presently, under the direction of Dr. Camille Kamga, the UTRC represents USDOT Region II, including New York, New Jersey, Puerto Rico and the U.S. Virgin Islands. Functioning as a consortium of twelve major Universities throughout the region, UTRC is located at the CUNY Institute for Transportation Systems at The City College of New York, the lead institution of the consortium. The Center, through its consortium, an Agency-Industry Council and its Director and Staff, supports research, education, and technology transfer under its theme. UTRC's three main goals are:

Research

The research program objectives are (1) to develop a theme based transportation research program that is responsive to the needs of regional transportation organizations and stakeholders, and (2) to conduct that program in cooperation with the partners. The program includes both studies that are identified with research partners of projects targeted to the theme, and targeted, short-term projects. The program develops competitive proposals, which are evaluated to insure the mostresponsive UTRC team conducts the work. The research program is responsive to the UTRC theme: "Planning and Managing Regional Transportation Systems in a Changing World." The complex transportation system of transit and infrastructure, and the rapidly changing environment impacts the nation's largest city and metropolitan area. The New York/New Jersey Metropolitan has over 19 million people, 600,000 businesses and 9 million workers. The Region's intermodal and multimodal systems must serve all customers and stakeholders within the region and globally.Under the current grant, the new research projects and the ongoing research projects concentrate the program efforts on the categories of Transportation Systems Performance and Information Infrastructure to provide needed services to the New Jersey Department of Transportation, New York City Department of Transportation, New York Metropolitan Transportation Council , New York State Department of Transportation, and the New York State Energy and Research Development Authorityand others, all while enhancing the center's theme.

Education and Workforce Development

The modern professional must combine the technical skills of engineering and planning with knowledge of economics, environmental science, management, finance, and law as well as negotiation skills, psychology and sociology. And, she/he must be computer literate, wired to the web, and knowledgeable about advances in information technology. UTRC's education and training efforts provide a multidisciplinary program of course work and experiential learning to train students and provide advanced training or retraining of practitioners to plan and manage regional transportation systems. UTRC must meet the need to educate the undergraduate and graduate student with a foundation of transportation fundamentals that allows for solving complex problems in a world much more dynamic than even a decade ago. Simultaneously, the demand for continuing education is growing – either because of professional license requirements or because the workplace demands it – and provides the opportunity to combine State of Practice education with tailored ways of delivering content.

Technology Transfer

UTRC's Technology Transfer Program goes beyond what might be considered "traditional" technology transfer activities. Its main objectives are (1) to increase the awareness and level of information concerning transportation issues facing Region 2; (2) to improve the knowledge base and approach to problem solving of the region's transportation workforce, from those operating the systems to those at the most senior level of managing the system; and by doing so, to improve the overall professional capability of the transportation workforce; (3) to stimulate discussion and debate concerning the integration of new technologies into our culture, our work and our transportation systems; (4) to provide the more traditional but extremely important job of disseminating research and project reports, studies, analysis and use of tools to the education, research and practicing community both nationally and internationally; and (5) to provide unbiased information and testimony to decision-makers concerning regional transportation issues consistent with the UTRC theme.

Project No(s):
UTRC/RF Grant No: 49198-28-27

Project Date: May 2017

Project Title: Risk Analysis of Autonomous Vehicles in Mixed Traffic Streams

Project's Website:
http://www.utrc2.org/research/projects/risk-analysis-autonomous-vehicles

Principal Investigator(s):
Parth Bhavsar
Assistant Professor
Department of Civil and Environmental Engineering
Rowan University
Glassboro, NJ 08028
Email: bhavsar@rowan.edu

Co Author(s):
Kakan Dey
Assistant Professor
Department of Civil and Environmental Engineering
West Virginia University
Morgantown, WV 26506
Email: kakan.dey@mail.wvu.edu

Mashrur Chowdhury
Professor
Department of Civil Engineering
Clemson University
Greenville, SC 29607
Email: mac@clemson.edu

Plaban Das
Graduate Research Assistant
Rowan University
Glassboro, NJ 08028

Performing Organization(s):
Rowan University

Sponsor(s):
University Transportation Research Center (UTRC)

To request a hard copy of our final reports, please send us an email at utrc@utrc2.org

Mailing Address:

University Transportation Reserch Center
The City College of New York
Marshak Hall, Suite 910
160 Convent Avenue
New York, NY 10031
Tel: 212-650-8051
Fax: 212-650-8374
Web: www.utrc2.org

Board of Directors

The UTRC Board of Directors consists of one or two members from each Consortium school (each school receives two votes regardless of the number of representatives on the board). The Center Director is an ex-officio member of the Board and The Center management team serves as staff to the Board.

City University of New York

Dr. Robert E. Paaswell - Director Emeritus of UTRC
Dr. Hongmian Gong - Geography/Hunter College

Clarkson University
Dr. Kerop D. Janoyan - Civil Engineering

Columbia University
Dr. Raimondo Betti - Civil Engineering
Dr. Elliott Sclar - Urban and Regional Planning

Cornell University
Dr. Huaizhu (Oliver) Gao - Civil Engineering

Hofstra University
Dr. Jean-Paul Rodrigue - Global Studies and Geography

Manhattan College
Dr. Anirban De - Civil & Environmental Engineering
Dr. Matthew Volovski - Civil & Environmental Engineering

New Jersey Institute of Technology
Dr. Steven I-Jy Chien - Civil Engineering
Dr. Joyoung Lee - Civil & Environmental Engineering

New York Institute of Technology
Dr. Marta Panero - Director, Strategic Partnerships
Nada Marie Anid - Professor & Dean of the School of Engineering & Computing Sciences

New York University
Dr. Mitchell L. Moss - Urban Policy and Planning
Dr. Rae Zimmerman - Planning and Public Administration
Dr. Kaan Ozbay - Civil Engineering
Dr. John C. Falcocchio - Civil Engineering
Dr. Elena Prassas - Civil Engineering

Rensselaer Polytechnic Institute
Dr. José Holguín-Veras - Civil Engineering
Dr. William "Al" Wallace - Systems Engineering

Rochester Institute of Technology
Dr. James Winebrake - Science, Technology and Society/Public Policy
Dr. J. Scott Hawker - Software Engineering

Rowan University
Dr. Yusuf Mehta - Civil Engineering
Dr. Beena Sukumaran - Civil Engineering

State University of New York
Michael M. Fancher - Nanoscience
Dr. Catherine T. Lawson - City & Regional Planning
Dr. Adel W. Sadek - Transportation Systems Engineering
Dr. Shmuel Yahalom - Economics

Stevens Institute of Technology
Dr. Sophia Hassiotis - Civil Engineering
Dr. Thomas H. Wakeman III - Civil Engineering

Syracuse University
Dr. Riyad S. Aboutaha - Civil Engineering
Dr. O. Sam Salem - Construction Engineering and Management

The College of New Jersey
Dr. Thomas M. Brennan Jr - Civil Engineering

University of Puerto Rico - Mayagüez
Dr. Ismael Pagán-Trinidad - Civil Engineering
Dr. Didier M. Valdés-Díaz - Civil Engineering

UTRC Consortium Universities

The following universities/colleges are members of the UTRC consortium.

City University of New York (CUNY)
Clarkson University (Clarkson)
Columbia University (Columbia)
Cornell University (Cornell)
Hofstra University (Hofstra)
Manhattan College (MC)
New Jersey Institute of Technology (NJIT)
New York Institute of Technology (NYIT)
New York University (NYU)
Rensselaer Polytechnic Institute (RPI)
Rochester Institute of Technology (RIT)
Rowan University (Rowan)
State University of New York (SUNY)
Stevens Institute of Technology (Stevens)
Syracuse University (SU)
The College of New Jersey (TCNJ)
University of Puerto Rico - Mayagüez (UPRM)

UTRC Key Staff

Dr. Camille Kamga: *Director, UTRC*
Assistant Professor of Civil Engineering, CCNY

Dr. Robert E. Paaswell: *Director Emeritus of UTRC and Distin*guished Professor of Civil Engineering, The City College of New York

Dr. Ellen Thorson: *Senior Research Fellow*

Penny Eickemeyer: *Associate Director for Research, UTRC*

Dr. Alison Conway: *Associate Director for Education*

Nadia Aslam: *Assistant Director for Technology Transfer*

Dr. Wei Hao: *Post-doc/ Researcher*

Dr. Sandeep Mudigonda: *Postdoctoral Research Associate*

Nathalie Martinez: *Research Associate/Budget Analyst*

Tierra Fisher*: Office Assistant*

Andriy Blagay: *Graphic Intern*

TECHNICAL REPORT STANDARD TITLE PAGE

1. Report No.	2.Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Risk Analysis of Autonomous Vehicles in Mixed Traffic Streams		5. Report Date May 2017 6. Performing Organization Code
7. Author(s) Parth Bhavsar, Rowan University Kakan Dey, West Virginia University Mashrur Chowdhury, Clemson University Plaban Das, Rowan University		8. Performing Organization Report No.
9. Performing Organization Name and Address Rowan University		10. Work Unit No. 11. Contract or Grant No. 49198-28-27
12. Sponsoring Agency Name and Address University Transportation Research Center The City College of New York 137th Street and Convent Ave, New York, NY 10031		13. Type of Report and Period Covered Final, 6/1/15 - 5/31/17 14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

The objective of this study was to identify the risks associated with the failure of autonomous vehicles in mixed traffic streams and develop strategies to minimize these risks.

Three distinct and interconnected phases were used to conduct the risk analysis; i) risk identification, ii) risk estimation and iii) evaluation. To identify the risks, the autonomous vehicle system was first disintegrated into vehicular components (i.e., sensors, actuators and communication platforms). Because an autonomous vehicle will share the roadways with human drivers for many years after their deployment, transportation infrastructure components play an important role in the final risk analysis.

A fault tree model was developed for each vehicular component failure and each transportation infrastructure component failure. The failure probabilities of each component were estimated by reviewing relevant literature and publicly available data. The fault tree analysis revealed the autonomous vehicle failure probability to be about 14% resulting from a sequential failure of vehicular components (i.e., particularly those responsible for automation) in the vehicle's lifetime. Subsequently, the failure probability due to autonomous vehicle components and due to transportation infrastructure components were combined. An overall failure probability of 158 incidents per 1 million miles of travel was determined possible as a result of malfunctions or disruptions in vehicular or infrastructure components, respectively. To validate the results, real-world data from the California Department of Motor Vehicles autonomous vehicle testing records were utilized in this study.

The most critical combinations of events that could lead to failure of autonomous vehicles, known as minimal cut-sets, were also identified and ranked based on their corresponding failure probabilities. Based on the fault tree analysis, 22 strategies were identified that would minimize the failure probability of autonomous vehicles. Finally, these identified strategies were evaluated using benefit-cost analysis.

17. Key Words Autonomous vehicles, mixed traffic streams, risk analysis, fault tree analysis		18. Distribution Statement	
19. Security Classif (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No of Pages 57	22. Price

Form DOT F 1700.7 (8-69)

DISCLAIMER

ACKNOWLEDGEMENT

This research project was supported by a grant from the Region 2 University Transportation Research Center (UTRC).

EXECUTIVE SUMMARY

Autonomous vehicles are expected to revolutionize the future transportation system by automating driving tasks, thereby eliminating driver-related, accident-causing factors, such as inattention, fatigue and driving under the influence of drugs or alcohol. Autonomous vehicles rely on various sensors, actuators, and communication platforms to sense the roadway infrastructure and other road users. The continuous evolution in computing, sensing, and communication technologies can improve the performance of autonomous vehicles. Although the automotive companies are racing to be the first to sell autonomous vehicles to the public, a new combination of sophisticated computing and communication technologies will present new challenges, such as interaction of autonomous vehicles with non-autonomous vehicles. It is essential to address these potential safety risks before mass implementation of autonomous vehicles. A comprehensive risk analysis of autonomous vehicles in mixed traffic streams, designed to explore the root causes of potential failure, could lead to safe and reliable autonomous vehicles. The objective of this study was to identify the risks associated with the failure of autonomous vehicles in mixed traffic streams and develop strategies to minimize these risks.

Three distinct and interconnected phases were used to conduct the risk analysis; i) risk identification, ii) risk estimation and iii) evaluation. To identify the risks, the autonomous vehicle system was first disintegrated into vehicular components (i.e., sensors, actuators and communication platforms). Because an autonomous vehicle will share the roadways with human drivers for many years after their deployment, transportation infrastructure components play an important role in the final risk analysis.

A fault tree model was developed for each vehicular component failure and each transportation infrastructure component failure. The failure probabilities of each component were estimated by reviewing relevant literature and publicly available data. The fault tree analysis revealed the autonomous vehicle failure probability to be about 14% resulting from a sequential failure of vehicular components (i.e., particularly those responsible for automation) in the vehicle's lifetime. Subsequently, the failure probability due to autonomous vehicle components and due to transportation infrastructure components were combined. An overall failure probability of 158 incidents per 1 million miles of travel was determined possible as a result of malfunctions or disruptions in vehicular or infrastructure components, respectively. To validate the results, real-world data from the California Department of Motor Vehicles autonomous vehicle testing records were utilized in this study.

The most critical combinations of events that could lead to failure of autonomous vehicles, known as minimal cut-sets, were also identified and ranked based on their corresponding failure probabilities. Based on the fault tree analysis, 22 strategies were identified that would minimize the failure probability of autonomous vehicles. Finally, these identified strategies were evaluated using benefits-costs analysis.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION

Transportation systems and services have constantly evolved throughout history. Individuals used horses as the primary mode of transportation for many years (*1*). The first steam engine automobile was demonstrated in 1801 in England. These first-generation automobiles had the same speed as horses (*1*). With the invention of the combustion engine, automobiles became more efficient to travel from one place to another with faster speeds (*1*). However, automobiles were not as safe as riding horses because horses can be tamed, while automobiles would have mechanical issues as well as crashes due to human errors. The National Highway Traffic Safety Administration (NHTSA) reported 90 deaths per day in 2013 due to traffic crashes on U.S. highways, with distracted driving responsible for nine deaths out of the 90 (*2*). Identifying causes due to these crashes and finding their solutions are challenging as human behavioral factors are responsible for 94% of all road crashes in the U.S. (*3*). Furthermore, researchers have found that skilled drivers with advanced driver training and education, are prone to take high risks which can lead to significantly higher number of crashes than those attributed to most drivers (*4*). Thus, by eliminating the human driver, an autonomous vehicle can significantly reduce the probability of crashes and fatalities on U.S. highways. Fagnant and Kockelman (*5*) predicted that autonomous vehicles could eliminate more than 4 million crashes and save more than 21,000 lives per year with a 90% market penetration.

An increased use of automobiles in the 21st century is causing congested roadways. The American Society of Civil Engineers' (ASCE) report card for the year 2014 stated a loss of $160 billion in time and fuel consumption due to traffic congestion, which is higher than the combined total of the annual gross domestic product (GDP) of 130 countries (*6; 7*). In addition to the loss of revenue and resources, congested conditions on any roadway have a tendency to increase risky driving behaviors (*8*). One of the solutions to reduce congestion and increase safety is the introduction of autonomous vehicles to existing vehicle fleets. Automotive companies and academic researchers have been developing and testing autonomous vehicle technologies to improve the safety and efficiency of surface transportation systems.

Autonomous vehicles have the potential to become a safe, sustainable, and personal mode of transportation. However, these vehicles are equipped with highly tuned sensors and actuators, which are responsible for their autonomous navigation. Despite the many benefits of autonomous vehicles, these advanced components create a new set of challenges. Hence, it is necessary to evaluate these technologies before implementation. Furthermore, it is also necessary to identify strategies to integrate autonomous vehicles into current streams of traffic. According to disengagement reports submitted to the California Department of Motor Vehicles (CA DMV) by various original equipment manufacturers (OEMs) who are testing autonomous vehicles, other non-autonomous vehicles driven by human drivers were the primary cause for a significant number of incidents (*9-13*). Table 1 presents a summary of crashes from recent reports. These reports also include disengagement incidents in which the operator disengages autonomous driving and controls the vehicle manually. About 2,700 disengagements were reported because of unexpected autonomous driving situations such as potholes, poor lane markings, construction zones, and adverse road weather conditions (*14-16*). In addition, various hardware and software systems responsible for autonomous driving are also prone to disruptions and/or hacking. Researchers recently developed a system consisting of low-power lasers and a pulse generator that can mislead autonomous vehicle sensors such as LIDAR into seeing objects where none exist (*17*). Researchers also demonstrated that hackers could remotely take over the control of autonomous vehicle brakes, accelerators, and other critical safety components (*18*). Considering potential risks during the transition phase (i.e., from conventional vehicles to 100% autonomous vehicles in the transportation system) as well as the vulnerability of other vehicular and communication technologies, it is essential to evaluate the failure risks of autonomous vehicles. This study focuses on the transition phase in which autonomous vehicles will become a part of the current traffic mix of conventional vehicles.

Table 1: California DMV Autonomous Vehicle Crash Report

Automobile Company	Year	Autonomous Vehicle Information	Other Party Information
GM Cruise LLC	May 2017	Moving	Bicyclist rear ended the autonomous vehicle
Google Auto LLC	March 2017	Moving	Human driver rear-ended while creeping forward with traffic at red light
GM Cruise LLC	March 2017	Stopped in traffic	Human driver clipped the front of autonomous vehicle while turning
GM Cruise LLC	March 2017	Moving	Human driver rear-ended after traffic light turned green
Google Auto LLC	December 2016	Moving	Human driver collided into autonomous vehicle side doors while making left turn
Google Auto LLC	October 2016	Moving	Human driver rear-ended at a yield sign
Google Auto LLC	September 2016	Moving	Human driver violated red light and collided with right side of autonomous vehicle
Google Auto LLC	September 2016	Stopped in traffic	Human driver rear-ended autonomous vehicle while it was yielding to oncoming vehicles

The remainder of this report is organized as follows: In the next section, a review on autonomous vehicle architecture is summarized along with the diverse autonomous vehicle risk analysis methods used by other researchers. In Section 3, the proposed research methodology is presented. Risk identification is included in Section 4 and development of fault trees and risk estimation results are discussed in Section 5. The fault tree models are evaluated with real-world data and presented in Section 6. Section

7 presents risk minimization strategies and a benefits-costs analysis. Finally, conclusions along with the limitations of this study are provided in Section 8.

1.1 Objectives

The primary objective of this research is to perform a detailed risk analysis of autonomous-connected vehicles in a mixed traffic stream. The overall scopes of this detailed risk analysis:

1) to determine the hierarchical sequences of events that may result in the failure of an autonomous vehicle due to either vehicular component failures or infrastructure component failures,
2) to develop the strategies to minimize risks related to autonomous vehicles , and
3) to perform a benefit-cost analysis to determine the most economical measures to minimize risks of autonomous vehicles.

2. LITERATURE REVIEW

2.1 System Disassembly

To identify the potential risks related to a system, the first step is to divide the whole system into basic components. A detailed behavior analysis for each basic component was performed to establish the relationships between the components and overall system performance in this research. An analysis of the more sensitive components was especially helpful in developing a detailed risk assessment. However, to prepare for the behavior analysis, the research team had to first conduct a thorough literature search to identify and establish the relationships between failures of the autonomous vehicles and causal factors. This information was utilized to develop the fault trees on autonomous vehicle failure.

The exponential growth of processor speeds and availability of affordable and efficient sensors assisted the development of the machine vision-based autonomous navigation system. Researchers have explored several technologies such as LIDAR (light detection and ranging), radar, camera vision, and acoustics to develop viable and economic solution for autonomous driving (*19-21*). Among them, LIDAR is the most widely used sensor. This sensor collects kinematical and physical information about the surroundings (*22*). Radar transmits radio waves into the environment to scatter back information on obstacles around the vehicle to be aware of other vehicles ahead and behind including fixed objects. This sensor keeps a digital eye on the other cars and instructs the system to speed up or slow down depending on the behavior of other drivers. It also assists the automotive parking feature. To improve self-driving performance and the reliability of autonomous cars, researchers have also utilized high performance computing, fast processing, and high capacity data storage to develop a nearly 360-degree awareness of the surroundings by real-time analysis of collected data from multiple sensors. Furthermore, researchers have integrated the machine-based vision system with GPS, and internal measuring units for better position estimation (*23-25*).

The current advanced driver assistance systems such as adaptive cruise control (ACC), collision warning, automatic braking, a lane departure warning system, and a pedestrian detection system have already been adopted by OEMs and are available in the current vehicle fleet. These features help reduce errors due to drivers and improve safety performance of the conventional vehicle. These features will also be available in an autonomous vehicle as an individual sub-system or an integrated component of an autonomous driving system to improve the safety and performance of autonomous vehicles. Table 2 presents a summary of these features with their benefits on overall transportation systems.

Table 2: Summary of accident causes and solutions through automotive features

Accident causes	Potential Solution	Sensors	Applied Algorithms	Benefits/Improvements
Rear-end collision, monotony driving, driving on long trips	Intelligent adaptive cruise control system	- Radar - LIDAR	Fuzzy logic or neuro-controllers (*26-28*)	- Reduced rear-end collisions - Reduced fuel consumption (1.1 to 10.7% achievable) - Maximum use of highway capacity
Drivers' delay in recognizing/judging the "dangerous" situation	Automotive collision warning/ avoidance system	- Camera vision	Neural network (*29*)	- Reduced crashes - Handle critical situation safely and precisely - Automatic braking
Temporary and involuntary fade of a driver's vision by falling asleep, fatigue, using a mobile phone, and chatting, which causes the vehicles to leave their designated lane	Lane departure warning	- Camera vision - Global positioning system	Particle filtering (*30*), Edge distribution function (*31*)	-Reduced crashes -Prevention of unintentional deviation of vehicles from the center of road - Diagnose road edges even in extreme lighting conditions
Drivers' misjudging the traffic signs and signals, or disobey them while approaching to the intersection	Intersection collision avoidance system	- Camera vision - Loop detector - Radar	Neural network (*32*)	- Reduced intersection collisions - Safe intersection movements
Lack of speed control while driving, inappropriate steering wheel angle, unsafe driving under unfavorable conditions	Electronic stability control	- Wheel encoder - LIDAR - Radar	Fuzzy logic PID controller (*33*)	- Reduced crashes - Improved lateral stability of vehicles in extreme conditions
Unsafe pedestrian road crossings, inattentive driving, delay in response	Pedestrian detection system	- Camera vision - Infrared sensors	Shape analysis (*34*), Probabilistic human template (*35*), Gabor filters and support vector mechanics (*36*), Neural networks (*37*)	-Detect pedestrian movement - Guide the vehicles to a safe route based on pedestrian movements

2.2 Risk Analysis of Autonomous Vehicles

Risk analysis of autonomous vehicles identifies undesirable events and sequences of events leading to autonomous navigation failure, which could lead to road crashes, passenger fatalities, pedestrian injuries, vehicle damage, and property damage. Risk analysis methods can be categorized into three different classes: i) situation-based analysis, ii) ontology-based analysis, and iii) fault tree analysis.

Researchers have used situation-based risk analysis to predict the probability of collisions between approaching vehicles in mixed (autonomous and non-autonomous vehicles combined) traffic streams, where risks or threats are identified based on the knowledge of similar previous events (*38-42*). The ontology based approach includes a hierarchical semantic network of basic entities and basic events generated from their interrelationships (*43; 44*).

The fault tree based approach focuses on determining potential causes of failure of the system that may result in a safety hazard or economic loss. The fault tree analysis method encourages analysis to contemplate how a particular component could impact the overall performance of the system and seeks to identify the causes of undesired events (*45*). However, to understand the cause-effect process, a thorough review of the overall system is required (*46*). After the Challenger incident in 1986, the National Aeronautics and Space Administration (NASA) emphasized performing quantitative risk or reliability analysis using the fault tree method for its space missions' safety assessments (*47*). Researchers have utilized this method to assess the safety and reliability of construction, design and implementation for high-risk industries including aircraft manufacturers, (*48*), nuclear power plants, (*49*), and industrial plants. Moreover, the fault tree analysis is used to assess the potential for many other fields, such as the petrochemical industries (*50; 51*), bridge failure analysis (*52*), construction management (*53*), toxic goods transport (*54*), hazardous site management (*55*), and medicine industries (*56*).

Fault tree analysis has been used in risk assessments of autonomous vehicle features (i.e., features that are solely responsible for converting a traditional vehicle into an autonomous vehicle). Swarup and Rao disassembled the adaptive cruise control (ACC) system of an autonomous vehicle and investigated the causes of failures using the fault tree analysis method (*57*). In another study, Duran and Zalewski investigated the causes and effects of failures related to LIDAR and dual camera-based computer vision systems (*58*). The overall summary of different approaches conducted so far is summarized in Table 3.

Table 3: Summary of risk analysis techniques utilized for autonomous vehicles since 2006

Analysis Types	Authors	Parameters Considered	Algorithms	Limitations
Situation Based	Hillenbrand et al., 2006 (*38*)	Rear-end collision and crossing collision at intersection	Monte Carlo	- Only applicable for simple intersections - Risks from vehicular components were not considered
	Laugier et al., 2011 (*39*)	Collision risk assessment based on multiple sensors data	Hidden Markov Model and Gaussian Process	- High prices of multiple on-board sensors - High computation power required for parallel processing
	Martin, 2013 (*59*)	Interaction with other drivers on multilane highways	Game theory	- Only valid when each driver knows all possible trajectories and destinations of other drivers
	Platho et al., 2012 (*60*)	Road users and surrounding entities affecting users	Bayesian network	- Entities were separated from each other - Could fail in complex situations with multiple entities
	Furda and Vlacic, 2011 (*61*)	Attributes based on priori information, sensor measurements and V2X communication	Multi-criteria decision making (MCDM)	- Limited driving maneuvers were considered - High computational power required for real-time decision making
Ontology Based	Armand et al., 2014 (*43*)	Different relationships between design vehicle and various road entities (pedestrians, other vehicles, infrastructures, etc.)	Ontology framework	- Limited real-time applications - Depends on the frequency of GPS receiver - Not compatible for every driving scenario.
	Hulsen et al., 2011 (*62*)	Roads, lanes, traffic signs, traffic lights, and other road users	Ontology framework	- Fixed road geometry was considered without incorporating uncertainties - Qualitative analysis - Was not evaluated in real-world, only tested in simulation
	Pollard et al., 2013 (*63*)	Vehicle perception, visibility condition, weather, traffic signs and road types.	Ontology framework	- Separate model based on level of automation - High computational power required
	Kaloskampis et al., 2015 (*44*)	Estimation of risks related to pedestrian behavior using camera feeds	Ontology framework, Gaussian mixture model	- Other road users, weather conditions and road surfaces were not considered in study - Data from video feeds will require high computational power
Fault Tree Based	Swarup and Rao, 2015 (*57*)	Identification of potential threats of adaptive cruise control	Fault tree	- Qualitative analysis - Impacts of each cause were not ranked
	Duran and Zalewski, 2013 (*58*)	Risks associated to LIDAR and camera vision were investigated	Fault tree and Bayesian belief networks	- Other vehicular components were not included - Limited to vehicular components

3. METHOD

The research team adopted three distinct and interconnected phases as identified by White (*64*) to conduct risk analyses of autonomous vehicles in this research. They were:

i) risk identification,
ii) risk estimation, and
iii) evaluation of the fault-tree model.

The first crucial step in performing a risk analysis is risk identification of autonomous vehicle failure, which consists of compilation of different types of autonomous vehicle failure information including: i) the nature and extent of the failure sources, ii) the chain of events, iii) pathways and processes that connect the cause to the effect, and iv) the relationship between risk sources and impacts (*65*). Risk estimation can be performed by various analysis methods. In this study, the research team utilized the fault-tree analysis method. Then, the results of fault tree analysis were validated by comparing them with real-world data. Figure 1 illustrates the research approach adopted for conducting this risk analysis in this study. Based on the results of the analysis, risk minimization strategies were identified to minimize the risks related to autonomous vehicles. Finally, these risk minimization strategies were evaluated with benefits-costs analysis.

The autonomous vehicle in this study is defined as a fully autonomous passenger car or a similar vehicle (which closely represents Level 4 automation as defined by the National Highway Transportation Safety Association (NHTSA)[1] or Level 5 automation as defined by Society of Automotive Engineers (SAE)[2]) (*66; 67*) and does not include transit or other type of on- or off-the-road vehicles.

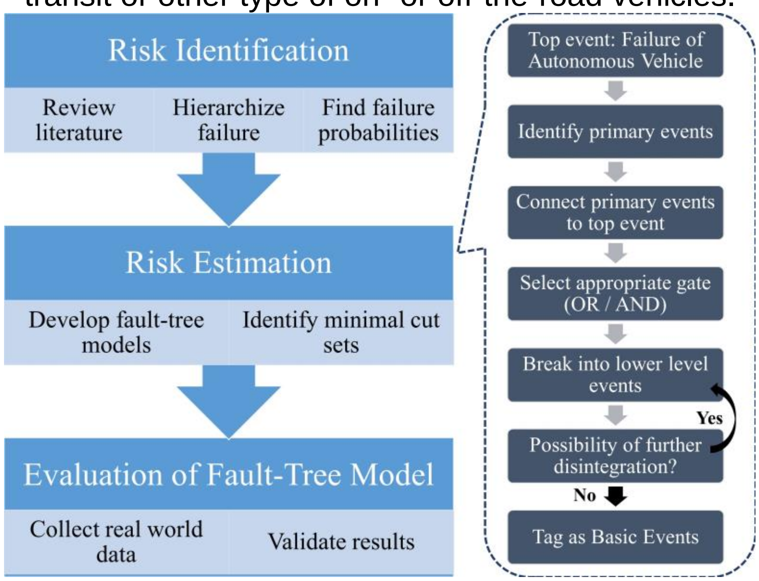


Figure 1: Research Methodology for autonomous vehicle risk analysis

1. NHTSA: In Level 4 automation, the vehicle can navigate, perform all driving control functions and monitor the roadway for an entire trip without any intervention of human driver.
2. SAE: In Level 5 automation, automated driving system can perform all aspects of dynamic driving task under all roadway and environmental conditions.

4. RISK IDENTIFICATION

Risk identification included disassembling the autonomous vehicle system into individual components, and analyzing the behavior of these components to determine the failure rate for each component. This task was divided into two sub-tasks:

1. Probability estimation through a literature search
2. Interview of experts to revise literature review conclusion

4.1 Probability Estimation through Literature search

This study's researchers conducted a literature review of published reports, peer-reviewed conference and journal papers, and other published materials to develop hierarchical and logical relationships between the top-level event (i.e., failure of an autonomous vehicle) and different autonomous vehicle components. It is expected that the transition from conventional vehicles (i.e., non-autonomous) to an autonomous vehicles will likely go through a gradual change over a long period (i.e., 5-10 years) in a regional surface transportation system (*68*). This suggests that autonomous vehicles will share the roadway with conventional vehicles such as cars, transit buses, trucks, as well as bicycle riders, motorcyclists, and pedestrians.

The risk identification process was divided into two sub-categories to estimate failure risks of autonomous vehicles due to different vehicular components and transportation infrastructure components. The first category focused on identifying system failures from autonomous vehicular components. The second category focused on identifying threats from infrastructure components, including threats from other non-autonomous vehicles.

4.1.1 Autonomous Vehicle Components

All vehicular components were divided into four major subsystems: hardware, software, communication, and human-machine interface. The sensors utilized to sense the roadways, such as LIDAR, GPS, wheel encoders, and the integration platform were included in the hardware subsystem, whereas the software subsystem consisted of data collection and processing software required for sensors and autonomous navigation. Vehicle-to-vehicle (V2V) or vehicle to infrastructure (V2X) communication platforms were included in the communication subsystem, and a human machine interface subsystem included a personal assistant system that filters the human voice for commands to control various autonomous driving functions. In this study, specific technologies that convert a conventional human operated vehicle into an autonomous vehicle, were considered. For example, LIDAR, the primary technology being used for autonomous navigation, can fail for several reasons, including laser malfunction and electrical failures (*58*). Camera vision is another important component on an autonomous vehicle, capable of providing physical information about surroundings (e.g., obstacles, road signs, and pedestrians). This system could fail due to misalignment, missing filter, dirty or damaged lens, and even improper lighting. The failure probability for each component along with reasons of failure are summarized in Table 4 based on a literature review. Failures of the vehicle's mechanical system were not in the scope of this study as it is not a part of the system that converts a conventional vehicle into an autonomous vehicle.

Table 4: Failure probabilities of autonomous vehicular components

Basic Events	Description	Methods	Experiment Type	Failure Probability (%)
LIDAR failure	Laser malfunction, mirror motor malfunction, position encoder failure, overvoltage, short-circuit, optical receiver damages.	Bayesian belief network	Simulation	10.0000% (*58*)
Radar failure	Detection curves drawn with respect to signal and noise ratios	Chi-square distribution	Mathematical modeling	20 000% (*69*)
Camera failure	Foreign particles, shockwave, overvoltage, short-circuit, vibration from rough terrain, etc.	Bayesian belief network	Simulation	4.9500% (*58*)
Software failure	System had to generate outputs from array definition language (ADL) statements	Extended Markov Bayesian network	Experiment (3000 runs)	1.0000% (*70*)
Wheel encoder failure	Encoder feedback unable to be transferred, which can cause loss of synchronization of motor stator and rotor positions	Kalman filter	Experiment	4.0000% (*71*)
GPS failure	Real-life tests performed with high sensitivity GPS in different signal environments (static and dynamic) for more than 14 hours	Least squares	Experiment (at 4 different locations)	0.9250% (*72*)
Database service failure	Using a new empirical approach, connectivity and operability data of a server system was collected	Generic Quorum-system evaluator (GQE)	Experiment (for 191 days)	3.8600% (*73*)
Communication failure	Wi-Fi: Periodic transmission of 1000-byte frames (average conditional probability of success after previous success considered)	In IEEE 802.11b network	Experiment (with 10 vehicles)	5.1250% (*74*)
	Possible LTE: Network unavailability during location update in mobility	Application of CAP theorem	Experiment	5.8800% (*75*)
Integrated platform failure	A two-state model with failure rates was developed to estimate the computer system availability	Markov chain model	Mathematical modeling	2.0000% (*76*)
Human command error	Analyzed NASA datasets from over 115 months; then validated by THERP, CREAM, and NARA	Human Reliability Analysis	Experiment (from December 1998 to June 2008)	0.0530% (*77*)

Basic Events	Description	Methods	Experiment Type	Failure Probability (%)
System failed to detect human command	System unable to detect accurate acoustic command: Driver inputs wrong command, and system unable to detect it.	Artificial neural networks (ANNs) on clean speech	Experiments (37 subjects: 185 recording)	1.4000% (*78*)

4.1.2 Transportation Infrastructure Components

Failure of the autonomous vehicle due to the surrounding infrastructure including other non-autonomous vehicles (i.e., human drivers) and transportation infrastructure components play an important role in the risk analysis. According to reports submitted by companies conducting the testing of autonomous vehicles, most crashes are due to human drivers sharing the road with autonomous vehicles (9–13). The non-autonomous vehicle driver errors will be a major issue at a low market penetration level of autonomous vehicles in mixed traffic streams. Crash records related to reckless driving, distraction, vehicle breakdown and tiredness, and incidents rate due to poor weather and road conditions were collected from the Virginia Department of Transportation (VDOT) and New York State Department of Transportation (NYSDOT) traffic crash reports involving non-autonomous vehicles (51, 52). The market penetration rate of 10% autonomous vehicles was assumed to calculate the failure probability of an autonomous vehicle traveling in a mixed traffic stream. To consider the worst-case scenario, it is assumed that 10% of total crashes on a roadway will affect the autonomous vehicle navigation in mixed traffic stream.

Data collected from DOTs were converted into crash rate per mile of autonomous vehicle travel to utilize as input (i.e., basic event failure probability) in the fault tree. A sample calculation box is provided in appendix A to present the failure probability calculation for an autonomous vehicle (AV), when it is involved in a crash due to reckless driving, tiredness or distraction from a non-autonomous vehicle (non-AV) driver.

Traffic crashes happened due to bad/poor road conditions were considered in the transportation infrastructure failures. Bicyclists and pedestrians involved in crashes were also analyzed. A study in Hawaii found that 83.5% crashes between motor vehicles and cyclists were caused by motorists and the other 16.5% crashes were caused by cyclists (53). Moreover, weather is a huge deterrent to autonomous vehicles, especially since not many of these autonomous vehicles have been tested in weather conditions other than clear, sunny days. In addition, crashes in construction work zones were considered; particularly rear-end crashes in work zones (54). Failure probabilities of these infrastructure components, as reported in the literature, were used in this paper and are presented in Table 5.

Table 5: Failure pobabilities of basic transportation system infrastructure components

Basic Events	Description	Number of Crashes	Failure Probability (% per Mile)	References
Non-autonomous vehicles crashes	Crashes due to reckless driving, tiredness, hardware and distractions considered	133,901 (per 100 million miles)	0.0134%	(*79; 80*)
Cyclists	Daily nine million bike trips made, and among them crashes where cyclists were responsible are included here.	3,090	4.0897×10^{-6} %	(*81-83*)
Pedestrians	Crashes happened where pedestrians at fault among the annually 42 billion walking trips	8,625	2.9337×10^{-6} %	(*81; 82; 84; 85*)
Construction zones	Among all work zones 41.33% percent were rear-end crashes	36,208	7.6264×10^{-6} %	(*86; 87*)
Weather related incidents	Adverse weather conditions like fog, mist, rain, severe crosswind, sleet, snow, dust/ smoke	22,375 (per 100 million miles)	0.0022%	(*80*)
Road conditions	Crashes related to improper lane marking and pavements conditions	656 (per 100 million miles)	6.5600×10^{-5} %	(*79*)

4.2 Interview Experts to Revise Literature Review Conclusion

The research team aimed to conduct an online survey to seek information related to autonomous vehicle failures from the subject matter experts (SMEs). The questionnaires, invitation email, and consent forms were submitted to the Rowan University Institutional Review Board for approval (Please see Appendix A for approval-letter and approved survey tools). After getting approval, the team collected publicly available contact information of experts in this field. The responses of the survey have been stored anonymously and any personally identifiable information will not be published in any reports and publications.

4.2.1 Online Survey Structure

The research team used the Delphi Survey method to collect the experts' opinion from this survey regarding the failure risk of autonomous vehicle systems. The Delphi Survey is a unique method to facilitate discussion among the experts through multiple questionnaires. It normally consists of more than one round where after each round the participants will review anonymous summary of previous round with their judgments. The experts will be allowed to revise their responses based on the replies of other members in their survey panel. Finally, this process will end when the desired consensus is achieved.

The role of the research team was to lead the interaction among the experts as the steering committee. The experts were grouped into three panels based on their areas of expertise. The three panels were 1) academic researchers' panel, 2) autonomous vehicle industry researchers, and 3) experts' panel to include researchers from automated navigation sensor companies. These groups probably would have different perspectives, so without separating the experts into different panels, it would be impossible to obtain a reasonable degree of consensus. The structural methodology of this survey is shown in Figure 2.

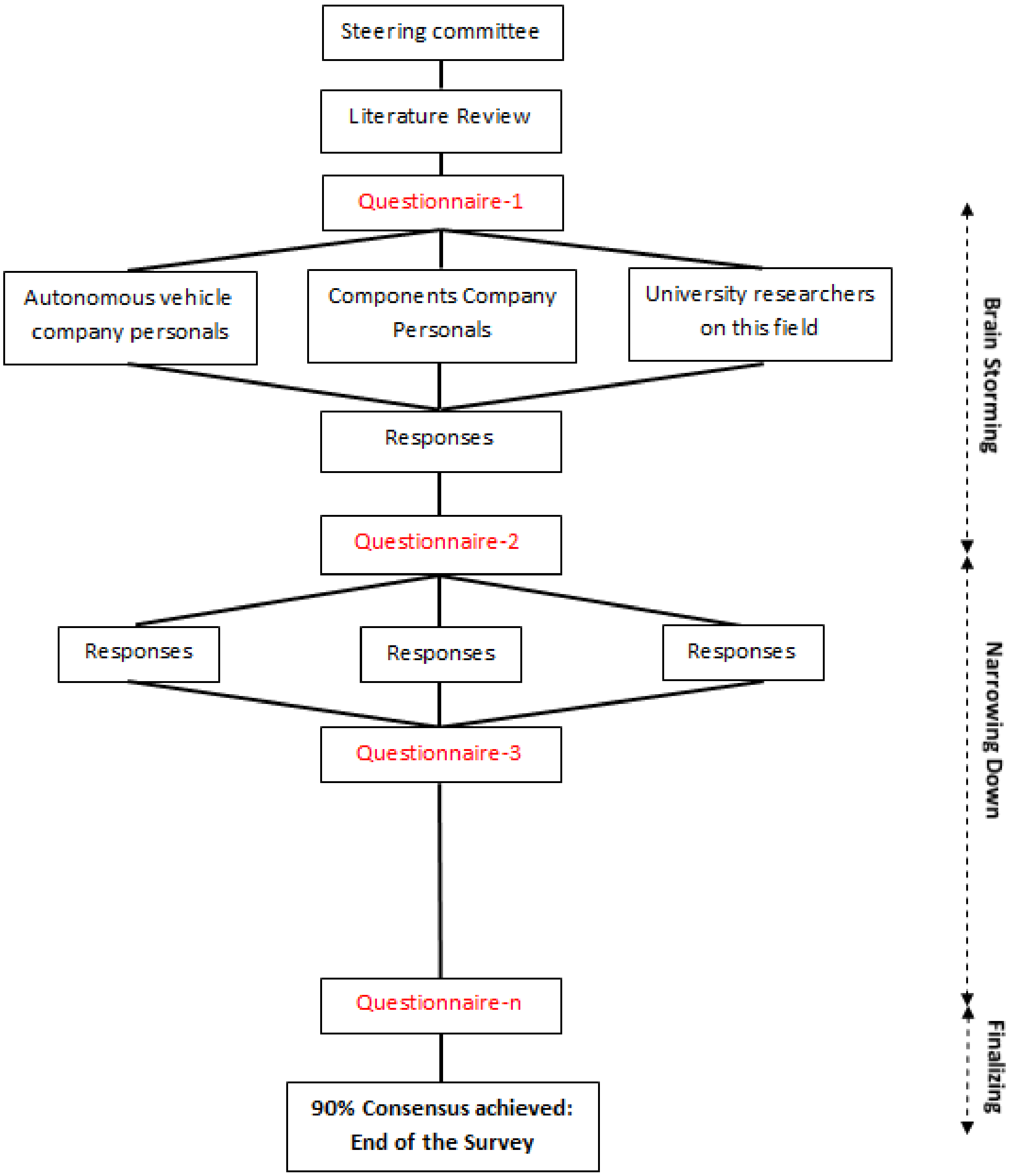


Figure 2: Autonomous Vehicle Delphi Survey Structure

4.2.2 Analysis Survey Results

Many methods can be used to analyze Delphi survey results and calculate the level of consensus. For example, the chi square test, McNemar's change test, the Wilcoxon matched-pairs signed-rank test, Spearman's rank-order correlation coefficient, Kendall's W coefficient of concordance and F tests. In this research, Kendall's W coefficient of concordance was used to measure the level of consensus between two consecutive rounds of Delphi surveys (*88*). Table 6 shows the interpretation of Kendall's W adopted in this study.

Table 6: Interpretation of Kendall's W

Kendall's W	Interpretation
W ≤ 0.3	Weak agreement
0.3 < W ≤ 0.5	Moderate agreement
0.5 < W ≤ 0.7	Good agreement
W > 0.7	Strong agreement

The research team invited a total of 140 people to respond to the first round of surveys. It is important to mention that due to limited responses from invited participants it was not possible to release any further rounds of survey. However, only seven experts responded back in this round, where about 40% of the responders were university researchers, 30% were researchers in industry and another 30% were a manager of a development team. Among these survey participants, about 40% had experience of "more than 9 years" working in the autonomous vehicle research field, and another 25% had "5–9 years" working experience.

The participants were asked to identify the primary sensor failure which could lead to overall autonomous vehicle failure. Among them about 85% of the participants agreed that LIDAR and camera vision could impact the success rate of autonomous vehicle navigation, while 55% believed GPS systems could be vulnerable to failure. The participants varied widely in their selection of failure probabilities for different vehicular components and transportation infrastructure components. For instance, 60% of the participants agreed that the failure probability of LIDAR could be between 3.01 and 6.00%. For camera vision, responses from 20% based their failure probability ratios on three options:1.01 to 3.00%, 3.01 to 6.00%, and 6.01 to 10.00%. The remaining 40% selected "greater than 10.00%." Moreover, 50% of responders selected the failure probability of the wheel encoder to be between 1.01 and 3.00%, where earlier the research team found that the failure probability of the same wheel encoder was 4.00% from their literature review. Even though around 60% thought communication system failure could fail the overall autonomous vehicle system, none held DSRC failure responsible. LTE communication failure was selected instead.

Participants also agreed that autonomous vehicles could be vulnerable to software and human-machine interaction system failures. Among the infrastructure components, the weather, human drivers, cyclists and pedestrians were considered as the reasons for autonomous vehicles failure by the maximum number of participants (about 70%). However, the participants provided a wide range of failure probabilities for these infrastructure components.

The research team utilized the Kendall's W coefficient of concordance to calculate the level of consensus and decided to continue the iteration till strong agreement is achieved (Kendall’s W equals to 0.7 or higher). For instance, 3 out of 5 participants selected 3.01 to 6.00% as the failure probability of LIDAR, and others selected greater than 10.00%.

Null Hypothesis: *There is no agreement among the participants upon the failure probability of LIDAR.*

Alternative Hypothesis: *The participants agreed upon the failure probability of LIDAR.*

For this hypothesis, Kendall’s W was 0.8 for the question concerning LIDAR failure probability. This suggests “strong agreement” among the participants. Also, the one-tailed p-value was 0.00302, which indicates no agreement among the participants to reject the null hypothesis. Detailed calculation is provided in Appendix C.

Similarly, Kendall’s W was calculated for the failure probability of camera vision. The value of W was equal to 0.2 which represents “weak agreement” among the participants. With a one-tailed p-value of 0.41, it is very likely that no agreement was reached among the experts.

4.2.3 Updated Failure Probabilities

The next steps include (1) updating failure probabilities of fault trees developed for this study and (2) obtaining answers of the same questions by informing participants about the updated results of the fault tree. However, due to the very small participant pool, it is not feasible to update the results. The research team decided to identify more participants and continue the survey process, and finally publish those results in reputed journals in future.

5. RISK ESTIMATION

The fault-tree analysis method was utilized to perform risk estimation in this study because of its capability to provide the shortest path to reach the top-level failure from a single component (i.e., basic event) failure. Based on the outcomes of the risk identification phase, fault-tree models were developed. The research team developed two fault trees models: (i) fault tree model for autonomous vehicle failure due to vehicular component failures and (ii) fault tree model for autonomous vehicle failure due to transportation infrastructure plus human failure while using the infrastructure. These models were combined afterward to estimate the overall risk of failure, i.e. failure of an autonomous vehicle in mixed traffic stream.

5.1 Fault Tree for Autonomous Vehicular Component Failures

The fault tree is developed by disintegrating an overall system into a subsystem, which can be further broken down into lower level components/events. This process continues until no further disintegration or division can take place. These terminating events are called “basic events.” The failure of the overall system is referred to as a “top-level event” and the events that link the top-level event with its basic events are called “intermediate/casual events.” The top-level event and basic events are interconnected based on the hierarchical and logical relationships between events that lead to failure of a top event. In a graphical representation of fault tree, these logical relationships are presented as “Gate.” The “AND” and “OR” gates are widely used to illustrate the relationship between input and output events. Risk estimation quantifies the failure rate of the top-level event, and is represented as a percentage in decimal format. This estimation takes all basic events into account and determines the failure rate based on Boolean algebra. The algebraic equations that are performed are determined by the gates used and the statistical model that was used when inputting the basic events.

The first fault-tree model focused on the failure of an autonomous vehicle due to vehicular components. The Isograph FaultTree+ software, which allows various statistical models to model basic event failure probability distribution, was used for the fault tree analysis (*34*). For this study, a “fixed probability” statistical model was used to perform the risk analysis (*34*). After allocating basic event failure probabilities and solving the fault tree, a failure rate of 14.22% was determined for the failure of an autonomous vehicle due to its components’ failure, which means that autonomous vehicle operations could fail 14.22 times over its lifetime due to component failure. It is important to note that the fault tree model included only components that are responsible for autonomous driving such as the LIDAR sensor. Components such as the internal combustion engine was not considered in this study. Figure 3 illustrates the fault tree with failure probabilities including only autonomous vehicle components.

5.2 Fault Tree for Transportation Infrastructure Component Failures

Following the same steps applied in the first fault tree, the second fault tree was constructed for transportation infrastructure components. For this study, components affecting infrastructure included other drivers of conventional vehicles sharing the roadway with autonomous vehicles. The top-level event for the second fault-tree model was “failure of autonomous vehicle due to infrastructure components.” This model included failure of the autonomous vehicle due to other road users, weather, construction zones or road conditions. The infrastructure-focused fault tree is illustrated in Figure 4. It represents a failure probability 0.01571% for the autonomous vehicle based on other road users and infrastructure.

5.3 Combined Fault Tree

The National Aeronautics and Space Administration (NASA) estimates the failure probabilities of basic events by applying different methods, such as experimental estimation and simulation modeling (*89*). Opinions of subject matter experts are also considered in probability estimations (*90*). The risk analysis of NASA’s missions often involves the integration of various risk models, which includes failure probabilities calculated by applying various methods (*89; 90*). Similarly, to estimate the failure probability of an autonomous vehicle traveling in a mixed traffic stream, the research team combined the failure probabilities of autonomous vehicular components and transportation infrastructure components estimated through their respective fault-tree models (illustrated in Figure 5) as described below.

The failure probabilities of individual vehicular components collected from literature are presented in Section 4.1.1; however, when these components become parts/subsystems of an autonomous vehicle, the car manufacturer will ensure that they remain operational throughout the life of the vehicle with periodic health monitoring and maintenance. A typical life time of a conventional vehicle is about 150,000 miles (*91*). Based on this information, it was assumed that the life of an autonomous vehicle is also 150,000 miles, and this assumption was used to estimate an autonomous vehicle failure probability per mile. Given that the overall probability of an autonomous vehicle failure in its lifetime due to vehicular components is 14.22%, the failure probability per mile can be estimated as 0.0000948% (i.e., 14.22%/150,000). However, the failure probability of this vehicle due to transportation infrastructure components is calculated 0.01571% per mile, as mentioned in the previous section. Furthermore, for the combined fault tree, the failure due to vehicular components and failure due to infrastructure components were assumed to be independent of each other, and can be combined with an ‘OR’ gate to estimate the failure probability of an overall autonomous vehicle system. The following equation was used to calculate the failure probability for the top-level event (i.e., failure of autonomous vehicle) of the combined fault tree. The ‘+’ sign in the equation represents the ‘OR’ gate. As shown in the following equation, an autonomous vehicle operation could fail 158 times in 1,000,000 miles of travel due to failure of either vehicular components, or infrastructure components, in a mixed traffic stream. The combined fault tree is shown in Figure 5.

$$P(A) = P(VC) + P(IC) = 0.000000948 + 0.0001571 = 0.000158048 \text{ per mile of travel}$$

where P(A) = overall failure probability of autonomous vehicle system per mile of travel.

P(VC) = autonomous vehicle failure due to vehicular components per mile of travel.

P (IC) = autonomous vehicle failure due to infrastructure components per mile of travel.

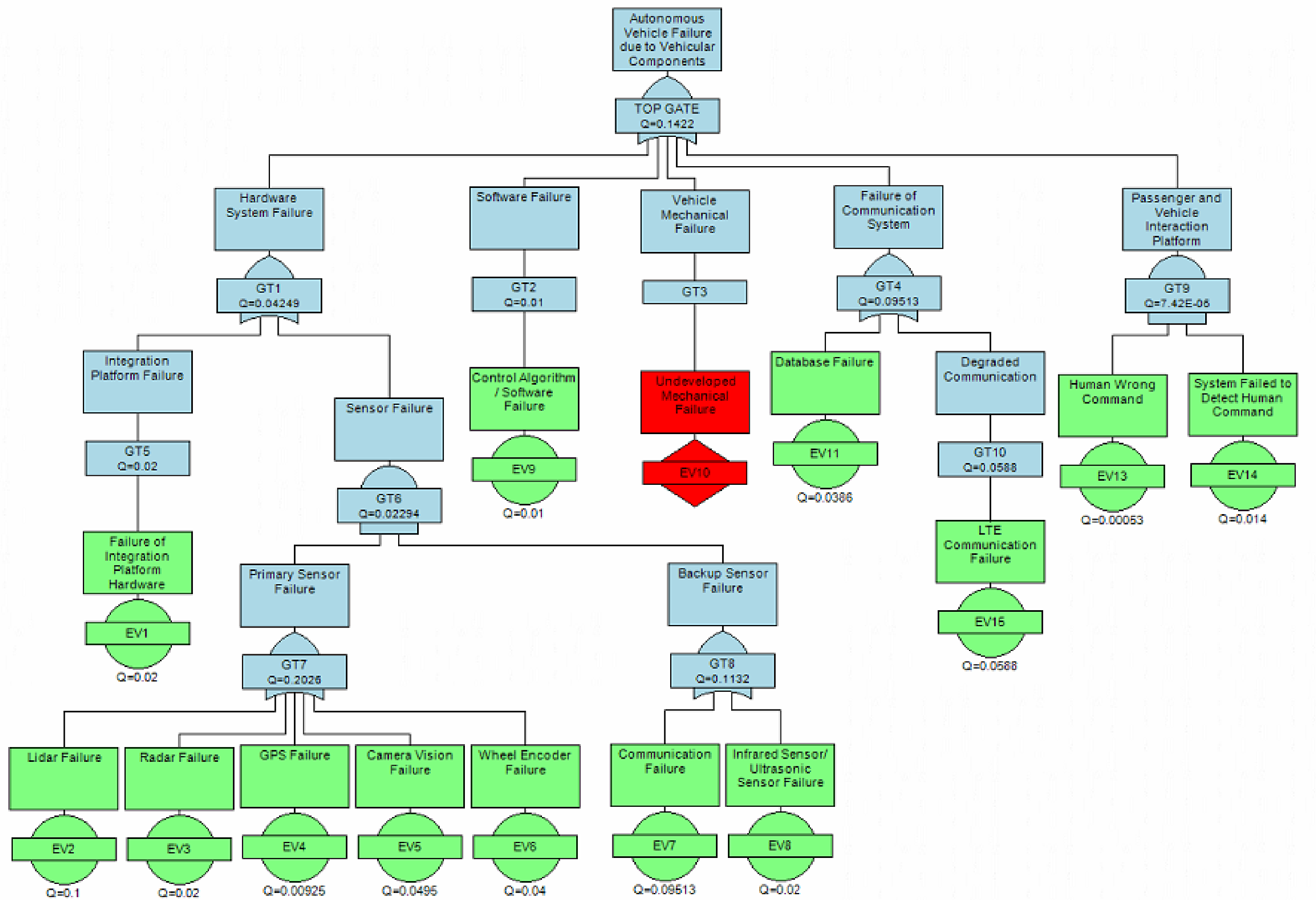


Figure 3: Fault Tree Analysis Considering Failure Due to Vehicular Components

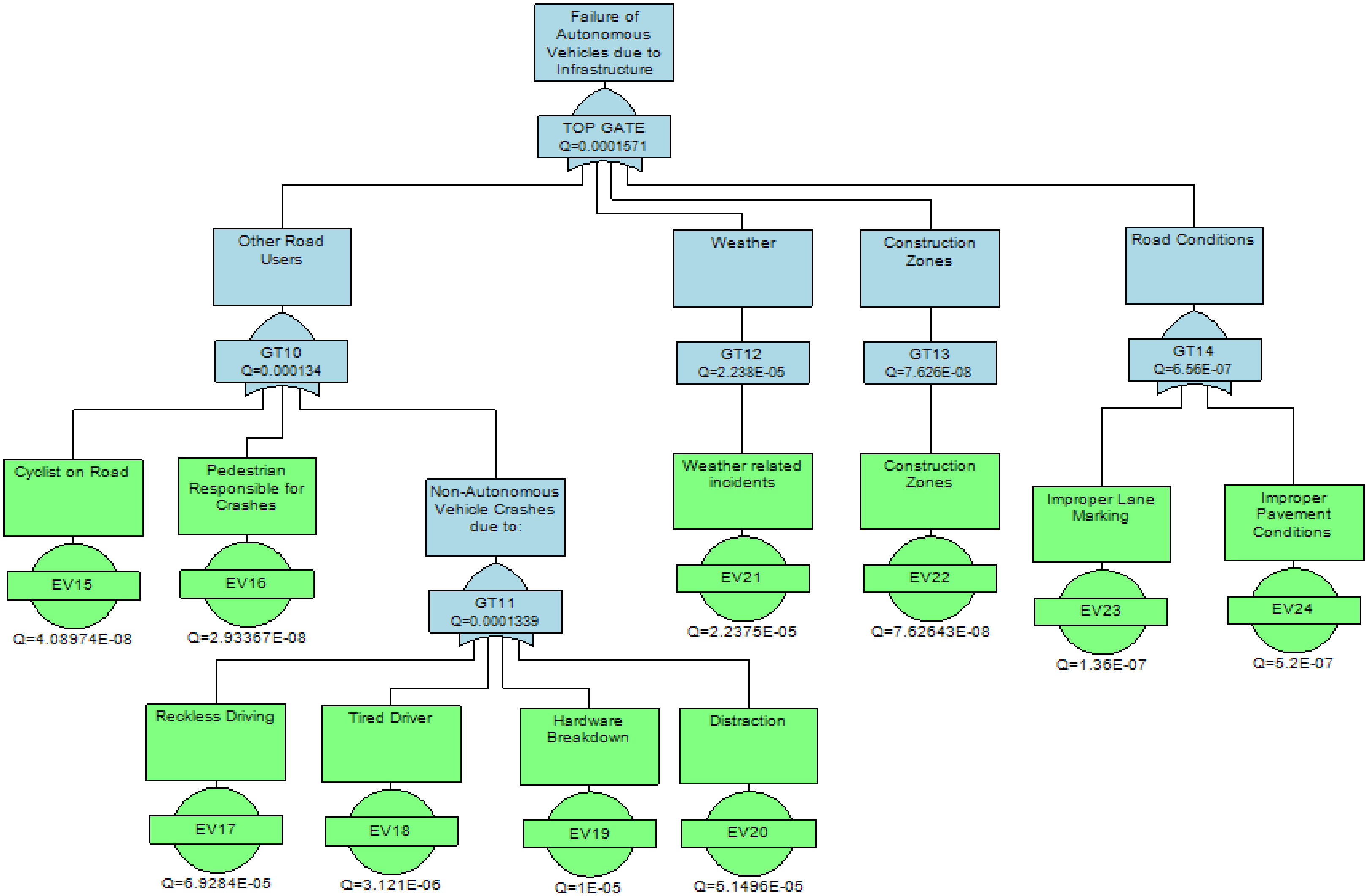


Figure 4: Failures Due to Other Road Users and Transportation Infrastructure Components

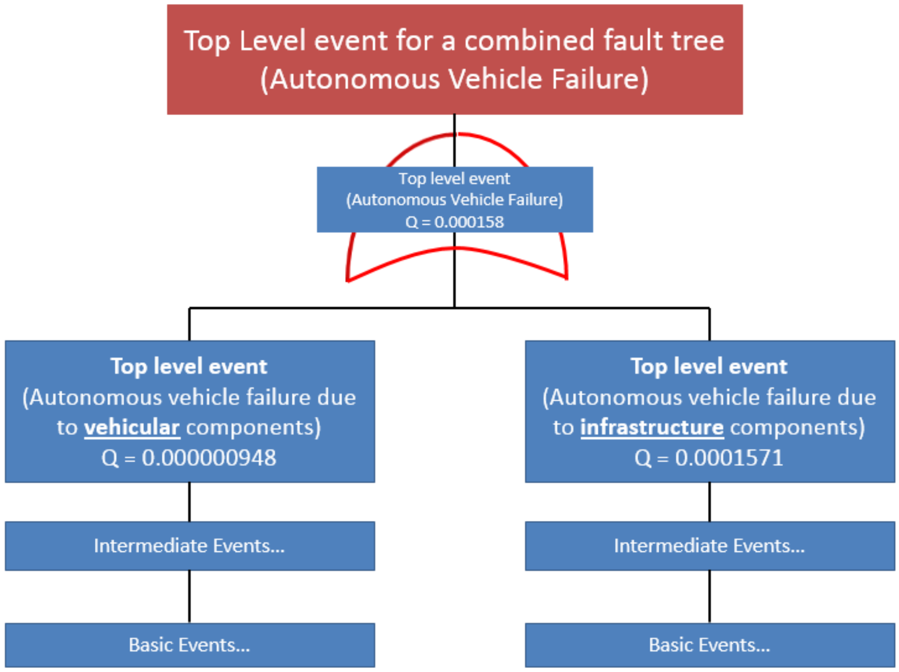


Figure 5: Failure of Autonomous Vehicles in Mixed Traffic Streams Using Fault Tree Models

5.4 Risk Hierarchy

The primary benefit of a fault tree analysis is its ability to develop the cut sets, which are essentially the hierarchical sequence of events. Cut sets can result in the failure of the main/top event. Cut sets can also help engineers and decision makers to prioritize which component failure risk need to be addressed first to improve the safety performance of an autonomous vehicle.

Ten cut sets were distinguished in the analyzed fault trees considering the failure probabilities of both vehicular components and infrastructure components. These cut sets were ranked based on their failure probabilities and are presented in Table 7. It was determined that the failure of the communication system could be the most vulnerable event among all basic events, which has a failure probability of 9.513%. Hardware system failure, which is caused by sensitive sensor and actuator failures, was the second most common problem with a failure probability of 4.249%.

Table 7: Minimal cut sets of autonomous vehicle components

Fault Tree Ranks	Cut sets	Boolean Expression	Failure Probability
1	Communication System (GT4)	EV11+EV12	9.5130%
2	Hardware System (GT1)	EV1+ [(EV2+ EV3+ EV4+ EV5+ EV6) * (EV7+EV8)]	4.2490%
3	Software System (GT2)	EV9	1.0000%
4	Non-autonomous Vehicles Crashes (GT11)	EV17+ EV18+ EV19+ EV20	0.0134%
5	Weather (GT12)	EV21	0.0022%
6	Vehicle-passenger interaction (GT9)	(EV13*EV14)	7.4200×10^{-4} %
7	Road Condition (GT14)	EV23+EV24	6.5600×10^{-5} %
8	Construction zones (GT13)	EV22	7.6264×10^{-6} %
9	Cyclists (GT10)	EV15	4.0897×10^{-6} %
10	Pedestrians (GT10)	EV16	2.9337×10^{-6} %

6. EVALUATION OF THE FAULT-TREE MODELS

Fault tree models can be evaluated qualitatively or quantitatively. It is important to validate the analyzed fault tree analysis model with real-world data. The qualitative validation method considers the basic events identification and their relationship with the top-level event(s). A quantitative method includes comparing the failure probabilities estimated through a fault-tree analysis to real-world data (*92*). The research team compared the results obtained from the fault tree models with the real-world data available from the California DMV autonomous vehicles testing records (*9*-*13*). According to CA DMV autonomous vehicle testing regulations, all autonomous vehicle manufactures and developers holding a permit to test, have to submit accident reports within 10 days of the incidents and an additional disengagement report annually (*93*). The summary of collected crash and disengagement data from the CA DMV is presented in Table 8, where each type of system failure was ranked based on the % of incidents.

Table 8: California DMV Autonomous Vehicles Testing Data

System Failure	Description	No of Incidents	% of Incidents	Real World Ranks vs Fault Tree Ranks*	References
Hardware System	Hardware discrepancy, issue with tuning and calibration, and unwanted maneuver	288	17.8439	3 (2)	(*9-11*)
Software System	Software discrepancy and unable to detect vehicle or obstacles	80	4.9566	5 (3)	(*9*)
Communication System	Planner data not received, drop off on received data, communication evaluation management failure	642	39.777	1 (1)	(*12; 13*)
Non-autonomous vehicles crashes	Non-autonomous vehicles behaviors at low penetration level of autonomous vehicles	68	4.2131	6 (4)	(*9-11*)
Vehicle-passenger interaction	Human uncomfortable to continue automation	487	30.1735	2 (6)	(*12*)
Construction zones	Signs, hands signals, lane closures, and sudden reduction of speed represent the construction zone scenarios	31	1.9207	7 (8)	(*9; 10*)
Road conditions	Lane marking and adverse road surface conditions	111	6.4125	4 (7)	(*9; 10*)
Weather	Rainy, sun glare, twilight, cloudy: poor sunlight conditions and night time are considered here	18	1.1152	8 (5)	(*9; 10*)

* Values in parenthesis represent the ranks of system failures estimated from fault tree analysis.

The comparison of ranks given to each basic event of system failure by the final combined fault-tree model versus the real-world data is presented in Figure 6. All basic failure events are ranked in the descending order of failure probability in the following figure (i.e., the failure probability decreases with the increase in rank). For example, a rank of 2^{nd} place for hardware system failure, from fault tree analysis, suggests that there is a high probability of failure due to hardware failure compared to failure due to construction zones (Rank 8).

From Figure 6, it could be inferred that the communication system failure is ranked 1 based on the fault tree risk analysis, which conforms to the real world autonomous vehicle test data. A significant difference in the ranking of failure due to 'Vehicle-passenger interaction' between the fault-tree analysis (ranked 6) and the real-world (ranked 2) could suggest that the software system and algorithms are going through technological advancements, which is captured in the fault-tree analysis but not reflected in the earlier real-world tests results. Furthermore, the lower ranking (i.e., higher failure probability) using real-world data includes disengagement events reported by various car manufacturers in which the primary cause of disengagement from autonomous driving is discomfort felt by the driver. The driver may experience discomfort and disengage from self-driving to manual driving, if (i) the driver perceives actions taken by the autonomous mode are not safe; OR (ii) the driver has interacted causing vehicle-passenger interaction to take over control; OR (iii) the autonomous vehicle failed to recognize the driver's command. However, with the improvement in algorithms and increased adaptation, this discomfort may reduce, thus reducing the failure probability. Lower real-world rankings (i.e., higher failure probability) were recorded based on weather events. Fault tree analysis of non-autonomous vehicle events compared to the real-world reports suggest that autonomous vehicles have not been tested in various weather conditions and at different penetration levels.

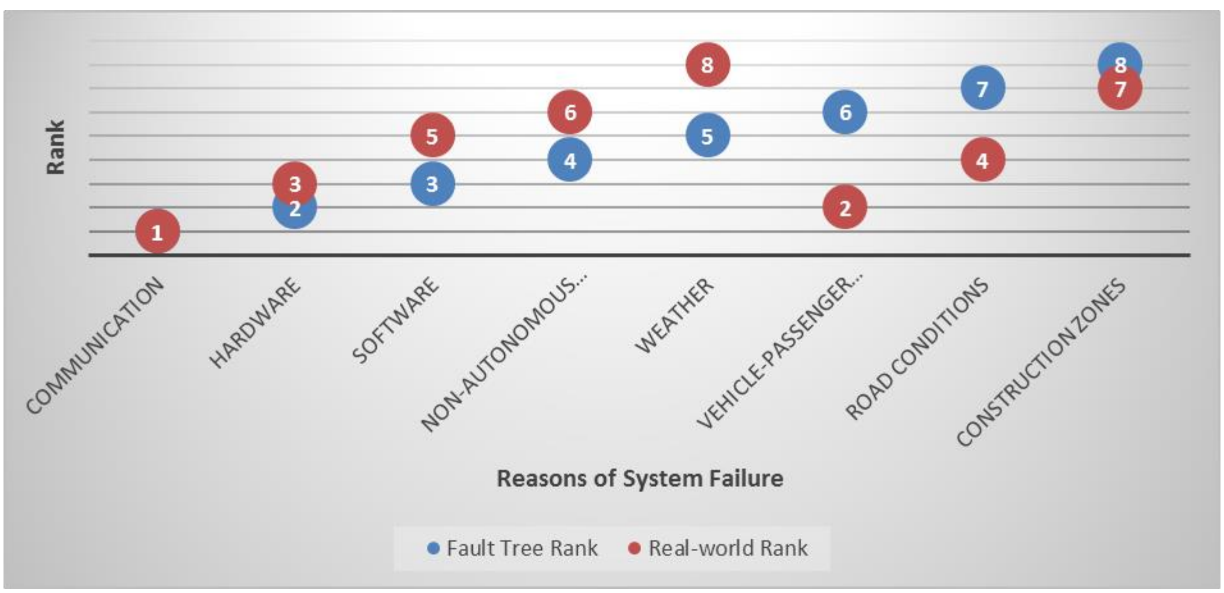


Figure 6: Comparison between the results of risk analysis and real-world incident percentages

7. RISK MINIMIZATION STRATEGIES

The identified cut sets can be utilized to develop risk minimization strategies to improve the safety of autonomous vehicles. This study's research team performed extensive reviews of system dynamics and advanced technologies, identifying 22 strategies to minimize the risks associated with autonomous navigation. These strategies are divided into two major categories. They are: i) legal measures, and ii) organizational measures. Legal measure can be explained as any specific activity that the government can enforce to pertain to all autonomous vehicle manufacturers and developers to reduce safety risks. An organizational measure is an activity that the government considers supportive of development and deployment of autonomous vehicles.

The 22 strategies are listed below according to their categories for different cut sets identified from risk analysis of autonomous vehicles:

Cut set 1: Failure of Communication System

1. Legal measure: Regulation implementing the Dedicated Short Range Communications (DSRC) devices installation in vehicle units.

2. Organizational measure: Required infrastructures development. Example: Installation of roadside DSRC devices for better communication

3. Organizational measure: Regulation of priority based (communication prioritization) vehicle-server and vehicle-vehicle communication system

Cut set 2: Hardware System Failure

1. Legal measure: Provision of installing additional sensors as back up.

2. Legal measure: Provision of hardware inspections periodically to ensure the safety of the system.

3. Legal measure: Installation of monitoring and warning system to alert the driver in case of hardware failure.

4. Organizational measure: Cloud assisted navigation system for autonomous navigation (using sensor information from other vehicles and road-side units) in case of hardware failure.

Cut set 3: Non-autonomous Vehicle Crashes

1. Organizational measure: Separate lanes for autonomous vehicles to reduce human error-related road crashes.

2. Organizational measure: Autonomous vehicles are allowed to drive on Bus/HOV lanes.

3. Legal measure: Installation of black box in autonomous vehicles for accident investigations.

Cut set 4: Weather

1. Legal measure: Provision of testing autonomous vehicles in worst weather/different lighting scenarios for *certain* percentage of total testing hours (before deployment).

2. Legal measure: Installation of advanced windshield wiper system which can automatically detect rain and turn on the wipers accordingly.

3. Legal measure: Provision of internal heating/cooling system installation for external sensors to avoid damage due to extreme temperatures.

Cut set 5: Software failure

1. Legal measure: Further research on self-adaptive software for software system improvements.

Cut set 6: Road surface conditions

1. Legal measure: Provision for responding to unusual or dangerous surface conditions (for example: potholes, unmarked lanes, etc.) by installing a detection system using additional sensors (radar and camera) focusing on the road surface.

2. Legal measure: Provision requiring upgrading the navigation system to work without lane markings.

Cut set 7: Construction zones

1. Organizational measure: Installation of V2I communication devices at all advisory signs before construction sites.

2. Organizational measure: Cloud assisted driving system based on information from construction site databases.

Cut set 8: Pedestrians and cyclists

1. Legal measure: Provision requiring pedestrians and cyclists tracking devices/ sensors (with 360-degree view).

Cut set 9: Wrong command to system

1. Legal measure: Provision requiring installing (at least) two methods of command input (voice, touch, keys, etc.).

2. Legal measures: Provision requiring automatic background sounds (e.g., from music, fans, etc.) be turned off when voice command is selected.

3. Legal measures: Installation of camera to monitor driver behavior to avoid misleading commands due to impairments.

7.1 Benefits-Costs Analysis

The research team conducted a benefit-costs analysis for implementing risk minimization strategies for autonomous vehicles. It will result in a comparison of costs of the proposed risk minimization strategies through benefit-costs analysis. This analysis also helps the policy makers to initiate necessary steps and allocation of funds for implementation of solutions.

One of the risk minimization strategies for hardware system failure is a provision requiring installation of additional sensors as back-up and a regulation requiring Dedicated Short Range Communications (DSRC) device installation in vehicle units to minimize communication failures. The research team focused on these two measures to perform benefits-costs analysis. The detail estimation steps along with assumptions are discussed in the following subsection.

7.1.1 Assumptions in B/C Analysis

1. Experts predicted that approximately 75% of vehicles will navigate autonomously by the year of 2040 (*68; 94*). Based on these studies, it was assumed that all traditional vehicles will be replaced by autonomous vehicles by the year of 2050. Furthermore, to achieve the expected risk minimization in autonomous navigation, the autonomous vehicle penetration should be at least 10% or more, and this penetration should be attained by the year 2030.

2. U.S. population trends adopted in this study follow the trends described in the World Bank website, which states that the U.S. population is growing by approximately 3.12 million people per year (*95*).

3. Discount rate is used to calculate the present value of the future cash flow. The U.S. Office of Management and Budget (OMB) utilizes two discount rates: 3% and 7%, to evaluate projects involving intergenerational benefits and costs (*96*). Furthermore, the European Union suggests a range of discount rates depending on economic conditions, nature of investor(s), and the nature of the sector under consideration from a minimum value of 3% to a maximum of 11% (*97*). Other researchers used between 2.5% and 8% for railway projects in developed countries (*98*). In this study, the research team used net present values (NPV) of costs and benefits and assumed a discount rate of 6.5%.

4. There were three benefits from risk minimization strategies considered in this study. They are 1) saving lives, i.e., fewer traffic deaths, 2) less traffic congestion yielding less time in heavy traffic, and 3) environmental improvement.

Saving lives:

With the evaluation of traffic safety laws, i.e. minimum legal drinking age (MLDA) laws (*99*), and strict implementation of them, the trend of traffic crash rate (fatalities per 100,000 people) is showing a decreasing tendency (*100*). The research team developed a regression equation based on the crash data of past 50 years. The crash data of past 50 years collected from NHTSA is shown in Figure 7.

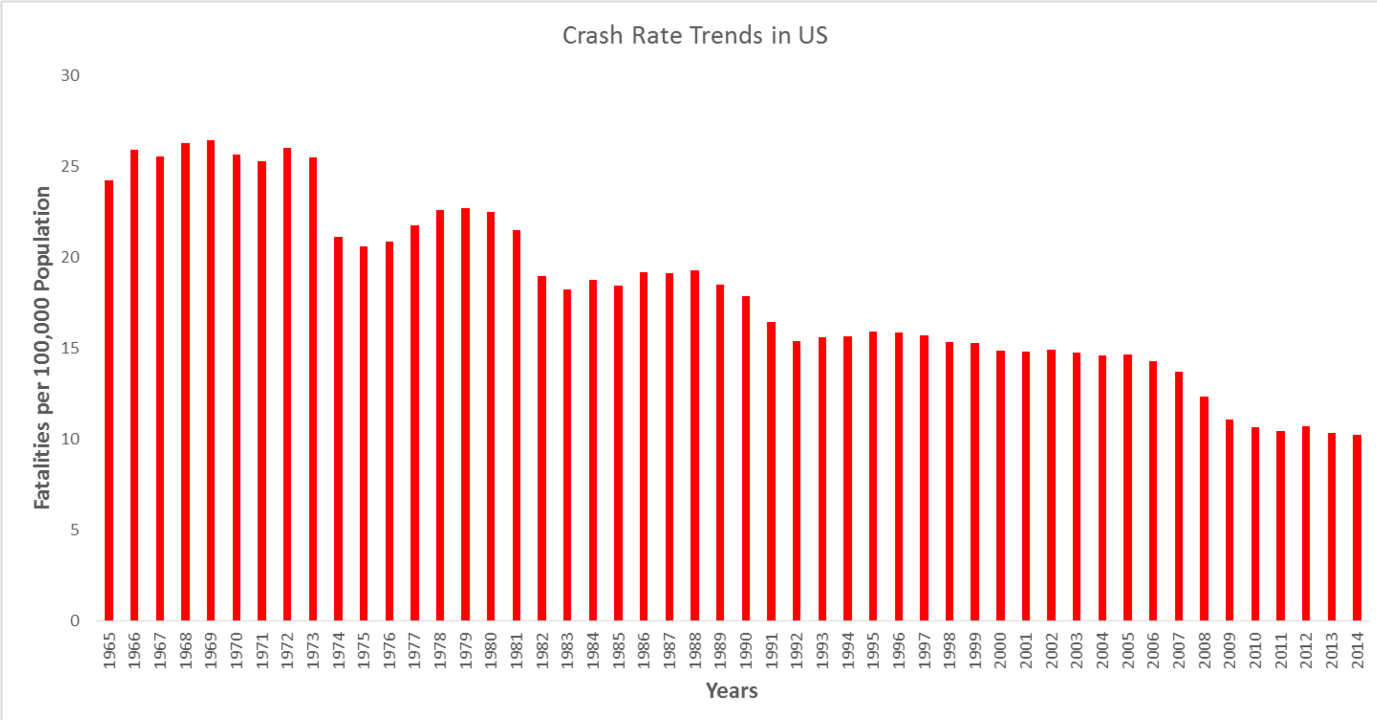


Figure 7: Crash rates (fatalities per 100,000 people) over last 50 years

The simple regression equation developed in this study was utilized to estimate the crash rate for 2030. The proposed regression equation is given below:

$$Crash\,rate = 26.38884 + (-0.32405) \times Year$$

The value of a statistical life depends on the socio-economic conditions of the person, i.e., the income of the life being considered and the health condition/ risk of that person dying (*101*). It is difficult to estimate the correct value of a life. However, researchers adopted several alternative techniques to estimate the value of a statistical life. Economists relied on experts' judgements using revealed preference (RP) surveys to determine statistically accurate values (*102*). Other researchers utilized meta-analysis of various parameters (*103-105*). The income elasticity plays an important role while estimating value of statistical life in low and high income population (*101*). Furthermore, mortality risk was used as a critical input for sound estimation (*106*). However, researchers also suggested that change in Gross Domestic Product (GDP) and Consumer Price Index (CPI) could transmit a downward bias over time (*107*). Meanwhile, Viscusi and Aldy proposed two regression techniques, i.e. ordinary least squares and robust estimation with Huber weights, to establish a wage-risk equation (*108*). US DOT embraced this wage-risk equation with an income elasticity of 0.55 and estimated the value of a statistical life equal to $6.2 million per life for the year of 2011. In this study, the research team used this value to calculate the value of lives saved after implementing risk minimization strategies.

Less traffic congestion yielding less time in heavy traffic:

With advance sensing equipment, autonomous vehicles can find optimal routes and energy management strategies, and follow speed adjustments, which can lead to fuel saving and reductions in travel time and congestion. Researchers predicted that autonomous vehicles can reduce 5% to 15% of road congestion with 10% and 90% market penetration, respectively, on arterial roadways (*5*). Some researchers argue that new road user groups (e.g., elderly persons, children and disabled persons) are going to use autonomous vehicles and could increase the congestion level (*111*). However, the research team did not consider these issues, i.e. new road users, in this study, and assumed the value of one hour travel is equivalent to $12.95 (*109*).

Environmental improvement:

The implementation of autonomous vehicles will also have potential of reducing environmental impacts/pollution. The reduced number of miles traveled will result in less tailpipe emissions. Four major exhaust pollutants emitted from tailpipe are considered in this analysis—carbon dioxide (CO_2), nitrogen oxides (NO_X), volatile organic compounds (VOC), and particulate matter (PM_{10}) (*112*). The average emission rate of these pollutants and the average monetized values are summarized in Table 9.

Table 9: Pollutants emission rate and monetized values

Pollutants	Emission Rate	Monetized Value	References
Carbon dioxide (CO_2)	367 g/VMT	$27.26 /ton	(*109; 113*)
Nitrogen oxides (NO_X)	0.8 g/VMT	$5,944 /ton	(*109; 113*)
Volatile organic compounds (VOC)	0.3 g/VMT	$325,231 /ton	(*109; 113*)
Particulate Matter (PM_{10})	0.11 g/VMT	$1,458 /ton	(*109; 113*)

5. The major disadvantage of autonomous vehicle is high purchase costs due to installation of different advanced technologies such as sensors, communication technology, guidance system and software for the autonomous navigation. Researchers estimate that most current autonomous navigation applications cost over $100,000 and with mass production this will fall to additional $10,000 for automation features after ten years (*5*).

The current costs of the back-up sensors and DSRC devices were collected from (*114*) and used in this study to conduct the benefits-costs analysis. The cost ranges are listed in Table 10 below. Then, the total number of autonomous vehicles expected was estimated to calculate the total cost of each additional sensor installed in the vehicles. This study's research team found that there are 0.797 cars per person (*115*) and assumed this demand value will not change in future.

Table 10: Costs of back-up sensors and DSRC device

No.	Sensors and Devices	Cost Ranges
1.	LIDAR	\$90-\$8000
2.	Radar	\$125-\$150
3.	Video Camera	Mono: \$125-\$150 Stereo: \$150-\$200
4.	GPS Device	\$80-\$6000
5.	Wheel Encoder	\$80-\$120
6.	DSRC Device	\$250-\$350

The benefits-costs ratios (BCRs) were calculated for the year of 2030 when autonomous vehicle market penetration rate will be 10% and 2050 when penetration will be 100% using the following equation. Tables 11 and 12 yield the results of benefits-costs analysis for installing additional sensors and a DRSC device in autonomous vehicles. A sample calculation of Back-up LIDAR benefits-costs ratio is provided in Appendix D.

$$BCR = \frac{Present\ Value\ of\ Total\ Benefits}{Present\ Value\ of\ Total\ Costs}$$

From the results of benefits-costs analysis, an inference can be drawn that due to high price of LIDAR and GPS device installation, these sensors as backup sensors would not be beneficial, even in the year of 2050, when market penetration is projected to be 100%. While the other sensors (Radar, video camera, wheel encoder, and DSRC device) could be cost effective, so installation costs of these sensors will be less burdensome due to the benefits of these sensors.

Table 11: Benefits-Costs Analysis for 2030 (Autonomous Vehicles Market Penetration 10%)

Sensors/ Devices	Crash Rate	Lives Saved	Values of Lives Saved (in million $)	Value of Travel Time Saved (in million $)	Value of Emission Reduction (in million $)	Total Benefits (in million $)	Net Present Value of Benefits (in million $)	Net Present Value of Total Costs (in million $)	Benefits Costs Ratio (BCR)
LIDAR	5.001	284.87	1766.18	356.13	144.15	2266.46	20429.47	247520.00	0.08
Radar	5.001	165.26	1024.64	356.13	144.15	1524.91	13745.24	4643.66	2.96
Video Camera	5.001	208.90	1295.19	356.13	144.15	1795.47	16184.05	6188.00	2.62
GPS Device	5.001	149.30	925.63	356.13	144.15	1425.90	12852.88	185640.00	0.07
Wheel Encoder	5.001	194.98	1208.85	356.13	144.15	1709.12	15405.74	5346.43	2.88
DSRC devices	5.001	108.29	671.43	356.13	144.15	1171.70	10561.53	10829.00	0.97

Table 12: Benefits-costs analysis for 2050 (autonomous vehicles market penetration 100%)

Sensors/ Devices	Crash Rate	Lives Saved	Values of Lives Saved (in million $)	Value of Travel Time Saved (in million $)	Value of Emission Reduction (in million $)	Total Benefits (in million $)	Net Present Value of Benefits (in million $)	Net Present Value of Total Costs (in million $)	Benefits Costs Ratio (BCR)
LIDAR	2.409	1603	9936.68	10683.75	432.45	21052.88	285826.66	2891200.00	0.09
Radar	2.409	930	5764.71	10683.75	432.45	16880.91	229185.49	54180.97	4.23
Video Camera	2.409	1175	7286.85	10683.75	432.45	18403.05	249851.03	72280.00	3.46
GPS Device	2.409	840	5207.67	10683.75	432.45	16323.87	221622.78	2168400.00	0.10
Wheel Encoder	2.409	1097	6801.06	10683.75	432.45	17917.26	243255.64	43368.00	5.61
DSRC devices	2.409	609	3777.51	10683.75	432.45	14893.70	202205.97	126490.00	1.60

7.2 Advantages and Disadvantages of Identified Strategies

The research team conducted further research to identify the advantages and disadvantages of each risk minimization strategy proposed in this study. Table 13 represents the complete list of advantages and disadvantages of risk minimization strategies.

Table 13: Advantages and Disadvantages of Identified Risk Minimization Strategies

Risk Minimization Strategies	Advantages	Disadvantages
Cut set: Failure of Communication System		
Installation of DSRC devices	V2V communication	Costly, hacking risk
Installation of roadside DSRC	V2I application	Costly, hacking risk
Regulation of priority based V2I and V2V communication	High efficiency	High penetration rate required
Cut set: Hardware System Failure		
Installation of additional sensors	Backup sensors	Costly, space restriction
Hardware inspections periodically	Reduce chances of failure	Human inspection errors
Warning system in case of hardware failures and safely stop the vehicle.	Safe navigation	Sudden stop
Cloud assisted navigation system	Less computation power on vehicle	Unreliable cloud system
Cut set: Non-Autonomous Vehicle Crashes		
Separate lanes	No non-AV involved crashes	Costly
On Bus/ HOV lanes	Lanes are less crowded	Less room for busses and carpooling
Installation of black box	Better crash investigation	Denial of installation
Additional training/ materials for human drivers	All drivers would be aware of how AVs operate	Younger drivers more hesitant, Costly
Cut set: Weather		
Testing in extreme weather	More data available for development of better technologies	Costly
Standards for extreme weather performance	Less liability in court	Incapable of driving in some situations
Forcing manual driving in bad weather	Keeps the driver safe	Not fully autonomous
Internal heating/ cooling system for sensors	Less damage from weather	Costly

Cut set: Software Failure		
Self-adaptive algorithm for software system improvements	Evolution in algorithm	Not fully developed
Cut set: Road Surface		
Sensors to evaluate road conditions	Avoids obstacles better	Additional cost
Navigate without lane markings	Safer without marking	Limited distances
Sharing surface condition data	Planned navigation	Storing data
Cut set: Construction Zone		
Communication devices to construction sites	Safer work zone	Additional cost, law enforcement
Sharing construction zone data	Planned navigation	Storing data
Cut set: Pedestrians and Cyclists		
Pedestrians and cyclists tracking	Less crashes	Not fully developed
Testing for pedestrians and cyclists safety	Safe navigation	Costly
Cut set: Wrong Command System		
At least two methods of inputting commands	Safer backup system	Complexity in system
Automatic background sounds truing off for voice command	Increase in understanding of commands	Consumer dissatisfaction
Monitor driver to identify impairments	Drivers more aware	Inaccurate judgments

8. CONCLUSIONS

Autonomous vehicles have the potential to transform existing transportation systems into a safe, and efficient next generation transportation system. However, performing a comprehensive risk analysis of an autonomous vehicle could lead to a safer roadway environment. Tackling the risks related to these early autonomous vehicle technologies would help fix considerable issues before their mass deployment on public roads. Successful identification of the risks related to both the vehicle and the surrounding infrastructure would help researchers and developers to improve the technology.

This study utilized a fault tree-based risk analysis method to identify the most critical basic events that could lead to an autonomous vehicle failure. Findings from the fault tree analysis were used to develop risk minimization strategies to eliminate or reduce component failure risks that will improve overall autonomous vehicle reliability. However, continuous innovation in computing and communication technologies can significantly reduce this failure probability. In addition, from benefits-costs analysis it was found that installing back-up sensors and a DSRC device could be beneficial.

However, due to limited availability of autonomous vehicle testing data it was not possible to conduct statistical validation. It is important to note that the number of experts responding to the survey was 7 out 140 (which is 5.0% of the total experts invited). This number of participants was too low to draw a strong inference. Furthermore, each basic event was assumed independent in this study, though correlations between these events may exist in some cases.

In the future, interdependency among the basic events (i.e., vehicular sensors) should be investigated to conduct a risk analysis of autonomous vehicles. Furthermore, the failure probabilities of sensors or platforms should be validated from field tests of autonomous vehicles. Variation in the performance of sensors over time (i.e., time dependency on reliability) should be considered in future research.

9. REFERENCES

[1] Wolf, W. *Car mania: a critical history of transport*. Pluto Press, 1996.
[2] NHTSA. *Traffic Safety Facts 2013: A Compilation of Motor Vehicle Crash Data from the Fatality Analysis Reporting System and the General Estimates System.* Publication DOT HS 812 139, 2015.
[3] Petridou, E., and M. Moustaki. Human factors in the causation of road traffic crashes. *Eur J Epidemiol,* Vol. 16, No. 9, 2000, pp. 819-826.
[4] Allan F. Williams, and B. O'Neill. On the road driving records of licensed race drivers. *Accident Analysis Prevention,* Vol. 72, No. 3-4, 1974, pp. 260-272.
[5] Fagnant, D. J., and K. Kockelman. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part a-Policy and Practice,* Vol. 77, 2015, pp. 167-181.
[6] Schrank, D., B. Eisele, T. Lomax, and J. Bak. 2015 Urban Mobility Scorecard.In, The Texas A&M Transportation Institute and Inrix, Inc., 2015.
[7] National Accounts Main Aggregates Database.In, United Nations Statistics Division, 2015.
[8] Salomon, I., and P. L. Mokhtarian. Coping with congestion: Understanding the gap between policy assumptions and behavior. *Transportation Research Part D: Transport and Environment,* Vol. 2, No. 2, 1997, pp. 107-123.
[9] Google. Autonomous vehicles annual disengagement report.In, California Department of Autonomous Vehicles, 2016.
[10] Delphi. Autonomous vehicles annual disengagement report.In, California Department of Autonomous Vehicles, 2016.
[11] Nissan. Autonomous vehicles annual disengagement report.In, California Department of Autonomous Vehicles, 2016.
[12] Mercedes-Benz. Autonomous vehicles annual disengagement report.In, California Department of Autonomous Vehicles, 2016.
[13] Volkswagen. Autonomous vehicles annual disengagement report.In, California Department of Autonomous Vehicles, 2016.
[14] Vincent, J. *Google's self-driving cars would've hit something 13 times if not for humans*, The Verge. http://www.theverge.com/2016/1/13/10759424/google-self-driving-car-accidents-driver-disengagements. Accessed 15 February, 2016.
[15] Fingas, J. *Self-driving cars can be fooled by fake signals.* Engatget. http://gizmodo.com/6-simple-things-googles-self-driving-car-still-cant-han-1628040470. Accessed 15 February, 2016.
[16] Sorokanich, R. *6 Simple Things Google's Self-Driving Car Still Can't Handle*, Gizmodo. http://www.engadget.com/2015/09/05/self-driving-car-lidar-exploit. Accessed 15 February, 2016.
[17] Harris, M. *Researcher Hacks Self-driving Car Sensors.* IEEE Spectrum, IEEE Spectrum. http://spectrum.ieee.org/cars-that-think/transportation/self-driving/researcher-hacks-selfdriving-car-sensors. Accessed 15 February, 2016.
[18] Simonite, T. Your Future Self-Driving Car Will Be Way More Hackable.In *MIT Technology Review*, Massachusetts Institute of Technology, 2016.
[19] S. Park, T. Kim, S. Kang, and K. Heon. A Novel Signal Processing Technique for Vehicle Detection Radar. *2003 IEEE MTT-S Int'l Microwave Symposium Digest*, 2003, pp. 607-610
[20] Chieh-Chih, W., C. Thorpe, and A. Suppe. LADAR-based detection and tracking of moving objects from a ground vehicle at high speeds. *Intelligent Vehicles Symposium, 2003. Proceedings. IEEE*, 2003, pp. 416-421.
[21] John Hancock, Eric Hoffman, Ryan Sullivan, Darin Ingimarson, Dirk Langer, and M. Hebert. High-Performance Laser Range Scanner. *SPIE Proceedings on Intelligent Transportation Systems*, 1997.
[22] Fernandes, R., C. Premebida, P. Peixoto, D. Wolf, and U. Nunes. Road Detection Using High Resolution LIDAR.In *Vehicle Power and Propulsion Conference (VPPC), 2014 IEEE*, 2014. pp. 1-6.

[23] Wende, Z. LIDAR-based road and road-edge detection.In *Intelligent Vehicles Symposium (IV), 2010 IEEE*, 2010. pp. 845-848.
[24] Jihyun, Y., and C. D. Crane. LADAR based obstacle detection in an urban environment and its application in the DARPA Urban challenge.In *Control, Automation and Systems, 2008. ICCAS 2008. International Conference on*, 2008. pp. 581-585.
[25] Qingquan, L., C. Long, L. Ming, S. Shih-Lung, and A. Nuchter. A Sensor-Fusion Drivable-Region and Lane-Detection System for Autonomous Vehicle Navigation in Challenging Road Scenarios. *Vehicular Technology, IEEE Transactions on,* Vol. 63, No. 2, 2014, pp. 540-555.
[26] Germann, S., and R. Isermann. Nonlinear distance and cruise control for passenger cars.In *American Control Conference*, Seattle, WA, 1995. pp. 3081–3085.
[27] H. Holzmann, C. Halfmann, S. Germann, M.Würtenberger, and R. Isermann. Longitudinal and lateral control and supervision of autonomous intelligent vehicles. *Control Engineering Practice,* Vol. 5, 1997, pp. 1599–1605.
[28] Chakroborty, P., and S. Kikuchi. Evaluation of the general motors based car-following models and a proposed fuzzy inference model. *Transportation Research: Emerging Technologies, Part C,* Vol. 7, 1999, pp. 209–235.
[29] Eskandarian, A., and S. Thiriez. Collision avoidance using a cerebellar model arithmetic computer neural network. *Computer-Aided Civil Infrastructure Engineering,* Vol. 13, September 1998, pp. 303–314.
[30] Apostoloff, N., and A. Zelinsky. Robust vision based lane tracking using multiple cues and particle filtering.In *Intelligent Vehicles Symposium, 2003. Proceedings. IEEE,* 2003. pp. 558-563.
[31] Lee, J. A machine vision system for lane-departure detection. *Computer Vision and Image Understanding,* Vol. 86, 2002, pp. 52-78.
[32] Yang, S. X., and M. Meng. Neural network approaches to dynamic collision-free trajectory generation. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics),* Vol. 31, No. 3, 2001, pp. 302-318.
[33] Y. Jia, J. Song, and Q. Sun. Dynamic Model and Control Method for Motor Vehicle with Electronic Stability Program. *Journal of Highway and Transportation Research and Development,* Vol. 21, No. 5, 2004, pp. 132-136.
[34] Gavrila, D. M., J. Giebel, and S. Munder. Vision-based pedestrian detection: the PROTECTOR system.In *Intelligent Vehicles Symposium, 2004 IEEE*, 2004. pp. 13-18.
[35] Nanda, H., and L. Davis. Probabilistic template based pedestrian detection in infrared videos.In *Intelligent Vehicle Symposium, 2002. IEEE, No. 1*, 2002. pp. 15-20 vol.11.
[36] Suard, F., V. Guigue, A. Rakotomamonjy, and A. Benshrair. Pedestrian detection using stereo-vision and graph kernels.In *Intelligent Vehicles Symposium, 2005. Proceedings. IEEE*, 2005. pp. 267-272.
[37] Liang, Z., and C. Thorpe. Stereo- and neural network-based pedestrian detection.In *Intelligent Transportation Systems, 1999. Proceedings. 1999 IEEE/IEEJ/JSAI International Conference on*, 1999. pp. 298-303.
[38] Hillenbrand, J., and K. Kroschel. A Study on the Performance of Uncooperative Collision Mitigation Systems at Intersection-like Traffic Situations.In *2006 IEEE Conference on Cybernetics and Intelligent Systems*, 2006. pp. 1-6.
[39] Laugier, C., I. E. Paromtchik, M. Perrollaz, M. Yong, J. D. Yoder, C. Tay, K. Mekhnacha, and A. Nègre. Probabilistic Analysis of Dynamic Scenes and Collision Risks Assessment to Improve Driving Safety. *IEEE Intelligent Transportation Systems Magazine*, Vol. 3, No. 4, 2011, pp. 4-19.
[40] Käfer, E., C. Hermes, C. Wöhler, H. Ritter, and F. Kummert. Recognition of situation classes at road intersections.In *2010 IEEE International Conference on Robotics and Automation*, 2010. pp. 3960-3965.
[41] Gindele, T., S. Brechtel, and R. Dillmann. A probabilistic model for estimating driver behaviors and vehicle trajectories in traffic environments.In *13th International IEEE Conference on Intelligent Transportation Systems*, 2010. pp. 1625-1631.

[42] Vacek, S., T. Gindele, J. M. Zollner, and R. Dillmann. Situation classification for cognitive automobiles using case-based reasoning.In *2007 IEEE Intelligent Vehicles Symposium*, 2007. pp. 704-709.
[43] Armand, A., D. Filliat, and J. Ibañez-Guzman. Ontology-based context awareness for driving assistance systems.In *2014 IEEE Intelligent Vehicles Symposium Proceedings*, 2014. pp. 227-233.
[44] Mohammad, M. A., I. Kaloskampis, Y. Hicks, and R. Setchi. Ontology-based Framework for Risk Assessment in Road Scenes Using Videos. *Procedia Computer Science,* Vol. 60, 2015, pp. 1532-1541.
[45] Ericson, C. A. Fault Tree Analysis - A History.In *17th International System Safety Conference* System Safety Society, Orlando, FL 1999.
[46] Waller, R. A., and V. T. E. Covello. *Low Probability High Consequence Risk Analysis*. Plenum Press, 1984.
[47] Michael Stamatelatos, William Vesely, Joanne Dugan, Joseph Fragola, Joseph Minarick, and J. Railsback. *Fault Tree Handbook with Aerospace Applications*. NASA Office of Safety and Mission Assurance, Washington, DC, 2002.
[48] Volkanovski, A., M. Cepin, and B. Mavko. Application of the fault tree analysis for assessment of power system reliability. *Reliability Engineering & System Safety*, Vol. 94, No. 6, 2009, pp. 1116-1127.
[49] Alonso, J. G. C. A method to determine environmental risk in chemical process industries. Presented at Ninth international symposium loss prevention and safety promotion in the process industries, 1998.
[50] Schlechter, W. P. G. Facility risk review as a mean to addressing existing risks during the life cycle of a process unit, operation or facility. *International Journal of Pressure Vessels and Piping,* Vol. 66, No. 1-3, 1996, pp. 387–402.
[51] Davis-McDaniel, C., M. Chowdhury, W. C. Pang, and K. Dey. Fault-Tree Model for Risk Assessment of Bridge Failure: Case Study for Segmental Box Girder Bridges. *Journal of Infrastructure Systems,* Vol. 19, No. 3, 2013, pp. 326-334.
[52] Chapman, C. Project risk analysis and management- PRAM the generic process. *International Journal of Project Management*, Vol. 15, No. 5, 1997, pp. 273-281.
[53] Tiemessen, G., and J. P. V. Zweeden. Risk assessment of the transport of hazardous materials. *Ninth international symposium loss prevention and safety promotion in the process industries*, 1998, pp. 299-307.
[54] Hurst, N. W., Young, S., Donald, I., Gibson, H., & Muyselaar, A. Measures of safety management performance and attitudes to safety at major hazard sites. *Journal of Loss Prevention in the Process Industr,* Vol. 9, No. 2, 1996, pp. 161-172.
[55] Bogen, K. T. *Uncertainty in environmental health risk assessment* Garland Publishing, New York, NY, 1990.
[56] Ammar, H. H., B. Cukic, A. Mili, and C. Fuhrman. A comparative analysis of hardware and software fault tolerance: Impact on software reliability engineering. *Annals of Software Engineering,* Vol. 10, 2000, pp. 103-150.
[57] Swarup, M. B., and M. S. Rao. Safety Analysis of Adaptive Cruise Control System Using FMEA and FTA *International Journal of Advanced Research in Computer Science and Software Engineering,* Vol. 4, No. 6, 2014, pp. 330-337.
[58] Duran, D. R., E. Robinson, A. J. Kornecki, and J. Zalewski. Safety analysis of Autonomous Ground Vehicle optical systems: Bayesian belief networks approach.In *Computer Science and Information Systems (FedCSIS), 2013 Federated Conference on*, 2013. pp. 1419-1425.
[59] Martin, A. Interactive Motion Prediction using Game Theory.In *Institute of Automatic Control Engineering, No. Master of Science*, University of Padua, Padova, Italy, 2013. p. 100.
[60] Platho, M., H. M. Groß, and J. Eggert. Predicting Velocity Profiles of Road Users at Intersections Using Configurations.In *2013 IEEE Intelligent Vehicles Symposium (IV)*, 2013. pp. 945-951.
[61] Furda, A., and L. Vlacic. Enabling Safe Autonomous Driving in Real-World City Traffic Using Multiple Criteria Decision Making. *IEEE Intelligent Transportation Systems Magazine,* Vol. 3, No. 1, 2011, pp. 4-17.

[62] Hülsen, M., J. M. Zöllner, and C. Weiss. Traffic intersection situation description ontology for advanced driver assistance.In *2011 IEEE Intelligent Vehicles Symposium (IV)*, 2011. pp. 993-999.
[63] Pollard, E., P. Morignot, and F. Nashashibi. An ontology-based model to determine the automation level of an automated vehicle for co-driving.In *Proceedings of the 16th International Conference on Information Fusion*, 2013. pp. 596-603.
[64] White, D. Application of systems thinking to risk management: A review of the literature. *Journal of Management History (Archive) merged into Management Decision,* Vol. 33, No. 10, 1995, pp. 35-45.
[65] White, A. V., and I. Burton. *Environmental Risk Assessment*. John Wiley & Sons, 1980.
[66] Aldana, K. *U.S. Department of Transportation Releases Policy on Automated Vehicle Development.* U.S. Department of Transportation, Online. Accessed April 20, 2017
[67] Committee, S. O.-R. A. V. S. Taxonomy and definitions for terms related to on-road motor vehicle automated driving systems. *SAE Standard J3016*, 2014, pp. 01-16.
[68] Litman, T. Autonomous Vehicle Implementation Predictions: Implications for Transport Planning. Presented at Transportation Research Board 94th Annual Meeting, Washington DC, 2015.
[69] Swerling, P. Radar probability of detection for some additional fluctuating target cases. *IEEE Transactions on aerospace and electronic systems*, Vol. 33, No. 2, 1997, pp. 698-709.
[70] Bai, C. G. Bayesian network based software reliability prediction with an operational profile. *Journal of Systems and Software*, Vol. 77, No. 2, 2005, pp. 103-112.
[71] Goel, P., G. Dedeoglu, S. I. Roumeliotis, and G. Sukhatme. Fault detection and identification in a mobile robot using multiple model estimation and neural network.In *Robotics and Automation, 2000. Proceedings. ICRA '00. IEEE International Conference on, No. 3*, 2000. pp. 2302-2309 vol.2303.
[72] Kuusniemi, H. User-level reliability and quality monitoring in satellitebased personal navigation.In *Institute of Digital and Computer Systems, No. Doctor of Technology*, Tampere University of Technology, Finland. p. 180.
[73] Amir, Y., and A. Wool. Evaluating quorum systems over the Internet.In *26th International Symposium on Fault-Tolerant Computing (FTCS-26)*, IEEE Computer Society Press, Los Alamitos, CA, 1996. pp. 26–35.
[74] Eriksson, J., H. Balakrishnan, and S. Madden. Cabernet: vehicular content delivery using WiFi.In *Proceedings of the 14th ACM international conference on Mobile computing and networking*, 2008. pp. 199-210.
[75] Li, Y., Z. Yuan, C. Peng, and S. Lu. CAP on mobility control for 4G LTE networks. Presented at Proceedings of the 3rd Workshop on Hot Topics in Wireless, New York City, New York, 2016.
[76] Goyal, A., S. S. Lavenberg, and K. S. Trivedi. Probabilistic modeling of computer system availability. *Annals of Operations Research Part III: Simulation and Computers,* Vol. 8, No. 1, 1987, pp. 285-306.
[77] Faith Chandler, Addison Heard, Mary Presley, Alexander Burg, Ed Midden, and P. Mongan. NASA Human Error Analysis.In, National Aeronautics and Space Administration, 2010. p. 37.
[78] Dupont, S., and J. Luettin. Audio-visual speech modeling for continuous speech recognition. *IEEE Transactions on Multimedia*, Vol. 2, No. 3, 2000, pp. 141-151.
[79] NYSDOT. Summary of Motor Vehicle Crashes: 2014 Statewide Statistical Summary.In, New York State Department of Motor Vehicles, 2015. p. 6.
[80] VDOT. Virginia Traffic Crash Facts 2014.In, Virginia Highway Safety Office, Virginia Department of Motor Vehicles, 2015.
[81] Santos, A., N. McGuckin, H. Y. Nakamoto, D. Gray, and S. Liss. *Summary of Travel Trends: 2009 National Household Travel Survey.* Publication FHWA-PL-ll-022, 2011.
[82] Schroeder, P., and M. Wilbur. *2012 National survey of bicyclist and pedestrian attitudes and behavior, volume 1: Summary report.* Publication DOT HS 811 841, 2013.
[83] NHTSA. *Bicyclists and Other Cyclists: 2014 data (Traffic Safety Facts).* Publication DOT HS 812 282, 2016.
[84] ---. *Pedestrians: 2014 data (Traffic Safety Facts).* Publication DOT HS 812 270, 2016.

[85] J . Richard Kuzmyak, and J. Dill. Walking and Bicycling in the United States.In *TR News, No. 280*, Transportation Research Board, Washington, DC, 2012.
[86] Ullman, G. L., M. D. Finley, J. E. Bryden, R. Srinivasan, and F. M. Council. Traffic Safety Evaluation of Nighttime and Daytime Work Zones.In *National cooperative highway research program*, Transportation Research Board, Washington, D.C., 2008. p. 89.
[87] FHWA. *Facts and Statistics - Work Zone Injuries and Fatalities.* FHWA, U.S. Department of Transportation. http://www.ops.fhwa.dot.gov/wz/resources/facts_stats/injuries_fatalities.htm. Accessed January 20, 2016.
[88] Cafiso, S., A. Di Graziano, and G. Pappalardo. Using the Delphi method to evaluate opinions of public transport managers on bus safety. *Safety Science*, Vol. 57, 2013, pp. 254-263.
[89] H. Dezfuli, A. Benjamin, C. Everett, G. Maggio, M. Stamatelatos, and R. Youngblood. *NASA Risk Management Handbook.* Publication NASA/SP-2011-3422, 2011.
[90] Safie, F. M., R. G. Stutts, and Z. Huang. Reliability and probabilistic risk assessment — How they play together.In *2015 Annual Reliability and Maintainability Symposium (RAMS)*, 2015. pp. 1-5.
[91] Lu, S. *Vehicle Survivability and Travel Mileage Schedules* Publication DOT HS 809 952, 2006.
[92] Tupper, L. L., M. Chowdhury, and J. Sharp. Tort Liability Risk Prioritization Through the Use of Fault Tree Analysis. Presented at Transportation Research Board 93rd Annual Meeting, Washington DC, 2014.
[93] Pinto, C. How Autonomous Vehicle Policy in California and Nevada Addresses Technological and Non-Technological Liabilities. *Intersect: The Stanford Journal of Science, Technology, and Society; Vol 5 (2012)*, 2012.
[94] IEEE. Look Ma, No Hands!In, Institute of Electrical and Electronics Engineers, Online, 2012.
[95] *Population growth (annual %).* World Bank, Online. Accessed April 12, 2017.
[96] Arrow, K., M. Cropper, C. Gollier, B. Groom, G. Heal, R. Newell, W. Nordhaus, R. Pindyck, W. Pizer, P. Portney, T. Sterner, R. S. J. Tol, and M. Weitzman. Determining Benefits and Costs for Future Generations. *Science*, Vol. 341, No. 6144, 2013, p. 349.
[97] Florio, M., and S. Vignetti. Cost-benefit analysis of Infrastructure Projects in an Enlarged European Union: an Incentive-Oriented Approach.In, Centro Studi Luca d'Agliano, University of Milano, 2003.
[98] RAILPAG. *Railway Project Appraisal Guidelines*, 2005.
[99] Fell, J. C. *An Examination of the Criticisms of the Minimum Legal Drinking Age 21 Laws in the United States from a Traffic-Safety Perspective* 2008.
[100] McCartt, A. T., D. G. Kidd, and E. R. Teoh. Driver Cellphone and Texting Bans in the United States: Evidence of Effectiveness. *Annals of Advances in Automotive Medicine*, Vol. 58, 2014, pp. 99-114.
[101] Hammitt, J. K., and L. A. Robinson. The Income Elasticity of the Value per Statistical Life: Transferring Estimates between High and Low Income Populations. *Journal of Benefit-Cost Analysis*, Vol. 2, No. 1, 2015, pp. 1-29.
[102] Aldy, J. E., and W. K. Viscusi. Age Differences in the Value of Statistical Life: Revealed Preference Evidence. *Review of Environmental Economics and Policy*, Vol. 1, No. 2, 2007, pp. 241-260.
[103] Miller, T. R. Variations between Countries in Values of Statistical Life. *Journal of Transport Economics and Policy*, Vol. 34, No. 2, 2000, pp. 169-188.
[104] Mrozek, J. R., and L. O. Taylor. What determines the value of life? a meta-analysis. *Journal of Policy Analysis and Management*, Vol. 21, No. 2, 2002, pp. 253-270.
[105] Bellavance, F., G. Dionne, and M. Lebeau. The value of a statistical life: A meta-analysis with a mixed effects regression model. *Journal of Health Economics*, Vol. 28, No. 2, 2009, pp. 444-464.
[106] Viscusi, W. K. The Value of Life: Estimates with Risks by Occupation and Industry. *Economic Inquiry*, Vol. 42, No. 1, 2004, pp. 29-48.
[107] de Blaeij, A., R. J. G. M. Florax, P. Rietveld, and E. Verhoef. The value of statistical life in road safety: a meta-analysis. *Accident Analysis & Prevention*, Vol. 35, No. 6, 2003, pp. 973-986.
[108] Viscusi, W. K., and J. E. Aldy. The Value of a Statistical Life: A Critical Review of Market Estimates Throughout the World. *Journal of Risk and Uncertainty*, Vol. 27, No. 1, 2003, pp. 5-76.

[109] *Flamingo Bus Rapid Transit: Application for the Fiscal Year 2013*, 2015.
[110] Polly Trottenberg, and R. Rivkin. *Treatment of the Value of Preventing Fatalities and Injuries in Preparing Economic Analyses – 2011 Revision*, 2011.
[111] Wadud, Z., D. MacKenzie, and P. Leiby. Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. *Transportation Research Part A: Policy and Practice*, Vol. 86, 2016, pp. 1-18.
[112] *Automobile Emissions: An Overview*, 1994.
[113] Chester, M., and A. Horvath. Environmental Life-cycle Assessment of Passenger Transportation: A Detailed Methodology for Energy, Greenhouse Gas and Criteria Pollutant Inventories of Automobiles, Buses, Light Rail, Heavy Rail and Air v.2.In, 2008.
[114] Xavier Mosquet, Thomas Dauner, Nikolaus Lang, Michael Rüßmann, Antonella Mei-Pochtler, a. Rakshita Agrawal, and F. Schmieg. Revolution in the Driver's Seat: The Road to Autonomous Vehicles.In, 2015. p. 30.
[115] *Transportation Energy Data Book: Edition 33*. Publication ORNL-6990, 2014.

APPENDIX A

Sample Transportation Infrastructure Component Failure Probability Calculation:

Number of crashes due to reckless driving (for non-AVs) = 69,284 per 100 million miles (*61*)
Number of crashes due to tiredness (for non-AVs) = 3,121 per 100 million miles (*61*)
Number of crashes due to distraction (for non-AVs) = 51,496 per 100 million miles (*61*)
Number of crashes due to vehicle breakdown (for non-AVs) = 10,000 per 100 million miles (*60*)
From above data, the total non-autonomous vehicle involved crashes = 133,901 per 100 million miles.
Failure probability of non-AVs due to driver tiredness, reckless driving, driver distractions or vehicle breakdown = $133{,}901/(100\times1000{,}000)\times100=0.1339\%$ per mile
Failure probability of an AV involved in a crash with a non-autonomous vehicle = $0.1339\times 10\%$ $=0.01339\%$ per mile

APPENDIX B

DHHS Federal Wide Assurance Identifier: FWA00007111
IRB Chair Person: Harriet Hartman
IRB Director: Sreekant Murthy
Effective Date: 7/15/2016

eIRB Notice of Approval

STUDY PROFILE

Study ID:	Pro2015000614		
Title:	Risk Analysis of Autonomous Vehicles in Mixed Traffic Streams		
Principal Investigator:	Parth Bhavsar	**Study Coordinator:**	None
Co-Investigator(s):	Plaban Das	**Other Study Staff:**	Mashrur Chowdhury Kakan Dey
Sponsor:	University Transportation Research Center: Region 2	**Approval Cycle:**	Twelve Months
Risk Determination:	Minimal Risk	**Device Determination:**	Not Applicable

Review Type:	Expedited	**Expedited Category:**	6 7
Subjects:	120		

CURRENT SUBMISSION STATUS

Submission Type:	Research Protocol/Study	**Submission Status:**	Approved
Approval Date:	7/15/2016	**Expiration Date:**	7/15/2017

Pregnancy Code:	No Pregnant Women as Subjects Not Applicable	**Pediatric Code:**	Not Applicable No Children As Subjects	**Prisoner Code:**	Not Applicable No Prisoners As Subjects

Protocol:	Protocol_20160326 Draft Survey tools_Delphi_Q2_20151104_ver1.docx Draft Survey tools_Delphi_Q1_20151021_vers_1.docx Clemson Approval Letter.pdf Draft Survey tools_personal_20151104_ver1.docx	**Consent:**	There are no items to display	**Recruitment Materials:**	Draft Mail_20160130.docx

* **Study Performance Sites:**

Clemson University — Glenn Department of Civil Engineering | Lowry Hall, Clemson, SC 29634 (864) 656-3000

To: _______________

Subject: Request for Participation in Autonomous Vehicles Research Study

Dear Mr. __________,

We, the research team of Rowan University, NJ and Clemson University, SC, are writing to you to request your participation in a brief survey on the safety and reliability of future autonomous vehicles. As it is predicted that fully autonomous vehicles, which is expected to be safer than human drivers, will surge into the market within 2030. To ensure safety of autonomous vehicles' passengers, our research team is working on the evaluation of the risks associated with each component and their failure rates to determine the reliability of whole autonomous vehicles system in mixed traffic stream using the probabilistic risk assessment method of fault tree. As this field still requires extensive research, so the experts' opinions and judgments could be the best way to disintegrate this system and determine the failure rates of these components. We found that the Delphi Survey method would serve this purpose as this survey allows multiple round interactive anonymous discussions between the participants using the questionnaire.

We found that you are currently working on autonomous vehicles infrastructures and technologies, your opinions and judgements could guide us to improve this technology and ensure the safety of people. We are requesting you to confirm your participation to completing up to five 10 minutes questionnaires for a total of less than one hour over a period of 1 to 1.5 months. Please click the link below to go to the survey web-site (or copy and paste the link into your internet browser). This link would be valid until ________, 2016.

Survey Link:

The survey will be conducted anonymously and any personally identifiable information will not be associated with your responses to any reports of these data. If you have any question, please feel free to contact me at "______" or "_______".

Thank you for your time and participation. The compiled results of this survey will be readdressed to all participants.

Sincerely

____

ONLINE SURVEY (ALTERNATE CONSENT)

You are invited to participate in this online research survey entitled "Risk analysis of autonomous vehicles in mixed traffic stream". This project is funded by Region 2, University Transportation Regional Center (UTRC2). The research team includes researchers from Rowan University, Glassboro, NJ and Clemson University, Clemson, SC. You are included in this survey because we have identified you as an expert in autonomous vehicle research/development/implementation arena. The anticipated number of subjects to be enrolled in the study will be 60.

The purpose of this research study is to identify risk associated with the failure of autonomous vehicles, especially when they are being used in mixed traffic streams along with conventional vehicles. We are using fault tree analysis, a probabilistic risk assessment method, to identify risk associated with failure of the main event (i.e. failure of an autonomous vehicle). The fault tree analysis requires disintegration of the system (i.e. an autonomous vehicle) into basic components and identifying failure probabilities of each component. A fault tree for any system represents the hierarchical sequences of events (i.e. from basic events to main events) with logical gates (such as 'and' gate or 'or' gate) that provides path of failure from each basic event (lowest level event) to the main event. The dependency of the main event on these basic events and failure probabilities of these basic events determine the overall failure of the system.

We are using Delphi Method for this survey and brief explanation of the project and the survey method is provided in this video. Each survey may take approximately 10 minutes to complete. Your participation is voluntary. If you do not wish to participate in this survey, do not respond to this online survey. Completing this survey indicates that you are voluntarily giving consent to participate in the survey. We expect the study to last next three months.

There are no risks or discomforts associated with this survey. There may be no direct benefit to you; however, by participating in this study, you may help us identify risk associated with autonomous vehicle deployment. Your opinions and judgements could guide us to improve this research (and eventually autonomous vehicle technology) by identifying risk minimization strategies and ensure the safety of people.

Your response will be kept confidential. We will store the data in a secure computer file and the file will be destroyed once the data has been published. Any part of the research that is published as part of this study will not include your individual information. If you have any questions about the survey, you can contact me at the address provided below, but you do not have to give your personal identification.

Please complete the checkbox below.

To participate in this survey, you must be 18 years or older. Place a check box here ☐

Completing this survey indicates that you are voluntarily giving consent to participate in the survey ☐

Version #: 1
Version Date: 20160309

Survey Tools for Experts

1. We are using Delphi method for this research project which requires an expert to complete six or more than six surveys, would you be willing to participate in this process?
    a. Yes, I am onboard for the entire process
    b. May be with less number of surveys
    c. No
2. Please describe your role in the field of autonomous vehicle research, development, evaluation and/or implementation?
    a. Researcher in university
    b. Researcher in industry
    c. Developer in industry
    d. Manager of the developing team
    e. Reporter/investigator of technology news website/paper/magazine
    f. Project Manager from Public agency such as department of transportation and department of motor vehicle
3. How long have you been working in this role
    a. Less than a year
    b. 1-3 years
    c. 3-5 years
    d. 5-9 years
    e. More than 9 years
4. The next step of the research project is personal interview via video conferencing. Would you be willing to participate in this step?
    a. Yes
    b. No
    c. No comments

V-1
03/04/2016

Survey Tools for Experts

Section A: (This section for Delphi)

1. What would be the possible causal factors related to autonomous vehicles failure? (You can select multiple options)
a) LIDAR b) RADAR c) Camera d) DGPS system e) Wheel encoder f) backup sensor fails g) communication failure h) data service failure i) integration platform failure j) software failure k) hacking
2. Are there any other factors could be the reason of autonomous car failure; those are not listed in question 1?

3. What would be the probability failure of LIDAR? Please provide a brief description of your opinions.
a) < 1.00
b) 1.01-3.00
c) 3.01-6.00
d) 6.01-10.00
e) > 10.01
f) Not applicable
4. What would be the failure probability of RADAR? Please provide a brief description of your opinions.
a) < 1.00
b) 1.01-3.00
c) 3.01-6.00
d) 6.01-10.00
e) > 10.01
f) Not applicable
5. What would be the failure probability of camera? Please provide a brief description of your opinions.
a) < 1.00
b) 1.01-3.00
c) 3.01-6.00
d) 6.01-10.00
e) > 10.01
f) Not applicable
6. What would be the failure probability of DGPS system? Please provide a brief description of your opinions.
a) < 1.00
b) 1.01-3.00
c) 3.01-6.00
d) 6.01-10.00
e) > 10.01

f) Not applicable
7. What would be the failure probability of wheel encoder? Please provide a brief description of your opinions.
a) < 1.00
b) 1.01-3.00
c) 3.01-6.00
d) 6.01-10.00
e) > 10.01
f) Not applicable
8. What would be the probable rate of communication system will fail? Please provide a brief description of your opinions.
a) < 1.00
b) 1.01-3.00
c) 3.01-6.00
d) 6.01-10.00
e) > 10.01
f) Not applicable
9. What would be the probable rate of data service system will fail? Please provide a brief description of your opinions.
a) < 1.00
b) 1.01-3.00
c) 3.01-6.00
d) 6.01-10.00
e) > 10.01
f) Not applicable
10. What would be the failure probability of integration platform? Please provide a brief description of your opinions.
a) < 1.00
b) 1.01-3.00
c) 3.01-6.00
d) 6.01-10.00
e) > 10.01
f) Not applicable
11. What would be the failure probability of software? Please provide a brief description of your opinions.
a) < 1.00
b) 1.01-3.00
c) 3.01-6.00
d) 6.01-10.00
e) > 10.01
f) Not applicable
12. What would be the possibility of autonomous vehicles are hacked? Please provide a brief description of your opinions.
a) < 1.00

b) 1.01-3.00
c) 3.01-6.00
d) 6.01-10.00
e) > 10.01
f) Not applicable

13. Researchers found that these infrastructures failure may lead to autonomous vehicles failure. If you do agree with these components failure, could you rank them based on their significances? (For example: the component could be the cause of autonomous car failure most significantly, that should be ranked as 1)

a) Weather/ different lighting conditions	Rank..
b) Potholes on pavements	Rank..
c) Lane marking	Rank..
d) No uniform signs and signal patterns	Rank..
e) Fake signal	Rank..
f) Communication failure	Rank..

14. What would be other possible infrastructure elements led to autonomous vehicle failure, you would like to suggest?

15. Do you think user wrong command could lead to autonomous vehicle failure?
a) Yes b) No

16. If answer of question 14 is yes, then what would be the probability of human wrong command?
a) < 1.00
b) 1.01-3.00
c) 3.01-6.00
d) 6.01-10.00
e) > 10.01
f) Not applicable

V – 1 03/04/2016

Section B (This section will not merge with Delphi):

1. How many backup sensors does your company plan on installing in case of a failure any primary sensor?
a) 0 b) 1 c) 2 d) varies for particular sensors

2. If question 2 answer is "Varies for particular sensors", please provide a brief explanation of your backup plan.

3. Where will the collected data from the autonomous car be stored?
a) Inside the car
b) In any distance server
c) In cloud

4. Who will be responsible for data storage from autonomous cars?
a) Autonomous car manufacturer
b) Government
c) Not applicable
d) ....

5. How does the autonomous car assure the data privacy of the users? Please provide a brief description.

6. like the black box (flight data recorder) is placed in an aircraft for the purpose of facilitating the investigation of aviation accidents and incidents. Is there any plan to set something like that to investigate whether the car itself is responsible for the accident or human wrong command?

V – 1 03/04/2016

APPENDIX C

<u>The responses of the question asking failure probability of Lidar:</u>

Participants	Set of Options (failure probability ranges) in the question				
	A: < 1.00	B: 1.01 to 3.00	C: 3.01 to 6.00	D: 6.01 to 10.00	E: > 10.00
1	0	0	5	0	0
2	0	0	5	0	0
3	0	0	5	0	0
4	0	0	0	0	5
5	0	0	0	0	5

Number of experts, m = 5

Number of options, n = 5

Now, $R = \sum_{i=1}^{n}(R_i - \bar{R})^2$ = 200, where for each option, R_i is the sum of the rating participants *j* provides to a specific option: $R_i = \sum_{j=1}^{m} r_{ij}$ and $\bar{R}$ is the mean of the R_i.

Kendall's W = $\frac{12 \times R}{m^2 \times (n^3 - n)}$ = 0.8

<u>The responses of the question asking failure probability of Camera:</u>

Participants	Set of Options (failure probability ranges) in the question				
	A: < 1.00	B: 1.01 to 3.00	C: 3.01 to 6.00	D: 6.01 to 10.00	E: > 10.00
1	0	5	0	0	0
2	0	0	5	0	0
3	0	0	0	5	0
4	0	0	0	0	5

5	0	0	0	0	5

As we mentioned before, m = 5, and n = 5,

Now, $R = \sum_{i=1}^{n}(R_i - \bar{R})^2$ = 50

Kendall's W = $\frac{12 \times R}{m^2 \times (n^3 - n)}$ = 0.2

APPENDIX D

Population in the year of 2030

$$= \text{Population in the year of 2011} + \text{Population growth rate} \times \text{number of years}$$

So, Population in the year of 2030 $= 312000000 + 3120000 \times 19 = 371280000$

Total Benefits Calculation:

$Crash\ rate\ per\ 100{,}000\ people = 26.38884 + (-0.32405) \times Year = 26.38884 + (-0.32405) \times 66 = 5.001$

$Traffic\ Crash\ Deaths = \frac{Total\ Population}{100000} \times Crash\ Rate = \frac{371280000}{100000} \times 5.001 = 18569.07$

$$Reduction\ in\ Death\ (\%) due\ Back\ LIDAR\ Implementation = Value from\ fault\ tree \times Market\ penetration\ of\ autonomous\ vehicle = 0.15341 \times 0.1 = 0.015341$$

$Lives\ saved = Traffic\ Crash\ Deaths \times Reduction\ in\ Death\ (\%) due\ Back\ LIDAR\ Implementation = 284.87$

$Monetory\ value\ of\ lives\ saved = Lives\ saved \times Statistical\ Value\ of\ a\ life = 284.87 \times \$6200000 = \$1766180000$

$Monetory\ value\ of\ travel\ time\ saved = Travel\ time\ saved \times Cost\ of\ one\ hour\ travel = (0.1 \times 0.05 \times 5500000000) \times \$12.95 = \$356130000$

$Reduction\ in\ CO_2\ Emission = Travel\ mileage\ saved \times Emission\ rate = (0.1 \times 0.05 \times 5500000000 \times 30) \times 367 = 3027750000000\ gm = 3337522.115\ tons$

$Monetory\ value\ of\ Reduction\ in\ CO_2\ Emission = Reduction\ in\ CO_2\ Emission \times Cost\ in\ emission\ reduction = 3337522.115 \times \$27.26 = \$90980852.86$

$$Monetory\ value\ of\ Reduction\ Emission\ (CO_2 + NO_X + VOC + PM) = 90980852.86 + 43244101.26 + 3977744.341 + 5946063.923 = \$144148762.4$$

$Total\ Monetory\ value\ of\ Benefits\ in\ 2030 = Monetory\ value\ of\ lives\ saved + Monetory\ value\ of\ travel\ time\ saved + Monetory\ value\ of\ Reduction\ Emission = \$2266460000$

So, $Net\ present\ worth\ factor = \frac{(1+i)^N - 1}{i(1+i)^N} = \frac{(1+0.065)^{14} - 1}{0.065(1+0.065)^{14}} = 9.01384233$

$Net\ present\ Total\ Benefit = Total\ Monetory\ value\ of\ Benefits\ in\ 2030 \times Net\ present\ worth\ factor = \$2266460000 \times 9.01384233 = \$20429470000$

Total Costs Calculation:

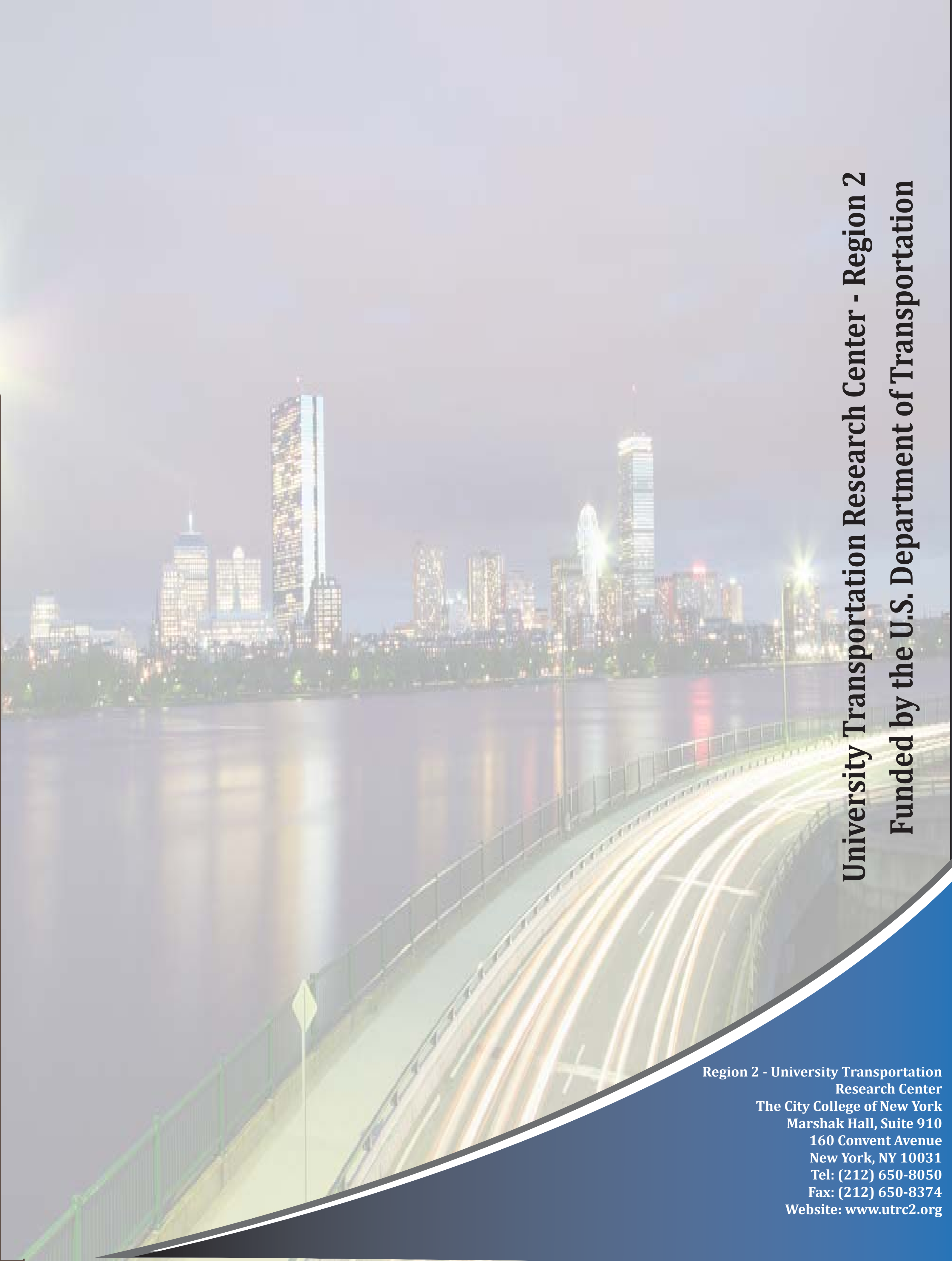
$Expected\ number\ of\ vehicles\ in\ 2030 = \frac{Population\ in\ 2030}{1.2} = 309400000$

$$Expected\ number\ of\ autonomous\ vehicles\ in\ 2030 =$$
$$Expected\ number\ of\ vehicles\ in\ 2030 \times Market\ penetration\ of\ autonomous\ vehicle = 30940000$$

$$Back-up\ LIDAR\ cost = Expected\ number\ of\ autonomous\ vehicles\ in\ 2030 \times LIDAR\ unit\ cost = 30940000 \times \$8000 = \$247520000000$$

<u>Benefits Costs Calculation:</u>

$$BCR = \frac{Net\ Present\ Total\ Benefits}{Back-up\ LIDAR\ cost} = \frac{\$20429470000}{\$247520000000} = 0.08$$



University Transportation Research Center - Region 2

Funded by the U.S. Department of Transportation

Region 2 - University Transportation Research Center
The City College of New York
Marshak Hall, Suite 910
160 Convent Avenue
New York, NY 10031
Tel: (212) 650-8050
Fax: (212) 650-8374
Website: www.utrc2.org