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FREIGHT PLANNING AND OPERATION MODELS TO INCORPORATE EMERGING INNOVATIVE TECHNOLOGIES

Final Report

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DISCLAIMER

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EXCUTIVE SUMMARY

Recent rapid explosion of new technologies have created opportunities to address critical freight transportation challenges across all modes in urban, suburban and rural areas. Some examples of new technologies include expansion of e-commerce, last mile deliveries by unmanned aerial vehicles (UAVs) or delivery robots, and potential applications of automated and connected vehicles in freight transportation (e.g. truck platooning). These new technologies are also influencing consumer behavior and thereby reshaping freight supply chains at the urban, regional, and international level. *First*, the project will develop diffusion of innovation based models to predict how the adoption of autonomous trucks will be in the future by freight organizations. *Second*, we will analyze and model the potential emissions impacts of last mile delivery robots.

Third, we will address how truck platooning will be incorporated in transportation planning models such as how many trucks will be allowed in a platoon, platoon speed, platooning hours, freeway platooning zones, etc. *Fourth*, assess the role and feasibility of technological innovations in intermodal transportation. Finally, the project will summarize the findings, challenges, and scope for future research.

The rapid explosion in recent years of innovative technologies such as truck platooning, smart parking systems, collaborative and shared logistics techniques, and connected autonomous vehicles has created opportunities to address ongoing freight transportation challenges. These new technologies are having profound impacts on both consumer and corporate behavior, and they are reshaping the way organizations are thinking about urban, regional, and international freight transportation. If we are to understand how these innovations are changing the field of freight transportation, we must first understand organizational innovation adoption behavior. There is a wealth of research regarding individual innovation adoption behavior research, but there is limited material on the behavior of organizations. Individual adoption methods are not immediately applicable to organizations, and so research is needed to help bridge the gap between individual and organization innovation adoption behavior.

One of the most important concepts in innovation adoption models is the idea of peer effects. Peer effects are a relatively new concept in the literature, and they address the fact that agents in a network tend to react not only to their own desires and needs but also the actions of their peers. Depending on the formation of the network, agents will have varying degrees of influence over the decisions of their peers. Incorporating peer effects into an innovation adoption methodology is of critical importance.

Goals and Objectives: (1) Identify the various innovation and organization-specific variables that influence organizational innovation adoption behavior; (2) develop a generalized methodology for predicting how organizations will respond to an innovation within a network; (3) gather data on connected autonomous trucks from freight transportation organizations; (4) generate a prediction for the adoption rate of connected autonomous trucks; and (5) discuss future research directions.

E-Commerce and package deliveries are growing at a fast pace and several start-ups have already began pilot studies to deliver packages and groceries to consumers utilizing Autonomous Delivery Robots (ADRs). These ADRs are electric powered motorized vehicles that can deliver items or packages to customers without the intervention of a delivery person. ADRs can be divided into two types. Sidewalk autonomous delivery robots (SADRs) are pedestrian sized robots that only utilize sidewalks or pedestrian paths. On-road or simply road autonomous delivery robots (RADRs) are vehicles that travel on roadways shared with conventional motorized vehicles. The results show that RADRs can provide substantial cost savings in many scenarios but in all cases, at the expense of substantially higher vehicle miles per customer served. Unlike sidewalk autonomous delivery robots (SADRs), it is possible the RADRs will contribute significantly to additional vehicle miles per customer served.

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1.0 INTRODUCTION

Recent rapid explosion of new technologies have created opportunities to address critical freight transportation challenges across all modes in urban, suburban and rural areas. Some examples of new technologies include expansion of e-commerce, last mile deliveries by unmanned aerial vehicles (UAVs) or delivery robots, and potential applications of automated and connected vehicles in freight transportation (e.g. truck platooning). These new technologies are also influencing consumer behavior and thereby reshaping freight supply chains at the urban, regional, and international level.

First, the project will develop diffusion of innovation based models to predict how the adoption of autonomous trucks will be in the future by freight organizations. Second, we will address how truck platooning will be incorporated in transportation planning models such as how many trucks will be allowed in a platoon, platoon speed, platooning hours, freeway platooning zones, etc. Third, we will model the potential emissions impacts of last mile delivery robots. Fourth, assess the role and feasibility of technological innovations in intermodal transportation. Finally, the project will summarize the findings, challenges, and scope for future research.

This report’s introduction will further explicate the motivation for research. Section 2 will reviews package delivery trends, and Section 3 presents parking and curb regulations at the municipal level. Section 4 will explain the methodology and data collection of US cities and their accommodations for curbside loading needs, and Section 5 presents analysis and discussion. Lastly, Section 6 presents final conclusions.

2.0 PREDICTING THE ADOPTION OF CONNECTED AUTONOMOUS VEHICLES BY TRANSPORTATION ORGANIZATIONS USING PEER EFFECTS

2.1 INTRODUCTION

The concept of Connected Autonomous Vehicles (CAVs) has gained much popularity over the last decade. Many modern vehicles are implementing some automation technologies such as lane departure warnings, adaptive cruise control, and collision avoidance systems, and test vehicles have already been allowed onto public roads in some areas (Bagloee et al., 2016; Steward, 2017; The Tesla Team, 2016). There are many expected benefits for CAVs, including reduced collisions and increased safety, increased mobility for disabled persons, a reduction in traffic congestion, more environmentally sustainable vehicles, increased road capacity, reduced fuel consumption, consistent travel times, and an increase in productivity. (Anderson et al., 2014; Bagloee et al., 2016; Bansal and Kockelman, 2017; Bullis, 2011; Fagnant and Kockelman, 2015; Kunze et al., 2011; Lutin et al., 2013; Maddox, 2012).

However, despite the potential benefits to CAV technology, a number of issues with CAVs remain unresolved. Aside from operational concerns, questions about legality, liability, security, privacy, and infrastructure must be addressed before CAVs can be fully adopted by the public. However, it is difficult to prepare for these problems unless policymakers and legislators know how quickly the public is likely to adopt CAVs.

Some studies have already been performed to estimate the adoption of CAVs for private consumers (Lavasani et al., 2016; Talebian and Mishra, 2018), but despite the depth of research in the field of innovation adoption behavior, one area of study that has received less attention from academia is the behavior of organizations such as corporations and governmental agencies. While some studies have been performed regarding organizational innovation adoption behavior (Crossan and Apaydin, 2010; Damanpour, 1991; Damanpour and Schneider, 2006; Kim and Srivastava, 1998; Pierce and Delbecq, 1977; Rye and Kimberly, 2007; Simpson et al., 2019; Subramanian and Nilakanta, 1996), these studies tend to be theoretical in nature, examining the effects of specific aspects of organizational adoption behavior such as managerial influence (Damanpour and Schneider, 2006; Leonard-Barton and Deschamps, 1988) or the structure of the organization (Damanpour, 1992; Moch and Morse, 1977; Pierce and Delbecq, 1977). While these studies are useful in that they provide further insight into the factors that influence organizational innovation adoption behavior, they fail to establish a solid baseline from which other works may begin (Crossan and Apaydin, 2010).

The purpose of this study is to establish a generalized methodology for estimating organizational innovation adoption behavior using a hypothetical dataset regarding the adoption of Connected Autonomous Trucks (CATs). Utilizing the findings of previous studies in the field of organizational innovation adoption behavior, a discrete choice modeling framework is developed to estimate the adoption of CATs by transportation organizations. This model incorporates elements from both traditional innovation adoption theories and peer effects research.

The remainder of the report is organized as follows. The following section discusses the technological innovations currently in development in the transportation field and the various innovation and organizational variables that influence the innovation adoption process. Section 3 provides details about the methodology used in the report, and section 4 contains a breakdown of the data gathered to test the model. Section 5 provides the results of the model and concludes the study with a discussion of the findings and information about future research opportunities in this field.

2.2 LITERATURE REVIEW

2.2.1 Organizational Innovations in Transportation

Over the last several years, a number of new technologies have created opportunities to address many of the challenges facing transportation organizations. Innovations such as CAVs, truck platooning, drone transportation, smart parking systems, and collaborative/shared logistics systems may very well reshape the field of transportation. These innovations are influencing the behavior of consumers and organizations alike, altering the network of freight supply chains at all levels. While this report focuses on the adoption of CATs, the methodology has been generalized so that it can be utilized for any number of innovations within the field of transportation. Therefore, it is important to briefly discuss these innovations and the state of research surrounding them.

2.2.1.1 Connected autonomous vehicles

The idea of self-driving cars has long been a fantasy of both transportation planners and the general public, but recent advancements in automation technologies point to the promise of truly autonomous vehicles in the near future. While most vehicles currently being sold possess some small degree of automation such as adaptive cruise control, collision avoidance systems, parking assist, route assignment via GPS, and lane departure warning systems, true connected autonomous vehicles (CAVs) have not yet been made available to the general public (Bagloee et al., 2016; Bansal and Kockelman, 2017; Fagnant and Kockelman, 2015). Companies such as Google, Tesla, and Uber are currently testing prototype CAVs on specific roads in the United States (Bagloee et al., 2016; Steward, 2017; The Tesla Team, 2016), and both federal and state-level DoTs are examining potential regulations concerning future autonomous vehicles (Lari et al., 2015; U.S. Department of Transportation, 9/16).

According to the National Highway Traffic Safety Administration (NHTSA), autonomous vehicles are divided up into different levels based on the degree of automation, from minor automation features at level one to complete automation with no driver controls at level five (Lutin et al., 2013). Most modern vehicles can be categorized as a level 1 or 2 autonomous vehicle, but the term “connected autonomous vehicle” tends to refer to levels 3 through 5. Level 3 CAVs may become commercially available as soon as 2020, with the higher levels of automation arriving in the following years (Fagella, 2017). On top of driving autonomously, CAVs must also be able to communicate with other vehicles, pedestrians, the infrastructure, or a centralized control center to operate without introducing significant disruption to the flow of traffic (Milakis et al., 2015; O’sullivan, 2010).

Integrating CAVs into the fleet is expected to have many benefits. The most commonly referenced benefit is an increase in vehicle safety and a reduction in collisions (Bagloee et al., 2016; Bansal and Kockelman, 2017; Bullis, 2011; Fagnant and Kockelman, 2015; Lutin et al., 2013). By removing human distractions and relying on the much faster reflexes of an autonomous system, advocates of CAVs hope to greatly reduce or even eliminate collisions altogether (Anderson et al., 2014; Lutin et al., 2013; Maddox, 2012). Other anticipated benefits include a reduction in congestion, more environmentally friendly vehicles, greater mobility for those unable to drive, increased road capacity, reduced fuel consumption, increased productivity, and more predictable travel times (Anderson et al., 2014; Bagloee et al., 2016; Fagnant and Kockelman, 2015; Kunze et al., 2011).

CAVs may also have additional benefits to freight transportation. Automation may reduce the number of drivers required to move goods, greatly reducing the overall cost of transportation operations and providing a possible answer to driver shortage issues (Rossman, 2017; Shankwitz, 2017). Between reducing labor costs and increased fuel efficiency, CAVs have the potential to alleviate the two largest costs of freight transportation organizations (Anderson et al., 2014; Bagloee et al., 2016; Bullis, 2011; Fagnant and Kockelman, 2015; Kockelman et al., 2017; Shankwitz, 2017). Automation will also increase the comfort of drivers, which may in turn help organizations address the issue of frequent driver turnaround. Overall productivity may also increase if CAVs lead to changes in regulations regarding the number of hours of service a driver may work before he or she is required to rest.

CAVs will also likely be attractive to organizations responsible for public transportation systems for similar reasons. Research has shown that individuals may be wary about the prospect of transitioning to shared CAVs, but using automated public transportation systems is less of a concern (Fagnant et al., 2015; Fagnant and Kockelman, 2018; Lam et al., 2016; Litman, 2017; Menouar et al., 2017). Automated bus services could greatly increase total passenger capacity while requiring minimal infrastructure changes, and reducing the cost of operating a public transit system would allow for lower tolls, leading to increased utility for public transportation options (Bishop, 2000).

It should be noted that the technology required to enable CAVs will also have additional use in transportation organizations outside of freight. The imaging and short-range communications technology will be useful in monitoring traffic, re-routing in case of detours, enabling smart parking systems, and reducing collisions in traditional vehicles (Milakis et al., 2015; O'sullivan, 2010).

2.2.1.2 Truck platooning

Truck platooning is the act of using connectivity technology to link two or more trucks into a convoy. The lead truck may be automated or manned, and all other trucks in the convoy automatically react to the actions of the lead truck. Because the trucks rely on automation technology rather than human reaction times, they are able to maintain a much smaller headway than is safe in traditional driving. The potential benefits of truck platooning include lower fuel consumption, reduced emissions, and increased driver safety (ACEA, 2016).

Most of the research that has been conducted so far in Truck Platooning focuses on investigating ways to minimize fuel consumption and energy usage by efficiently implementing the technology. The most common optimization solutions involve adjusting the platoon speeds and the headways between the trucks (Alam et al., 2015; Deng and Ma, 2014; Kunze et al., 2011; Tsugawa et al., 2011; Van De Hoef et al., 2015). Also, another important aspect in truck platooning is managing and integrating the technology with normal traffic flow conditions. Another focus of the literature is on how truck platoons interact with normal traffic patterns. Current traffic models are unable to account for truck platoons, and so updated models are presented in the literature to account for the disruption caused by the platoons (Farokhi and Johansson, 2013; Larsson et al., 2015). Studies on how to implement truck platoons, the infrastructure required to support platoons, vehicle-to-vehicle communication technologies, and required automation are also found in the literature (Bergenhem et al., 2012; Gehring and Fritz, 1997; Nowakowski et al., 2015).

2.2.1.3 Drones in transportation

Drones, also sometimes referred to as "unmanned aerial vehicles," have been used by militaries for some time. However, the use of drones by civilian transportation organizations has only recently begun to attract the attention of investors. Drones come in a wide variety of shapes and sizes, and the term can be used to describe flying vehicles from hand-held devices to vehicles the size of commercial airplanes. However, organizations seem to be focusing primarily on the applications that the smaller drones can offer, including the transportation of medical supplies (Amukele et al., 2017; Lippi and Mattiuzzi, 2016; Thiels et al., 2015), passenger transportation (Clarke, 2014a), monitoring traffic patterns (Kim et al., 2017), air cargo transportation (Chalupníčková et al., 2014; Kim et al., 2017; Kim and Davidson, 2015)and augmenting ground-based freight transportation by assisting with last-mile operations (Campbell et al., 2018; Clarke, 2014a; Tavana et al., 2017).

There are a number of potential benefits to using drones to assist in transportation operations, aside from the obvious reduction in manpower necessary to transport goods. Drones would be largely immune to traffic issues that may delay ground or air-based freight operations, and would be able to travel virtually anywhere within a certain radius of the operation's center (Amukele et al., 2017; Chalupníčková et al., 2014). They would have a much lower overhead cost than today's delivery vehicles, and would prove to be easier to monitor, as well (Amukele et al., 2017; Chalupníčková et al., 2014; D'Andrea, 2014). An underexamined aspect of drones in transportation is that drones would produce far less CO_2 and other emissions compared to the trucks which are used today (Goodchild and Toy, 2018).

However, there are also a number of drawbacks to drone technology that have not yet been addressed. One of the most prevalent concerns regarding drone adoption revolves around privacy and security. Drones could be used to monitor traffic and improve transportation, but they could also easily be used to spy on citizens and gather data without consent (Clarke, 2014a, 2014b; D'Andrea, 2014; Rao et al., 2016). Similar to CAVs, there is the problem of drone decision-making capabilities potentially being insufficient to deal with real-time events. Without adequate reaction and decision-making capabilities, drones may prove to be little more than dangerous, high-speed projectiles (Clarke, 2014c; Clarke and Moses, 2014; Kim et al., 2017; Lippi and Mattiuzzi, 2016). Drones may also be hijacked if they are not adequately protected from cyberattacks (Clarke and Moses, 2014) There is little safety data on civilian drone usage to draw upon to predict how dangerous drones may actually become if their use becomes widespread (Amukele et al., 2017).

While there are many concerns surrounding civilian drone use, most research on the technology and its applications tend to be positive about the eventual adoption of drones in transportation. Researchers are focusing on improving the technology to make drones economically viable and capable of carrying larger payloads (D'Andrea, 2014; Floreano and Wood, 2015), ensuring the safety of drone operations (Clarke, 2014a, 2014b, 2014c; Clarke and Moses, 2014; Kim et al., 2017; Lippi and Mattiuzzi, 2016), theorizing ways that drone technology might be applied to freight operations (Amukele et al., 2017; Chalupníčková et al., 2014; Kim et al., 2017; Kim and Davidson, 2015; Tavana et al., 2017), measuring the environmental impact of drone usage (Goodchild and Toy, 2018), and integrating drones into current transportation processes (Campbell et al., 2018; Tavana et al., 2017)

2.2.1.4 Smart parking

Smart parking technology enables communication between drivers and the parking lot. This can take the form of reserving parking spaces ahead of time, directing drivers to the most convenient open parking space, or gathering data on parking lot preferences and providing insight for future infrastructure projects. The results of smart parking systems include more optimal parking space usage and better traffic flow through parking facilities.

Much of the current research in this field is focused on identifying the most critical aspects of smart parking systems and providing algorithms that optimize the performance of the parking lot by balancing proximity to the destination, costs, and overall utilization of parking capacity in real time (Bachani et al., 2016; Geng and Cassandras, 2012; Hanif et al., 2010; Polycarpou et al., 2013; Shin and Jun, 2014). Another focus of research is how best to allow drivers to reserve parking spaces while still balancing cost and overall capacity (Hanif et al., 2010; Wang and He, 2011). Other research in this field focuses on problems such as how to best establish sensors and other pieces of infrastructure needed for smart parking technology to function (Chinrungrueng et al., 2007), or the potential costs and benefits of adopting smart parking systems (Mahmud et al., 2013; Pala and Inanc, 2007).

2.2.1.5 Collaborative and shared logistics

Collaborative and shared logistics refer to the strategy of utilizing unused capacity in both passenger and freight transportation systems. Collaboration can be horizontal (between competitors) or vertical (between different parts of a supply chain) (Saenz et al., 2015). Collaboration between transportation organizations can result in more optimal systems, improved reliability, reduced delivery time, and increased cost efficiency (Angerhofer and Angelides, 2006; Bates et al., 2017; de Souza et al., 2014; Guo et al., 2016; O'sullivan, 2010; Tyan et al., 2003).

Research on this subject is largely computational in nature. Organizations involved in collaborative and shared logistics recognize that there is a benefit to the system, but sophisticated technology is required to achieve the optimal solution, as resource allocation and vehicle routing problems are constantly changing (Curtois et al., 2017; Dai and Chen, 2009; de Souza et al., 2014; Gonzalez-Feliu et al., 2013; Guajardo and Rönnqvist, 2015; Stefansson, 2006; Trentini et al., 2012; Verdonck et al., 2013). The literature discusses models that range from full-system collaboration transportation management (Feng and Yuan, 2007; Gonzalez-Feliu et al., 2013; O'sullivan, 2010; Stefansson, 2006; Trentini et al., 2012; Verdonck et al., 2013), to models that deal with very specific situations such as last-mile and less-than-truckload transportation (Dai and Chen, 2009; de Souza et al., 2014).

2.2.2 Factors in Innovation Adoption

The study of innovation adoption behavior stretches back to the 1930s when a new variety of corn was introduced to farmers in the American Midwest, and it has remained a popular domain for research to this day (Ryan and Gross, 1950). Researchers have studied innovation adoption in nearly every field, including health care (Berwick, 2003; Cain, 2002; Greenhalgh et al., 2004; Plsek, 2003; Rye and Kimberly, 2007), transportation (Lavasani et al., 2016; Orbach and Fruchter, 2011; Shafiei et al., 2014; Talebian and Mishra, 2018; Wolf et al., 2015; Zsifkovits and Günther, 2015), information systems and technologies (AlAwadhi and Morris, 2008; Kijsanayotin et al., 2009; Lin and Anol, 2008; Martins, 2013; Wang and Wang, 2010; Zhou, 2012), communications (Daft and Lengel, 1986; Fidler and Johnson, 1984; Leonard-Barton and Deschamps, 1988; Van

Slyke et al., 2007), education (Borrego et al., 2010; Graham et al., 2013; Mintrom and Vergari, 1998), and entertainment (Atkin, 1993; Kim et al., 2009; Leong et al., 2011), to name a few. These studies provide insight into why some innovations have successfully permeated throughout society while others fail to reach their market potential. By analyzing the psychological (Marcati et al., 2008; Ram and Sheth, 1989; Sheth and Stellner, 1979; Wood and Swait, 2002), sociological (Boahene et al., 1999; Mahler and Rogers, 1999; Valente, 1996; Valeri et al., 2016), and economic factors (Bishop et al., 2010; Gopalakrishnan and Damanpour, 1997; Greenhalgh et al., 2004; Mahler and Rogers, 1999; Rogers, 2003) that influence innovation adoption behavior, researchers have been able to come to understand not only why innovations succeed or fail but also how potential adopters may respond to future innovations.

Because innovation adoption behavior is such an advanced field of research, there are many variables that have been identified as influencing adoption behavior. Different variables are chosen for any given study depending on the field of research and the theoretical framework that is being used, but there are several common elements to most innovation adoption studies. The variables can generally be grouped into innovation variables, organization variables, and social variables, as demonstrated by Table 1.

Depending on the innovation, there may be additional, non-universal variables which may need to be considered. For example, CAT adoption studies may need to include variables such as driver opinion, organization fleet sizes, average miles traveled per trip, and whether the organization owns, contracts with, or rents their vehicles. These additional variables should be considered on a case-by-case basis.

Table 1: Organizational innovation adoption variables

Variable	Type	Definition	Sources
Relative Advantage	Innovation	The degree to which an innovation is perceived as being better than the idea or system it supersedes	(Aubert and Hamel, 2001; Cain, 2002; Greenhalgh et al., 2004; Hoerup, 2001; Premkumar et al., 1997; Rogers, 2003; Sahin, 2006)
Compatibility	Innovation	The degree to which an innovation is consistent with the goals and needs of the adopter	(Aubert and Hamel, 2001; Greenhalgh et al., 2004; Hoerup, 2001; Meyer and Goes, 1988; Premkumar et al., 1997; Rogers, 2003; Sahin, 2006)
Observability	Innovation	The degree to which an innovation's effects are easily noticed and understood	(Aubert and Hamel, 2001; Cain, 2002; Greenhalgh et al., 2004; Meyer and Goes, 1988; Parisot, 1997; Rogers, 2003; Sahin, 2006)
Complexity	Innovation	The degree to which an innovation is difficult or understand	(Greenhalgh et al., 2004; Meyer and Goes, 1988; Plsek, 2003; Premkumar et al., 1997; Rogers, 2003; Sahin, 2006).
Trialability	Innovation	The degree to which an innovation may be experimented with on a limited basis	(Aubert and Hamel, 2001; Greenhalgh et al., 2004; Hoerup, 2001; Plsek, 2003; Rogers, 2003; Sahin, 2006)
Reinventability	Innovation	The degree to which an innovation is able to be modified for purposes other than its original intended use	(Greenhalgh et al., 2004; Meyer et al., 1997; Robinson, 2009)
Perceived Risk	Innovation	The degree of uncertainty surrounding the Innovation	(Greenhalgh et al., 2004; Hudson et al., 2019; Martins, 2013; Meyer and Goes, 1988; Ram and Sheth, 1989; Schoettle and Sivak, 2014; Sheth and Stellner, 1979)
Organizational Size	Organizational	A description of the size of the organization in question, typically in terms of employment	(Damanpour, 1992; Frambach and Schillewaert, 2002; Moch and Morse, 1977; Pierce and Delbecq, 1977; Premkumar et al., 1997; Rogers, 2003; Subramanian and Nilakanta, 1996)

Table 1 Cont.

Variable	Type	Definition	Sources
Specialization	Organizational	A measurement of the knowledge and expertise of an organization's members	(Damanpour, 1991; Moch and Morse, 1977; Rogers, 2003; Subramanian and Nilakanta, 1996)
Formalization	Organizational	A measurement of how strictly an organization requires its members to follow established rules and protocol	(Kim and Srivastava, 1998; Rogers, 2003; Subramanian and Nilakanta, 1996).
Centralization	Organizational	The degree to which power and control in a system are concentrated in the hands of relatively few individuals	(Frambach and Schillewaert, 2002; Kim and Srivastava, 1998; Moch and Morse, 1977; Pierce and Delbecq, 1977; Rogers, 2003).
Privatization	Organizational	The degree to which an organization is controlled by private owners, rather than the general public	(Aarons et al., 2009; Damanpour, 1991; Damanpour and Schneider, 2008; Hartley, 2005; Rainey et al., 1976; Van der Wal et al., 2008; Van der Wal and Huberts, 2008)
Managerial Innovativeness	Social	The degree to which the decision-maker(s) of an organization are inclined to innovate	(Aguila-Obra and Padilla-Meléndez, 2006; Damanpour and Schneider, 2008, 2006; Leonard-Barton and Deschamps, 1988; Rogers, 2003).
Governmental Influences	Social	The degree to which regulations and legislation restricts or promotes the adoption of the innovation	(Hall and Van Reenen, 2000; Litman, 2017; Welch and Thompson, 1980)
Public Opinion	Social	The perceived attitude of the public toward the innovation	(Burstein, 2003)

2.2.2.1 Innovation Variables

The first innovation variable that most studies mention is “Relative Advantage” (Aubert and Hamel, 2001; Cain, 2002; Greenhalgh et al., 2004; Hoerup, 2001; Premkumar et al., 1997; Rogers, 2003; Sahin, 2006). Relative advantage is the degree to which an innovation is perceived as being better than the idea or system it supersedes. It can be stated in economic terms if saving time, energy or money is the primary goal of the innovation. It could also be considered in social terms if it is considered desirable or prestigious to adopt an innovation (Rogers, 2003). Relative advantage is based on the perception of the potential adopter; not every individual will place the same value on the advantages an innovation may bring (Cain, 2002). Some studies choose to separate relative advantage from cost (Hoerup, 2001), but the prevailing tendency is to assume that cost is a factor included in relative advantage (Hoerup, 2001; Rogers, 2003).

“Compatibility” is the degree to which an innovation is consistent with the goals and needs of the adopter (Aubert and Hamel, 2001; Greenhalgh et al., 2004; Meyer and Goes, 1988; Premkumar et al., 1997; Rogers, 2003; Sahin, 2006). This attribute is also largely based on the perception of potential adopters. An innovation may be intended to solve a problem or meet a need, but if the adopter does not recognize the need for the innovation, he or she is less likely to choose to adopt (Sahin, 2006). The perception of compatibility for an innovation is mostly reliant on effective marketing. Everything from the name of the innovation to the intended purpose and use of the innovation effects potential adopters’ perceived compatibility (Hoerup, 2001).

“Observability” – sometimes referred to as visibility - is a measure of how easily the effects of an innovation are noticed and understood, especially by other potential adopters (Aubert and Hamel, 2001; Greenhalgh et al., 2004; Meyer and Goes, 1988; Rogers, 2003; Sahin, 2006). Observability is important to adoption rate because an innovation which is easily observable will be noticed and accepted more rapidly than an innovation which is difficult to observe (Rogers, 2003). Direct observation is often a key factor in motivating potential adopters to more thoroughly investigate an innovation (Parisot, 1997). Some effects of innovations may be readily apparent to a casual observer, whereas other aspects may be much harder to observe (Aubert and Hamel, 2001; Rogers, 2003). Observability is often inversely correlated with perceived complexity, because more complex innovations are more difficult to understand, and so it is more difficult to perceive the effects they may have (Cain, 2002).

Like compatibility, “complexity” is largely based on the perception of the potential adopter. Complexity is the belief that an innovation will be either difficult to use or difficult to understand. Complexity is an inherently negative attribute of an innovation (Greenhalgh et al., 2004; Meyer and Goes, 1988; Premkumar et al., 1997; Rogers, 2003; Sahin, 2006). More complex innovations are less likely to be adopted and will permeate throughout a field more slowly than simpler innovations. Proper instruction and a user-friendly interface can reduce the perceived complexity of an innovation, causing it to be diffused more rapidly (Cain, 2002; Sahin, 2006). Innovations which can be adopted in small, manageable pieces over time can also greatly increase the innovation’s attractiveness (Greenhalgh et al., 2004; Plsek, 2003; Rogers, 2003). Some studies prefer to capture the effect of complexity with its opposite attribute, which is typically referred to as “Ease of Use” (Aubert and Hamel, 2001; Venkatesh et al., 2016).

“Trialability” is a measurement of how easily an innovation can be tested before full adoption (Aubert and Hamel, 2001; Greenhalgh et al., 2004; Rogers, 2003; Sahin, 2006). The adoption of innovations is a process of reducing the uncertainty surrounding an innovation, and the ability to test an innovation before fully adopting it is an effective way to reduce uncertainty (Rogers, 2003). Trialability is especially important early in the diffusion process, because at that time there are few existing examples of the innovation succeeding. As more people successfully adopt the innovation, potential adopters have more references to draw from to reduce their uncertainty, reducing the impact of an innovation's trialability (Hoerup, 2001; Plsek, 2003).

"Risk" is the degree of uncertainty surrounding the innovation (Greenhalgh et al., 2004; Meyer and Goes, 1988; Sheth and Stellner, 1979). Risk is typically viewed in the context of the innovation's relative advantage, as it can be considered in physical, economic, social, or political terms, and it is dependent on the perception of the individual adopter (Greenhalgh et al., 2004; Martins, 2013; Meyer and Goes, 1988; Ram and Sheth, 1989; Sheth and Stellner, 1979).

"Reinvention" is the degree to which an innovation is able to be modified for purposes other than its original intended use (Greenhalgh et al., 2004; Meyer et al., 1997; Robinson, 2009). Innovations that are perceived to be flexible are likely to be perceived as more

advantageous (Greenhalgh et al., 2004). In addition, an innovation with a high reinvention capacity is more likely to be perceived as compatible with the adopter's needs (Robinson, 2009).

2.2.2.2 Organization Variables

"Organizational size" is the most commonly discussed organizational characteristic for innovation adoption studies. The size of an organization can be measured as total employment, the number of clients or customers, or the annual budget/revenue of an organization. Larger organizations tend to display greater innovativeness than organizations which are smaller (Frambach and Schillewaert, 2002; Premkumar et al., 1997; Rogers, 2003; Subramanian and Nilakanta, 1996). Some studies suggest that organizational size is merely a useful proxy for other organizational variables such as specialization and centralization, and that size is not actually indicative of greater innovativeness (Moch and Morse, 1977; Pierce and Delbecq, 1977). While further research is needed to determine whether or not organizational size in isolation promotes innovative behavior, there does seem to be a correlation between the size of an organization and its ability or desire to innovate (Damanpour, 1992; Frambach and Schillewaert, 2002; Moch and Morse, 1977; Pierce and Delbecq, 1977; Rogers, 2003; Subramanian and Nilakanta, 1996).

"Specialization" is defined as the level of knowledge and expertise that the organization can draw upon (Damanpour, 1991; Moch and Morse, 1977; Rogers, 2003; Subramanian and Nilakanta, 1996). Highly specialized members of an organization will require less training to acquire the skills necessary to adopt innovations. Specialization is a counterbalance for the complexity of an innovation; if an organization has highly specialized members, then that organization will be better able to adopt and integrate complex innovations (Damanpour, 1991; Moch and Morse, 1977; Subramanian and Nilakanta, 1996).

"Centralization" is defined as "the degree to which power and control in a system are concentrated in the hands of relatively few individuals" (Frambach and Schillewaert, 2002; Kim and Srivastava, 1998; Moch and Morse, 1977; Pierce and Delbecq, 1977; Rogers, 2003). More centralized organizations tend to be slower to adopt than less centralized organizations, as the decision-makers are further removed from the places where the innovation is needed (Frambach and Schillewaert, 2002; Kim and Srivastava, 1998; Moch and Morse, 1977; Rogers, 2003). However, once the decision to adopt has been made, organizations which are more centralized tend to implement the innovations more quickly (Frambach and Schillewaert, 2002; Rogers, 2003).

"Formalization" is the degree to which an organization expects its members to follow pre-established protocol (Kim and Srivastava, 1998; Rogers, 2003; Subramanian and Nilakanta, 1996). More formal organizations are less likely to consider innovation as a solution to a problem, but they are also better able to implement an innovation after the adoption decision has been made (Kim and Srivastava, 1998; Rogers, 2003; Subramanian and Nilakanta, 1996).

“Organizational slack” is a quantification of the resources that are available to an organization that have not been committed to other tasks (Cheng and Kesner, 1997; Nohria and Gulati, 1996; Subramanian and Nilakanta, 1996). Businesses often view organizational slack as a negative attribute, but high levels of organizational slack indicate that the organization is able to experiment with innovations (Cheng and Kesner, 1997; Nohria and Gulati, 1996; Subramanian and Nilakanta, 1996). Higher levels of organizational slack are associated with lower perceived risk, which is intuitive because many of the resources that would be devoted to adopting and implementing an innovation will not be needed for other tasks (Moses, 1992).

“Privatization” is the degree to which an organization is controlled by private owners rather than the general public. Many organizations are strictly public or private, but there are other organizations that can be most accurately described as “quasi-public,” and so the degree of privatization for each organization needs to be accounted for. Private organizations tend to be more innovative than public organizations, as public organizations tend to be less focused on competition and more focused on public opinion (Aarons et al., 2009; Damanpour, 1991; Damanpour and Schneider, 2008; Hartley, 2005; Van der Wal et al., 2008; Van der Wal and Huberts, 2008). Contrary to popular belief, public organizations do not tend to have higher formalization than private organizations (Rainey et al., 1976). Also of note is that the decisions of public organizations tend to be less influenced by many of the other organizational characteristics, and they tend towards lower estimations of relative advantage for innovations than private organizations (Damanpour, 1992; Rainey et al., 1986; Van der Wal et al., 2008).

2.2.2.3 Social Variables

Another factor to consider is the effect of managerial innovativeness. An organization with an innovative manager or a manager which champions a particular innovation will be much more likely to adopt (Aguila-Obra and Padilla-Meléndez, 2006; Damanpour and Schneider, 2008, 2006; Leonard-Barton and Deschamps, 1988; Rogers, 2003). Youth and advanced education tend to be correlated with increased managerial innovativeness (Hambrick and Mason, 1984).

Governmental influences must also be taken into account when examining organizational innovation adoption behavior. In some cases, regulations have been introduced that encourage or even mandate adoption (Litman, 2017). However, legislation can just as easily discourage or prohibit the use of a particular innovation. The weight of these influences must be examined on a case-by-case basis (Hall and Van Reenen, 2000; Welch and Thompson, 1980). In a similar manner, it is important to consider the influence that public opinion may have on an organization’s decision to adopt an innovation. While organizations are typically less influenced by social factors, public opinion is still a powerful indicator of what an organization will decide to do (Burstein, 2003).

2.2.2.4 Peer Effects

One important factor to consider in innovation adoption studies is the effect of social influences on the adopter (Bass, 2004; Boahene et al., 1999; Clearfield and Osgood, 1986; Mahajan et al., 1995; Mahler and Rogers, 1999; Rogers, 2003; Valente, 1996; Wright and Charlett, 1995). Individuals tend to make decisions based on not only their own interests but the actions of their peers. Figure 1 illustrates the impact of peer effects on a network.

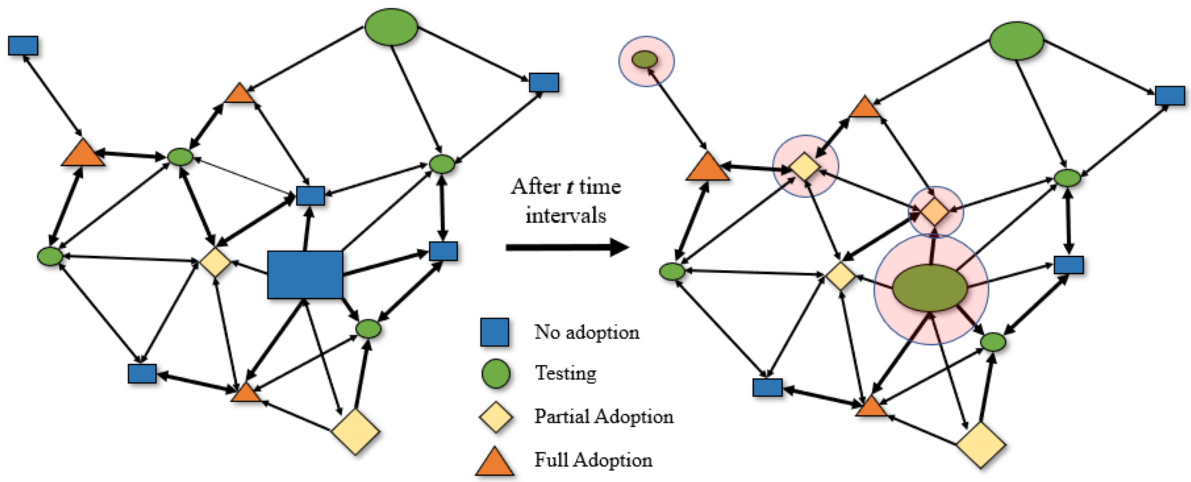

Figure 1: Impact of peer effects on a network

The left panel of Figure 1 shows a network of organizations in one of four adoption states. The thickness of arrows in which each organization is connected with other shows the strength of connection, and size of each node represent their firm size in terms of employees. Organizations which change their adoption decision due to peer influences are highlighted. Each organization is connected with others to form a sub-network. The peer effect literature in non-transportation domains suggest that organizations who have adopted a specific innovation will potentially affect others who are in their subnetwork (Bramoullé et al., 2009; Calvó-Armengol et al., 2009). Similarly, organizations who have not adopted and pose a negative view towards the innovation may affect others towards non-adoption or deferred adoption. The current literature lacks quantification of peer effects, i.e. some organizations adoption decisions because of their size, business pattern, geographical operation boundaries, etc.

One of the difficulties that must be considered when developing a peer effects model is how to establish the social network. It is often difficult to determine whether or not there should be a link between two agents, and the way that the network is structured can have a large impact on the results of the peer effects evaluation (Bramoullé et al., 2009; Dugundji and Walker, 2005; Le Pira et al., 2017a). This report proposes that the social network can be formed using a modification of the gravity model, where the links between nodes depends on the distance between the nodes and the respective weights of the nodes.

An important aspect of peer effects is the concept that not all players are equal in their ability to influence their peers (Ballester et al., 2006). Depending on factors such as personality, position within the social network, experience, and authority, individuals have widely varying levels of influence over their peers (Calvó-Armengol et al., 2009). Agent-based modeling techniques may be particularly useful in accounting for this heterogeneity (Biondo et al., 2017; Le Pira et al., 2017b; Marcucci et al., 2017). When applying the concept of peer effects to organizations, this variability in influence is greatly magnified due to the extreme heterogeneity found in organizations (Frambach and Schillewaert, 2002; Marcucci and Gatta, 2016; Ryan and Tucker, 2012). Organizations which are larger tend to have greater spheres of influence than smaller organizations.

Recent studies have demonstrated the power of these peer effects in other fields, but innovation adoption behavior studies have not yet incorporated many of the findings that this research has provided (Ballester et al., 2006; Calvó-Armengol et al., 2009; Goldsmith-Pinkham and Imbens, 2013; Kline and Tamer, 2014; Liu et al., 2012; Noll et al., 2014). Innovation adoption studies almost always include some way of measuring how peers of a potential adopter influence the decision-making process (Bass, 2004; Escobar-Rodríguez and Carvajal-Trujillo, 2014; Martins, 2013; Massiani and Gohs, 2015; Rogers, 2003; Venkatesh et al., 2016). While organizations tend to be much less reliant on social influences than individuals (Pierce and Delbecq, 1977), informal communication networks and inter-organizational competition are still strong social influences that must be considered (Czepiel, 1975).

2.3 METHODOLOGY

Data is gathered on *N* organizations, including all relevant characteristics and perceived attributes for the innovation. The innovation is denoted as set *I*, where *i* can take values from 1 to 4 (such as 1= complete rejection of the innovation, 2= a decision to test a prototype of the innovation, 3= a partial adoption, and 4 = full adoption). The dependent variable is denoted as Y_{ni}, which is the choice that organization n makes regarding adoption of the innovation *i*. Y_{ni} is an integer with values from 1 to 4 and the vector of all Y_{ni} outcomes is denoted as **Y**. Each organization n also has K attributes, which are denoted as the *K*-vector X_n (organization size, number of employees, centralized or decentralized business approach, local, regional or national operation etc.) and each alternative as unique characteristics such as X_i (capital cost of the innovation, operation and maintenance cost of the innovation, technological advantages, reduction in labor cost, annual profit accrued etc.). We can form an *N* by *K* matrix **X**, where the nth row is equal to the vector X_n (Goldsmith-Pinkham and Imbens, 2013).

The organizations will be connected in a network, and this network will be captured in the adjacency matrix **M**, where the typical element M_{pq} is a continuous variable greater than 0. Greater values of M_{pq} indicate that strong communication, competition, or influence exists between organizations p and q. Because some organizations are more influential than others, Matrix **M** is not symmetrical. A graph theory model is used to generate matrix **M**. We first define a δ-dimensional coordinate system. We then place each organization within the δ-dimensional space (Talebian and Mishra, 2018). The distance between each organization D_{pq} is calculated as

$$\boldsymbol{D_{pq}} = \sqrt{\sum_{A \in S} \sigma_A \left(\frac{V_{A_{ip}} - V_{A_{jq}}}{maxV_A} \right)^2} \quad \textbf{(1)}$$

where S is the set of characteristics that define the δ-dimensional space, V_{A_p} is the value of attribute A for organization p, and σ_A is the weight given to attribute A. We also assign a weight W_n to each organization according to the organizational size and fleet size. W_n is calculated as

$$\boldsymbol{W_n} = \sum_{C \in R} \frac{Z_{C_{in}}}{maxZ_C} \quad \textbf{(2)}$$

where R is the set of H attributes that define the weight of the organizations, and $Z_{C_{in}}$ is the value of attribute C for organization p. M_{pq} is then calculated as

$$\boldsymbol{M_{pq}} = \frac{W_{ip}}{D_{pq}} \quad \textbf{(3)}$$

Note that M_{pq} does not account for the weight of organization q because $M_{pq} \neq M_{qp}$. The influence of organization p on organization q is dependent only on the distance between them in the δ-dimensional space and the weight of organization p. Although M_{pq} will always be greater than zero, very low values for M_{pq} may indicate that there is no significant connection between organizations i and j. Therefore, a cutoff value γ should be determined on a case-by-case basis where all M_{pq} lower than γ are assumed to be equal to 0. Once M_{pq} is defined, we can calculate the influence that the organizational network exerts on organization n using equation 4:

$$\boldsymbol{\theta_n = \frac{1}{R_p}\sum_{q=1}^{N} M_{qp}Y_q \textbf{ for all } M_{qp} \neq 0} \tag{4}$$

where θ_n is the influence of the organizational network on organization n, and $R_n = \sum_{q=1}^{N} M_{qp}$ for all $M_{qp} \neq 0$.

The organization's choice for a specific innovation can be obtained using discrete choice models. We propose to utilize a linear in parameter specification to determine the utility of an organization *n* towards an innovation *i*, i.e. U_{in}. : $U_{in} = \boldsymbol{\beta}_i'\boldsymbol{X}_{in} + \varepsilon_{in}$ where $\boldsymbol{X}_{in}$ is a $K_i \times 1$ vector of exogenous covariates (including organizational characteristics such as number of employees, geography of operation, centralized or decentralized business, number of CEOs, male female employee ratio etc., and innovation attributes such as capital cost, operation and maintenance cost, expected annual profit, labor cost reduction, etc.). $\boldsymbol{\beta}_i'$ is the corresponding $K_i \times 1$ vector of coefficients and ε_{in} denotes all the unobserved factors that influence the innovation function for outcome *i* in organization *n*.

The choice modeling framework can be unordered or ordered. In unordered framework, the stochastic components ε_{in} in the latent innovation adoption functions U_{in} are assumed to be independent and identically distributed (*i.i.d.*) across different adoption outcomes and organizations. Moreover, the identical distribution is assumed to be standard type-1 extreme value distribution (also known to as Gumbel distribution). Given these assumptions on the stochastic term ε_{in}, $P_n(i)$ is:

$$\boldsymbol{P_n(i) = \frac{\exp(\beta_i' X_{in})}{\sum_{\forall I} \exp(\beta_j' X_{jn})}} \tag{5}$$

The $\sum_{i=1}^{I} K_i$ parameters in the multinomial model are estimated by maximizing the log-likelihood (ML) function obtained by taking the natural logarithm of the product of probabilities of observed severity outcomes given by Equation (2) as follows:

$$\boldsymbol{LL = \sum_{n=1}^{N}\left(\sum_{i=1}^{I} \delta_{in}\right)} \tag{6}$$

where δ_{in} is defined as 1 if the observed adoption outcome for organization n is i and zero otherwise. In the ordered framework, latent propensity y_n^* is translated into observed innovation adoption outcomes by threshold parameters. We propose a linear-in-parameter specification for the observed part of y_n^* and a standard logistic distribution that is *i.i.d.* across organizations for the stochastic component ε_n. The equation system for the ordered logit model is (McKelvey and Zavoina, 1975):

$$\boldsymbol{y_n^* = \beta' X_n + \rho' \theta_n + \varepsilon_n} \tag{7}$$

$$\begin{aligned}\boldsymbol{P_n(i)} &= \boldsymbol{P(\psi_{i-1} < y_n^* < \psi_i)} \\ &= \boldsymbol{P(\psi_{i-1} < \beta' X_n + \rho' \theta_n + \varepsilon_n < \psi_i)} \\ &= \boldsymbol{P(\psi_{i-1} - \beta' X_n - \rho' \theta_n < \varepsilon_n < \psi_i - \beta' X_n - \rho' \theta_n)}\end{aligned} \tag{8}$$

$$= \boldsymbol{F(\psi_i - \beta' X_n - \rho' \theta_n) - F(\psi_{i-1} - \beta' X_n - \rho' \theta_n)}$$

where $\boldsymbol{X_n}$ is $K \times 1$ vector of covariates and $\boldsymbol{\beta}$ is the corresponding $K \times 1$ vector of coefficients; $\psi_i' s$ are threshold parameters; $\psi_0 = -\infty\ and\ \psi_{I+1} = \infty;\ F(.)$ is the standard logistic cumulative distribution function. The model structure requires that the thresholds to be strictly ordered for the partitioning of the latent risk propensity measure into the ordered innovation in adoption categories$(i.e., -\infty < \psi_1 < \psi_2 < \cdots < \psi_{I-1} < \infty)$. The parameters in the ordered logit model ($\boldsymbol{\beta}$ and $\psi_i' s$) can be estimated using the ML method.

2.3.1 Demonstrating Peer Effects on a Network

In order to help demonstrate the effectiveness of the proposed methodology, an example problem has been provided. Because the framework for choice modelling has been discussed extensively in other works, the example problem will focus exclusively on the generation of the peer effect network and the value of θ_n for all organizations.

The example dataset includes 2 spatial variables, a weight variable, and a decision variable for 10 organizations. Both of the spatial variables are distributed between 1 and 10, the weight variable is distributed between 1 and 6, and the decision variable is ordered from 1 to 4 as discussed in the above methodology section. Table 2 contains the example dataset.

Given the information provided in Table 2, the distance between each organization D_{pq} can be calculated using equation 1. For example, the value of $D_{1,3}$ would be calculated as

$$D_{1,3} = \sqrt{\left(\frac{(2-1)}{10}\right)^2 + \left(\frac{(2-7)}{10}\right)^2} = 0.5099 \quad (9)$$

Table 2: Example dataset

Organization	Spatial Variable 1	Spatial Variable 2	Weight Variable	Decision
1	2	2	5	1
2	2	8	6	4
3	1	7	5	1
4	1	2	2	3
5	6	2	6	1
6	7	1	2	2
7	4	4	3	2
8	7	8	3	1
9	10	3	4	2
10	8	4	5	1

Table 3 provides the distance matrix containing all of the values of D_{pq} calculated using equation 1. The distance matrix is, of course, mirrored over the diagonal. The diagonal itself is zero, as the distance between an agent and itself is zero.

Using the distance matrix and the weight variable, the values of M_{pq} can be calculated using equations 2 and 3. For example, the value of $M_{1,3}$ would be calculated as

$$M_{1,3} = \frac{\left({}^{5}/_{6}\right)}{0.51} = 1.634 \quad (10)$$

Table 3: Example distance matrix

0.00	0.60	0.51	0.10	0.40	0.51	0.28	0.78	0.81	0.63
0.60	0.00	0.14	0.61	0.72	0.86	0.45	0.50	0.94	0.72
0.51	0.14	0.00	0.50	0.71	0.85	0.42	0.61	0.98	0.76
0.10	0.61	0.50	0.00	0.50	0.61	0.36	0.85	0.91	0.73
0.40	0.72	0.71	0.50	0.00	0.14	0.28	0.61	0.41	0.28
0.51	0.86	0.85	0.61	0.14	0.00	0.42	0.70	0.36	0.32
0.28	0.45	0.42	0.36	0.28	0.42	0.00	0.50	0.61	0.40
0.78	0.50	0.61	0.85	0.61	0.70	0.50	0.00	0.58	0.41
0.81	0.94	0.98	0.91	0.41	0.36	0.61	0.58	0.00	0.22
0.63	0.72	0.76	0.73	0.28	0.32	0.40	0.41	0.22	0.00

Table 4 provides the network adjacency matrix **M** containing all values of M_{pq} calculated using equations 2 and 3.

Table 4: Example network adjacency matrix

0.000	1.389	1.634	8.333	2.083	1.634	2.946	1.067	1.034	1.318
1.667	0.000	7.071	1.644	1.387	1.162	2.236	2.000	1.060	1.387
1.634	5.893	0.000	1.667	1.179	0.982	1.964	1.370	0.846	1.094
3.333	0.548	0.667	0.000	0.667	0.548	0.925	0.393	0.368	0.458
2.500	1.387	1.414	2.000	0.000	7.071	3.536	1.644	2.425	3.536
0.654	0.387	0.393	0.548	2.357	0.000	0.786	0.476	0.925	1.054
1.768	1.118	1.179	1.387	1.768	1.179	0.000	1.000	0.822	1.250
0.640	1.000	0.822	0.589	0.822	0.714	1.000	0.000	0.857	1.213
0.827	0.707	0.677	0.736	1.617	1.849	1.096	1.143	0.000	2.981
1.318	1.156	1.094	1.145	2.946	2.635	2.083	2.021	3.727	0.000

For this example, we choose the cutoff point for M_{pq} to be equal to 1.7. This was the value that limited the network to the 25 strongest links out of a possible 90, and this value was chosen to ensure that the following figure would be clear and informative. Applying this cutoff value to matrix **M** generates the adjusted network adjacency matrix provided by Table 5.

Using the data contained in Table 5, we create a visualization of the network where the strength of the connection between the nodes is represented by the thickness of the line. Figure 2 provides this visualization.

Table 5: Adjusted example network adjacency matrix

0	0	0	8.333	2.083	0	2.946	0	0	0
0	0	7.071	0	0	0	2.236	2.000	0	0
0	5.893	0	0	0	0	1.964	0	0	0
3.333	0	0	0	0	0	0	0	0	0
2.500	0	0	2.000	0	7.071	3.536	0	2.425	3.536

0	0	0	0	2.357	0	0	0	0	0
1.768	0	0	0	1.768	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1.849	0	0	0	2.981
0	0	0	0	2.946	2.635	2.083	2.021	3.727	0

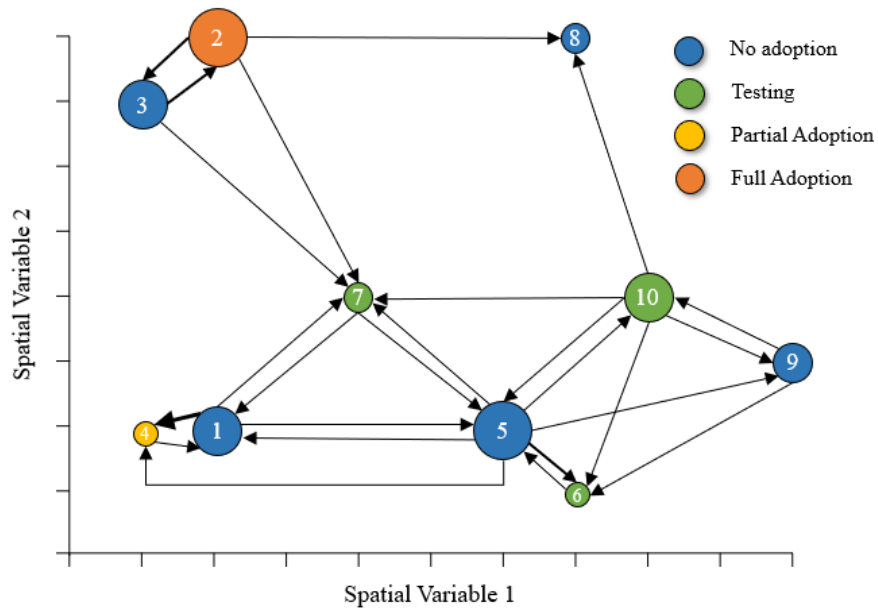

Figure 2: Visualization of example network

Using equation 4, we are able to generate the θ_n term for the network influence on each agent, as shown by Table 6. For example, the value of θ_9 would be calculated as:

$$\boldsymbol{\theta_9 = \frac{(2.425 * 1 + 3.727 * 2)}{2} = 4.94} \tag{12}$$

We can see that in this example, the organization that was most strongly influenced to adopt in the future was organization 3. This is intuitive because it was very close to organization 2, and organization 2 had both a high weight value and had chosen to fully adopt.

Table 6: Visualization of example network

Organization	**Influence of Network $\boldsymbol{\theta_n}$**
1	5.35
2	5.89
3	28.28
4	5.17
5	4.06
6	4.73
7	4.31
8	6.02
9	4.94
10	3.26

2.3.2 Survey Sampling Methodology

While it would be ideal to survey the entire population to obtain the most accurate dataset, it is rarely a feasible option to do so. Increasing the sample size carries with it an increased cost, and so optimal survey design must find a balance between obtaining an accurate dataset and minimizing cost. In the literature, the most common approaches to estimate the optimal sample size are Cochran's formula and Yamane's formula.

Cochran's formula has two variations depending on whether or not the population is considered to be infinite or finite. The infinite population formula can be calculated as:

$$n_0 = \frac{z^2 pq}{e^2} \tag{11}$$

where n_0 is the sample size, z is the critical value for the desired confidence level, e is the desired level of precision, p is the degree of variability, and q is equal to $1 - p$. When the population is considered finite, the formula can be calculated as:

$$n = \left[\frac{n_0}{1 + \frac{(n_0 - 1)}{N}}\right] = \left[\frac{z^2pq/_{e^2}}{1 + \frac{\left(z^2pq/_{e^2} - 1\right)}{N}}\right] \tag{12}$$

where N is the population size, and n is the sample size corrected for a finite population. Yamane's formula provides an alternative estimation for optimal sample size at a 95% confidence level. The formula can be calculated as:

$$n = \frac{N}{1 + N(e^2)} \tag{13}$$

This modified formula is most appropriate when the size of the total population is relatively small. For large populations, the difference between the two formulas will be negligible.

For most studies, finding information about the population is relatively straightforward because of the United States Census datasets. However, because this study is directed at freight transportation organizations and their employees, the available information about our population is significantly more limited. According to the American Trucking Association and the U.S. Department of Transportation, there are roughly 900,000 for-hire carriers in the United States. Of those companies, 91.3% operate 6 or fewer trucks, and 97.4% operate fewer than 20 trucks. 7.8 million people were employed in jobs that relate to trucking activity, and 3.5 million people were employed as truck operators (American Trucking Association, 2019).

While this does not give us extremely detailed information about the population we are interested in, it does provide enough information to calculate the optimal sample size. Assuming the standard values of 95% confidence level and ±5% level of precision, and assuming the maximum degree of variability at 0.5, Cochran's formula gives us an optimal sample size of 385. Including the population size has a negligible effect on the optimal sample size because the population in this scenario is very large, and the modified Cochran's formula was intended for small populations. The population in this scenario is large enough to be considered infinite for Cochran's formula.

In order to be thorough, we also calculated the optimal sample size using Yamane's formula. The sample size from Yamane's formula is 400. While there is a slight discrepancy between the two formulas, both Cochran and Yamane's formulas suggest roughly the same sample size. To ensure that we obtain an accurate dataset, we choose to obtain the larger recommended sample size of 400 responses.

2.3.3 Survey Methodology

The survey was split into three main sections. The first section contained questions about the respondent's organization, and the other two sections presented two hypothetical CAT models and asked the respondent how they thought their organization would react to the given scenarios. From these sections, we are able to construct the social network, estimate the organizations' decisions to adopt or reject CATs, and establish the values of the other covariates in $\boldsymbol{X}_n$.

2.3.3.1 Social Network

For this study, the δ-dimensional space of our social network consists of 4 dimensions. Respondents were asked to identify 1) regions of the United States in which their organization operates, 2) whether they own and operate their own vehicles, rent their vehicles, or contract with other vehicle owners, 3) the types of cargo that they typically transport, and 4) the average distance that one of their vehicles will usually drive per trip. Organizations that have similar values for these variables are more likely to be in competition with each other due to possessing similar business models or providing similar services in the same area.

Aside from the average distance question, each of these questions was designed to be "mark all that apply," which means that a respondent could potentially select multiple answers. For example, it is reasonable to expect that some organizations would operate in all regions of the United States. However, allowing for multiple answers to these questions causes problems when using equation 4 from the previous section, as that equation expects single values for each variable rather than a set of values. Therefore, for this particular case study, we have slightly modified the distance equation to account for the possibility of an organization possessing multiple values for the same variable. The total distance D_{pq} between organization p and organization q is calculated here as:

$$D_{pq} = \sqrt{\sum_{A \in S} \sigma_A \left(1 - \frac{\left|V_{A_p} \cap V_{A_q}\right|}{\left|V_{A_p} \cup V_{A_q}\right|}\right)^2} \tag{14}$$

where S is the set of characteristics that define the δ-dimensional space, V_{A_p} is the set of values for attribute A for organization p, and σ_A is the weight given to attribute A. With this framework, the maximum distance for each of the four variables is 1 when there are no values in common, and 0 when all values are in common. In the case where some but not all values are shared between two organizations, the distance for that variable will be somewhere between 0 and 1.

The weights for each organization are determined from three variables: the number of truck drivers employed by the organization, the number of trucks owned, rented, or contracted by the organization, and the size of the organization's total market. Because these questions did not need to be structured as "mark all that apply," we can use equation 5 from the previous section without issue.

2.3.3.2 Adoption Decision

For this case study, Y_{ni} is an integer given values from 1 to 4 corresponding to the decision to reject, test, partially adopt, and fully adopt CATs, respectively. Both sections of the survey that discuss CAT adoption begin with a description of a hypothetical CAT model, as seen in the figures below. The first section loosely describes a level 3 autonomous truck, and the second section describes a level 4 autonomous truck that is introduced 10 years after the first generation of level 3 autonomous trucks was introduced.

After these descriptions, the respondent is asked three direct questions about how they believe their organization would respond to the presented CAT model. The first question asks if their company would be likely to purchase or contract with at least one CAT model for experimentation. The second question asks if their organization would be likely to replace older trucks at the end of their lifespan with the CAT model, and the third question asks if they would replace its working fleet with CATs. If the respondent answers negatively to the first question, then the decision variable for that organization is set to "reject." If, instead, the respondent answers positively, then we move to the second question. A negative response to the second question sets the decision variable to "test," and a positive response leads to the third question. Negative responses to the third question set the decision variable to "partial adoption," and positive responses set the decision as "full adoption."

When calculating Y_q for equation 7 in the methodology section, we convert the decision variable into a numeric value. We allow "reject" to be equal to -1 to account for negative word of mouth effects. "Test" is set to 0, since an organization that is testing CATs will likely not have formed strong opinions yet. "Partial adoption" is set to 1, and "full adoption" is set to 2. This allows for organizations to be influenced by members of their network to reject or accept CATs.

2.3.3.3 Other Covariates

Each of the other covariates included in $\boldsymbol{X}_n$ are tied to individual questions in the survey. The variables included in this study are listed and defined in Table 7.

Note that not all of these variables may be applicable to other innovation adoption studies. For example, physical risk in this particular case is meant to represent the fear that autonomous vehicles may result in collisions that would not have happened in standard models. An innovation such as a new computer software would likely not need to include a variable like physical risk into its model. Any future innovation adoption study should consider which variables will be required to accurately model adoption behavior.

Table 7: Variables included in stated-preference survey

Variable	Definition
Specialization	A measurement of the knowledge and expertise of an organization's members
Centralization	The degree to which power and control in a system are concentrated in the hands of relatively few individuals
Formalization	A measurement of how strictly an organization requires its members to follow established rules and protocol

Relative Advantage	The degree to which an innovation is perceived as being better than the idea or system it supersedes
Complexity	The belief that an innovation will be either difficult to use or understand
Physical Risk	The degree to which the innovation is likely to cause physical damage
Financial Risk	The degree to which the innovation is likely to cost more money than it will make
Liability Risk	The degree to which the innovation is likely to result in legal troubles
Cost Effectiveness	The degree to which the innovation is expected to be less costly to operate
Familiarization	A measure of how much an organization knows about the innovation
Advocate or Champion	Whether or not an individual exists in an organization who is advocating for the adoption of the innovation
Preparedness	A measurement of how ready an organization is to adopt the innovation
Government Regulations	The degree to which regulations and legislation restricts or promotes the adoption of the innovation
Competition	The effect that decisions of competing organizations has on the adoption decision

2.4 DATA

Data was gathered from 400 organizations across the United States. An effort was made to ensure that the responses were not skewed towards large or small organizations, and so organizational size responses are relatively symmetric. Descriptive statistics of the survey results are presented in Table 8.

Small companies with 50 or fewer employees numbered 145, mid-sized companies between 50 and 500 employees numbered 129, and large companies with over 500 employees had 126 responses. As shown by Figure 3, most companies transported at least two types of cargo, and large organizations were very likely to transport multiple cargo types.

Table 8: Descriptive statistics of the survey results

Variable	Level	Frequency	Variable	Level	Frequency
Age			Number of employees		
	Under 20 years	3 (1%)		1-10	59 (15%)
	21-25 years	15 (4%)		11-50	86 (22%)
	26-30 years	37 (9%)		51-100	63 (16%)
	31-35 years	42 (11%)		101-250	30 (8%)
	36-40 years	64 (16%)		251-500	36 (95)
	41-45 years	55 (14%)		501-1,000	39 (10%)
	46-50 years	58 (15%)		1,001-2,500	24 (6%)
	51-55 years	49 (12%)		Over 2,500	63 (16%)
	56-60 years	38 (10%)			
	61-65 years	28 (7%)	Number of trucks		
	Over 65 years	11 (3)		1-10	72 (18%)
Education				11-50	91 (23%)

	Some high school	5 (1%)		51-100	66 (17%)
	High school/GED	87 (22%)		101-250	38 (10%)
	Some college	81 (20%)		251-500	28 (7%)
	Trade/Vocational	41 (10%)		501-1000	30 (8%)
	Associate's	53 (13%)		1001-2500	22 (6%)
	Bachelor's	101 (25%)		Over 2500	53 (13%)
	Master's	25 (6%)			
	Professional Degree	1 (0.3%)	Operating Regions		
	Doctorate	6 (2%)		Northwest U.S.	150 (38%)
Employment				Southwest U.S.	181 (45%)
	Less than one year	34 (9%)		South U.S.	242 (61%)
	1-2 years	70 (18%)		Midwest U.S.	221 (55%
	3-5 years	91 (23%)		Northeast U.S.	186 (47%)
	5-10 years	77 (19%)		Outside of U.S.	15 (4%)
	11-15 years	52 (13%)			
	16-20 years	38 (10%)	Market Size		
	21-25 years	16 (4%)		Local	62 (16%)
	Over 25 years	22 (6%)		Regional	113 (28%)
				National	163 (41%)
Cargo Types				International	27 (7%)
	Live Animals	20 (5%)		Global	35 (9%)
	Foodstuffs	185 (46%)			
	Construction Material	194 (49%)	Average Trip		
	Fuels	60 (15%)		0-50 miles	30 (8%)
	Chemicals	106 (27%)		51-200 miles	111 (28%)
	Textiles	130 (33%)		201-500 miles	136 (34%)
	Machinery/Electronics	197 (49%)		Over 500 miles	123 (31%)
	Motorized Vehicles	106 (27%)			
	Waste or Scrap Metals	86 (22%)	Vehicle		
	Other	70 (18%)		Own	304 (76%)
				Rent	100 (25%)
				Contract	121 (30%)
Organization (likert-7)				μ	σ
	Employees have specialized skillsets for specific tasks			2.330	1.165
	Company authority is heavily centralized			2.348	1.281
	Company values stability over innovation			2.915	1.429
1st-Gen CAT (likert-7)	My company would experiment with CATs			3.640	1.908
	My company would begin replacing old trucks with CATs			4.078	1.817

	My company would fully convert to CATs	4.213	1.805
	CATs will be better than standard models	4.048	1.782
	CATs will be more complex than standard models	3.243	1.505
	CATs will cause more collisions than standard models	3.440	1.453
	CATs will be more financial risk than standard models	3.365	1.566
	CATs will be more liability risk than standard models	2.965	1.498
	CATs will be more cost effective than standard models	3.753	1.583
	Members of my company are familiar with CATs	4.328	1.686
(binary)	Members of my company are advocating for CATs	0.310	0.462
(likert-7)	My company is prepared to adopt and implement CATs	4.368	1.830
	Govt. regulations would encourage CAT adoption	4.005	1.654
	Our competitors would likely experiment with CATs	3.590	1.645
	Our competitors would likely adopt CATs	3.908	1.620
	Our competitors' decisions would not affect our adoption	3.088	1.437
2nd-Gen CAT			
(likert-7)	My company would experiment with 2nd-Gen CATs	3.293	1.767
	My company would replace old trucks with 2nd-Gen CATs	3.625	1.707
	My company would fully convert to 2nd-Gen CATs	3.773	1.734
	2nd-Gen CATs will be better than standard models	3.278	1.575
	2nd-Gen CATs will be more complex than standard models	3.245	1.419
	2nd-Gen CATs will cause more collisions than standard models	3.640	1.599
	2nd-Gen CATs will be more financial risk than standard models	3.505	1.576
	2nd-Gen CATs will be more liability risk than standard models	3.293	1.559
	Success of 1st-Gen CATs encourage adoption of 2nd-Gen	3.160	1.687
	My company would adopt 2nd-Gen to stay competitive	3.528	1.704
	CATs will be more cost effective than standard models	2.998	1.805
	Our competitors would likely adopt 2nd-Gen CATs	3.583	1.590

Each respondent was asked to predict how their company would respond to hypothetical CAT scenarios as shown in Table 9.

Based on the responses given to questions about these scenarios, each organization was marked as either rejecting, testing, partially adopting, or fully adopting CATs. Figure 4 shows the initial adoption decisions by organizational size for the first-generation CAT.

Table 9: Description of CAT adoption scenarios

	First-Generation CAT	Second Generation CAT
Availability	Available immediately	Available 10 years after first-generation CAT
Driver Requirement	Autonomous, but requires driver	Autonomous, does not require driver
Fuel Efficiency	5% greater fuel efficiency	5% greater fuel efficiency
Safety	10x less likely to be involved in a collision	100x less likely to be involved in a collision
Cost	\$10,000 higher price compared to standard models	\$10,000 higher price compared to standard models
Testing	Has not been extensively used outside of prototype tests	20% of all trucks at this time are autonomous

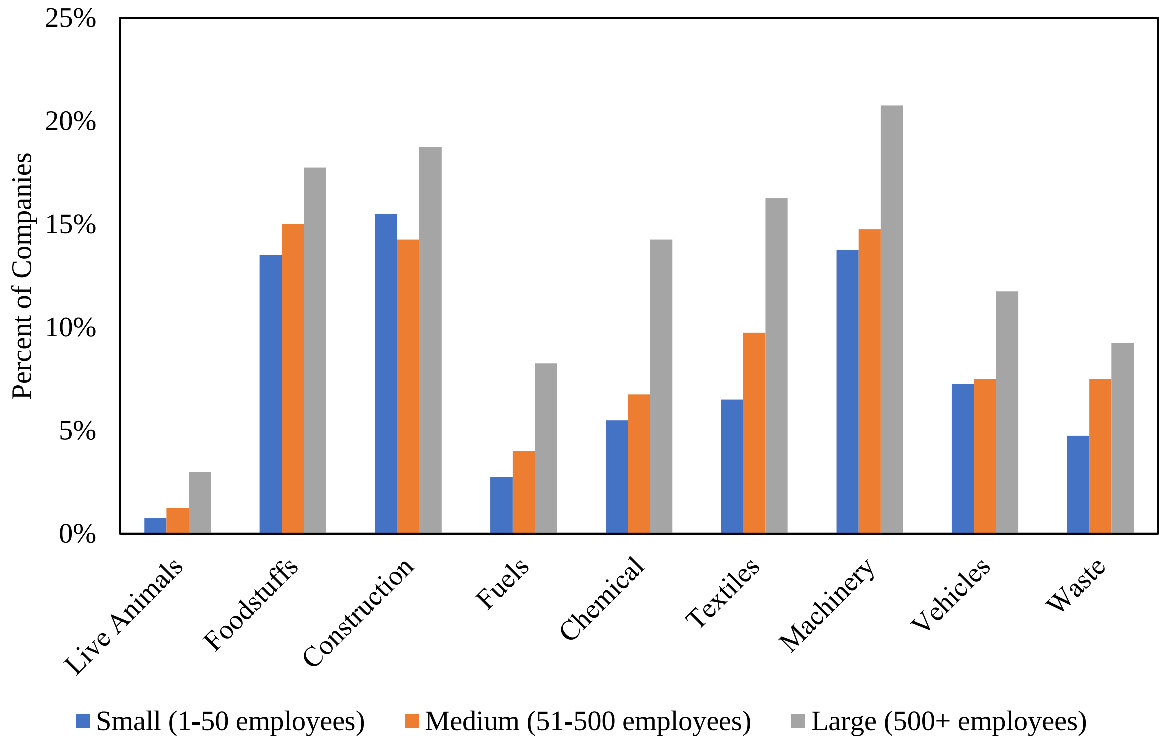

Figure 3: Distribution of cargo types by company size

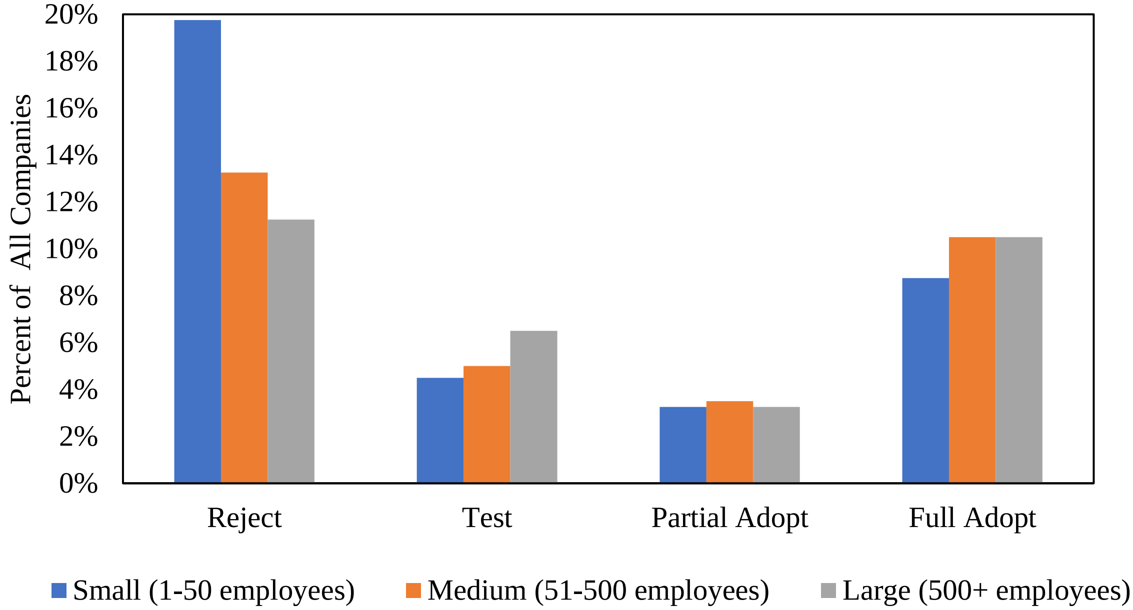

Figure 4: First-generation CAT adoption decisions by organizational size

Interestingly, the majority of the organizations stated that they would either reject CATs or choose to fully adopt, regardless of organizational size. Small organizations were much more likely to reject CATs, which is intuitive because of the inherent risk associated with new, revolutionary technologies such as CATs. As Figure 5 demonstrates, CATs are considered to be very risky, even among organizations that stated that they wanted to fully adopt first-generation CATs as soon as they become available.

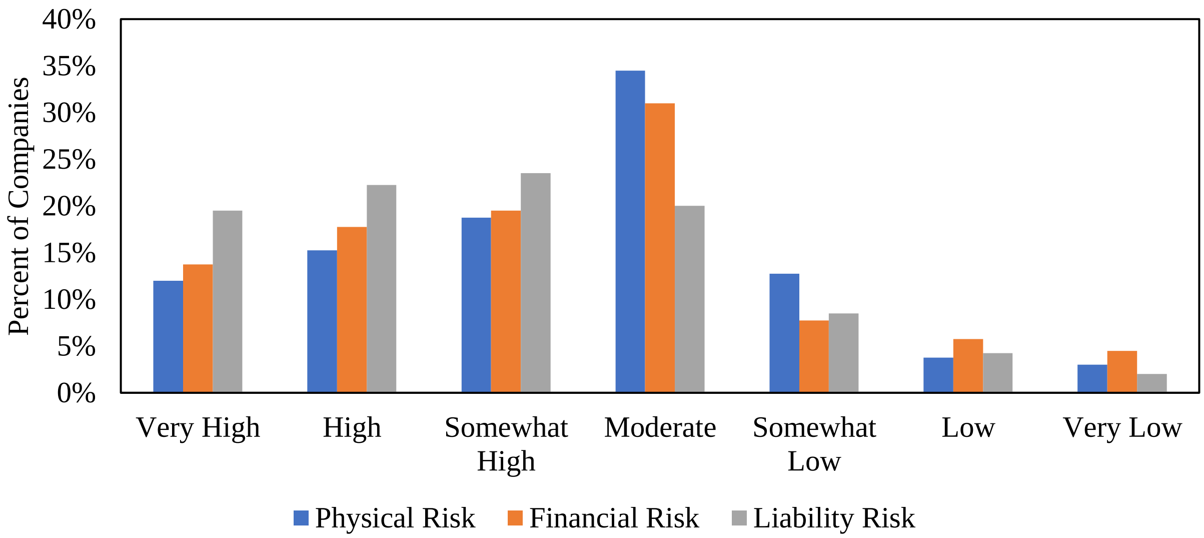

Figure 5: Levels of perceived risk for first-generation CATs

Less than 20% of respondents believed that adopting CATs is a low-risk decision. Unlike the general public, which is primarily concerned with the physical risk of automated vehicles, organizations seem to be most concerned about potential liability risks.

Figure 6 shows the initial adoption decisions by organizational size for the second-generation CAT.

Compared to the first-generation adoption decisions in Figure 4, the second-generation CATs show a slight reduction in the number of rejections and an increase in the number of full adoptions. It should be noted that some of the companies that chose to partially or fully adopt the first-generation CAT did not show the same enthusiasm for upgrading to the second-generation CAT, indicating that they may be satisfied with the advantages provided by first-generation CATs.

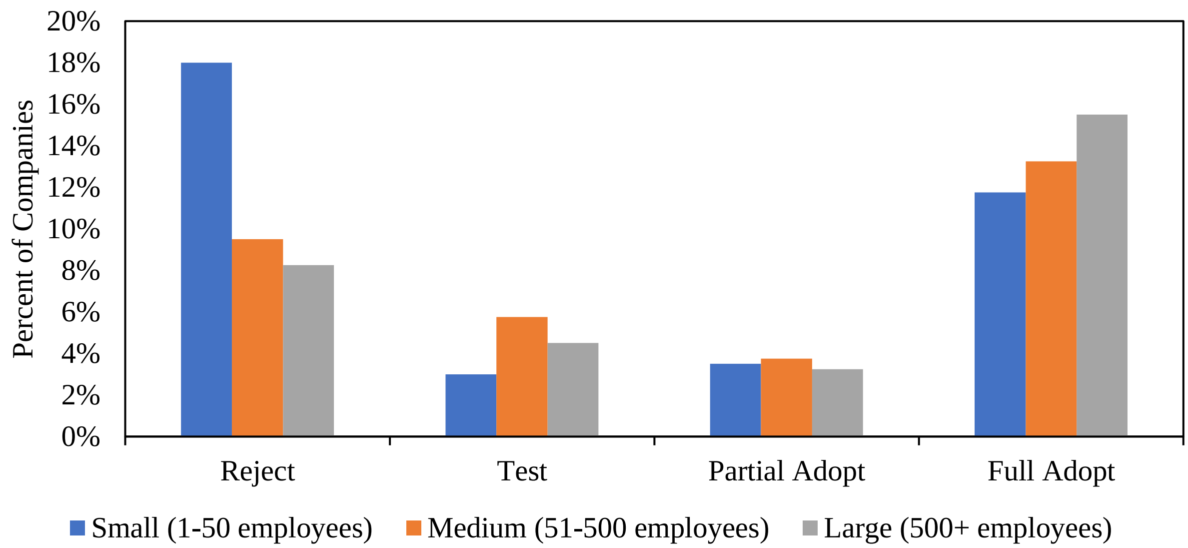

Figure 6: Second-generation CAT adoption decisions by organizational size

2.5 RESULTS, DISCUSSION, AND CONCLUSION

2.5.1 Results

Using the data gathered from the stated preference survey, we are able to construct our discrete choice model for the first-generation CAT. Each of the variables and coefficients included in the $\boldsymbol{\beta}_i'\boldsymbol{X}_{in}$ term from equation 1 is presented in Table 10.

Interestingly enough, the variables pertaining to the perceived level of risk are highly insignificant, with the exception of financial risk when combined with competition. This is a surprising result, as one would anticipate perceived risk to be highly correlated with the decision to adopt CATs. However, there is a logical explanation for this insignificance. When examining the levels of perceived risk shown above in Figure 5, it becomes clear that almost the entire population considers CATs to be higher risk, including the organizations that chose to adopt. The

Table 10: Second-generation CAT adoption decisions by organizational size

Logit Model Results				*Marginal Effects*			
Variable Name	Coeff.	S.E.	*p*-Value	Reject	Test	Partial Adoption	Full Adoption
Age (36 to 45 years)	-0.3753	0.2802	0.1804	0.084	-0.003	-0.035	-0.046
(46 to 55 years)	-0.4887	0.2917	0.0939	0.110	-0.007	-0.045	-0.058
Education (Bachelor's or higher)	0.3304	0.2520	0.1898	-0.071	-0.004	0.030	0.044
Relative Advantage	2.4609	0.2803	0.0000	-0.458	-0.073	0.148	0.382
Cost Effectiveness	1.3003	0.2643	0.0000	-0.269	-0.020	0.109	0.180
Champion	1.7157	0.2874	0.0000	-0.320	-0.073	0.118	0.275
Centralization	0.7445	0.3241	0.0216	-0.174	0.025	0.068	0.081
Cargo (Foodstuffs)	0.6626	0.2432	0.0064	-0.142	-0.005	0.060	0.087
(Waste)	-0.9741	0.3202	0.0024	0.227	-0.035	-0.088	-0.104
Region (Midwest US)	-0.6317	0.2793	0.0074	-0.139	-0.010	0.059	0.091
(Northwest US)	0.6619	0.2943	0.0245	0.135	0.005	-0.057	-0.084
Market Size: National	0.6842	0.2554	0.0074	-0.145	-0.009	0.061	0.093
Average Trip Length (Over 500 miles)	-0.3858	0.2773	0.0074	0.086	-0.003	-0.036	-0.047
Annual Mileage (Less than 100,000 miles)	0.5177	0.3006	0.0850	-0.110	-0.007	0.047	0.070
(100,000 to 200,000 miles)	0.6414	0.3176	0.0434	-0.133	-0.013	0.057	0.090

Decision Thresholds	Estimate	S.E.	*z*-Value
Reject/Test	2.3515	0.4247	5.537
Test/Partial Adoption	3.7958	0.4602	8.248
Partial Adoption/Full Adoption	4.8137	0.4906	9.811

Null Log-Likelihood	-497.968
Final Log-Likelihood	-322.302
AIC	680.605
BIC	752.451
Adj. Rho-Square	0.353
Observations	400

level of perceived risk is a poor indicator of behavior because both adopters and rejecters agree that first-generation CATs are a high-risk innovation. The "Complexity" variable is also insignificant, presumably for similar reasons.

To ensure that the model accurately fits the gathered data, we use k-fold cross validation. The data is divided into k = 5 folds of 80 observations each; the model is trained on k – 1 folds and tested on the excluded fold. This process repeats until every fold had been used as the test set, and the validation model outputs are combined. The cross-validation model correctly predicts 66.5% of the observations' behaviors. The predicted and actual values are presented in Table 11.

Figure 7 demonstrates a representation of the network. Note that the distances between organizations in this figure are not completely to-scale, since the figure is attempting to replicate a 4-dimensional space in two dimensions.

The larger and therefore more influential organizations tend to be clustered around the center, suggesting that they are very close to one another. This is intuitive, as the larger organizations are also likely to have broad business interests that cause them to come into competition with other organizations. Conversely, small organizations are likely to operate only in their local area, and so they will not often be competing with faraway companies.

The network displayed in Figure 7 does not account for peer effects because initial decisions will be made without knowledge of other organizations' choices. However, the peer effect network will be critical to understanding how the network evolves over time. Utilizing equations 4-7 and 11 from the above sections, we generate the peer effects network and find the variable θ_p for each organization in the network. At the initial time period T = 0, θ_p has a minimum value of -0.95822, a maximum value of 2.01002, a mean of 0.73354, and a standard deviation of 0.33236. This means that the majority of the organizations are influenced to adopt by their network, but a minority will actually be influenced to reject CATs due to negative word-of-mouth from their competitors.

Table 11: Predicted and actual decisions for first-generation CAT adoption

	Predicted "Reject"	**Predicted "Test"**	**Predicted "Partial Adopt"**	**Predicted "Full Adopt"**	**Sum**
Reject	154	12	3	8	177
Test	25	16	3	20	64
Partial Adopt	10	2	13	15	40
Full Adopt	25	6	5	83	119
Sum	214	36	24	126	

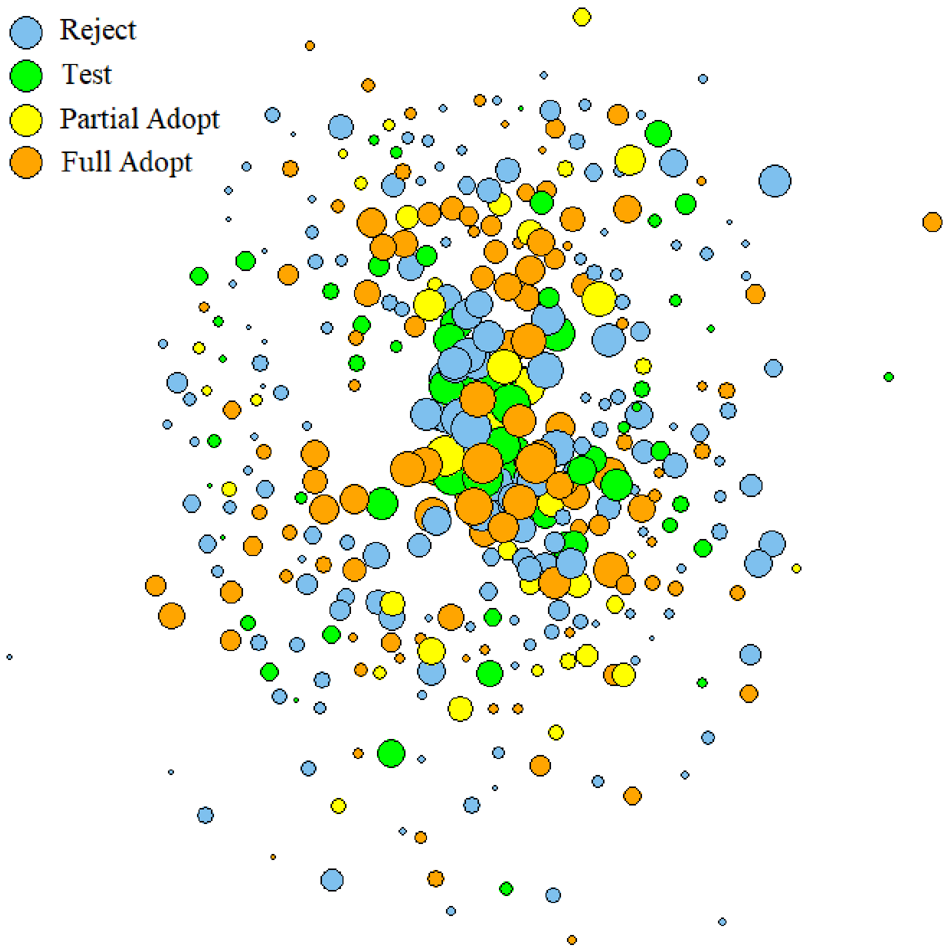

Figure 7: Visual representation of the initial first-generation cat decision network

The cutoff value γ was chosen to be 1.65; this value eliminated 84.5% of the connections between organizations, leaving an average of 62 connections for each organization. Selecting values smaller than 1.65 had little change on the network, indicating that the eliminated connections were not significant. Values greater than 1.65 caused the network to dissolve into smaller, isolated networks dominated by a few large organizations by removing too many connections.

Establishing the coefficient associated with θ_p is more complicated, since the influence of peer effects cannot be measured in a stated-preference survey. However, it is possible to establish lower and upper bounds on the coefficient based on expected social behavior. Peer effects will influence some organizations to change their behavior, and so a coefficient which does not result in any behavioral change is too small. Peer effects are also not strong enough to completely change the network to a single behavior, and so an upper bound on the coefficient's value can be established, as well. Based on these criteria, we estimate that the coefficient for the peer effects variable should be somewhere between 0.65 and 0.9. Figures 8-11 demonstrate the influence of peer effects on the network over time at different coefficient values.

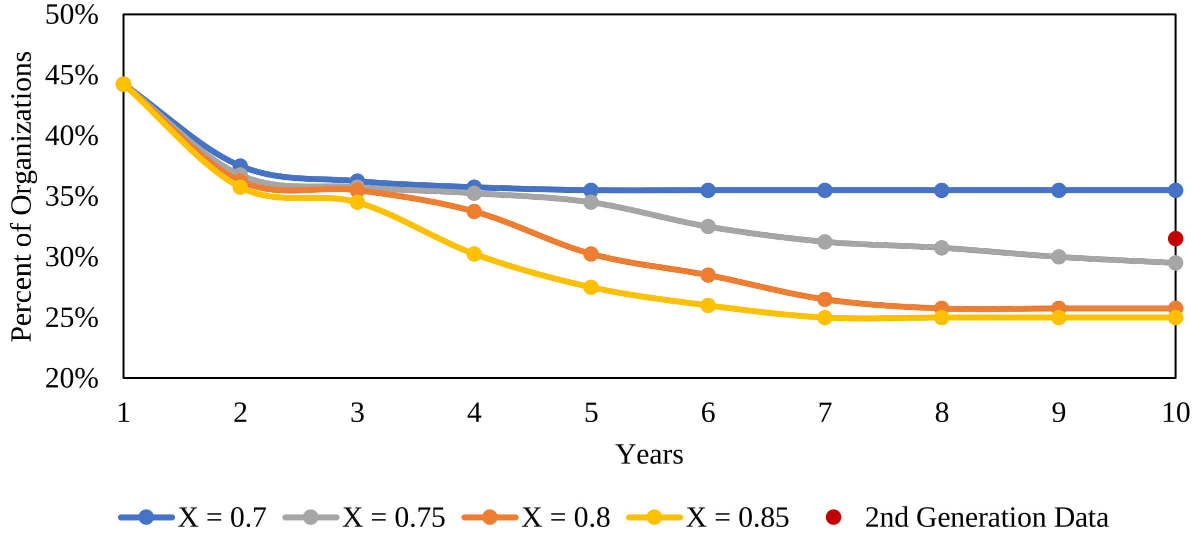

Figure 8: The changes to "reject" decisions over time based on peer effect coefficient values

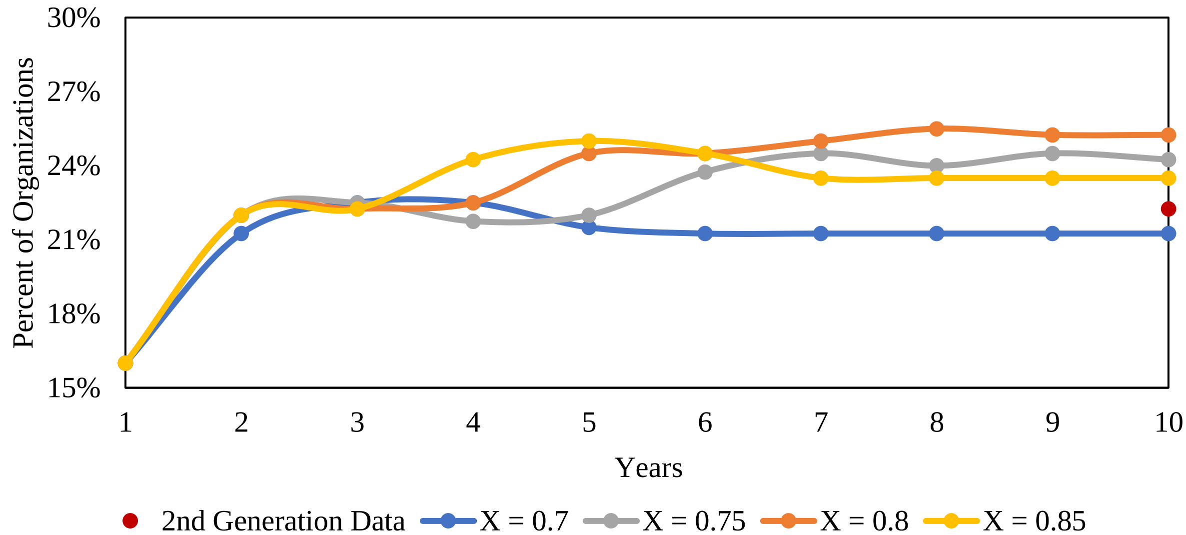

Figure 9: The changes to "test" decisions over time based on peer effect coefficient values

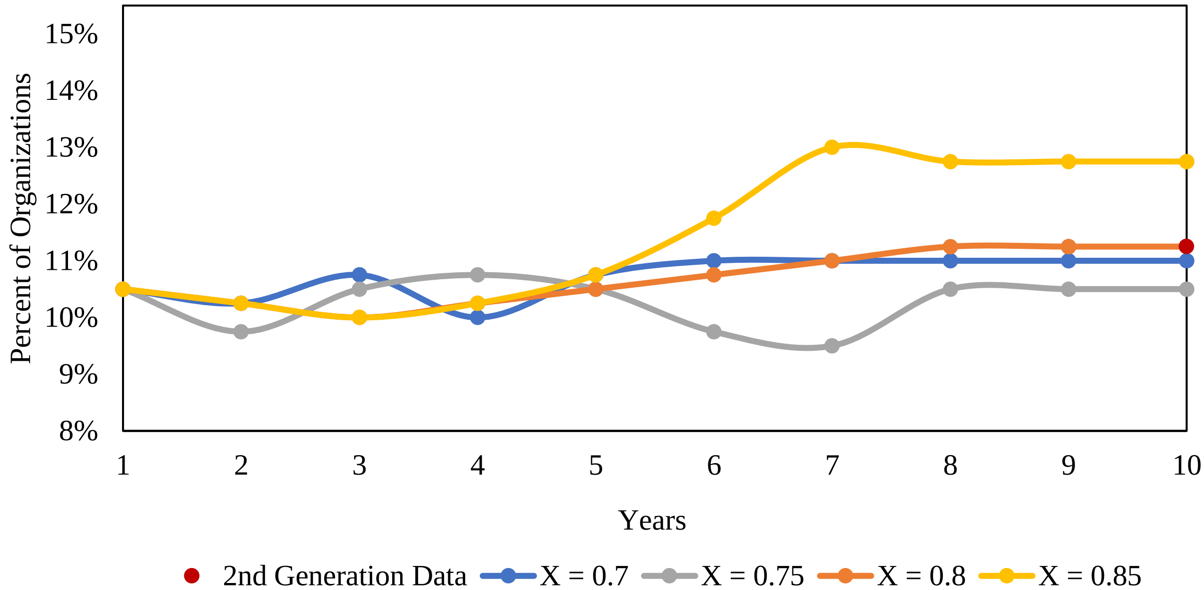

Figure 10: The changes to "partial adoption" decisions over time based on peer effect coefficient values

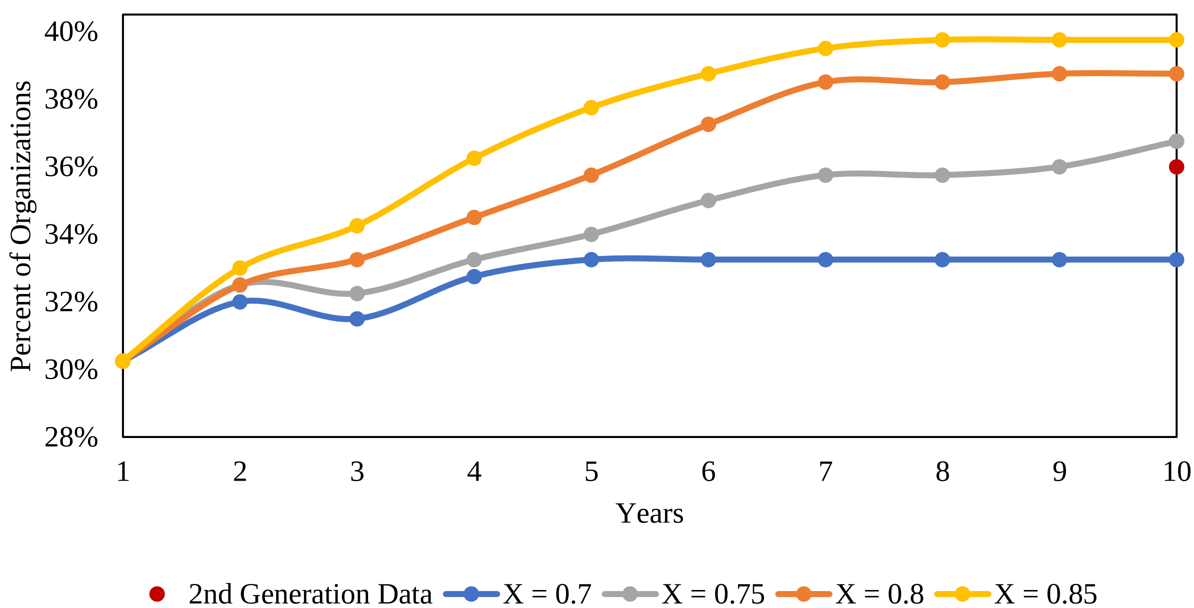

Figure 11: The changes to "full adoption" decisions over time based on peer effect coefficient values

As expected, the most drastic change in behavior comes in the time immediately after the initial decisions are made. This is because the initial decisions are made without knowledge of other organizations' behavior, whereas decisions in subsequent time periods are adjusted based on the influence of peer effects. Therefore, we should expect organizational adoption behavior to change quickly in the early time periods and then achieve a more stable decision after all of the organizations have had time to adjust their behavior to better match their peers.

It is difficult to say with certainty what value we should place for the coefficient of the peer effects variable within the established bounds of 0.65 and 0.9, but we can compare the results of each coefficient value with the decisions on second-generation CATs generated by the stated-preference survey. With the technological improvements promised by second-generation CATs, we would expect there to be a relatively sharp increase in partial and full adoptions and a decrease in rejections. Based on this information, we would expect that the peer effect coefficient should be somewhere between 0.7 and 0.75.

2.5.2 Discussion

Despite the expected benefits of autonomous vehicle technology, the majority of organizations are hesitant to adopt the hypothetical first-generation CAT. There are many potential reasons for this reluctance to adopt. As discussed earlier, one of the primary reasons why organizations may choose to reject CATs is an aversion to the physical, financial, and liability risks associated with autonomous vehicle technology. At the time of writing, the technologies needed to create safe and dependable autonomous vehicles are still in development, and so many of the respondents do not trust the idea of self-driving trucks. Until autonomous vehicles are more thoroughly tested – likely by the general public – the perceived risk associated with CATs is likely to be one of the greatest barriers to adoption.

It is also possible that some of the perceived risk of CATs comes from a lack of familiarity and education surrounding the technology. It is reasonable to assume that most people have at least heard of the concept of self-driving cars, but because CAVs are not commercially available at this time, there are many people who do not understand how they will work. While this study did not find a statistically significant link between the respondents' familiarity with CATs and their hypothetical adoption rate, most innovation adoption studies claim that an increase in education about an innovation tends to correlate with an increased adoption rate (Aubert and Hamel, 2001; Rogers, 2003). Again, more widespread use of CAVs by the general public will promote education on autonomous technologies, but manufacturers and developers can boost early adoption through demonstrations and by providing more information on how the vehicles are capable of operating themselves.

Another barrier preventing the early adoption of CATs is the fact that the expected benefits of the technology are not yet proven. While autonomous vehicles are predicted to reduce fuel consumption and collisions, it is still uncertain if those expectations will be met. Even though the survey designed for this report clearly stated that the first and second-generation CAT models would have reduced fuel consumption and collisions, many of the respondents did not believe that they would be cost effective, and the majority of the respondents said that the models possessed a high risk of collisions. Until the general public comes to the consensus that CAVs are safe and efficient, there will be companies that will hesitate to adopt them due to the uncertainty surrounding their benefits.

Finally, the adoption of CATs may be slower than CAVs simply due to inertia. The freight transportation industry has a history of innovating slowly compared to other industries and private consumers (Simpson et al., 2019). Unless the benefits of CATs are so high that non-autonomous freight transportation operations are unable to compete, it is very likely that the adoption of CATs will be slower than the adoption of CAVs.

3.0 LAST MILE DELIVERY ROBOTS

3.1 INTRODUCTION

E-Commerce and package deliveries are growing at a fast pace and several start-ups have already began pilot studies to deliver packages and groceries to consumers utilizing Autonomous Delivery Robots (ADRs). These ADRs are electric powered motorized vehicles that can deliver items or packages to customers without the intervention of a delivery person. ADRs can be divided into two types. Sidewalk autonomous delivery robots (SADRs) are pedestrian sized robots that only utilize sidewalks or pedestrian paths. On-road or simply road autonomous delivery robots (RADRs) are vehicles that travel on roadways shared with conventional motorized vehicles.

Autonomous delivery robots (ADRs) that travel on sidewalks and roads are being tested in several US cities by startups. Even large delivery companies like FedEx are also testing this technology (FedEx, 2020). Online retailers like Amazon are also testing a drone prototype that can deliver packages under five pounds to customers in less than 30 minutes; this is noteworthy because 75% to 90% of Amazon deliveries weigh less than five pounds (Vincent and Gartenberg, 2019).

The potential of autonomous vehicles for passenger transportation has been studied extensively. In comparison, significantly less work focuses on the potential of autonomous vehicles in the logistics and parcel delivery sector. There are few studies focusing on urban deliveries or short-haul freight trips. Given the relatively short range of SADRs, these small robots are usually complemented by a "mothership" van that can transport SADRs near the delivery zone or service area.

ADRs benefits could include cheaper costs of delivery for businesses, faster service to customers, energy conservation and sustainability, safety for delivery personnel, and accuracy delivering the right package to the right customer. However, there are scant academic publications studying ADRs. Some studies have focused on ADRs optimal wayfinding or optimizing the joint scheduling of both trucks and ADRs, for example Boysen et al. (2018). There are numerous studies related to the mechanical, electrical, or computational design of robots but these studies are mostly irrelevant to study the implications of ADRs for last mile logistics.

3.2 ADR CHARACTERISTICS

This subsection compares the characteristics of SADR and RADR vehicles.

3.2.1 SADR Characteristics

An internet search found five companies most prominently covered in the news as SADR makers. Among them Starship Technologies has received ample media coverage. **Error! Reference source not found.** compares the five SADRs found. **Error! Reference source not found.** shows that most of the vehicles are relatively slow and light (less than 100 pounds) as speed and gross weight are limited by regulations in many cities and states (Jennings and Figliozzi, 2019).

Table 12: SADR Characteristics

	Weight (lbs)	Speed (mph)	Capacity (lbs)	Capacity (chambers)	Range (mi)
Starship Technologies	40	4	40	1	2
Domino's DRU	**Unknown**	12	21 (approx.)	4*	12
Dispatch's Carry	Unknown, but it requires two people to lift the device	4	100	4	12 hr battery ⇒ up to 48 mi
Thyssenkrupp's TeleRetail	60	35	77	1	10
Marble	80	4	**Unknown**	1	**Unknown**

*NOTE: Domino's Robotic Unit has 4 compartments and they are all accessible at the same time

3.2.2 RADR Characteristics

The internet search by the authors found out that there are less companies prototyping RADRs. **Error! Reference source not found.** compares the three RADRs found. Novel designs such as NURO are considerable smaller and lighter than conventional delivery vans. The other two vehicles (uDelv and AutoX) are based on existing conventional vehicles/chassis that have been automated or somewhat modified to fit autonomous deliveries. NURO is smaller and lighter than conventional vehicles but at the expense of a limited range and capacity. RADRs can be complemented by specialized vans, usually called "mother ship" vans, that can be utilized to drop off and pickup several RADRs. On the other hand, even the small RADRs are designed to operate autonomously and sharing roadways with conventional motorized vehicles (Jennings and Figliozzi, 2020).

Table 13: RADRs Characteristics

	Capacity (parcels)	**Capacity (lbs)**	**Max Speed (mph)**	**Approx. Size** L x W x H in feet	**Vehicle Weight (lbs)**	**Range (miles)**
Nuro	40 parc. (*,**) or 12 large grocery bags	250	25	8'x.3,6' x 6'	1,500	10
uDelv	32 parc.	700	25	15'x 6'x 6'	4,167	60
AutoX	11.1 to 15.4 cuft	Unknown	80 (*)	16' x 6' x 5'	3,900	560

Notes: (*) Estimated, (**) Not in separate compartments

3.3 REGULATORY FRAMEWORK

3.3.1 SADR Regulations

SADRs are still a novel and not widely used technology; only a few states and cities have regulations in place (Jennings and Figliozzi, 2019). San Francisco is one of the most restrictive places with regulations on SADRs; it requires not only a speed and weight limit, but also requires a permit for each device, with a limit of nine Autonomous Delivery Device permits for the city overall. These permits are valid for up to 180 days, and no more than one permit may be held by one permittee. San Francisco is currently the only place to require permits for SADRs. The device is also required to emit a warning noise to notify pedestrians and cyclists that the device is nearby. Interestingly, despite all the other regulations San Francisco has on SADRs, there is no weight limit for SADRs in San Francisco.

While San Francisco might be the most restrictive place for SADRs, Arizona might be the least restrictive. Like San Francisco, Arizona does not have a defined weight limit for SADRs. Arizona requires only that the vehicle is electric, travels at less than 10 mph (16 kph), is actively controlled or monitored, follows pedestrian laws, and yields to pedestrians. Arizona does not require insurance policies, braking systems, headlight systems, contact information, or a serial number plate, like many other places do.

Regarding size and weight limits, Washington DC and Florida have weight limits of 50 pounds. The 50-pound limit restricts SADR companies as many ADRs weigh more than 50 pounds. Starship Technologies' ADR weighs 40 pounds, which provides a competitive advantage in locations with low weight limits (*29*). Other places such as Wisconsin, Ohio, and Idaho have less strict regulations, with weight limits of 80 to 90 pounds. Finally, there are other places where weight limitations allow almost all, if not all, ADRs currently on the market. These include Utah, with a 150-pound limit, Austin, Texas, with a 300-pound limit, and Arizona and San Francisco, California, with no weight limits.Almost all places have a speed limit for ADRs of 10 miles per hour, the exception being San Francisco with a speed limit of 3 miles per hour. A summary of other key regulatory aspects are included in Table 14.

Table 14: Regulations on Sidewalk Autonomous Delivery Robots

	Date code was enacted?	Yields to pedestrians, cyclists, and other users?	Insurance policy required?	Braking system required?	Headlight system required at night?
Arizona	3/28/18	Yes, pedestrians only	No	No	No
San Francisco	12/22/17 revised 3/29/18	Yes, pedestrians and cyclists	No, but must pay for damages caused by device	No	No
Utah	3/19/2018	Yes, pedestrians only	Yes	Yes	Yes
Virginia	2/24/17	Yes, pedestrians only	Yes	Yes	Yes
Wisconsin	6/21/17	Yes	No	Yes	Yes
Washington D.C.	9/15/16	Yes	No	No	No
Florida	7/1/17	Yes	Yes	No	No
Ohio	9/29/17	Yes, pedestrians only	Yes	Yes	Yes

Idaho	7/1/17	Not specified	No	No	No
Austin, Texas	7/20/17	Yes	Yes	No	No

3.3.2 RADR Regulations

Since RADR vehicles utilize state-of-the-art technology to navigate streets without human intervention, regulators have mainly focused on their safety implications. Regulation of autonomous vehicles and their testing and use is not yet fully agreed upon. The US federal government has only outlined suggested legislation regarding autonomous vehicles and has left it up to individual states to determine laws. As of January 2014, early crafters of self-driving vehicle regulation in the US were Nevada, California, Florida, and Washington D.C. All of these states' regulations required—the vehicle to be autonomous; the operator to have a driver's license (except Washington D.C.; not specified); manual override features; and insurance in the millions of dollars for testing purposes (except Washington D.C.; not specified). Some regulatory frameworks also included additional requirements—removal of liability from the original vehicle manufacturer when modified to be autonomous; a visual indicator to the operator when the vehicle is in autonomous mode; a system to alert the operator of malfunctions; a human operator present to monitor the vehicle's performance; and directions for the Department of Motor Vehicles of the state to create rules for testing.

The National Conference of State Legislatures' Autonomous Vehicles State Bill Tracking Database has the most up-to-date information regarding legislation for each state. According to NCSL, as of March 2019, ten additional states had pending legislation in 2014 and have already enacted legislation regarding autonomous vehicles; these states include Arizona, Colorado, Hawaii, Massachusetts, Michigan, New York, South Carolina, Texas, Washington, and Wisconsin. Additionally, 19 states which did not have pending legislation in 2014, have enacted legislation: Alabama, Arkansas, Connecticut, Georgia, Illinois, Indiana, Louisiana, North Carolina, North Dakota, Pennsylvania, Tennessee, Utah, Virginia, Arizona, Delaware, Idaho, Maine, Minnesota, and Ohio.

3.4 METHODOLOGY

The reminder of this chapter focuses on a comparison between conventional vans and RADRs. The methodology used for comparing conventional (or standard) vans with uDelv's RADR is presented. The methodology is based on continuous approximations. As indicated by Daganzo et al. (2012), these types of analytical approximations are "particularly well suited to address big picture questions" because they are parsimonious and tractable, yet realistic when the main tradeoffs are included. This type of modeling approach has been successfully used in the past by many authors to model urban deliveries and key tradeoffs of new technologies (Langevin et al., 1996; Franceschetti et al., 2017; Ansari et al., 2018).

The following notation is used throughout the paper. Sub-indexes C and R are used for representing conventional and RADR vans respectively.

$n =$ Total number of customers served.
$k_l =$ Routing constraint (constant value), representing non-Euclidean travel on sidewalks and roads.

$a =$ Area (units length squared) of the service area, where n customers reside
$\delta = n/a$, customer density
d = Distance between the depot and the geometric center of the service area
$T =$ Maximum duration of shift or tour (same for all vehicle types)
$l_i(n) =$ Average distance a vehicle travels to serve n customers for vehicle type i
$m_i =$ Minimum number of vans for vehicle type i
$R_i =$ Range of a vehicle for vehicle type i
$Q_i =$ Capacity of a vehicle (number of parcels) for vehicle type i
$\tau_i =$ Total van time necessary to make n deliveries for vehicle type i
$\phi =$ Stop percentage (percent of the time a vehicle is stopped due to traffic control)
$s' =$ Average speed of the vehicle, not including ϕ
$s'_h =$ Average speed of the vehicle while on a highway, not including ϕ
$s = s'\phi =$ Average speed of the vehicle
$s_h = s'_h\phi =$ Average speed of the vehicle while on a highway
$t_0 =$ Time it takes to wait for the customer to pick up their order from the vehicle or delivery person.
$t_u =$ Time it takes the vehicle and/or driver to unload the delivery.
$t = t_0 + t_u =$ Total time vehicle is idle (i.e., not traveling) during a delivery.
$c_{h,i} =$ Cost per hour of operating vehicle type i, including cost of a driver if applicable.
$c_{d,i} =$ Cost per delivery for vehicle type i

To compare RADRs and conventional vans, we must be able to calculate time, distance, and cost for each vehicle, given the same delivery problem and the constraints inherent to each delivery technology. The average distance $l(n)$ to serve n customers can be estimated as a function of customer density, number of vehicles, network characteristics and route constraint coefficients, and the distance between the depot and the delivery area. In this paper, the equation used to calculate the distance traveled to visit n customers by a conventional van is:

$$l_i(n) = 2d + k_l\sqrt{an}$$

In the previous equation, d represents the average distance from the depot or distribution center (DC) to the customer(s). The parameter d is multiplied by two, the number of times the vehicle goes to and from the service or delivery area (SA). The parameter k_l is a constant value representing network characteristics and routing constraints in the SA (Figliozzi, 2007, 2008, 2009). The average area (mi^2) of the SA where customers are located is represented by a. The number of parcels or stops is represented by n.

Aother important number to consider when dealing with last mile deliveries is the time it takes to make n deliveries. A formula that can be used to calculate the route duration time accounting not only for driving time but also waiting for the customer and unloading the parcels is (Figliozzi, 2011):

$$\tau_i = \frac{2d}{s_h} + \frac{k_l\sqrt{an}}{s} + (t_0 + t_u)n$$

In the previous equation the first term represents the driving time and the second term represents the time it takes to park, wait for or go to the customer and unload the parcels (this is used for conventional vans). To determine the maximum number of deliveries that can be made by the conventional van within a shift of duration T, the equation for the maximum number of customers that a conventional van can deliver is:

$$n = \left\lfloor \frac{k_l^2 a + 2s^2Tt - \frac{4ds^2t}{s_h} - k_l^2\sqrt{\left(\frac{4ds^2t}{k_l^2 s_h} - \frac{2s^2Tt}{k_l^2} - a\right)^2 - \frac{4t^2s^2}{k_l^2}\left(\frac{s^2T^2}{k_l^2} + \frac{4d^2s^2}{k_l^2 s_h^2} - \frac{4s^2Td}{k_l^2 s_h}\right)}}{2s^2t^2} \right\rfloor \tag{15}$$

This equation provides the maximum number of customers n that can be served with one conventional van when any parameter changes (for example when t, d, and a change). Hence, each value of n provided in the tables represent the maximum number of customers that can be served by one conventional van given a set of parameter values. The floor function is used in equation to avoid a fractional number of customers. In turn, the customer density, δ, also may change. The conventional van's capacity, range, and constraints are as follows:

$$m_C \geq \left\lceil \frac{n}{Q_C} \right\rceil \tag{16}$$

$$2d + k_l\sqrt{an} \leq R_C \tag{17}$$

These constraints are always satisfied in the scenarios analyzed, given the high value of R (range) and the large capacity of conventional vans.

To compare the performance of a RADR against a conventional van, it is necessary to estimate the minimum number of RADRs necessary to deliver to n customers while satisfying delivery constraints. Range constraints are important for RADRs because the range of the uDelv is considerably smaller than the range of a conventional van. Therefore, m_R, the optimum number of RADRs is given by the following optimization problem:

Min m_R subject to these constraints

$$\frac{k_l\sqrt{an}}{\sqrt{m_R}} + 2d < R_R \tag{18}$$

$$\frac{k_l\sqrt{an}}{\sqrt{m_R}} + 2d < R_R \text{ , and} \tag{19}$$

$$m_R \geq \left\lceil \frac{n}{Q_R} \right\rceil \text{ and } m_R \in \mathbb{N} \tag{20}$$

The cost per delivery for any delivery method is calculated taking two aspects into account—the cost of time of each vehicle (including driver if appropriate) and the number of vehicles that are required. In the case of a conventional van, the cost of delivery is estimated as follows:

$$c_{d,i} = \frac{c_{h,i}\ \tau_i\ m_i}{n} \tag{21}$$

Note that τ_i ($\tau_i \leq T$) is the tour time and n is the total number of parcels delivered, as defined previously.

3.5 DATA AND SCENARIO DESIGN

For our research, we made several assumptions to compare RADRs with conventional vans. The total time the vehicle is idle (or not traveling) due to a delivery, t, is the same for all vehicles. The service area *a* is the same for all vehicles; however, if the tour-time constraint is not met and additional vehicles are required, the service area is split into equal sub-areas.

3.5.1 Vehicle Characteristics

A conventional van is defined as a delivery van in the traditional sense, with rear storage for parcels and a human driver and a delivery person. A RADR is defined as a vehicle which operates fully autonomously to deliver parcels. These methods of transporting parcels in the last mile of deliveries are compared in terms of distance, time and cost efficiency.

This research utilizes uDelv vehicles in the numerical case studies because the uDelv vehicle is designed with the idea of delivering to multiple customers in one tour; since parcels are compartmentalized, people can only take parcels intended to be delivered to them. The uDelv vehicle has the capability to travel on highways, while the Nuro van is restricted to local streets with a maximum speed of 35 mph. The AutoX can also travel on highways; however, its single storage compartment is not ideal and the carrying capacity was not specified in any publication. Thus, uDelv was chosen as the RADR test vehicle in this research as it can travel on any road with minimum risk of theft when delivering multiple parcels and since its carrying capacity is known. A summary of the assumed vehicle characteristics is shown in Table 15.

Table 15: Table 15Default values for variables used in calculations.

Variable	Description of Variable	Units	uDelv Van	Conventional Van
T	shift time (max)	hours	10	10
R_i	range of vehicle (max)	miles (km)	60 (96.6)	n/a
Q_i	capacity (max)	unitless	32	200
$c_{h,i}$	cost per hour of operation	USD	30	40
s'	full unlimited vehicle speed in residential	mph (kph)	30 (48.3)	30 (48.3)
s'_h	full unlimited vehicle speed on highway	mph (kph)	60 (96.6)	60 (96.6)
s	vehicle speed in residential	mph (kph)	21 (33.8)	21 (33.8)
s_h	vehicle speed on highway	mph (kph)	42 (67.6)	42 (67.6)
k_l	routing constraints	unitless	0.7	0.7
ϕ	stopping b/c traffic/signals	unitless	0.3	0.3

3.5.2 Vehicle Costs

While autonomous vehicles are beginning to be tested across the United States, the costs associated with manufacturing autonomous vehicle are still significantly higher than those of conventional vehicles. Based on a 2015 estimate, the additional cost of including the Light Detection and Ranging (LIDAR) sensors to allow a vehicle to be fully autonomous (level 4+) is \$30,000 to \$85,000 per vehicle, and over \$100,000 per vehicle for LIDAR and other sensors and software. The cost of automation equipment for mass-produced autonomous vehicles could eventually fall between \$25,000 and \$50,000 per vehicle. Once market share of autonomous vehicles becomes at least 10%, the cost of automation equipment could lower to \$10,000 per vehicle. The price of implementing automation about 20 to 22 years after introduction is expected to be \$3,000 per vehicle, eventually reaching a low of \$1,000 to \$1,500 per vehicle.

In this research, it is assumed that RADRs are operating at Level 5. Level 3 is also called "Condition Automation" when all tasks can be controlled by the autonomous system in some specific (easier) situations, but the human driver must be ready to take back control at any time. Level 5 is called "Full Automation" and in this case, the autonomous system can handle all roadway conditions and environments, i.e. drivers are not needed.

It is assumed that trucking values of time utilize a value of \$40/hour as the base cost for conventional vans because these require a human driver. It was not possible to find the cost of production of the uDelv vehicles. The \$30/hr operating cost of a RADR is obtained from the cost of conventional van but without labor costs and then adding a 15% increase for the more expensive autonomous vehicle technology.

3.6 RESULTS

Multiple scenarios are created by varying three key variables—time per delivery, service area, and distance between the depot and the service areas. These parameters are denoted by t, a, and d respectively, and only one parameter is varied at a time. The default values for these parameters are 3 minutes, 100 mi^2 (259 km^2), and 10 miles (16.1 km) respectively.

The results of varying total delivery time t are shown in Table 16. As time t changes, there is a change in the number of customers served, as well as the delivery density and in some cases, a change in m_R—the RADR fleet size. There are some noteworthy trends: (i) more RADRs than conventional vans are required in most scenarios, (ii) conventional vans generate less vehicle miles per delivery, (iii) conventional vans spend less time per delivery but (iv) the cost per delivery is lower in all cases when RADRs are utilized.

The results of varying the area of service a are shown in Table 17. As a decreases, there is a rapid increase in the number of customers served as well as the delivery density. The RADR fleet size is higher than in Table 16, as a higher number of customers can be served with a conventional van when the density is high. The trends (i) to (iv) observed are maintained but the differences between RADRs and conventional vans have increased. For example, with the highest density of 16.3 customers per mile2 (6.9 cust/km2) the number of miles driven by RADRs have increased threefold. However, the cost per delivery is lower in all cases when RADRs are utilized.

The results of varying depot–service area distance d are shown in Table 18. As d increases, there is also a rapid decrease in the number of customers served (utilizing equation (3)) as well as the delivery density. The RADR fleet size is also larger in Table 18 than in Table 16. The differences regarding vehicle-miles are larger, for example with the highest distance of 24 miles (38.8 km) the number of miles driven by RADRs increases more than threefold. Unlike previous tables, the cost per delivery is not always lower when RADRs are utilized. There is a breakeven point when the distance d is around 12–15 miles. For RADRs distance driven and fleet size increases rapidly for large values of d and this is caused by the relatively low RADR range.

Up to this point, it has been assumed that RADRs and conventional vans can travel at the same speed and with the same delivery time t per customer. However, the literature review indicates that picking up and delivering parcels may still involve a person even if the vehicle is automated (*5*) and that urban areas are complex environments with many deliveries/stops and interactions with pedestrians and cyclists (*6*). Hence, it is likely that RADRs will be designed with high safety standards and would require extra time to park, unload/load, and avoid conflicts with pedestrians and/or cyclists.

Table 16: Results Varying *t*

t (min)	3	4.5	6	7.5	9	10.5	12	13.5	15
n	118	85	67	56	48	42	37	33	30
δ cust/mi^2	1.18	0.85	0.67	0.56	0.48	0.42	0.37	0.33	0.3
(cust/km^2)	(0.46)	(0.33)	(0.26)	(0.22)	(0.19)	(0.16)	(0.14)	(0.13)	(0.12)
m_R	4	3	3	2	2	2	2	2	1
Delivery distance per customer, mi (km)									
uDelv	1.32	1.47	1.75	1.65	1.84	2.03	2.23	2.43	1.94
	(2.13)	(2.36)	(2.82)	(2.65)	(2.97)	(3.27)	(3.59)	(3.91)	(3.13)
Convent.	0.81	0.99	1.15	1.29	1.43	1.56	1.69	1.82	1.94
	(1.31)	(1.6)	(1.86)	(2.08)	(2.3)	(2.5)	(2.72)	(2.94)	(3.13)
Time spent delivering (vehicle-hours) per customer (min)									
uDelv	5.8	7.7	9.7	11.2	13.1	14.9	16.8	18.7	19.6
Convent.	5.1	7	8.9	10.7	12.5	14.3	16.1	17.8	19.6
Cost per delivery ($)									
uDelv	2.90	3.84	4.86	5.60	6.54	7.47	8.42	9.36	9.80
Convent.	3.39	4.67	5.91	7.12	8.32	9.51	10.71	11.90	13.07

Table 17: Results Varying *a*

a (mi^2)	10	25	40	55	70	85	100	115	130
n	163	149	140	133	127	122	118	114	110
δ cust/mi^2	16.3	5.96	3.5	2.42	1.81	1.44	1.18	0.99	0.85
(cust/km^2)	(6.29)	(2.3)	(1.35)	(0.93)	(0.7)	(0.56)	(0.46)	(0.38)	(0.33)
m_R	6	5	5	5	4	4	4	4	4
Delivery distance per customer, mi (km)									
uDelv	0.91	0.96	1.09	1.2	1.15	1.24	1.32	1.4	1.49
	(1.46)	(1.54)	(1.75)	(1.93)	(1.85)	(2)	(2.13)	(2.26)	(2.4)
Convent.	0.3	0.42	0.52	0.6	0.68	0.75	0.81	0.88	0.94
	(0.48)	(0.68)	(0.83)	(0.97)	(1.09)	(1.2)	(1.31)	(1.41)	(1.52)
Time spent delivering (vehicle-hours) per customer (min)									
uDelv	4.5	4.8	5.1	5.4	5.4	5.6	5.8	6	6.2
Convent.	3.7	4	4.3	4.5	4.7	4.9	5.1	5.3	5.4
Cost per delivery ($)									
uDelv	2.27	2.39	2.54	2.68	2.69	2.80	2.90	3.01	3.11
Convent.	2.45	2.67	2.85	3.00	3.14	3.27	3.39	3.51	3.62

Table 18: Results Varying d

d (miles)	0	3	6	9	12	15	18	21	24
n	125	123	120	118	116	114	112	110	107
δ cust/mi^2	1.25	1.23	1.2	1.18	1.16	1.14	1.12	1.1	1.07
(cust/km^2)	(0.48)	(0.47)	(0.46)	(0.46)	(0.45)	(0.44)	(0.43)	(0.42)	(0.41)
m_R	4	4	4	4	4	4	4	5	7
Delivery distance per customer, mi (km)									
uDelv	0.63	0.83	1.04	1.25	1.48	1.71	1.95	2.58	3.82
	(1.01)	(1.33)	(1.67)	(2.02)	(2.38)	(2.75)	(3.13)	(4.15)	(6.14)
Convent.	0.63	0.68	0.74	0.8	0.86	0.92	0.98	1.05	1.13
	(1.01)	(1.09)	(1.19)	(1.28)	(1.38)	(1.48)	(1.58)	(1.69)	(1.81)
Time spent delivering (van/human hours) per customer (min)									
uDelv	4.8	5.1	5.4	5.7	6	6.4	6.7	7.6	9.4
Convent.	4.8	4.9	5	5.1	5.2	5.2	5.3	5.5	5.6
Cost per delivery ($)									
uDelv	2.39	2.54	2.70	2.86	3.02	3.19	3.36	3.82	4.71
Convent.	3.19	3.25	3.31	3.37	3.44	3.50	3.57	3.63	3.72

To illustrate the importance of an additional time penalty for delivery, Table 19 shows the results when the conventional van delivers on t minutes but the RADR delivers on $t+3$ (min). Vehicle-miles are significantly lowered when a conventional van is utilized. Unlike Table 16, the RADR does not dominate in terms of cost per delivery. In Table 19, the conventional van is more economical up to the point when $t = 9$ minutes for the conventional van and $t = 12$ minutes for the uDelv.

Table 19: Results Varying t with +3 (min) penalty for RADR

t (min) Covent.	**3**	**4.5**	**6**	**7.5**	**9**	**10.5**	**12**
t (min) uDelv.	**6**	**7.5**	**9**	**10.5**	**12**	**13.5**	**15**
n	67	56	48	42	37	33	30
δ cust/mi^2	0.67	0.56	0.48	0.42	0.37	0.33	0.3
(cust/km^2)	(0.26)	(0.22)	(0.19)	(0.16)	(0.14)	(0.13)	(0.12)
m_R	3	2	2	2	2	2	1
Delivery distance per customer, mi (km)							
uDelv	1.75	1.65	1.84	2.03	2.23	2.43	1.94
	(2.82)	(2.65)	(2.97)	(3.27)	(3.59)	(3.91)	(3.13)
Convent.	0.81	0.99	1.15	1.29	1.43	1.56	1.69
	(1.31)	(1.6)	(1.86)	(2.08)	(2.3)	(2.5)	(2.72)
Time spent delivering (van/human hours) per customer (min)							
uDelv	9.7	11.2	13.1	14.9	16.8	18.7	19.6
Convent.	5.1	7	8.9	10.7	12.5	14.3	16.1
Cost per delivery ($)							
uDelv	4.86	5.60	6.54	7.47	8.42	9.36	9.80
Convent.	3.39	4.67	5.91	7.12	8.32	9.51	10.71

3.7 DISCUSSION

RADRs are more competitive than conventional vans but are mostly limited by their short range and limited storage capacity. The short range can be addressed by more and better batteries. Though this would be at the expense of additional vehicle weight and cost, batteries are one of the major barriers to the electrification of freight (Feng and Figliozzi, 2013).

The largest uncertainties related to RADRs are perhaps the cost and regulatory barriers. The rate and speed of adoption of RADRs will greatly depend on the costs and ease of entry into the delivery market, as discussed by previous studies focusing on the adoption of autonomous trucks by freight organizations as discussed in an earlier chapter. It is assumed that packages transported are small, as Amazon reported most packages delivered are less than 5 pounds. If larger packages are considered, then RADR vans may not be a feasible option since a driver or other type of equipment would be necessary for the delivery. This is an important limitation and indicates that full automation would not be easily achieved for special or more cumbersome deliveries.

Large-scale introduction of RADRs can also bring about new business and service models that are made possible by 24-hour operations since autonomous delivery robots are not subject to limitations like driver fatigue as well as lunch and rest breaks. On the other hand, RADRs can bring about more congestion unless they become more efficient than conventional vans in terms of vehicle-miles per customer visited.

Since RADRs deliver freight, they can prioritize safety of pedestrians and other road users over the safety of the freight being carried by the RADR. Hence, RADRs are not faced with potential ethical issues that passenger autonomous vehicles are likely to face regarding tradeoffs between the safety of passengers and other vulnerable road users such as pedestrians and/or cyclists. Because of this advantage, it is likely that RADRs may be widely used before autonomously driven passenger vehicles. On the other hand, urban freight is complex and the tasks associated to parking, unloading, and delivering may be more difficult to automate than is currently expected. High safety standards for RADRs may result in high delivery times per customer, which in turn decreases RADRs economic appeal as shown in the previous section.

4.0 CONCLUSIONS

In conclusion, the imminent widespread availability of autonomous vehicle technology within the next decade presents a significant opportunity and challenge for the freight transportation industry. Our research, which employed a novel methodological approach incorporating peer effects and real-world data on organizational innovation adoption behavior, revealed that most organizations are inclined to either fully embrace or outright reject the first-generation Commercial Autonomous Trucks (CATs), with fewer opting for testing or partial adoption. Interestingly, the level of perceived risk, encompassing financial, physical, and liability aspects, did not strongly influence adoption behavior, as both adopters and rejecters acknowledged the inherent risks associated with early CAT adoption. Moreover, smaller organizations exhibited a higher likelihood of rejecting CATs, possibly due to lower risk tolerance, resource constraints, and a lack of specialized personnel to leverage this transformative technology.

It is important to note that our stated-preference survey was conducted in the United States during March and April of 2020, a period marked by the unexpected outbreak of COVID-19 and the ensuing economic turbulence, which could have influenced the survey responses. Future investigations should explore how the frequency of technological updates affects adoption rates, as our study was limited to two generations of CATs set ten years apart, whereas real-world technological advancements are expected to be more frequent and incremental. This aspect should be a focal point for forthcoming research.

While the methodology employed in this report was tailored for organizational CAT adoption, it has been designed to be adaptable for a wide range of organizational innovation adoption studies. This opens up the possibility of analyzing various innovations not only in the freight transportation industry but across different sectors. Such studies could shed light on how peer effects are shaped by the nature of the innovation and the underlying social network structure, providing insights into why and to what extent certain innovations are embraced.

Switching gears, the study on road automated delivery robots (RADRs) has highlighted their potential to reduce delivery costs in many scenarios, which is likely to entice delivery companies seeking to meet the rising demands of e-commerce. However, RADRs exhibit limitations, particularly in long-distance routes with numerous customers, leading to longer delivery times per customer due to safety concerns and frequent interactions with traffic, pedestrians, and cyclists. From a public policy perspective, the adoption of RADRs may significantly increase vehicle-miles related to package delivery, surpassing conventional vans in this regard. Moreover, the convergence of increased vehicle-miles per delivery with the growth of e-commerce has the potential to exacerbate congestion and high curb utilization issues in urban areas. This research serves as an initial step in understanding the trade-offs between RADRs and conventional vans, but it also underscores the need for future research to explore narrower delivery windows, consider additional parameters such as costs, speed, range, and capacity, and assess second-order effects, both in terms of potential externalities and benefits related to automated deliveries

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