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MODELING ADOPTION OF AUTONOMOUS VEHICLE TECHNOLOGIES BY FREIGHT ORGANIZATIONS

Final Report

by

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DISCLAIMER

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EXCUTIVE SUMMARY

Over the last few years, a rapid explosion of new technologies has created opportunities to address critical freight transportation challenges in urban, suburban, and rural areas. These innovations include truck platooning, smart parking systems, collaborative and shared logistics techniques, and connected autonomous vehicles. These new technologies are influencing consumer behavior and reshaping freight supply chain management at the urban, regional, and international level. In order to understand how these innovations are changing the field of freight transportation, it is essential to understand how organizations choose to adopt innovations. Adoption methods available from consumer behavior research are mostly based on individuals, and there is limited material on the behavior of organizations in regards to innovation adoption. The general adoption methods cannot be directly used in modeling adoption of innovations by organizations without further study and modifications.

Approaches to innovation adoption can be broken into two sections: theoretical and methodological approaches. The theoretical approaches attempt to identify the forces that cause an organization to accept or reject an innovation. Once the forces have been identified, the theoretical approaches explain how the forces interact and influence the adoption process. Methodological approaches are composed of modeling techniques which can be applied to innovations in order to generate predictions of adoption patterns. By identifying the benefits and drawbacks of each approach, it is possible to select the most appropriate theoretical and methodological approach for organizational adoption.

Goals and Objectives: (1) Identify the emerging technologies which are influencing freight planning and operations; (2) review the existing theoretical and methodological approaches for innovation adoption, focusing on applications for organizational innovation adoption; (3) survey stakeholders to identify their inclinations towards the emerging technologies; (4) develop a predictive model of the adoption of connected autonomous vehicles by freight organizations; and (5) outline future research steps necessary to meet the evaluation needs of local agencies, MPOs, and state DOTs.

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1.0   INTRODUCTION

Over the last several years, a number of new technologies have created opportunities to address many of the challenges facing freight transportation organizations. Innovations such as connected autonomous vehicles (CAVs), truck platooning, smart parking systems, and collaborative/shared logistics systems may very well reshape the field of freight transportation. These innovations are influencing the behavior of consumers and organizations alike, altering the network of freight supply chains at all levels.

Despite the many potential benefits of incoming transportation technologies, there are a number of barriers that need to be resolved before widespread adoption of these innovations is possible. For example, CAVs face unresolved issues such as liability in case of a collision, balancing between communication and security/privacy, safety concerns, reliability of the automation system, necessary infrastructure changes, and regulatory legislation for CAV manufacturers. There is much more work to be done beyond simply developing the CAV technology, and the same may be said for each of the upcoming freight innovations (J. M. Anderson et al., 2014; Fagnant & Kockelman, 2015; Kockelman et al., 2017).

However, it is difficult to address these issues without first having information about the rate at which these innovations will be adopted. Transportation planners need to know where and when these innovations will appear in order to prepare suitable legislation and infrastructure to accommodate the new vehicles. Innovation adoption studies often focus on individual adoption rather than organizational adoption, or only discuss organizational adoption in a generalized manner. Most studies for organizational innovation adoption focus on attempting to identify characteristics of organizations that promote adoption (Damanpour, 1991; Hoerup, 2001; N. Kim & Srivastava, 1998; Moch & Morse, 1977; Pierce & Delbecq, 1977; Rogers, 2003; Subramanian & Nilakanta, 1996) or investigate the process of adoption within an organization (Eveland, 1979; Fidler & Johnson, 1984; Leonard-Barton & Deschamps, 1988; Meyer & Goes, 1988; Rogers, 2003). This pattern holds true for freight innovation adoption predictions. For example, while there have been studies that predict the market penetration rate of CAVs for individuals (Bansal & Kockelman, 2017; Bansal, Kockelman, & Singh, 2016; Lavasani, Jin, & Du, 2016), the issue of CAV technology and the freight industry has received little attention from academia. The literature only briefly mentions CAVs in freight transportation (Catapult Transport Systems, 2017; Fagnant & Kockelman, 2015; Kockelman et al., 2017) or focuses on the costs and benefits of implementing CAVs for freight without approaching the question of demand (Kunze, Ramakers, Henning, & Jeschke, 2011; Rossman, 2017; Shankwitz, 2017). Research is needed in the area of predictive analysis regarding the potential market penetration rate of CAVs and other emerging technologies in freight organizations.

There are a number of disparate theories regarding the adoption of innovations, including diffusion of innovations (DoI, the unified theory of acceptance and use of technology (UTAUT), technology acceptance model (TAM). The primary objective of this research is to provide a systematic overview of the innovation adoption literature, analyzing the theoretical and methodological alternatives in the context of transportation innovations. Each of these approaches has specific benefits and drawbacks which may make them appropriate for different types of innovation adoption studies. Once these approaches have been identified, and the most appropriate

method has been selected, a preliminary case study is performed to demonstrate how freight organizations may choose to adopt CAVs.

The remainder of this report is organized as follows: the following chapter contains a review of the literature, composed of a section reviewing the aforementioned emerging technologies, a section explaining the differences between the three primary theoretical approaches to predicting innovation adoption, and a section discussing the various potential methodological approaches to predicting and measuring innovation adoption. The review of the literature is followed by a chapter containing a more detailed description of the chosen literature is followed by a chapter containing a more detailed description of the chosen methodology for the preliminary case study as well as a brief description of the data gathered for analysis. This is followed by a chapter containing the results of our model, the implications of the results, and a sensitivity analysis performed on the model output. The final chapter contains a discussion of the study limitations, ongoing research, and a conclusion which summarizes the major findings of the project.

2.0   LITERATURE REVIEW

2.1   ORGANIZATIONAL INNOVATIONS IN TRANSPORTATION

2.1.1 Connected Autonomous Vehicles

Decades ago, self-driving vehicles were nothing more than a fantasy. Today, advancements in technology point to a near future where autonomous vehicles will be a reality. Most major automobile manufacturers are predicting that conditional automation will be available as early as 2020, with more sophisticated automation technology available by 2030 (Fagella, 2017). 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, Tavana, Asadi, & Oliver, 2016; Bansal & Kockelman, 2017; Fagnant & 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, Douma, & Onyiah, 2015; U.S. Department of Transportation, 9/16). All signs point to driverless vehicles joining the fleet within the next ten years. CAVs have the potential to revolutionize transportation, and there has been significant research and development on the operational side of making automated vehicles a reality.

The freight transportation industry stands to benefit from integrating connected autonomous vehicle technology. One benefit would be a reduction in collisions, which translates to safer working conditions, increased profits, and reliability (J. M. Anderson et al., 2014; Bagloee et al., 2016). Of arguably greater interest to freight organizations, CAV technology is predicted to increase fuel efficiency, reducing consumption by up to 10-15% (J. M. Anderson et al., 2014; Bagloee et al., 2016; Bullis, 2011; Fagnant & Kockelman, 2015; Kockelman et al., 2017). Integrating CAVs into the fleet would also reduce the labor required to move goods, further reducing the cost of operations. Freight organizations are already attempting to address a shortage of drivers, and CAV technology may be the solution to the labor shortage (Rossman, 2017). The highest costs associated with long-distance trucking are driver salary and fuel costs, and CAVs have the potential to greatly reduce both of these costs (Shankwitz, 2017). Reducing the manpower required to operate the vehicles may also allow organizations to be more productive, because laws that regulate the number of hours a driver may legally travel might not apply to driverless vehicles.

However, there are a number of barriers to overcome before widespread adoption is possible (Fagnant & Kockelman, 2015). Safety concerns, legality and liability questions, security/privacy matters, and infrastructure changes must be identified and addressed before autonomous technology reaches maturity (Fagnant & Kockelman, 2015; Kockelman et al., 2017).

In order for policymakers to make informed decisions about these issues, it is essential to have an estimate of the rate at which these innovations will be adopted. Transportation planners need to

know where and when these innovations will appear in order to prepare suitable legislation and infrastructure to accommodate the new vehicles.

While studies are being conducted in regards to individual adoption of CAVs, it is difficult to predict how policymakers and planners will react to autonomous freight vehicles. Unlike individual CAVs, state and federal DOTs have not yet released significant regulations or guides for integrating CAVs into the freight industry (29). Without sufficient data on autonomous freight adoption, it is difficult to identify and address the various changes to infrastructure, policy, and logistics that will need to be made as freight organizations switch to automation. It is, therefore, critical to develop a model to predict the adoption rate of CAVs for freight organizations.

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, Besselink, Turri, Martensson, & Johansson, 2015; Deng & Ma, 2014; Kunze et al., 2011; Tsugawa, Kato, & Aoki, 2011; Van De Hoef, Johansson, & Dimarogonas, 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 & Johansson, 2013; Larsson, Sennton, & Larson, 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, Hedin, & Skarin, 2012; Gehring & Fritz, 1997; Nowakowski, Shladover, Lu, Thompson, & Kailas, 2015).

2.1.3 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, Qureshi, & Shaikh, 2016; Geng & Cassandras, 2012; Hanif, Badiozaman, &

Daud, 2010; Polycarpou, Lambrinos, & Protopapadakis, 2013; Shin & 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; H. Wang & 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, Sunantachaikul, & Triamlumlerd, 2007), or the potential costs and benefits of adopting smart parking systems (Mahmud, Khan, Rahman, & Zafar, 2013; Pala & Inanc, 2007).

2.1.4 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, Ubaghs, & Cuevas, 2015). Collaboration between transportation organizations can result in more optimal systems, improved reliability, reduced delivery time, and increased cost efficiency (Angerhofer & Angelides, 2006; Bates, Knowles, & Friday, 2017; de Souza, Goh, Lau, Ng, & Tan, 2014; Guo, Peeta, & Mannering, 2016; O'sullivan, 2010; Tyan, Wang, & Du, 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, Laesanklang, Landa-Silva, Mesgarpour, & Qu, 2017; Dai & Chen, 2009; de Souza et al., 2014; Gonzalez-Feliu, Morana, Grau, & Ma, 2013; Guajardo & Rönnqvist, 2015; Stefansson, 2006; Trentini et al., 2012; Verdonck, Caris, Ramaekers, & Janssens, 2013). The literature discusses models that range from full-system collaboration transportation management (Feng & 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 & Chen, 2009; de Souza et al., 2014).

2.2   INNOVATION ADOPTION THEORETICAL APPROACHES

The study of how innovations are adopted by both individuals and organizations has a long history of academic research, reaching back to the 1930s with studies of hybrid corn diffusion (B. Ryan & Gross, 1950) and continuing to the present day. Over the nearly ninety years of research, various theoretical models for how innovations are adopted have been developed. Each of the models attempts to simplify the incredibly complex socioeconomic interactions involved in the acceptance and adoption of innovations into a finite number of influencing factors, but the number of factors interaction between them varies from model to model. This study identifies three theoretical approaches that are well suited for organizational innovation adoption: Diffusion of Innovations (DoI), Unified Theory of Acceptance and Use of Technology (UTAUT), and the Technology Acceptance Model (TAM). Many terms are repeated by these theoretical approaches, and so a brief overview of the terminology found in the literature is contained in Table 1.

Table 1: Overview of relevant terminology.

Term	Definition	Theories	Effect on Adoption when Increased
Relative Advantage	The degree to which an innovation is perceived as being better than the idea or system it supersedes	DoI, UTAUT	Positive
Compatibility	The degree to which an innovation is consistent with the goals and needs of the adopter	DoI, UTAUT, TAM	Positive
Observability	The degree to which an innovation's effects are easily noticed and understood	DoI, TAM	Positive
Complexity	The degree to which an innovation is difficult to operate or understand	DoI, UTAUT, TAM	Negative
Trialability	The degree to which an innovation may be experimented with on a limited basis	DoI,	Positive
Reinventability	The degree to which an innovation is able to be modified for purposes other than its original intended use	DoI	Positive
Perceived Risk	The uncertainty an individual has concerning the innovation	DoI	Negative
Subjective Norm/Image	The individual's perception that people who are important think he should or should not adopt an innovation or behavior	DoI, UTAUT, TAM	Neutral
Experience	The degree of knowledge or practical wisdom the adopter possesses regarding a system or innovation	UTAUT, TAM	Either Positive or Negative
Voluntariness	The degree to which an individual believes he or she is able to choose a behavior, rather than having the behavior forced upon him or her	UTAUT, TAM	Negative
Perceived Output Quality	The degree to which the innovation is expected to perform the required functions adequately	UTAUT, TAM	Positive
Gender	The gender of the individual adopting the innovation	UTAUT	Neutral
Age	The age of the individual adopting the innovation	UTAUT	Neutral
Social Network	The network of communication channels between agents in a system	DoI, UTAUT	Neutral
Perceived Ease-of-Use	The degree to which a person believes that using a system would be free of effort	UTAUT, TAM	Positive

Perceived Usefulness	The degree to which a person believes that using the innovation would enhance his or her performance	UTAUT, TAM	Positive
Social Factors	The individual's internalization of how the surrounding culture and interpersonal connections influence behavior	UTAUT	Either Positive or Negative
Perceived Behavioral Control	The individual's perception that they are capable of performing a behavior	UTAUT	Positive
Behavioral Intent	An evaluation of the benefits and disadvantages of performing a behavior, leading to a decision about the behavior	TAM	Either Positive or Negative

2.2.1 Diffusion of Innovations

One of the most widely utilized methods of predicting the market penetration rate of new innovations is the theory of diffusion of innovations (Greenhalgh, Robert, Macfarlane, Bate, & Kyriakidou, 2004; Hoerup, 2001; Kumar, Sarkar, & Swami, 2009; Lavasani et al., 2016; Mahajan, Mason, & Srinivasan, 1985; Mahajan, Muller, & Bass, 1991, 1995; Mahler & Rogers, 1999; Peres, Muller, & Mahajan, 2010; Premkumar, Ramamurthy, & Crum, 1997; Rogers, 2003; Sahin, 2006; Straub, 2009; Sultan, Farley, & Lehmann, 1990; Wisdom, Chor, Hoagwood, & Horwitz, 2014; Zsifkovits & Günther, 2015). The theory of diffusion of innovations was first formalized in the 1960s by Everett Rogers, who defined it as "The process by which an innovation is communicated through certain channels over time among the members of a social system" (Rogers, 2003). The diffusion of innovations contains four main elements: innovation, communication, time, and a social system.

Rogers defines an innovation as "an idea, practice, or object that is perceived as new by an individual or other unit of adoption" (Rogers, 2003). Whether or not an innovation is actually new does not matter; only the *perception* of being new is important. Innovations are often thought of as inventions or tools, but an innovation can be new information, methodologies, technology, or strategies as well as physical objects. Innovations may come in all forms, but there are a number of universal attributes that influence how quickly they are diffused throughout a social system. The five most commonly recognized attributes are: relative advantage, compatibility, complexity, trialability, and observability. Other attributes may include perceived risk, available infrastructure, reinventability, and affordability (Cain, 2002; Greenhalgh et al., 2004; Hoerup, 2001; Moore & Benbasat, 1991; Rogers, 2003; Sahin, 2006; Tornatzky & Klein, 1982; Wisdom et al., 2014).

Communication is defined as the process by which individuals generate and share information in an effort to reach a mutual understanding (Rogers, 2003). Individuals pass information through communication channels, which range from mass media channels such as radio, television, and newspapers to interpersonal channels such as face-to-face or phone conversations. The more similar individuals are to one another, the stronger the communication process becomes (Centola, 2011; Rogers, 2003; Rogers & Bhowmik, 1970).

The inclusion of the time element into diffusion of innovations theory allows for adopting individuals to undergo the innovation-decision process rather than forcing them to make an instant decision on whether or not to adopt an innovation. The innovation-decision process is an activity where the potential adopter attempts to gather and process information about the innovation in order to gradually decrease their uncertainty about the innovation (Rogers, 2003). The process has five main steps: Initial knowledge, persuasion, decision, implementation, and confirmation. The DoI process is illustrated in Figure 1:
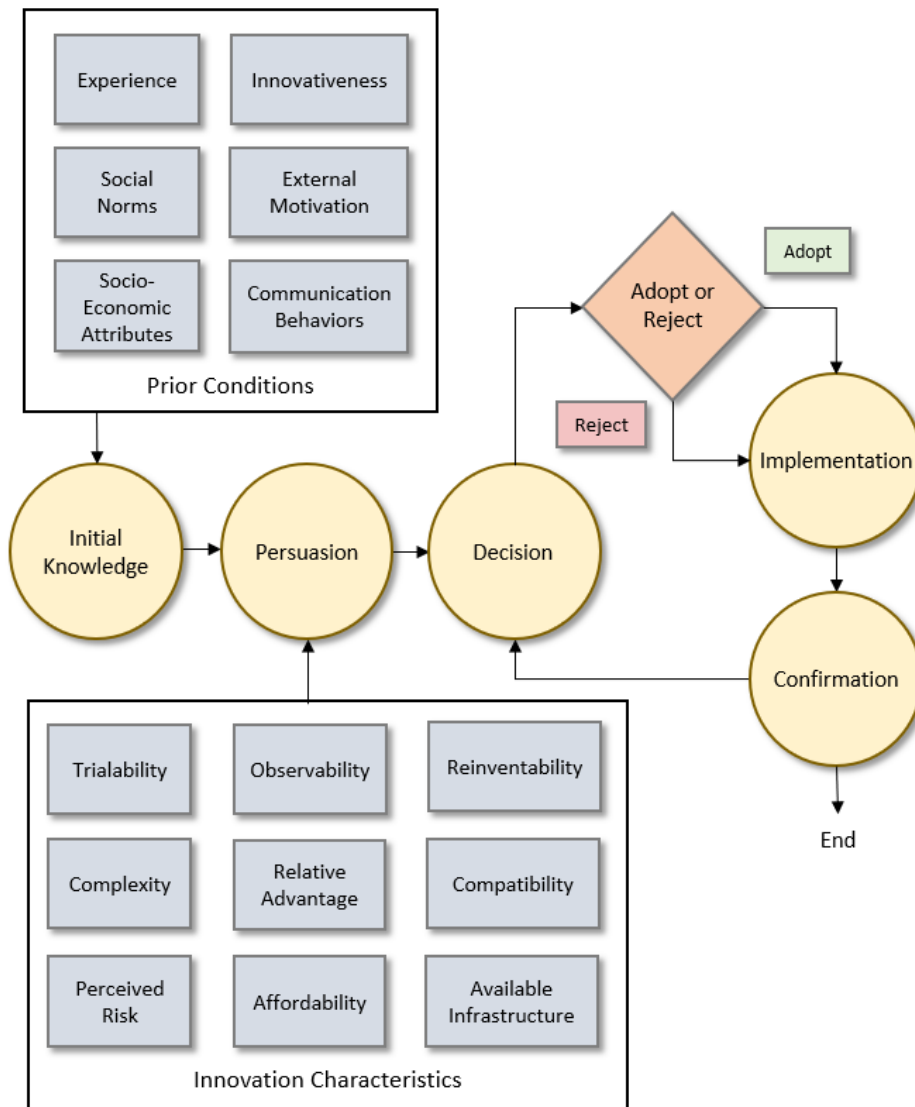
Figure 1: Diffusion of Innovations model of innovation adoption behavior.

The final component of the diffusion of innovations theory is the social system, defined as "the set of interrelated units engaged in joint problem solving to accomplish a common goal" (Rogers, 2003). The social system is the means by which individuals communicate their knowledge of the innovation. The structure of the social system can influence the degree and

quality of information that is passed to the individuals. For example, a system with several influential opinion leaders and change agents will cause adoption to occur more rapidly than a system without leadership figures (Rogers, 2003).

One of the chief advantages to diffusion of innovations theory is that it provides a flexible framework that can be adjusted to fit any innovation (Straub, 2009). Diffusion of innovations theory has been adapted to fit a variety of research fields, including health care (Cain, 2002; Greenhalgh et al., 2004), information systems (Aguila-Obra & Padilla-Meléndez, 2006; Moore & Benbasat, 1991; Premkumar et al., 1997; Thong, 1999), transportation (Lavasani et al., 2016; Orbach & Fruchter, 2011; Shafiei, Stefansson, Ásgeirsson, & Davidsdottir, 2014; Urban, Hauser, & Roberts, 1990; Wolf, Schröder, Neumann, & de Haan, 2015; Zsifkovits & Günther, 2015), marketing and advertising (Horsky & Simon, 1983; Radas, 2006), and communication (Daft & Lengel, 1986; Fidler & Johnson, 1984; Leonard-Barton & Deschamps, 1988). It has also been successfully applied to both individual and organizational innovation adoption. Table 2 provides an abbreviated list of works which implemented diffusion of innovations theory. The list of works is necessarily abbreviated due to the abundance of research that has been conducted in this field.

Table 2: Abbreviated list of works with Diffusion of Innovations theory.

Source	Field	Innovation
(Aguila-Obra & Padilla-Meléndez, 2006)	Information Technology	Various Internet-Based Technologies
(Diederen, Van Meijl, Wolters, & Bijak, 2003)	Agriculture	Various Agriculture Innovations
(Greenhalgh et al., 2004)	Health Care	Various Health Care Innovations
(Guidolin & Mortarino, 2010)	Energy Systems	Solar Energy Production
(Hoerup, 2001)	Education and Computer Technology	Computer Integration in Schools
(Horsky & Simon, 1983)	Communication, Advertising and Marketing	Telephonic Banking
(Lavasani et al., 2016)	Transportation	Connected Autonomous Vehicles
(Mahler & Rogers, 1999)	Communication	Telecommunication Services in Banks
(Moore & Benbasat, 1991)	Information Technology	Generalized Information Technology
(Nordhoff, Van Arem, & Happee, 2016)	Transportation	Connected Autonomous Vehicles
(Orbach & Fruchter, 2011)	Transportation	Hybrid/Electric Vehicles
(Premkumar et al., 1997)	Information Technology	Electronic Data Interchange

(Shafiei et al., 2014)	Transportation	Hybrid or Alternate Fuel Vehicles
(Horsky & Simon, 1983)	Communication, Advertising and Marketing	Telephone Systems
(Thong, 1999)	Information Technology	Information Systems
(Urban et al., 1990)	Transportation	New Automobiles
(Wolf et al., 2015)	Transportation	Hybrid/Electric Vehicles
(Zsifkovits & Günther, 2015)	Transportation	Hybrid or Alternate Fuel Vehicles

2.2.2 Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) is the result of an analysis of eight behavioral models: Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivational Model (MM), Theory of Planned Behavior (TPB), a hybrid TAM and TPB model, Model of PC Utilization (MPCU), Diffusion of Innovations Theory, and Social Cognitive Theory (SCT) (Martins, 2013; Oshlyansky, Cairns, & Thimbleby, 2007; Straub, 2009; Venkatesh, Morris, Davis, & Davis, 2003). The theory is designed to explain the adoption of innovations by individuals within an organization (Venkatesh, Thong, & Xu, 2016). UTAUT identifies four constructs which are direct determinants of user acceptance and usage behavior: performance expectancy, effort expectancy, social influence, and facilitating conditions (AlAwadhi & Morris, 2008; Escobar-Rodríguez & Carvajal-Trujillo, 2014; Martins, 2013; Pynoo et al., 2011; Venkatesh et al., 2003). Age, gender, experience, and voluntariness are modifiers of these four constructs. Some studies have amended UTAUT to include other factors such as anxiety, habits, price value, trust, and hedonic motivation, but the four core constructs are always present and significant influences for adoption behavior (Escobar-Rodríguez & Carvajal-Trujillo, 2014; Moran, Hawkes, & Gayar, 2010; Venkatesh, Thong, & Xu, 2012; Zhou, 2012). Figure 2 shows the general form of the UTAUT conception of innovation adoption.
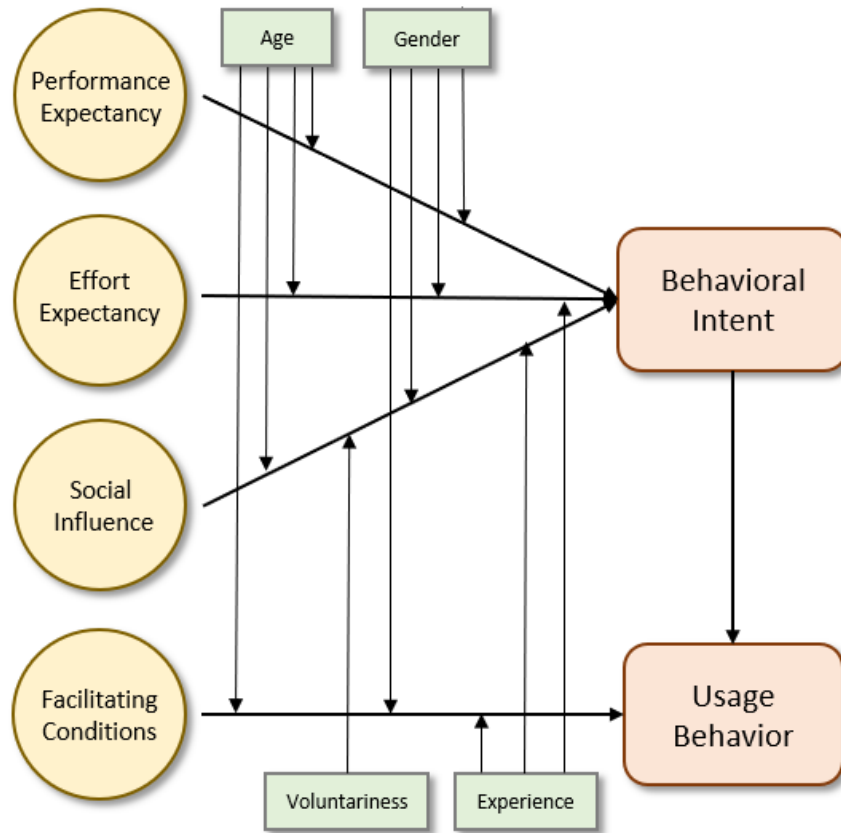
Figure 2: UTAUT model of innovation adoption behavior.

Performance expectancy is the degree to which an individual believes that the innovation will help him or her attain a better performance in a task. The performance expectancy is the strongest predictor of behavioral intent and is always a significant factor in all types of innovation adoption (Pynoo et al., 2011; Venkatesh et al., 2003). Performance expectancy is formed from five factors: perceived usefulness, extrinsic motivation, compatibility, relative advantage, and outcome expectations. The two modifiers that influence the performance expectancy are gender and age, with young men placing the most emphasis on performance expectancy (Venkatesh et al., 2003; H.-Y. Wang & Wang, 2010).

Effort expectancy is the degree to which an individual believes the system will be easy to use. Effort expectancy is most important during the adoption decision process and decreases in significance during implementation (Pynoo et al., 2011; Venkatesh et al., 2003). Perceived ease of use, complexity, and observed ease of use are the three factors that form the effort expectancy of an innovation. Effort expectancy is moderated by gender, age, and experience, with older, inexperienced women placing higher importance in effort expectancy (Venkatesh et al., 2003; H.-Y. Wang & Wang, 2010).

Social influences are the sum of factors that cause an individual to perceive that other important people believe he or she should adopt and utilize the innovation. The social influence construct is also sometimes referred to as the "subjective norm" or "image" (Venkatesh et al.,

2003, 2016). When the decision to adopt is voluntary, social influences are not especially strong indicators of behavior. However, when the decision is mandated by an authoritative figure, social influences are much stronger (Pynoo et al., 2011). Social influences are moderated by age, gender, experience, and voluntariness, with additional emphasis placed on older, female, inexperienced individuals (Venkatesh et al., 2003; H.-Y. Wang & Wang, 2010).

The final construct of the UTAUT model is "facilitating conditions," which is defined as the degree to which an individual believes that the infrastructure necessary to support the adoption and use of an innovation already exists. The facilitating conditions construct is formed from perceived behavioral control, compatibility, and available infrastructure (Venkatesh et al., 2003). Unlike the other constructs of the UTAUT model, facilitating conditions have a direct influence on usage behavior beyond what is explained by behavioral intent (AlAwadhi & Morris, 2008; Moran et al., 2010; Pynoo et al., 2011). Facilitating conditions are moderated by age and experience, with older and more experienced individuals attaching higher importance to facilitating conditions (Venkatesh et al., 2003; H.-Y. Wang & Wang, 2010). Figure 2.3 shows the four UTAUT constructs and their influencing factors.
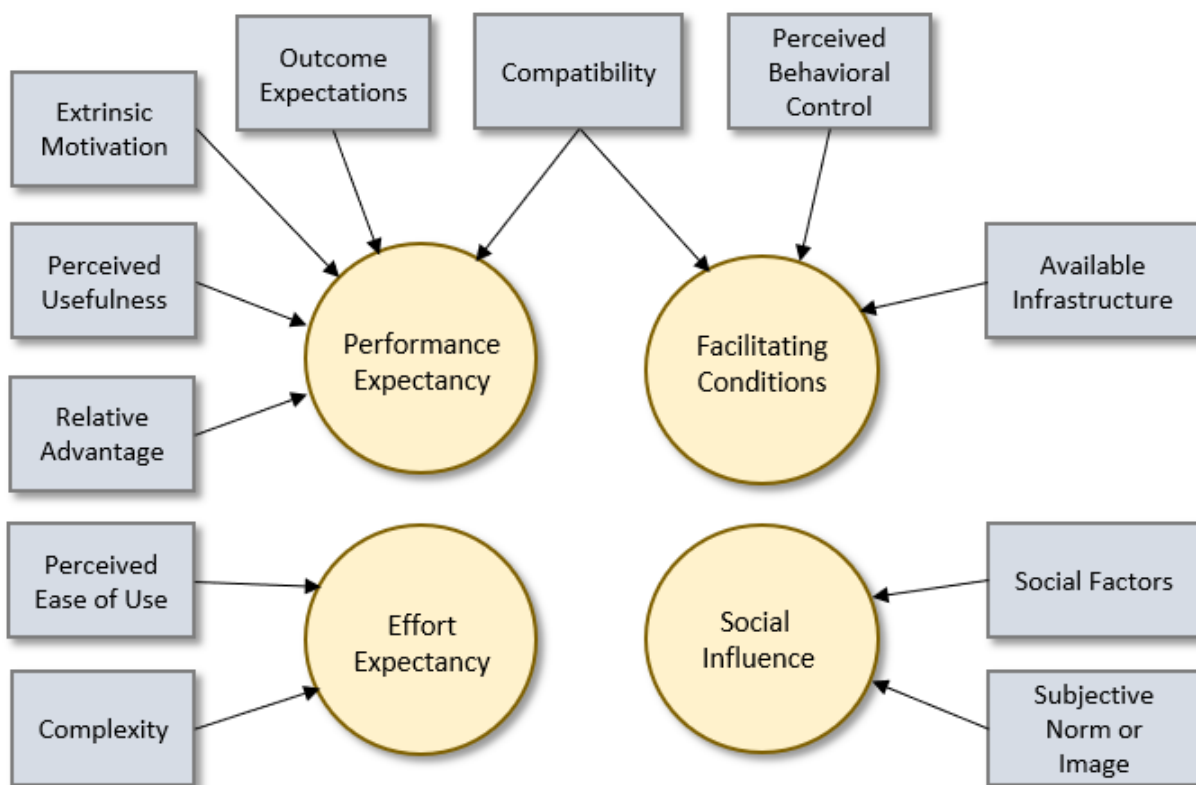
Figure 3: Visualization of UTAUT constructs and influencing factors.

While UTAUT was originally intended for use within the field of information technology, the model has been adapted by some to work in other fields. Table 3 provides a list of some of the works which have implemented UTAUT.

Table 3: List of works with UTAUT.

Source	Field	Innovation
(Moran et al., 2010)	Education and Computer Technology	Tablet PCs
(Pynoo et al., 2011)	Education and Computer Technology	Digital Learning Environments
(Escobar-Rodríguez & Carvajal-Trujillo, 2014)	E-commerce	Online Airline Ticket Purchasing
(AlAwadhi & Morris, 2008)	Information Technology	E-government Services
(Martins, 2013)	Information Technology	Internet Banking Services
(C.-P. Lin & Anol, 2008)	Information Technology and Communication	Instant Messagers
(Marchewka & Kostiwa, 2007)	Information Technology and Communication	Online Bulletin Boards
(Chiu & Wang, 2008)	Information Technology and Education	Web-Based Learning
(Zhou, 2012)	Information Technology	Location-Based Services
(H.-Y. Wang & Wang, 2010)	Information Technology	Mobile Internet Devices
(Kijsanayotin, Pannarunothai, & Speedie, 2009)	Health Care and Information Technology	Various Information Technologies
(Carlsson, Carlsson, Hyvonen, Puhakainen, & Walden, 2006)	Communication	Mobile Devices and Services
(Im, Hong, & Kang, 2011)	Technology Adoption	MP3 Player and Internet Banking

2.2.3 Technology Acceptance Model

The Technology Acceptance Model (TAM) was developed from psychological models such as the Theory of Reasoned Action (TRA) and Theory of Planned Behavior (TPB) (Mathieson, 1991; Yousafzai, Foxall, & Pallister, 2010). The foundation of TAM is the theory that the use of an innovation is explained by user motivation, which is in turn influenced by external stimulus such as the innovation's features and capabilities (Legris, Ingham, & Collerette, 2003; C. A. Lin & Kim, 2016; Marangunić & Granić, 2015; Mathieson, 1991; Park, 2009; Straub, 2009; Szajna, 1996; Wu & Wang, 2005). User motivation is explained by three factors: perceived ease of use, perceived usefulness, and behavioral intent, each of which also has an effect on the others. Perceived ease of use influences the perceived usefulness of the innovation, while both perceived ease of use and perceived usefulness influence the behavioral intent of the potentially adopting individual (Marangunić & Granić, 2015; Venkatesh & Davis, 2000). The behavioral intent of the individual is the primary factor that determines whether the innovation will or will not be adopted (Wu & Wang, 2005).

The system characteristics that influence the perceived ease of use and perceived usefulness are subjective norm, image, compatibility, perceived output quality, and observability.

Other determinants such as perceived enjoyment, trust, and anxiety have been examined, but the relationships between these determinants and the constructs of TAM are not commonly recognized (Koufaris, 2002; Pavlou, 2003; Venkatesh, 2000). TAM distinguishes between subjective norm and image by defining the former as the influence of other individuals' opinions and the latter as the desire to please these other individuals. The weight of the subjective norm is moderated by experience and voluntariness, although the relationships are not significant in every case (Marangunić & Granić, 2015; Venkatesh & Davis, 2000). Aside from the subjective norm, TAM does not include explicit social variables (Mathieson, 1991). Other studies have found that gender may also indirectly influence the behavior of potential adopters, although there is insufficient research to determine if the effects can be generalized to any innovation (Gefen, Karahanna, & Straub, 2003). While some works propose accounting for additional system characteristics in TAM, the core of the model remains constant (Venkatesh & Bala, 2008). Figure 4 visualizes the TAM process for explaining innovation adoption and usage.
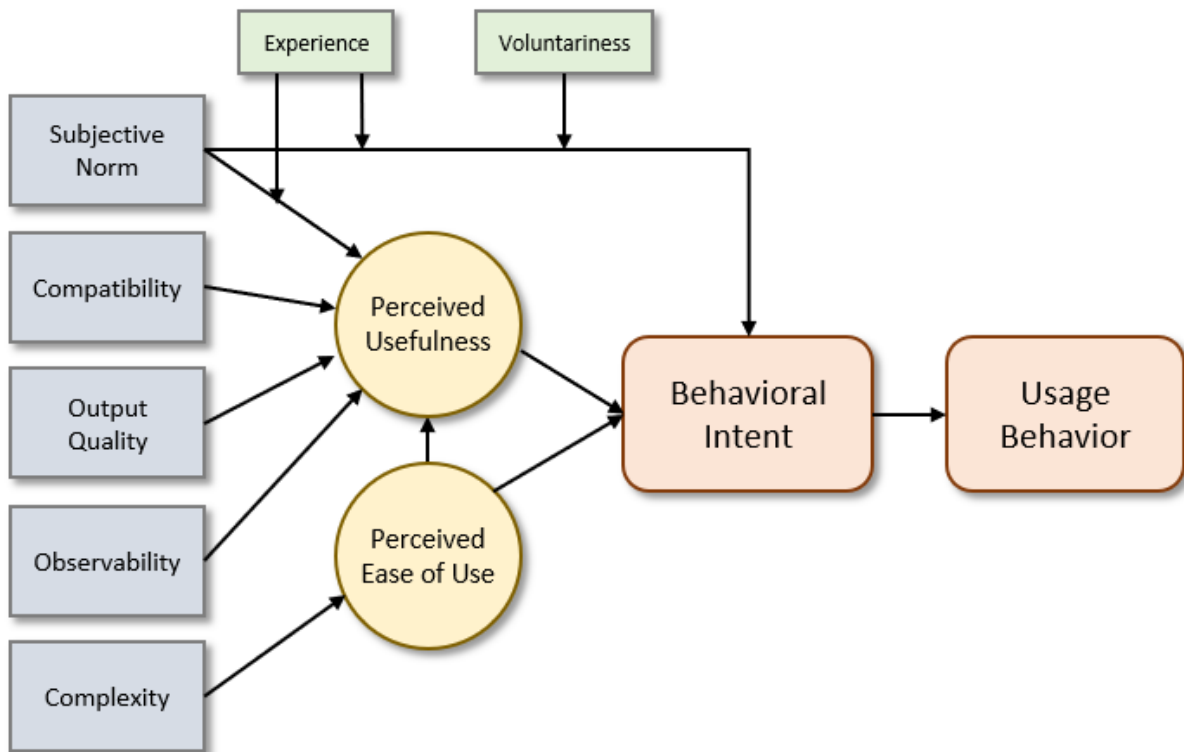
Figure 4: Technology Acceptance Model of innovation adoption behavior.

TAM processes have been applied primarily to information technology fields, although recent works have expanded TAM to work in other fields. Table 4 provides a list of works which have used TAM to evaluate innovation adoption.

Table 4: List of works with TAM.

Source	Field	Innovation
(Gefen & Straub, 1997)	Communication and Information Technology	E-Mail Systems
(Szajna, 1996)	Information Technology	E-Mail Systems
(Venkatesh & Davis, 2000)	Information Technology	Unspecified Organizational Information Systems
(Venkatesh, 2000)	Information Technology	Online Help Systems and Payroll Applications
(Koufaris, 2002)	E-Commerce and Information Technology	Web-Based Shopping Systems
(Pavlou, 2003)	E-Commerce and Information Technology	Web-Based Shopping Systems
(Gefen et al., 2003)	E-Commerce and Information Technology	Web-Based Shopping Systems
(Park, 2009)	Education	E-Learning Systems
(Yousafzai et al., 2010)	Information Technology	Internet Banking Systems
(F. Lin, Fofanah, & Liang, 2011)	Information Technology	E-Government Services and Systems
(Shroff, Deneen, & Ng, 2011)	Information Systems	E-Portfolio Systems
(Cheung & Vogel, 2013)	Education and Information Technology	E-Learning Systems
(C. A. Lin & Kim, 2016)	Marketing and Advertisement	Targeted Advertisements on social media

2.2.4 Other Innovation Adoption Theoretical Approaches

There are, of course, other theoretical approaches to understanding the adoption of innovations. The Concerns-Based Adoption Model (CBAM) is a popular theory that deals primarily with the integration of an innovation into regular practice (S. E. Anderson, 1997; Kaplan, 2011; Khoboli & O'toole, 2012; Straub, 2009; Tunks & Weller, 2009). However, CBAM is not concerned with the actual decision to adopt an innovation, which is the point of innovation adoption that this work is investigating. CBAM appears to be a promising approach to explain how an innovation becomes routinized within an organization, but it is unsuited for predicting the initial adoption of an innovation.

Another common construct for explaining innovation adoption is Utility Theory (UT). UT attempts to condense the various attributes of an innovation and its alternatives into a single term called "utility," which the potential adopter uses to weigh their alternatives before deciding on an alternative. While this approach is quite useful when the decision between two alternatives is relatively simple, such as deciding which mode of transportation to use when commuting, applying UT to more complex behavior problems like predicting the adoption of an innovation can be more difficult (Al-Alawi & Bradley, 2013; Eggers & Eggers, 2011; Michelsen & Madlener, 2012).

Furthermore, other theoretical approaches such as DoI, UTAUT, and TAM already account for utility within their models while also addressing other factors such as communication and social behaviors (Mathieson, 1991; Rogers, 2003; Venkatesh et al., 2012). For this reason, there are fewer works which attempt to rely solely on utility theory to explain the adoption of innovations than theories such as DoI, UTAUT, and TAM.

2.2.5 Comparison of Innovation Adoption Theoretical Approaches

DoI has been successfully implemented in a wide variety of fields, whereas UTAUT and TAM have very narrow applications in recent literature. This is partially due to the fact that UTAUT and TAM are more recent developments, but the fact that UTAUT and TAM were developed specifically for technological innovations also hampers their effectiveness in describing the adoption process of other innovations (Legris et al., 2003; Venkatesh et al., 2003). DoI is designed as a more general innovation adoption theoretical approach, and so it is easier to adapt to any type of innovation (Rogers, 2003).

UTAUT is the newest innovation adoption theory, and it was formed after taking into account both DoI and TAM as well as other human behavior theories (Venkatesh et al., 2003). Because it was initially designed to model innovation adoption by individuals within an organization, it is well suited for studies using that process (Venkatesh et al., 2016). However, in the case of an innovation that must be directly adopted by an organization, it is likely that significant adjustments to the approach would need to be made.

TAM is considerably more concise than the other two theoretical approaches. While this means that there are elements present in other models which are not found in TAM, studies have shown that TAM is capable of predicting behavioral intent and usage behavior to a degree similarly to the other models (Venkatesh et al., 2003). However, the base version of TAM does not directly account for social variables, which studies have shown are very important to understanding innovation adoption behavior (Legris et al., 2003; Mathieson, 1991) TAM also relies on self-reporting when forming its constructs, which is not always an accurate method of gathering data (Szajna, 1996; Wu & Wang, 2005).

2.3   INNOVATION ADOPTION METHODOLOGICAL APPROACHES

Just as there are many different theoretical models for how innovations are adopted throughout a system, there are several different methodological approaches to implement those theoretical models. These methodologies can be divided into two approaches: Top-Down, and Bottom-Up. Top-Down methodologies start by describing the behavior of the overall system and proceeds to observe how the behavior changes as changes are made to the system over time, whereas Bottom-Up methodologies define the behavior of individual agents and allow the system behavior to emerge from the actions of those individuals.

2.3.1 Top-Down Methodologies

The primary Top-Down methodological approach is System Dynamics (SD). SD models represent real-world processes and behaviors in terms of stocks and flows, with interacting

feedback loops regulating the flows between the stocks (Borshchev & Filippov, 2004; Forrester, 1994; Jifeng, Huapu, & Hu, 2008; Samara, Georgiadis, & Bakouros, 2012; Shafiei et al., 2014; Vlachos, Georgiadis, & Iakovou, 2007). A thorough understanding of the interlocking parts of the system is required to construct a SD model, as SD models are primarily used to simulate the effect of various changes after the system has already been constructed. SD models are most appropriate when the behavior of the current system is known and needs to be repaired or improved.

While SD models may be utilized in a variety of fields, their usage tends to follow a similar process (Forrester, 1994; Stave, 2003). The first step in utilizing an SD model is to identify the behaviors of the overall system and define the problem or behavior that the modeler wishes to further understand or improve. Once the system has been described, the modeler must translate the system description into explicit equations that will cause the system to behave similarly to its real-life counterpart. Once the model is able to mimic real behavior reasonably well, various changes can be made to the equations that govern the system's behavior. The modeler is able to simulate the outcome of these various changes and determine which changes to implement to increase the efficiency of the system (Forrester, 1994; Stave, 2003). Figure 5 demonstrates the SD process.
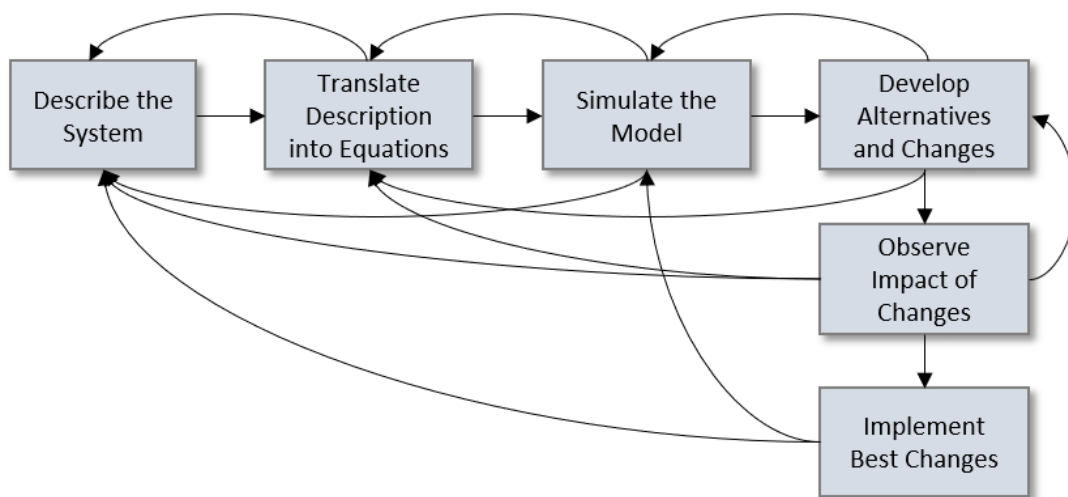
Figure 5: System Dynamics process.

Each step of the SD process loops back to previous steps as adjustments are made (Forrester, 1994; Jifeng et al., 2008; Stave, 2003). For example, assumptions about how the system behaves in the first step may be revealed to be inaccurate in the second step, or the observed impact of a change may reveal new emergent behaviors that must be accounted for in the equations that govern the simulation. As a result, SD models tend to be iterative processes that begin with wide-ranging assumptions about system behavior and result in a thorough understanding of the system in question (Forrester, 1994; Jifeng et al., 2008). By nature, SD is an aggregate modeling methodology. Individual agents are grouped into various stocks which flow back and forth based on universal rules, limiting the ability of a SD model to provide disaggregated information (Shafiei et al., 2014).

The Bass model is one of the most commonly used SD models (Bass, Krishnan, & Jain, 1994; Mahajan et al., 1995; Massiani & Gohs, 2015; Meade & Islam, 2006; Moch & Morse, 1977; Rogers, 2003). Bass estimates the adoption rate of an innovation by considering two forces: one is

positively influenced by the number of previous adopters, and one is independent of the previous adopters (Bass et al., 1994; Rogers, 2003). The component which is not influenced by the number of adopters is commonly referred to as the Coefficient of Innovation (CoN), or external influences. CoN accounts for influencing factors such as marketing, salespeople, and a potential adopter's personal innovativeness. The component influenced by the number of previous adopters is referred to as the Coefficient of Imitation (CoM), or internal influences. CoM is derived from peers of the potential adopter. When an individual has peers who have adopted an innovation, the peers will influence that individual to also adopt (Bass et al., 1994). For organizations, CoM is derived from other organizations within the same industry (Czepiel, 1975; Rogers, 2003). The Bass model lays the foundation for quantifying the social aspect of innovation adoption, which is central to diffusion of innovations theory. The Bass model is presented in equation 1.

$$n(t) = \frac{dN(t)}{d(t)} = p * [m - N(t)] + \left(\frac{q * N(t)}{m}\right) * [m - N(t)] \tag{1}$$

where $n(t)$ is the number of adopters at time t, m is the market potential, or maximum potential adopters of the innovation, $N(t)$ is the cumulative number of adopters at time t, p is the coefficient of innovation (CoN), and q is the coefficient of imitation (CoM) (Mahajan et al., 1995; Moch & Morse, 1977; Rogers, 2003). The Bass model is a differential equation, and it can be solved via integration to form equation 2.

$$N(t) = m\left(\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}\right) \tag{2}$$

Initially, very few potential adopters choose to adopt the innovation due to the diminished power of the imitative force. The initial number of adopters is near or equal to zero, making the power of the imitative force small. Therefore, early adopters almost exclusively adopt due to the innovative force (Lavasani et al., 2016; Mahler & Rogers, 1999; Rogers, 2003). However, as more adopters choose to accept the innovation, a point is reached where the adoption rate rapidly increases due to an increase in imitative influence. This point is referred to as the critical mass, and it typically occurs somewhere between 10 and 20% of the market potential (Mahler & Rogers, 1999). Once the point of critical mass has been achieved, an innovation is likely to gain universal adoption (Rogers, 2003). Once the innovation has been adopted by over half of the market potential, the remaining number of non-adopters is diminished to the point where the adoption rate begins to slow again.

2.3.2 Bottom-Up Methodologies

The two most prominent bottom-up methodological approaches are Cellular Automata Models (CAMs) and Agent-Based Models (ABMs). Both models begin by identifying the behavior individual agents or cells and allowing the system behavior to emerge from the simulation of the

network of individuals, allowing the modeler to examine the structure of highly complex systems (Bazghandi, 2012; Kiesling, Günther, Stummer, & Wakolbinger, 2012). These methodologies are most appropriate when the behavior of the system is not known, but individual behavior is known or can be predicted. The primary difference between the two methodologies is the level of complexity involved. CAMs are much less complex than ABMs, but CAMs also require much less initial information than most ABMs (Clarke, 2014). CAMs are most appropriate when the data regarding the individuals is scarce, or extreme granularity in results is less important than general trends, whereas ABMs are more appropriate when individual data is available and granularity in results is important (Clarke, 2014).

CAMs have been described as "the simplest modeling framework in which complexity can be demonstrated with terse conditions and minimal rules" (Clarke, 2014). The four elements of a CAM are (i) a collection of individuals represented as cells, typically assembled in a grid formation; (ii) a rule or series of rules determining which neighboring cells influence a given cell, typically all adjacent cells; (iii) a set of initial conditions and states for each cell in the system; and (iv) a set of rules which govern the state of each cell in the system. The CAM changes over time by applying the set of rules to each cell individually to determine what state the cell should be in during the next time interval, and then changing every cell at the same time (Clarke, 2014; Maerivoet & De Moor, 2005).

The simplest and most famous example of a CAM is the "Game of Life" developed in 1970 by John Conway (Couclelis, 1997; Maerivoet & De Moor, 2005). Using only two cell states and four rules, the Game of Life is capable of achieving many different types of behaviors. The Game of Life uses discrete rules such as "Any cell with fewer than two live neighbors dies," but the rules may be as complex as necessary, including probability functions and adjustable rules depending on the previous states of the model (Al-Ahmadi, See, Heppenstall, & Hogg, 2009; Clarke, 2014; Santé, García, Miranda, & Crecente, 2010; Soares-Filho, Cerqueira, & Pennachin, 2002; Weifeng, Lizhong, & Weicheng, 2003). Most real-world applications of CAMs use multiple rules or equations to govern the state changes of the cells in the system. CAMs are typically represented graphically as a grid where cells change states between iterations (Benjamin, Johnson, & Hui, 1996; D'ambrosio, Di Gregorio, Gabriele, & Gaudio, 2001; Dijkstra, Jessurun, & Timmermans, 2001; Esser & Schreckenberg, 1997; Mallet & De Pillis, 2006; Weifeng et al., 2003), although CAMs may also function in more irregular systems as well (Al-Ahmadi et al., 2009; Couclelis, 1997; Yeh & Li, 2002). Figures 6 and 7 show two examples of a typical CAM grid.
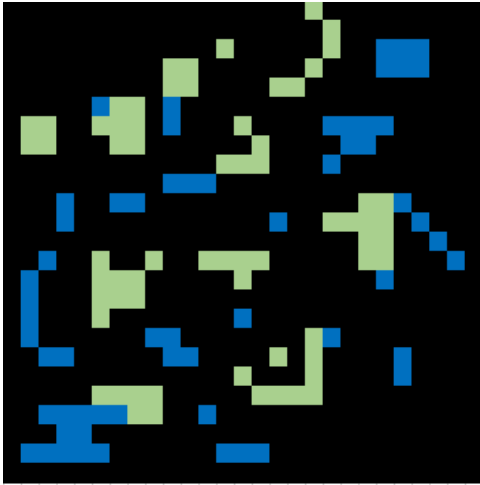
Figure 7: Example of a CAM simulation of vehicles passing through a signalized intersection.
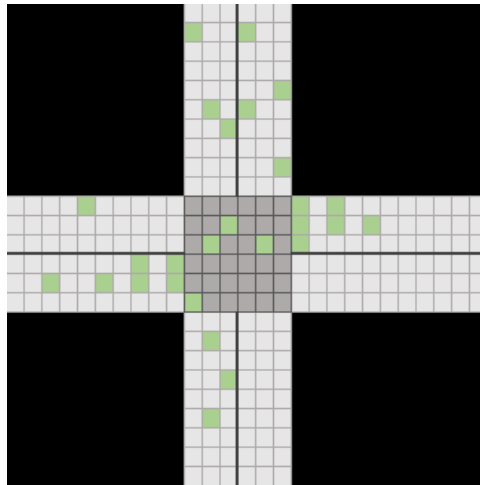
Figure 6: Example of a "Game of Life" style CAM with three possible cell states

ABMs are very similar to CAMs, but typically involve greater complexity than CAMs. ABMs allow individual agents to form connections to other agents based on any number of characteristics rather than by a series of universal rules. The ABM may contain a single agent type or multiple, and different rules may govern their interactions (Delre, Jager, & Janssen, 2007; S. Kim, Lee, Cho, & Kim, 2011; Wolf et al., 2015). The elements of an ABM are (i) individual agents possessing a number of attributes and characteristics; (ii) a set of decision-making heuristics, typically developed from gathering real-world data; (iii) a ruleset which is capable of learning and adapting to the behavior of the system over time; (iv) a method for agents to interact and change each other; and (v) a network or environment that can be influenced by the agents (Clarke, 2014; Günther, Stummer, Wakolbinger, & Wildpaner, 2011; Kiesling et al., 2012). Each agent acts independently while reacting to and learning from the environment and other agents (Delre et al., 2007; Günther et al., 2011). Figure 8 shows an example of an ABM network with four agent types or states represented by four different colored nodes and two connection types represented by links of different thicknesses. The agents' positions are often tied to geography, but they may be representative of any number of characteristics (Kiesling et al., 2012).
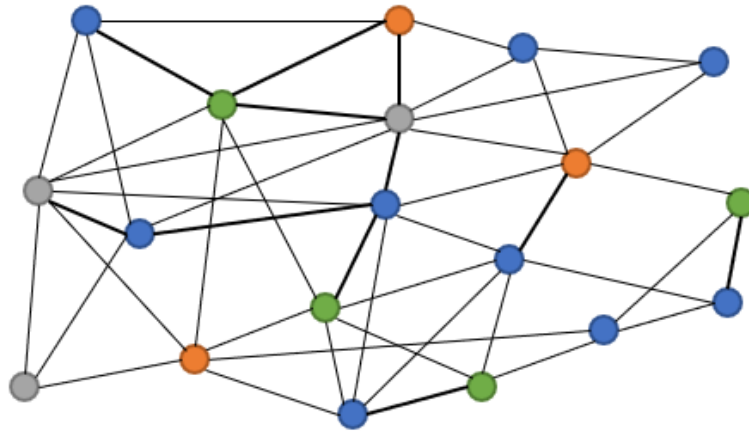
Figure 8: Example of a potential Agent-Based Network.

ABMs typically require a great deal of real-world data in order to synthesize a representative population and network of agents (Shafiei et al., 2012). The inclusion of individual characteristics for each agent means that the model is inherently disaggregated and is capable of providing a great deal of information about the emergent behavior of the global system. However, the significantly higher data required to construct an ABM means that it is poorly suited for fields where gathering data is difficult (Bazghandi, 2012; Borshchev & Filippov, 2004; Tran, 2012). Validating ABMs has also proven difficult, and many researchers are currently studying how to improve ABM validation (Clarke, 2014; Kiesling et al., 2012).

3.0   METHODOLOGY AND DATA

3.1   METHODOLOGY

To form a predictive model of CAV adoption by freight organizations, DoI and a Bass-based CAM are chosen. DoI is the most easily adapted to organizational adoption and has the most literature to draw on, providing substantial advantages for an initial modeling attempt. Given the scarcity of organizational adoption studies and relevant data, the Bass model is chosen as the simplest methodological approach that was still capable of providing reasonably accurate results. However, because the Bass model is, by nature, an aggregate modeling approach, it is necessary to use CAM techniques instead. Therefore, a CAM is constructed where the rules governing cell transitions are based on Bass model principles.

One of the difficulties in using the Bass model for forecasting is determining the values of CoN and CoM for the new innovation. Because these parameters represent multiple qualitative attributes, it is impossible to collect these values from a survey, and there are currently no methods of estimating the coefficient values from other, more easily gathered sources. CoN and CoM are traditionally estimated using regression methods after the innovation has been fully adopted. Therefore, to estimate an innovation's CoN and CoM values prior to adoption, it is necessary to compare the innovation in question to previously adopted innovations (Lavasani et al., 2016; Massiani & Gohs, 2015; Meade & Islam, 2006; Sultan et al., 1990). The diffusion model for organizational CAV adoption is generated by examining the adoption rate of multiple organizational innovations.

The Bass model parameters for individually adopted innovations are well-documented, but organizational adoption has received less attention. This is a problem because there are few studies providing data for organizational adoption parameters. Therefore, it is necessary to first investigate the rate of organizational innovation adoption and how it differs from individual adoption rates. To this end, we gather organizational innovation market penetration data from multiple sources and perform non-linear regression to calculate Bass model parameters. These parameters are then compared to Bass model parameters for individual organizations found in multiple sources. From this comparison, conclusions are drawn regarding the behavior of organizational innovation adoption and how it differs from individual adoption behaviors. Once the behavior of organizational innovations has been established, it is possible to estimate the Bass model parameters for freight organization CAV adoption by examining the estimated parameters for individual CAV adoption (Rogers, 2003). Figure 9 demonstrates the full process of estimating the market penetration of CAVs over time.
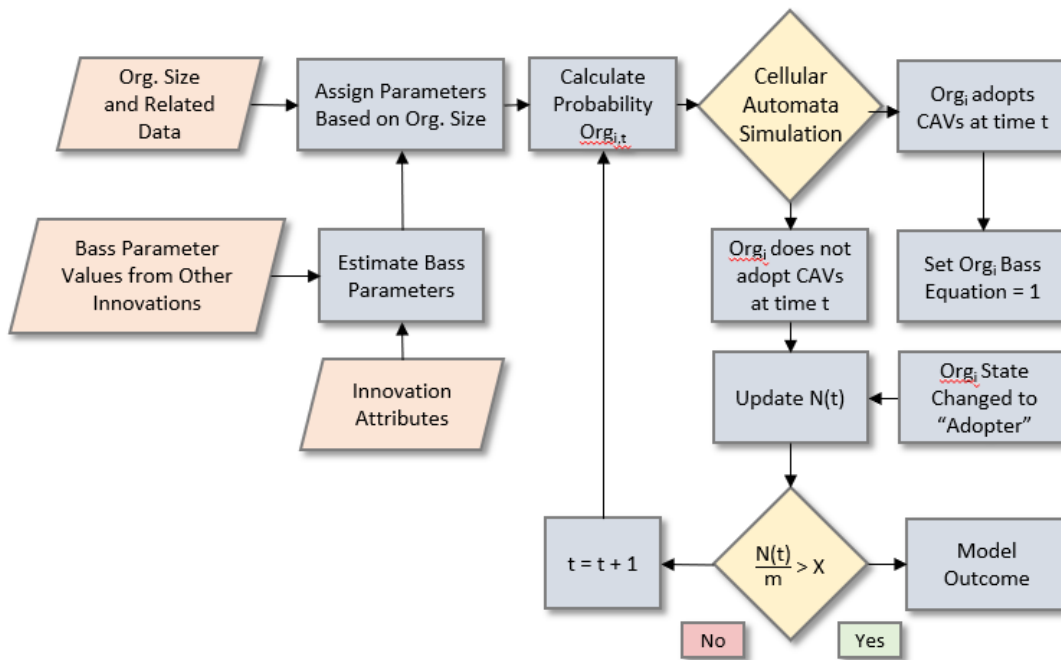
Figure 9: Flowchart of model process.

Organizations are heterogeneous, and so they may have slightly different values for CoN and CoM (S. P. Ryan & Tucker, 2012). As Figure 10 demonstrates, local organizations have lower ability to innovate than larger, national organizations, and so adoption models must account for this heterogeneity.
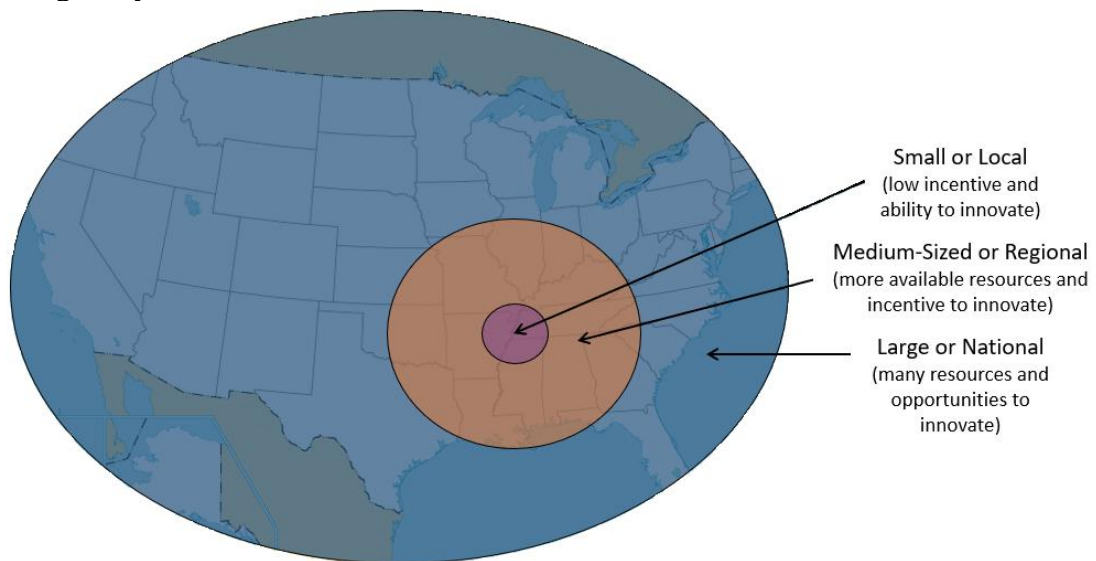
Figure 10: Spheres of influence and tendency to innovate for organizations of differing sizes.

To address organizational heterogeneity, each organization considered is assigned parameter values within the proposed range for CoN and CoM based on the number of employees in the organization. Organizational size is chosen as the independent variable because larger organizations are more inclined to innovate than smaller organizations (Frambach & Schillewaert, 2002; Mahajan et al., 1995; Rogers, 2003), and size is far easier to measure than other organizational attributes linked to innovativeness (Rogers, 2003). Therefore, a different value for CoN and CoM is assigned to organizations depending on whether they are categorized as small, medium-size, or large.

Once an organization has been assigned Bass parameter values, the Bass model for that organization becomes an equation to calculate the probability $Org_{i,t}$ that organization i will adopt a CAV at time t (Amini, Wakolbinger, Racer, & Nejad, 2012; Kumar et al., 2009). A CAM is developed to predict the adoption rate of CAVs by freight organizations where cells move from the "non-adopter" state to the "adopter" state with probability equal to $Org_{i,t}$ (Goldenberg, Libai, & Muller, 2002). To verify the reliability of the model output, the model is run 100 times, and an ANOVA test is performed to confirm that there is no statistically significant variation in the model output over multiple runs.

Because of the structure of the CAM, there is no mechanism to enable an "adopter" organization to move back to the "non-adopter" state at a later time interval. Therefore, after the organization has adopted the innovation, the odds of a second adoption decision are equal to 0. The model is run until the percentage of adopting innovations is greater than or equal to the parameter X, where X is a predetermined end condition value between 0 and 1. Just as in Bass models, each cell maintains communication with all other organizations. This is reasonable because organizations clearly exhibit some communicative behavior, however a formal social network does not exist between organizations (Czepiel, 1975).

3.2   DATA

In 2015, the North American Council for Freight Efficiency (NACFE) published a report investigating the adoption of 68 fuel efficiency innovations for 14 major North American fleets. These innovations are aggregated into seven categories: trailer aerodynamics, chassis, idle reduction, tires/wheels, powertrain, practices, and tractor aerodynamics. The study covers a span of 11 years, from 2003 to 2014 (NACFE, 2015), and it provides a solid foundation for the development of Bass model parameter values for freight organizations ("NACFE Conducts Extensive Benchmarking Study on Fleet Fuel Efficiency," 2016). Additional organizational innovation data is also gathered from other sources, including innovations such as ultrasounds, CT scanners, mammography (Van den Bulte & Lilien, 1997), oxygen steel furnaces and retail scanners in stores (Sultan et al., 1990). Figure 11 shows the market penetration of these organizational innovations. As the data was presented in terms of percentage adopted, the market potential m for all calculations is assumed to be 100%.
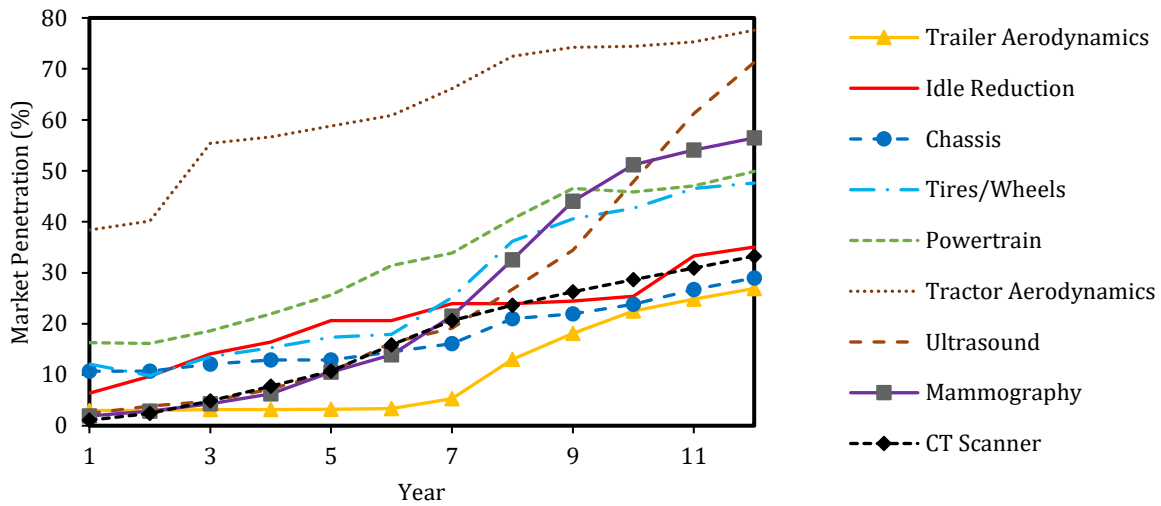
Figure 11: Market penetration of organizational innovations by year.

Regression estimations are performed on each technology category to determine CoN and CoM values. The regression equation is the same as equation 1, where the number of adopters is the dependent variable, and CoN and CoM are the independent variables. The results of the regression model and other reported organizational Bass model parameters are shown in Table 5 (NACFE, 2015; Sultan et al., 1990; Van den Bulte & Lilien, 1997).

Table 5: Estimated bass model parameters for organizational innovation adoption.

Technology Category	CoN (p)	CoM (q)	R^2
Trailer Aerodynamics	0.0043	0.1927	0.955
Idle Reduction	0.0122	0.0984	0.886
Chassis	0.0000	0.1300	0.899
Tires/Wheels	0.0038	0.1605	0.938
Powertrain	0.0167	0.0927	0.936
Tractor Aerodynamics	0.0713	0.0996	0.861
Mammography	0.0282	0.1858	0.933
CT Scanner	0.0288	0.0414	0.925
Ultrasound	0.0000	0.4887	0.821
Oxygen Steel Furnace	0.0190	0.4007	-
Retail Scanners	0.0390	0.5725	-
Ultrasound	0.0000	0.5340	-

Sultan et al. provided their own parameter values for the oxygen steel furnace, retail scanner, and ultrasound innovations and did not include the R^2 values associated with their findings (Sultan et al., 1990). While not a perfect fit, an R^2 value that is greater than 0.75 is reasonable for the number of data points available. Interestingly, the chassis, practices, and ultrasound categories

have a value of 0 for CoN. This could be due to these innovations appearing as undesirable to organizations for economic, political, or social reasons.

For comparison, Table 6 shows Bass model parameters for individual innovation adoption from other selected studies (Dodds, 1973; Jensen, Cherchi, Mabit, & Ortúzar, 2016; Lavasani et al., 2016; Massiani & Gohs, 2015; McManus & Senter Jr, 2009; Van den Bulte & Lilien, 1997).

Table 6: Bass model parameters for individual innovation adoption from selected studies

| Innovation	CoN (p)	CoM (q)	Reference
Internet	0.0067	0.3906	(Lavasani et al., 2016)
Cellphone	0.0017	0.2644	(Lavasani et al., 2016)
Electric Vehicles	0.0019	1.2513	(Massiani & Gohs, 2015)
Air Conditioner	0.0127	0.0462	(Van den Bulte & Lilien, 1997)
Electric Vehicles	0.0020	0.2300	(Jensen et al., 2016)
Electric Vehicles	0.0026	0.7090	(McManus & Senter Jr, 2009)
Color T.V.	0.0054	0.8369	(Dodds, 1973)
Cable T.V.	0.0089	0.4428	(Dodds, 1973)

When compared to individual adoption values, the CoN values for organizations are much larger, with the exception of the Chassis and Practices categories in Table 5.1. Conversely, the CoM value for individual adoption plays a larger role in the adoption rate than in organizational adoption. This indicates that organizations are more independent than individuals, and that the actions of one organization have less effect on other organizations than would be seen in individual adoption. This analysis is compatible with findings of other researchers studied organizational innovation adoption (Massiani & Gohs, 2015; Pierce & Delbecq, 1977). It is also intuitive that organizations would be less reliant on imitating other organizations, because most organizations are competing with one another, and they do not directly communicate as frequently as individuals. Therefore, an innovation that provides a relative advantage over current practices will more likely be adopted based on its own merit rather than because of outside pressures.

To predict the market penetration of CAVs for freight organizations in Shelby County, organizational data including number of employees, organization type, and sales volume is required. This dataset was obtained from InfoUSA. Each location is considered to be a unique firm within the dataset. Most organizations are located near major cities, with clusters around Memphis, Nashville, Chattanooga, Knoxville, and Johnson City. For simplicity, this study uses data from Memphis and Shelby County for analysis. This dataset contains 1,519 organizations in industries such as trucking, freight transportation and consolidation, and moving agencies.

K-Mean clustering is used to categorize the organizations into small, medium-sized, and large groups. Organizations with less than 85 employees per location are considered to be small, medium-sized organizations employ between 86-500 people, and large organizations contain over 500 employees. Small organizations with 10 or fewer employees per location are the most

common, and roughly 94% of all organizations within Shelby County qualify as small organizations.

The total fleet size of each organization is estimated based on the average yearly revenue of the organization. For-hire carriers have an average yearly revenue of roughly $200,000 per truck, where owner-operators average closer to $175,000 per truck (DAT, 3/13). Because information regarding the type of freight organization is not available, an average of $187,500 yearly revenue per truck is used to determine the fleet size of the organizations. Based on this estimate, Figure 12 shows the total fleet sizes per square mile by census tract, and Figure 13 shows a logarithmic histogram of the fleet size of each organization in the data set.
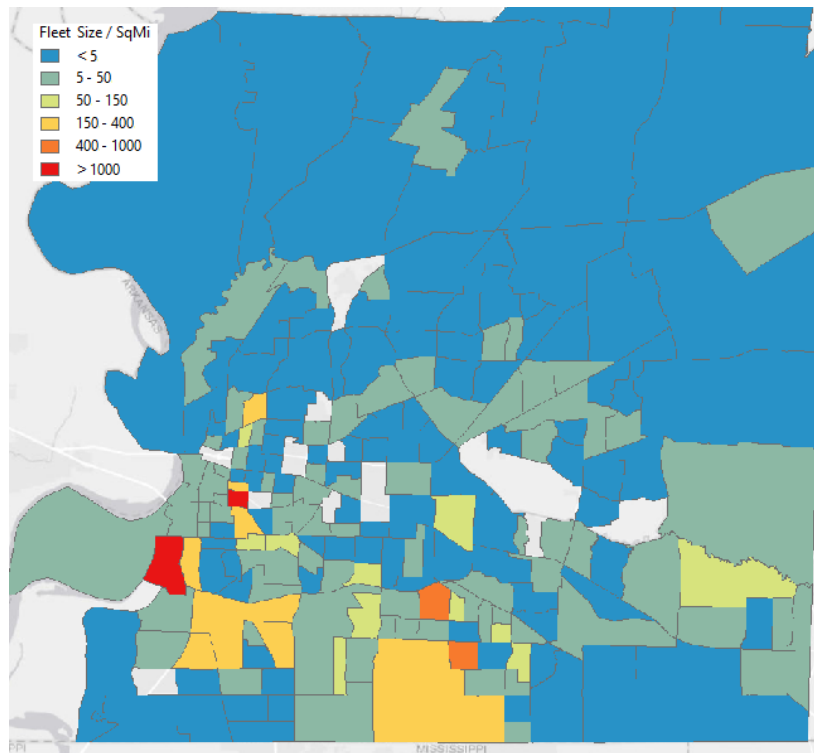
Figure 12: Total fleet size per square mile by census tract.
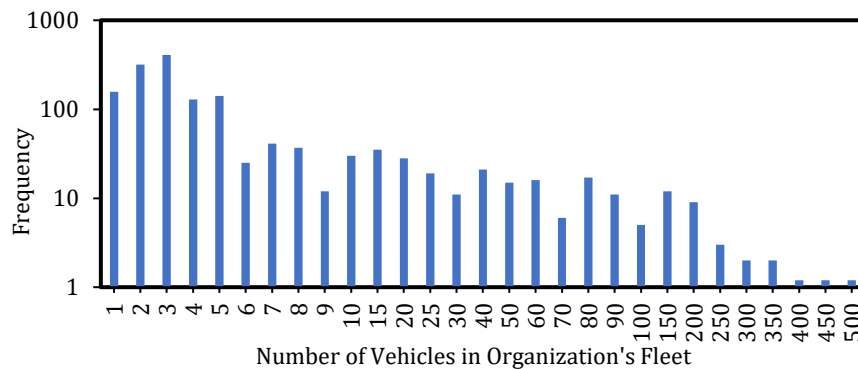
Figure 13: Histogram of organizational fleet size in Shelby County.

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4.0   CASE STUDY

4.1   RESULTS

It is reasonable to assume that the trend of higher CoN and lower CoM values for organizational adoption will also be true for CAVs. Lavasani et al. generated the following predictions for the Bass model parameters for individual CAV adoption: 0.001 for CoN, 0.3419 for CoM (Lavasani et al., 2016). These values are more conservative than the average values for other individual innovations seen in Table 2. This is reasonable because autonomous technology is revolutionary enough to warrant caution from new adopters (Bansal & Kockelman, 2017; Bansal et al., 2016; Fagnant & Kockelman, 2015; Lavasani et al., 2016). Organizations are likely to be conservative concerning autonomous technology for a number of reasons, and so the range of values for CoN and CoM selected for this study reflect this.

The CoN values selected for small, medium-sized, and large organizations are 0.005, 0.008, and 0.01, respectively. These values are more conservative than the values reported for most other organizational innovations such as trailer aerodynamics and powertrain, but still fall within the range of reasonable values. Selected CoM values are 0.08, 0.09, and 0.1 for small, medium-sized, and large organizations, all of which are conservative without deviating from the established range of values. Figure 14 demonstrates the projected adoption rates of CAVs for small, medium-sized, and large organizations. For the sake of comparison, other selected innovations are also included within the figure.
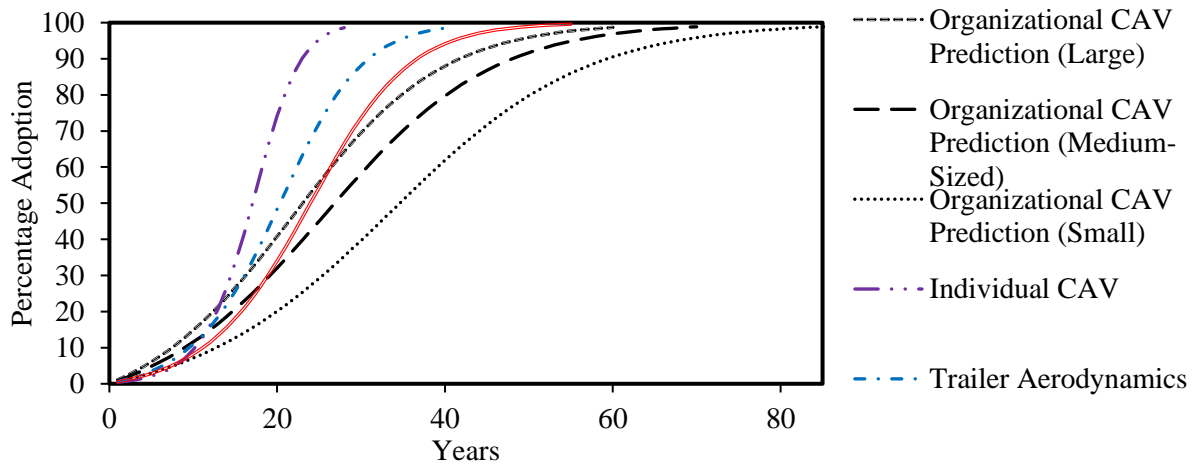
Figure 14: Projected market penetration of organizational innovations and individual CAV adoption rate.

Compared to the individual CAV prediction, organizational innovation adoption begins at a higher rate. However, as individual CAVs reach critical mass at roughly 10%, organizational adoption tends to lag behind. Both behaviors are explained by the general differences in CoN and CoM values between individual and organizational adoption. The large organization CAV prediction closely follows the other fuel efficiency innovation market penetration rates, and the

medium-sized and small organization predictions maintain the same general shape as the other adoption curves while deviating slightly in slope.

The Bass model parameters are then applied to the data for Shelby County organizations. 1,519 organizations are included in the Shelby County dataset, so the *m* Bass model parameter is set to 1,519. Figure 15 shows the CAV adoption curve for Shelby County locations using the estimated CoN and CoM values.
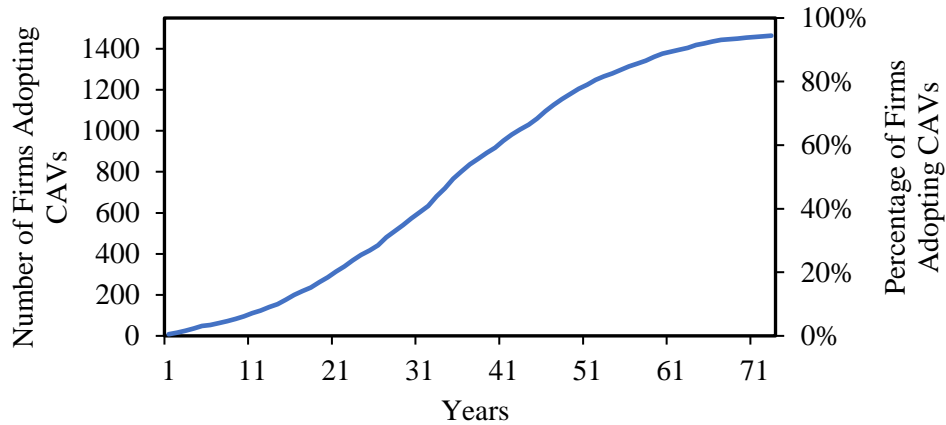
Figure 15: Total number of Shelby County firms adopting CAVs with time.

Because the number of small organizations is significantly larger than medium-sized and large organizations, the cumulative adoption curve most closely resembles the small organization prediction from Figure 6. The lack of a clear point of critical mass is typical of freight innovations (NACFE, 2015; Sultan et al., 1990; Van den Bulte & Lilien, 1997). Based on the assumed fleet size by organizational size and revenue, the market penetration of CAVs is predicted. The total assumed fleet size is equal to 21,000 trucks. Figure 16 shows the expected adoption curve of CAVs by freight organizations.
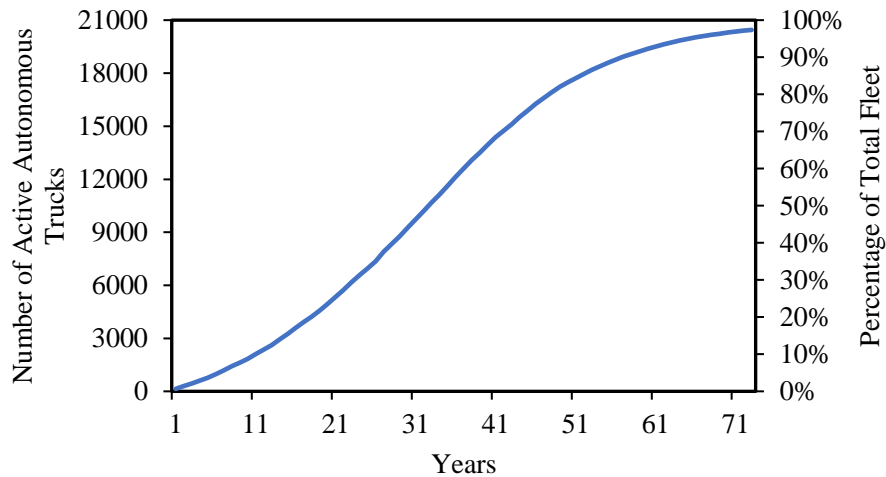
Figure 16: Total number of active autonomous vehicles over time.

The adoption curve is similar in shape to the curve of adopting firms, but it is slightly steeper. This is intuitive because larger organizations with bigger vehicle fleets are more likely to adopt than smaller organizations. Therefore, the number of active autonomous vehicles will grow at a faster rate during the initial phase of adoption, and the growth rate will decline as the number

of large organizations yet to adopt diminishes. The adoption rate is illustrated geospatially in Figures 17-19.
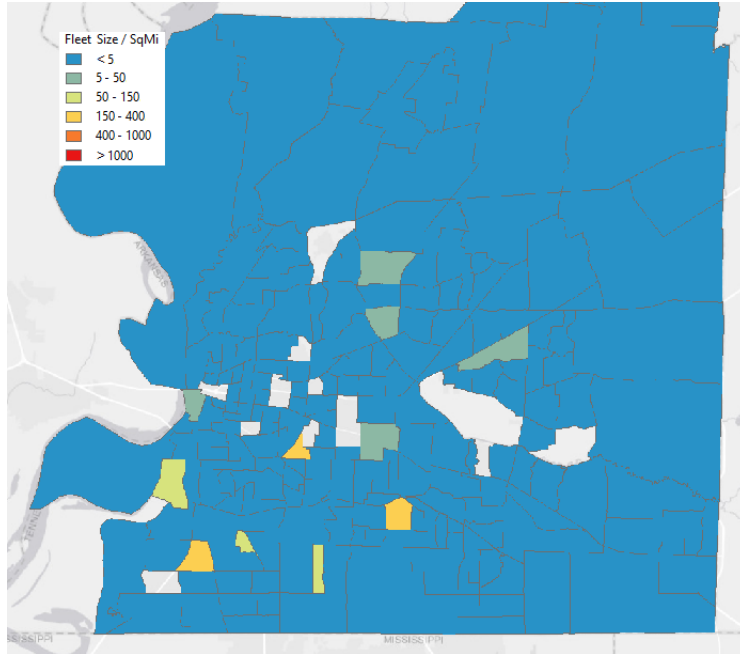
Figure 17: Autonomous truck fleet size by census tract per Square mile at t = 10 years.
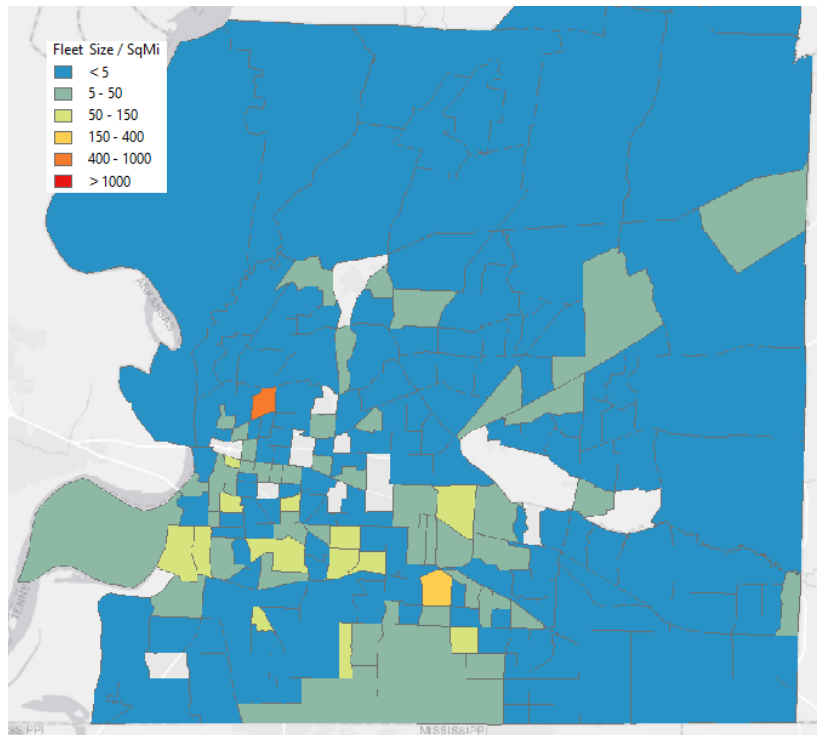
Figure 18: Autonomous truck fleet size by census tract per square mile at t = 40 years.
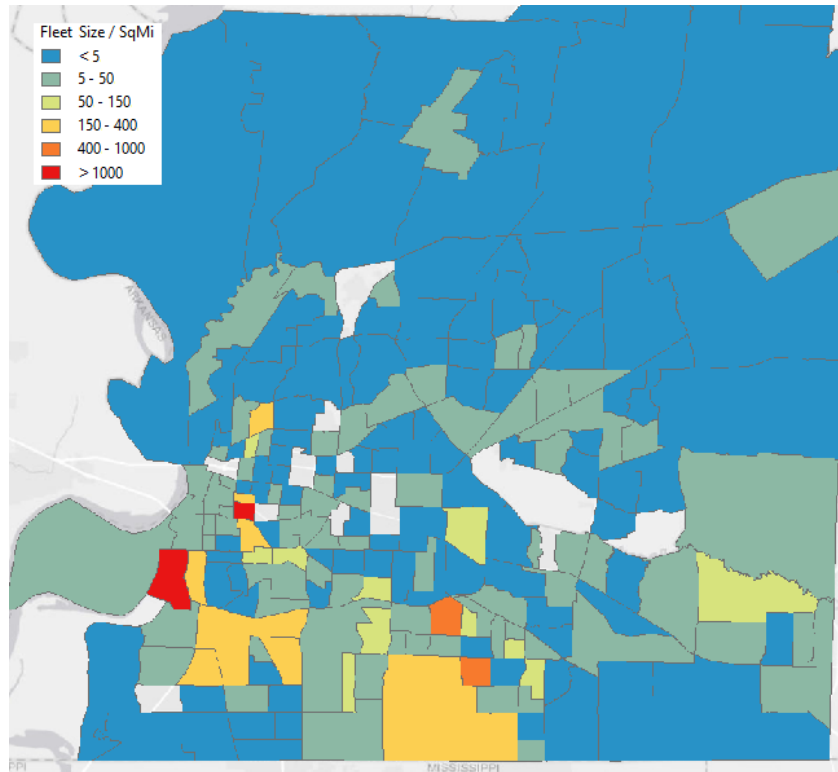
Figure 19: Autonomous truck fleet size by census tract per square mile at t = 70 years.

The data illustrated in the above Figures come from taking the average of 100 model results. To ensure that there is no statistically significant difference between model results, an ANOVA test is performed on the data. The results of the ANOVA test are described in Table 7.

Table 7: ANOVA test on the output of 100 model runs.

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1.87E+09	99	18930845	0.369233	0.9999	1.246962
Within Groups	3.69E+11	7200	51270742			
Total	3.71E+11	7299				

The test fails to reject the null hypothesis that there is no significant difference between the results of the model to a confidence interval of greater than 99.9%. Therefore, it is reasonable to conclude that the model provides stable results.

4.2 SENSITIVITY ANALYSIS

The predicted organizational CAV adoption relies on a number of variables, most of which are inferred from other innovations or estimated by other means. To ensure the accuracy of the

results, a sensitivity analysis is performed for the values of CoN and CoM. Table 8 shows the original and altered values tested under the sensitivity analysis.

Table 8: Original and altered values of variables used in sensitivity analysis.

Scenario	Organization size	CoN	CoM
	Small	0.005	0.08
Original	Medium	0.008	0.09
	Large	0.01	0.1
	Small	0.003	0.07
Conservative Reaction	Medium	0.006	0.08
	Large	0.008	0.09
	Small	0.007	0.09
Optimistic Reaction	Medium	0.01	0.1
	Large	0.012	0.11

Each of the values in Table 8 represents a potential scenario for organizational CAV adoption. If CAVs receive negative publicity, drivers resist CAVs, or if infrastructure/legislation prevent the rapid adoption of CAVs, then the more conservative values for CoN and CoM may be accurate. Conversely, if legislation promotes the adoption of CAVs, or if autonomous vehicles receive positive publicity due to a reduction in crashes or an increase in fuel efficiency, the adoption rates may align more closely with the more optimistic values. Figures 20-22 demonstrate the results of the potential adoption scenarios.
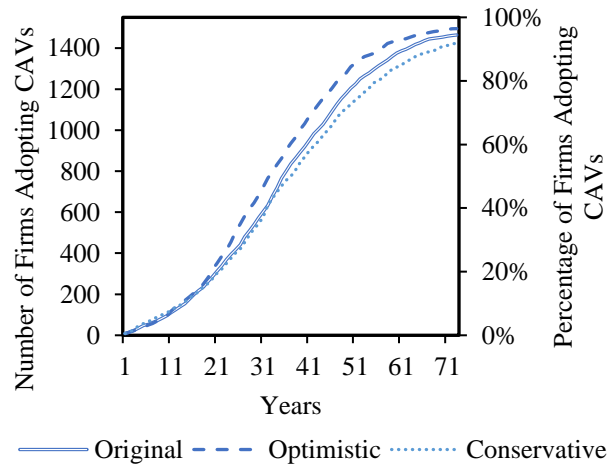
Figure 20: Organizational adoption varying CoM value with constant CoN value.
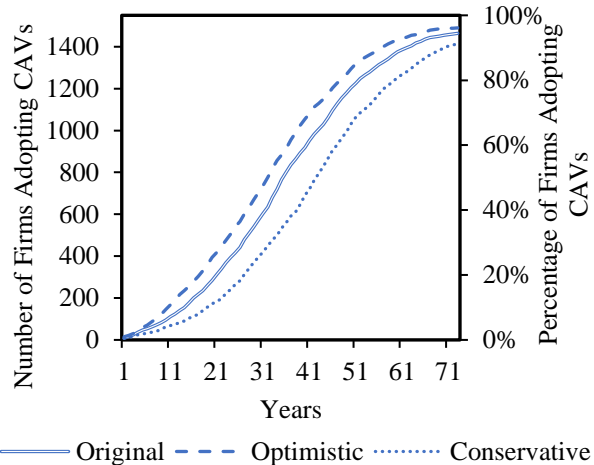
Figure 21: Organizational adoption varying CoN value with constant CoM value.
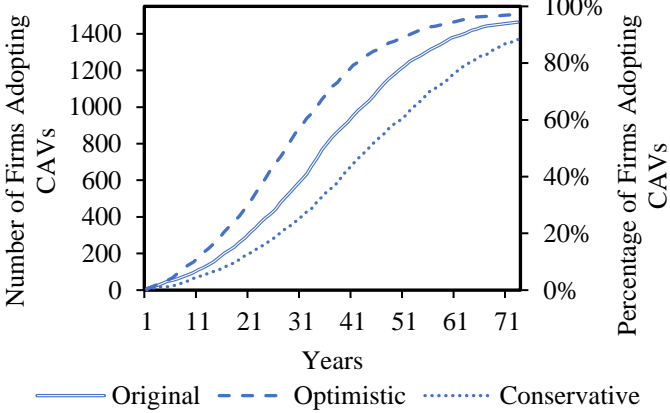
Figure 22: Varying both CoN and CoM values.

The scenarios described by Table 8 also impact the predicted number of active autonomous trucks. Figures 23-25 demonstrate the results of the potential adoption scenarios.
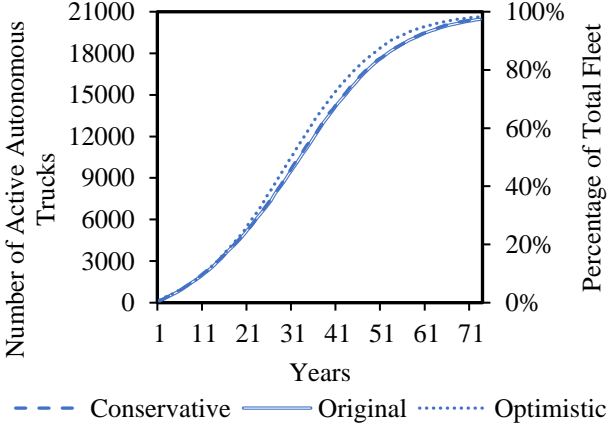
Figure 23: Autonomous truck prediction varying CoM value with constant CoN value.
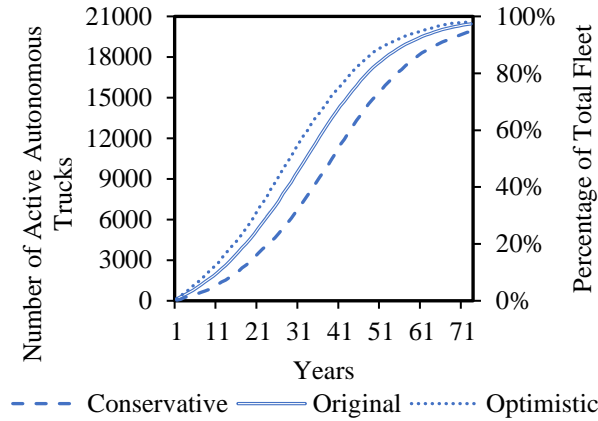
Figure 24: Autonomous truck prediction varying CoN value with constant CoM value.
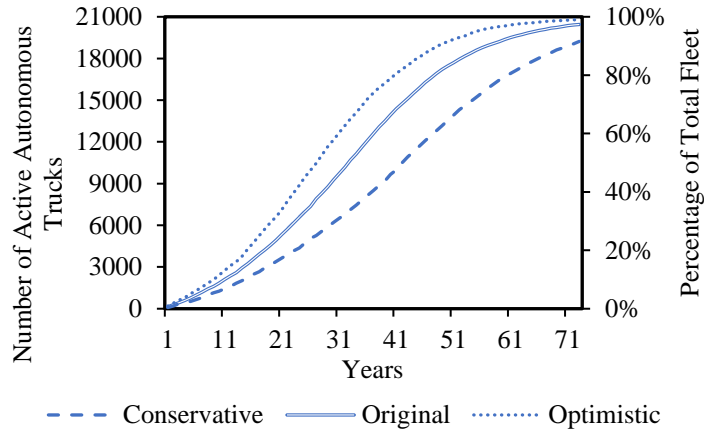
Figure 25: Autonomous truck prediction varying both CoN and CoM values.

Varying the CoN value has a much more substantial impact on the adoption rate than the CoM parameter. This indicates that changes earlier in the diffusion process have a greater impact on the total adoption process. Reducing or increasing the CoN value has a greater impact on the initial adoption rate than CoM, since CoM is multiplied by the fraction of previous adopters. Increasing initial adoption causes critical mass to be reached earlier, and this results in a faster overall market penetration rate. Similarly, reducing initial adoption pushes critical mass farther down the timeline and slows the adoption rate (Mahajan et al., 1995).

5.0   CONCLUSIONS

5.1   CONCLUSIONS

This study investigates the market penetration patterns of CAVs in freight transportation organizations using DoI and a CAM governed by Bass model principles. An accurate projection of the adoption rate of CAVs is critical to manufacturers and policy makers because it will allow them to prepare for and manage the new technologies and infrastructure changes that will accompany the introduction of CAVs to freight transportation. This paper provides several contributions to the literature. First and foremost, this paper supplies a prediction of the market penetration rate of CAVs for freight organizations. Second, it provides a model framework for predicting same market penetration rate for any city, county, or state, given that the appropriate data is provided. Third, it demonstrates the need for organizational heterogeneity when applying diffusion models such as the Bass model to organizations. Fourth, it identifies the benefits and drawbacks of the common innovation adoption theoretical and methodological approaches, providing a guideline for future innovation adoption studies. Finally, this paper provides additional insight into the process of organizational adoption of innovations through numerical analysis of adoption within Shelby County, the largest county in the State of Tennessee.

The projected market penetration rate is generated by examining the Bass model parameters of several other innovations, both individually and organizationally adopted. Organizational innovations provide a baseline for how freight organizations are likely to respond to an innovation, and individually adopted innovations are compared to the predicted market penetration rate of individually adopted CAVs to estimate the relationship between CAVs and other innovations. From these two observations, an estimated range of Bass model parameter values is generated for freight organizations adopting CAVs. Data on organizations within Shelby County is gathered, and organizations are assigned Bass model parameter values based on the number of employees at the organization.

Based on the estimated parameter values, the predicted market penetration of CAVs for freight transportation is much slower than most other innovations. This is justified because of the revolutionary nature of autonomous vehicles; such a drastic change from traditional transportation methods promotes caution in an industry that already adopts innovations at a slow pace. It may take up to 70 or more years for CAVs to fully integrate into the freight transportation industry. A sensitivity analysis is also conducted to understand how the Bass model parameter values impact the results of the model. Changing the CoN value has a greater impact on the model output because the changes in adoption rate are felt immediately, whereas a change in the CoM value only produces noticeable variation after critical mass is achieved.
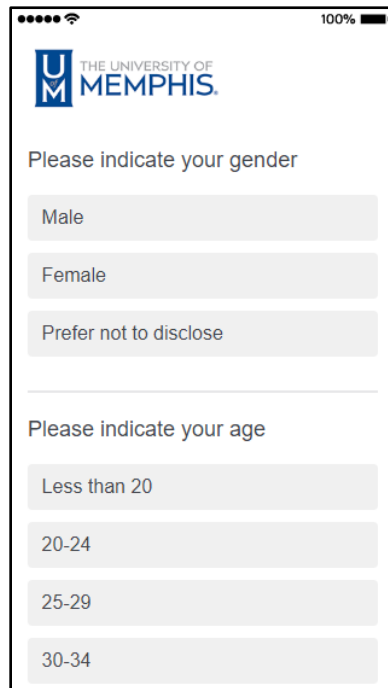
5.2   LIMITATIONS

This study includes limited heterogeneity into the CAM by assigning different Bass parameter values to organizations based on their size. However, some aggregation is still necessary when estimating Bass model parameters, and so organizations are grouped into three homogeneous groups in this study. In the absence of a more rigorous method of estimating CoN and CoM values

for an innovation which has not yet been adopted, it is very difficult to model complete heterogeneity between organizations. The model works well when there is limited data, as is often the case in freight transportation, but in more data-rich fields, the model may need to be altered to accommodate additional factors and variables which are aggregated into the CoN and CoM parameters. Given a comprehensive enough dataset to work with, other methodological and theoretical approaches may prove to be more appropriate.

The results of this study are also based upon assumptions of business practices and communication patterns by organizations. While there is sufficient backing in the literature for these assumptions, true practices can only be captured through the stakeholder survey. Future studies may also examine and further refine some of the assumptions made throughout this paper, specifically how best to assign Bass model parameter values to organizations. A larger dataset of organizational innovation Bass parameters may influence the estimated parameter values presented in this paper. Other directions for future research may include methods for including greater heterogeneity in adopting organizations, separate types of CAV technology innovations, and innovation generations within the context of organizational adoption.

5.3   FUTURE RESEARCH

While the current work makes certain assumptions about organizational behavior, it is essential that real data be gathered regarding the process of organizational adoption. The literature is scarce enough on the subject that gathering our own data through a stakeholder survey is necessary. The survey currently under construction is intended to (i) test the assumptions made about organizational innovation adoption behavior, (ii) determine how freight organizations actually feel about the emerging transportation technologies, (iii) examine the strength of informal communication and imitation forces on organizational adoption, and (iv) serve as a baseline for future studies on organizational innovation adoption. Figure 26 shows an example of the survey currently under construction.

Figure 26: Starting page of the survey on a cellphone.

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