INVESTIGATION OF TRANSPORTATION INNOVATIONS FOR FOOD DELIVERY AND TRUCK PLATOONS

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The undersigned, appointed by the dean of the Graduate School, have examined the thesis or dissertation entitled

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and hereby certify that, in their opinion, it is worthy of acceptance.

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ABSTRACT

Studies find that low-income areas are underserved by food retailers and have less access to healthy food, contributing to health disparities. A section of this thesis examines micromobility, drones, and ridesharing that may be suited to deliver food. Using estimated capacities and delivery speeds of several transportation modes, quantitative analysis showed that micromobility is a feasible means of delivery for short-distance, small-quantity orders. Vehicles were the only suitable option once quantity or distance increases, with trucks being the only option for large deliveries of food.

Regarding trucks, autonomous truck platooning has potential benefits such as energy savings, increased capacity, and improved safety. A section of this thesis discusses the novel issue of driver behavior interacting with truck platoons in work zones. This research investigates the effects of education, platoon signage, and the number of platooned trucks using a federated simulator study. The study found that education and the use of signage showed increased driver efficiency near platoons. There was a 13% increase in speed and 30% decrease in distance following a 2-truck platoon after education. Driver speed also increased by at least 14% and following distance increased by at least 24%, with signage added. Post-simulator survey results showed drivers strongly agree that education helps to clarify how to react to platoons. 90% of drivers admitted it is safer to not overtake the platoon, yet only 62% indicated they would follow it. Using the results of this research, transportation agencies could formulate policies better accommodate truck platoons as the technology grows.

CHAPTER 1: INTRODUCTION

This thesis investigates several transportation innovations that could improve the transport and delivery food to residents in urban food deserts. A food desert refers to areas with poor access to healthy and affordable food, that may contribute to social and spatial disparities in diet and health. This thesis will be broken into two major sections. Following this introductory chapter on the motivation behind studies that will be covered further, the second chapter will be an investigation of micromobility, delivery drones, and shared delivery services. This research will consider these methods against different food delivery scenarios, ranging from short-distance small quantity deliveries to large deliveries (e.g. from farm to market). The third chapter will cover a driving simulator study on human interactions with autonomous truck platoons in a highway work zone scenario. The section will focus on the results of the simulator study.

1.1 Motivation, on the topic of food deserts

In 2009, the United States Department of Agriculture (USDA) began mapping food access to identify communities with low availability of healthy food. It was estimated that approximately 23 million people lived in a food desert community (Karpyn et al., 2019). In its most recent 2019 report, the USDA's Economic Research Service determined that about 11 to 27 percent of U.S. citizens live in census tracts where a significant portion of residents have low income and low access to supermarkets (USDA, 2022). Low-income areas tend to have less supermarkets and more small convenience stores, meaning less availability to healthy food (Beaulac et al., 2009). A study found that lower healthy food availability was associated with a poorer-quality diet (Franco et al., 2009). Other studies found that an increase in access to supermarkets is associated with reduced obesity rates, and conversely access to convenience stores is associated with an increase in obesity rates (Larson et al., 2009; Morland et al., 2006). Further, racial disparities may also exist. Studies have found that healthy food is generally more available in white communities than non-white (Franco et al., 2009; Neff et al., 2009).

A comparison of food access data from 2010 to 2015 shows a decrease in vehicle availability and an increase in the number of households without vehicles over 0.5 miles from a grocery store (USDA, 2017). The number of low-income census tracts has also increased within this time. In 2019, there were approximately 4.7 million housing units with no vehicle beyond 0.5 miles from a grocery store (USDA, 2022). This information points towards a need for alternative low-cost means to access healthy food. As different transportation innovations emerge, it is worth investigating how these may be used for food delivery.

1.2 Motivation, on autonomous truck platoons

Autonomous vehicles, and specifically truck platooning, have the potential for many benefits including energy savings via drag reduction, increased capacity via shorter headways, improved safety, and increased comfort and safety for drivers. Autonomous truck platooning refers to a system in which multiple trucks travel in close precession using technology such as cooperative adaptive cruise control (CACC). Partially Automated Truck Platooning, a low form of automation (SAE level 1), is expected to be widely deployed in the near future. In regard to the subject of this thesis, autonomous truck platoons may be useful for efficiently transporting large amounts of produce between rural farms and urban markets. However, there are many unanswered questions that still surround truck platooning near work zones. For example, it is uncertain how truck platoon drivers will navigate lane closures, which may involve splitting platoons, and how human drivers will react to encountering a truck platoon near a work zone. Further, fatal crashes involving large trucks occur at a higher percentage around work zones. Between 2016 and 2020, 12.7% of all crashes involved at least one truck. This statistic increases to 33.1% near work zones (NHTSA, 2022). Because of these behavioral and safety issues, it is helpful to research driver interactions with truck platoons near work zones to help DOTs prepare for the widespread deployment of truck platoons.

Transportation simulators allow for human subject testing in a safe, controlled environment. They are widely used to conduct research on traffic safety, operations, and geometric design. Multi-modal simulators, including driving, bicycling, and pedestrian modes of travel, were valuable tools in several transportation studies (Chrysler et al., 2015; Fisher et al., 2011; Karamouzas et al., 2009; O'Hern et al., 2017; Wang et al., 2010). Most simulator studies use a single simulator and focus on one individual (Lehsing et. al., 2015). Participants are only exposed to programmed actors that do not replicate a broad range of human behavior. However, human driving behavior is highly dependent on interactions with other road users and these interactions are difficult to pre-program. Therefore, there is a need for federated simulators to investigate complex driver-to-driver interactions. A federated simulator can connect multiple simulators – driving, bicycling, walking, and wheeling simulators – to allow them to interact with one another in the virtual world. Interactions offer insights into how road users make decisions within the context of other drivers (Hancock and Ridder, 2003). Driving procedure near a work zone lane drop involves both the decisions made by platoon truckers and surrounding vehicles. Truckers will decide how best to disengage from the platoon and merge onto the open lane(s), while surrounding vehicles must react to the platoon and merge themselves. The analysis of driver behavior from the detailed output of federated driving simulators can provide insight into driver interactions with an autonomous truck platoon.

Research can aid the formulation of rules and regulations by investigating potential tradeoffs and supporting the effective take-up of certain policies. This study investigates the importance of public education in producing desirable driver behavior near truck platoons at work zones, whether signage on the back of platoons changes driver behavior, and whether the number of platooned trucks impacts behavior.

CHAPTER 2: FOOD DELIVERY VIA MICROMOBILITY AND DRONES

2.1 Literature Review

Studies find that low-income or African American residents are underserved by food retailers compared with advantaged areas. Low-income areas are found to have fewer supermarkets, chain stores, and/or midsized stores. Residents in low-income areas are less likely to own a car, thereby contributing to limited access to grocers. Low-income neighborhoods also tend to have more small, independent stores or convenience stores, which offer a poorer selection of healthy foods than a supermarket. Perception of a better selection and quality of fresh produce is associated with increased fruit and vegetable consumption (Beaulac et. al., 2009).

2.1.1 Considerations of User Preferences

Residents in low-income neighborhoods may also have nonregular work schedules, which negatively impacts their access to healthy food. A study by Widener et. al. (2017) found access to grocery stores differ drastically between daytime and nighttime hours. Many stores close, decreasing the availability of healthy food from where shift-workers are stationed. Public transportation also makes fewer and less frequent stops during nighttime hours. A study on Australian paramedics found that these shift-workers had difficulty making healthy food choices when they must often find food at unpredictable times (Anstey et. al., 2015). Elderly people may be uniquely affected by food deserts. A study on utilization of the Supplemental Nutrition Assistance Program (SNAP) among the elderly found significantly lower SNAP take-up rates compared with non-elderly adults (Fitzpatrick et. al., 2015). The study notes that limited access to food retailers in the immediate area, and transportation burdens that make accessing more distant retailers difficult, may be one explanation for low SNAP take-up among eligible elderly individuals. Low SNAP take-up also increases the reliance on food delivery programs like Meals-On-Wheels. The study suggests that policies providing transportation assistance to elderly individuals who are unable to access food retailers may improve food sufficiency. A well-designed spatial distribution of supermarkets leads to a low number of food-deserts (Apparicio et. al., 2007). High density, less motorized areas have more supermarkets than low density, highly motorized areas. Despite this, it is important to note that people may not want to shop at the food retailer nearest to them (Chavis & Jones, 2020). A survey of Baltimore, Maryland residents showed that 77% of people surveyed did not shop at the closest grocery store and a majority of people shop at 2-3 different stores.

2.1.2 Transportation Innovations

Recent innovations in transportation can be suitable for distributing food to residents of food deserts. Shared mobility can be used to deliver both groceries and prepared meals. Examples of shared grocery delivery services include Amazon Fresh, Google Express, Instacart, and Shipt. Examples of shared restaurant delivery services include Uber Eats, Grubhub, and DoorDash. A study analyzing food desert census tracts in eight states found that 93.0% of urban tracts were fully deliverable with online grocery apps (Brandt et. al., 2019). Dillahunt et. al. (2019) evaluated the feasibility of Shipt to deliver healthy food options. The study found that participants using Shipt purchased a higher percentage of healthy foods than participants who did not use the service. While it is unclear whether the app itself influenced these choices, the service allows participants access to healthy foods. Another innovation is the increased interest in micromobility by the public.

Examples of micromobility include bicycles and e-scooter services like Bird and Lime. Micromobility as a means to deliver food may be competitive against vehicle delivery in large cities where traffic congestion is an issue. For example, the company OjO has designed a scooter with a seat and basket for the purpose of delivery and Domino's Pizza has launched a new program to use e-bikes for food delivery (Lucas, 2019; Stankiewicz, 2019). Micromobility also helps to solve the first-mile/last-mile problem of public transit if people wish to do their own grocery shopping and not use delivery services. Mass transit remains the most efficient way to move large numbers of people long distances but getting to and from transit stations remains difficult (Zarif et. al., 2019). Micromobility can also help mediate inequities by providing low-cost transportation alternatives to expand reach with minimal infrastructure investments. Transportation infrastructure is often expensive to implement and run, and low-income communities may be left out. Micromobility services are not a fixed route system, and e-bikes or e-scooters may be deployed where they are most needed. Some cities use permit clauses that require a percentage of scooters to be deployed in underserved areas (Rivett et. al., 2020). An example of a micromobility system is the Nice Ride bike share system in Minneapolis-St. Paul, Minnesota. An investigation of Nice Ride found a significant relationship between bike station usage and the number of food-related businesses in the area of the station. Most survey respondents of the study indicated that they used the service for food-related trips, and most trips were diverted car trips (Schoner et. al., 2012).

A third innovation is food delivery via drones (e.g., Google Wing) and robots (e.g., Amazon Scout). Drone delivery of food had been accomplished by Domino's Pizza, with partner company Flirtey, and Google Wing in New Zealand and Australia, respectively (Business Insider, 2020; Slatt, 2017). The Federal Aviation Administration (FAA) granted Google Wing permission to begin delivering goods by drone in Virginia, in 2019 (CNBC, 2019). Uber Eats unveiled designs for a food delivery drone, also in 2019. The company plans to use drones conjunctively with their delivery drivers, whom will hand-off food to the customer (Carson, 2019). Additionally, DoorDash has begun using food delivery robots in northern California (Robotics Online, 2019). Figure 1.1 shows some examples of innovative transportation including e-scooter, robot, and drone delivery.

Figure 1.1 Examples of Innovative Delivery (BBC, 2022; Lonsdorf, 2017; Kelso, 2019)

Public transport may also be useful for delivering food. The TramFret test project in France used the Saint-Etienne tram system to deliver packages. The project reports that each tram car has a load capacity similar to a straight truck, and 17 tons of goods passed through the system over the six days of testing (Efficacity, 2016). A study on the feasibility of public transit for parcel delivery suggests that public transit could serve as an intermediate step in the delivery process. The other delivery innovations discussed in this review could be used in addition to public transit to solve the last-mile issue (Boysen et. al., 2020). Therefore, public transit could greatly extend the delivery range of the other food delivery innovations. Delivery involving public transit must also adapt to the timetables of the public transit system. A survey to assess the feasibility of public transit as a crowdshipping option found that people are more likely to adopt delivery via public transit if the delivery date and time schedule were flexible. Additionally, the survey found that crowdshippers would prefer if delivery points were located inside the transit station (Gatta et. al., 2019). Parcel lockers located inside or near public transit stops could hold deliveries for pick-up by another delivery driver or the recipient themselves. Parcel lockers are already being utilized in South Korea as a delivery drop-off option for customers. These lockers are placed inside high traffic areas in subway or bus stations around Seoul, but also gas stations and grocery stores (DHL, 2017; Korea Bizwire, 2019; Pulse, 2019).

Among the changes of COVID-19 quarantine on transportation practices, there are examples of how public transit systems was used for food delivery. Amidst COVID-19 quarantine orders, some public transit providers have partnered with local organizations and are using their resources to deliver food and supplies to at-risk individuals. For example, public transit in Austin, Texas partnered with the local Food Bank to deliver food and supply kits to customers using transit vehicles, focusing on clients with disabilities or medical conditions that prevent them from using public transit safely. Similarly, customers of paratransit services in Minnesota can now order food and household essentials online for delivery. Similar food delivery innovations are also present in Nevada, Iowa, and Michigan (Wanek-Libman, 2020).

2.1.3 Focus Groups

For this study, focus groups consisting mostly of representatives of food producers, distributors, and community sponsored agriculture (CSA) organizations were interviewed. The focus groups' suggestions were qualitative and provided insights into what food producers value when planning ways to make food more accessible. It was noted that most food producers currently use box trucks or vans to transport food. Volunteers helping those organizations would typically use their personal vehicles for food transport. One participant noted that their vehicle choice may depend on food demand. The participant mentioned that they might use a van during the low-demand season and a box truck during the high-demand season. The focus group participants also mentioned that the ability to transport food is greatly dependent on refrigeration of the transport vehicle. Some participants either use a refrigerated truck or are considering purchasing one in the future. Refrigeration capability is significant when considering partnering with agencies to aid in food transport.

Participants also seemed to value an "all-in-one" model for purchasing food either in person or online. A participant noted that they would prefer if customers were able to order and pay for food on one platform, where the farmer would gather produce for pick-up upon receiving the order, calling the model "cut-on-demand". Similarly, some participants supported stationing farmers markets close to existing grocery stores. These participants mentioned that customers may favor "one-stop" shopping: purchasing household supplies from the store and food from the adjacent farmers' market. Low-income and/or elderly customers may especially prefer this option if they have limited access to transportation, and typically do all their weekly shopping in one trip.

Some participants expressed curiosity in various transportation innovations. The same participant who suggested the "cut-on-demand" model also mentioned that food delivery services like Uber Eats and DoorDash could be responsible for picking up and transporting the order of produce. Other participants were curious about the potential for drones to perform similar deliveries.

2.1.4 Tradeoffs in Transportation Modes

Tradeoffs in delivery capability and capacity exist between the available innovations in grocery shopping and delivery. A report by Shin et. al. (2019) estimates the load capacity of electric bikes to be 300-600 pounds or about 20 packages. There are storage box attachments available for E-bikes with storage volumes ranging from 45 to 80 liters, suitable for small disposables to larger packages (Ebike4delivery, n.d.). Examples of E-bikes designed for delivery have a maximum speed ranging from 15 to 20 miles per hour (Lucas, 2019; Ebike4delivery, n.d.). Doole et. al. (2018) estimates a delivery cost per order around $2.45, in an evaluation of food orders in Paris, and assumes a delivery rate of five orders per hour per E-bike. Shin et. al. (2019) evaluated deliveries in West Baltimore and found E-bikes could cost $6.23 per order. However, the delivery mode in this study uses trucks and e-bikes conjunctively. Micromobility is not only used for delivery but may also increase accessibility for people to do their own grocery shopping. A survey of Nice Ride Minneapolis bike-share users found that the average distance traveled during a trip was 2.7 miles (Schoner et. al., 2012). The bicycles used in the program were not E-bikes with assistive pedaling and could travel at a speed of approximately 10 miles per hour. Electric bikes could travel at higher speeds.

E-scooters have less storage capacity than E-bikes. The scooter designed by OjO has a 300-pound weight limit (OjO Electric, 2019). The small rear basket is much smaller than E-bike attachments; however, insulated backpacks designed for delivery drivers are also available. OjO estimates 50 miles per full charge of the scooter's battery, with a top travel speed of 20 miles per hour.

The capacity of delivery drones is about five pounds; thus a drone cannot hold packages bound for multiple destinations (D'Andrea, 2014; Doole et. al., 2018; Lardinois, 2019). However, drones could be less expensive per order than e-bikes (Doole et. al., 2018), ranging between $0.28 to $1.35 per package and two deliveries per hour.

Third-party personal delivery vehicles can store 45 packages per vehicle and cost an estimated $1.78 per package. A delivery truck has a much higher storage capacity than all other methods. A truck has a maximum load capacity of 2.5 tons or 250 packages, and costs $8.87 per package (Shin et. al., 2019).

2.1.5 System Considerations of Delivery Modes

An investigation by Wygonik and Goodchild (2012) shows that vehicle miles traveled (VMT) are reduced when households are served by a delivery vehicle for their grocery shopping. There is also a reduction in households' fuel use and emissions from travel. Effective planning of the delivery service contributes greatly to the savings of VMT and CO2 emissions. The same study found that random assignment of customers to delivery vehicles had emissions reductions ranging from 17%-75%, whereas assignment based on proximity had reductions from 80%-90%. Emission reductions found in the study does not include the impact of refrigeration. A study by Heldt et. al. (2019) found that net emissions of home grocery delivery increases when driving and refrigeration are both considered, more significantly on hot days and in urban areas. However, refrigeration is not available for some of the grocery delivery innovations, nor is it required in some situations.

CO2 emissions are reduced more when delivery vehicles are electric. An E-van can consume five times less energy and generates 112 times less CO2 emissions than a standard combustion engine delivery van (Figliozzi, 2020). The study by Figliozzi (2020) found sidewalk autonomous delivery robots (SADRs) also greatly reduce emissions with respect to combustion engine vans when the delivery area surrounds robots' depot. Emissions reduction and efficiency diminishes when the SADRs must first be transported to the delivery site via truck. Road autonomous delivery robots (RADRs) were more efficient than E-vans when delivering to a low number of customers. Drones were most effective when time constrained and in low-delivery density scenarios. The study also notes that pedestrian safety caused by SADRs and air safety and congestion caused by drones are potential tradeoffs. Delivery drones are also found to be cheaper per order than delivery via E-bike (Doole et. al., 2018).

Some investigations have been done to evaluate the effect of COVID-19 and quarantine on grocery shopping. There is an increased reliance on home delivery of groceries and food when people avoid leaving their households. For some people, home cooking has become a more prevalent activity during COVID-19 stay-at-home orders. A desire to find adaptive ways of procuring food, and a need to use outside food sources when grocery stores are low on stock, spurs public realization that some local and domestic farmers can deliver direct (Worstell, 2020). It is still unclear what practices will remain, but many predict a wide-ranging transformation of US food systems after

COVID-19. As mentioned previously, food deserts may exist more frequently among low-income communities. COVID-19 will likely exacerbate this inequality (Power et. al., 2020). Low-income households are unable to stockpile food during the pandemic nor afford expensive varieties of products when supermarkets are bought out.

2.2 Quantitative Analysis

To evaluate tradeoffs between the delivery innovations, quantitative estimates were created for four delivery scenarios. A “quick trip” is a one-mile delivery containing two grocery bags (five pounds each). This could represent a quick or daily trip to a grocery store. An “short trip” is a three-mile delivery containing five grocery bags, representing a weekly trip to the grocery store. A “intermediate trip” is a ten-mile trip consisting of ten 20-lb. boxes. This could represent a small delivery from a producer to a CSA market. The “long trip” is a 20-mile delivery of 100 20-lb. boxes. This could represent a large shipment of produce from a farm to a market.

2.2.1 Delivery Capacities of Different Modes

As shown in Table 2.1, estimates on the load capacity, travel speed, and delivery cost of six different delivery methods (walking, e-bike, e-scooter, drone, car, and truck) were derived from values seen in the literature. All the assumed values are tabulated below.

Table 2.1 Assumed values for delivery methods

	Walking	E-bike	E-scooter	Drone	Car	Truck
Maximum speed	4 mph	20 mph (Lucas, 2019)	20 mph (OjO electric, 2019)	2 deliveries per hour (Doole et. al., 2018)	-	-
Assumed delivery speed	3 mph	15 mph	15 mph	-	30 mph	30 mph
Capacity (5-lb. bags)	2	3 (Ebike4delivery, n.d.)	3	1 (Doole et. al., 2018)	45 (Shin et. al., 2019)	250 (Shin et. al., 2019)
Capacity (20-lb. boxes)	N/A	1 (Ebike4delivery, n.d.)	1	N/A	11	250 (Shin et. al., 2019)
Cost	$2.45 per delivery	$2.45 per delivery (Doole et. al., 2018)	$2.45 per delivery	$1.35 per delivery (Doole et. al., 2018)	$1.78 per item (Shin et. al., 2019)	$8.87 per item (Shin et. al., 2019)

The maximum speed of walking is assumed to be 4 mph. The maximum speed of an E-bike and E-scooter are both assumed to be 20 mph. Estimates of delivery speed were generally calculated as the maximum speed of the vehicle with a reduction to represent various travel impedances such as steep hills, weather, traffic, etc. The maximum speed and travel speed of a delivery drone are not estimated. It is instead assumed that a delivery drone would be able to perform two deliveries per hour, regardless of distance, according to research by Doole et. al. (2018). The drone is also limited by a 5-lb. carrying capacity, so it would not be able to deliver the 20-lb. boxes.

The capacity of deliveries performed on foot is two bags and the cost is assumed to be the same as an E-bike or E-scooter. It is assumed that an on-foot deliver person would not feasibly carry a 20-lb. box any substantial distance. The capacity of an E-bike was calculated based on the assumption that the bicycle would have a delivery box attachment. Examining the storage capacity of existing commercial delivery boxes for E-bikes, it is estimated that an E-bike would be able to deliver three grocery bags, or one box, per trip. The capacity of an E-scooter was calculated assuming the vehicle would have a basket or bag attached for holding deliveries, and the driver would also wear a delivery backpack. The total capacity of an E-scooter with possible upgrades to storage is also three grocery bags, or one box, per trip. The delivery cost of an E-scooter is assumed to be the same as an E-bike since the capacities and travel speeds are comparable. For both an E-bike and E-scooter, the capacities are limited by volume, not weight. The assumed capacity of a car is 45 bags, or 11 boxes. The value of 45 bags is retrieved from estimates in the literature. The estimate of 11 boxes is calculated by dividing the value of 45 bags by the assumption that a box of produce has a size equivalence of about four grocery bags. The travel speed of a car or truck is assumed to be around 30 mph. However, for the "long" trip, this estimate is increased to 50 mph to include the expectation that a delivery vehicle would use freeways for the majority of the trip.

2.2.2 Feasibility of Food Delivery

Table 2.2 contains some estimates on delivery times and costs for various transportation modes, including some micro-mobility options. All quantitative estimates assume one vehicle fully completes the delivery. When the capacity of the vehicle cannot hold the entire load at once, multiple trips are required. The return trip to the origin to reload the vehicle is assumed to take the same amount of time as the delivery trip to the destination. The delivery is complete when the last sub-delivery is received by the destination. Any return trip to the origin upon completion of the delivery is not included in the total time.

Table 2.2 Estimates of delivery times and costs

Quick Trip	Walking	E-bike	E-scooter	Drone	Car	Truck
Distance	1 mile					
Number of items	2 bags; 5 pounds ea.					
Delivery Time	20 minutes	4 minutes	4 minutes	15 minutes	2 minutes	2 minutes
Number of trips	1	1	1	2	1	1
Total Time	20 minutes	4 minutes	4 minutes	45 minutes	2 minutes	2 minutes
Total Cost	$2.45	$2.45	$2.45	$2.65	$3.56	$17.74

Short Trip	Walking	E-bike	E-scooter	Drone	Car	Truck
Distance	3 miles					
Number of items	5 bags; 5 pounds ea.					
Delivery Time	N/A	12 minutes	12 minutes	15 minutes	6 minutes	6 minutes
Number of trips		2	2	5	1	1
Total Time		36 minutes	36 minutes	135 minutes	6 minutes	6 minutes
Total Cost		$4.90	$4.90	$6.75	$8.90	$44.35

Intermediate Trip	Walking	E-bike	E-scooter	Drone	Car	Truck
Distance	10 miles					
Number of items	10 boxes; 20 pounds ea.					
Delivery Time	N/A	40 minutes	40 minutes	N/A	13 minutes	13 minutes
Number of trips		10	10		1	1
Total Time		12.7 hours	12.7 hours		13 minutes	13 minutes
Total Cost		$24.50	$24.50		$17.80	$88.70

Long Trip	Walking	E-bike	E-scooter	Drone	Car	Truck
Distance	20 miles					
Number of items	100 boxes; 20 pounds ea.					
Delivery Time	N/A	N/A	N/A	N/A	24 minutes*	24 minutes*
Number of trips					10	1
Total Time					7.6 hours	24 minutes
Total Cost					$178.00	$887.00

*Calculated using higher delivery speed than other trip sizes (50mph vs. 30mph)

For a "short" trip, deliveries via walking, E-bike, and E-scooter are the cheapest options at $2.45 total cost. Delivery via E-bike and E-scooter are however five times faster than walking. Delivery via car is twice as fast as an E-bike or E-scooter, for about 43% more cost. In situations where delivery time is the most important consideration, a car may be recommended. All delivery methods, except drones, need only one trip to complete the delivery.

For an “intermediate trip”, an E-bike and E-scooter is still the cheapest option at $4.90 total cost. The car, however, costs 81% more ($8.90) but is has a delivery time 83% faster. When cost is a priority, the E-bike and E-scooter is the recommended option and when time is a priority, the car is the recommended option. If two or more E-bikes or E-scooters were tasked with the delivery, the total delivery time would be reduced significantly as no return trip is needed. However, in this case, the car would still be 50% faster.

For a “long” trip, the car is both the cheapest and fastest option due to the number of return trips required for an E-bike and E-scooter. Since an E-bike and E-scooter could only hold one box, a single delivery-person would require 10 trips or 12.7 total hours to complete the delivery. It should also be noted that an estimate of an E-scooter’s battery life is 50-miles per charge. To perform the “long” trip”, a total of 190 miles must be travelled and the E-scooter would need to be charged at least three times. These extreme values are presented to illustrate the infeasibility of such a mode due to multiple constraints.

For the “longer” trip, the car and truck are the only available option. While an E-bike or E-scooter is not limited by weight, one 20-mile roundtrip to deliver a single box would significantly deplete the battery. A delivery-person would also be very unlikely to take on the task of performing even a portion of this delivery. Furthermore, whereas a car could perform this delivery, 10 trips are required for a total of 7.6 hours. A truck could perform the delivery in a single trip for about 95% less time and almost five times more cost. In a scenario where speed and efficiency are most important, delivery via truck is recommended. In a scenario with a flexible schedule, and the delivery may be performed by multiple drivers over time, delivery via cars may be a more attractive option.

The calculations have shown that delivery via car and truck are the fastest of the examined options. For relatively short trips without major time constraints, delivery via E-bike, E-scooter, or even walking, may be a cheaper option. Delivery trips involving larger loads (e.g. boxes of produce) would be better performed via car or truck, leaving micromobility to be a viable option for short distance, light load delivery trips. For all the examined trip scenarios, drones were neither the fastest nor the cheapest option due to the weight limitation of 5-lbs. However, for single-item deliveries, a drone may be cheaper than an E-bike or E-scooter. Therefore, drones may still be a viable option for small single-order deliveries and a supplemental part of an entire food delivery system.

2.3 Discussion

The purpose of this literature review and quantitative analysis is to explore and understand the potential of using innovative transportation modes to address the urban food desert problem. Thus, the research used focus groups to understand the perspectives of urban farmers, food distribution, and consumers. The literature review revealed general characteristics of several innovative food delivery modes, including e-scooters, transit, drones, and robots. The literature also reported the experiences of different countries and products available in those countries. Quantitative analysis was performed, based on some simplifying assumptions. The analysis illustrated tradeoffs between the different transportation modes that were previously covered. Some delivery scenarios were clearly not appropriate for certain modes, either due to long delivery times or lack of capacity or both. The conclusion is that innovative transportation modes could be feasible or even desirable depending on the characteristics of communities to be served.

The next logical step in the research is to conduct field studies and demonstrations based on the results. The studies should be designed and implemented in a coordinated process involving research partners – farmers, distributors, transit agencies, and consumers – to ensure accuracy and realism of food delivery practices. One example study involves designing an optimum solution for a neighborhood such as the Ivanhoe Council community in Kansas City. Such a study will focus on consumers in a dense urban environment involving a relatively small area. A setting can showcase micromobility solutions and other modes, including e-scooters, e-bikes, walking, drones, and robots. Another example study involves the collection and distribution from the perspective of Community Supported Agriculture (CSA) such as Cultivate Kansas City.

Such a study involves aggregating from multiple growers and then distributing food to users who subscribe to the CSA. Based on the characteristics of the region served by the CSA, modes that serve longer distances may be explored. As seen in the analysis, these modes would very likely not include e-scooters and e-bikes but could still include ridesharing options. This may also include innovative solutions such as the use of transit for food distribution. Field demonstrations will reveal real world issues and possibilities to overcome them, and pave the way for the eventual design of reproducible transportation solutions for urban food deserts across the U.S.

Outside of field demonstrations, that may only focus on one community or business and monitor the real deliveries in or out of that area, deliveries across an entire city or transportation network may be explored. Using available traffic data, road network data, and locations of businesses and residents, a GIS software may be used to design a sample optimized delivery plan for neighborhoods across Kansas City, evaluate the feasibility of different delivery modes, and/or optimize locations for drone hubs to enhance city-wide food delivery efforts.

CHAPTER 3: AUTONOMOUS TRUCK PLATOONING

3.1 Literature Review

A technical library search of the term “truck platooning” yielded 426 records. At a glance, there appears to be a large amount of literature on the topic. The literature is extensive and illustrates the massive efforts to develop truck platooning across the world and evaluate it comprehensively, especially in North America, Europe, and Asia. However, a closer examination of these records reveals that certain topics are well-worn while others remain unexplored or unaddressed. Some extensively discussed issues include truck platoon control algorithms, efficiency savings, wireless communication, transport system considerations, logistics, impacts on the infrastructure, and human factors. The issue of truck platooning in and near work zones has hardly seen this level of research. The following literature review presents a broad look at literature on truck platooning, to paint an overall picture without delving into details, since most literature is not on point with the topic at hand.

3.1.1 Investigation of Truck Platooning Innovations

Unsurprisingly, much of the focus on the literature surrounds issues dealing with the truck platoons themselves. A control algorithm refers to the method in which trucks can automatically follow a lead truck that is driven by a human. Truck platoon control is a complex issue and encompasses multiple challenges such as formation of platoons, splitting, improving safety, dealing with subsystem failures, minimizing oscillations, and coordinating between multiple trucks. Different approaches have been utilized by researchers to tackle these issues, such as velocity trajectory optimization for formation and splitting control (Earnhardt et. al., 2021), a cooperative distributed approach using consensus algorithms for formation and modification (Saeednia and Menendez, 2017), and a multi-layer approach to ensure desired positions are maintained while attenuating disturbances (Zegers et. al., 2017). These examples illustrate the variety of explored solutions for different aspects of truck platoon control. Another focus of research comes from communications between connected and autonomous vehicles. Researchers have investigated various issues impacting communications such as limited range (Elhaki and Shojaei, 2021) as well as occlusion, moisture in the air, elevation and antenna position, interference, and road curvature and grade (Adam et. al., 2021).

A major motivating factor behind the deployment of commercial truck platooning is gains to efficiency. Truck platooning is expected to increase capacity via shorter headways and decrease fuel consumption via draft reduction through drafting. Zhang et. al. (2018b) surveyed the literature on possible improvements to fuel economy from truck platooning and Van De Hoef et. al. (2019) investigated solutions to reduce fuel consumption on platoon formation. A test by Borhan et. al. (2021) found that despite the potential for improved efficiency, platooning could result in increased fuel consumption under high traffic or on high grades. By these examples, it is shown that researchers aim to identify and improve the extent of gains to efficiency that may be brought on by truck platooning.

Further, You et. al. (2020) explored the use of truck platooning in solving the local container drayage problem (LCDP). LCDP refers to the transport distance between a local terminal and the customer that is short compared to the container packing and unpacking time. These issues are related to logistics and freight, and explore considerations that may be made when a truck platoon is introduced to the greater transportation system. Studies like the aforementioned illustrate the impact truck platooning may have on food delivery. As was explored in the previous chapter, truck-based deliveries are cost-effective when transporting a large delivery of food products (e.g. from an urban farm to the market). Truck platooning innovations may be an option for further increasing delivery capacity from food suppliers to underserved areas. They may be applicable to further enhance solutions to food deserts.

3.1.2 System Considerations of Truck Platoons

It may seem that studies on control algorithms and communications revolve around the platoons themselves. Studies on efficiency may also fixate on the platoons. Moving into topics of logistics and freight, the view widens to consider truck platoons as a member of the overall transportation system. Other authors investigate the impact truck platooning may have on the transportation network and infrastructure. Studies have been done on the effects of truck platoons towards pavement longevity and bridges, and platoon collisions against concrete barriers (Gungor and Al-Qadi, 2020; Sharma et. al., 2020; and Thulaseedharan and Yarnold, 2020). Pasquale et. al. (2018) characterized truck platoons as moving bottlenecks and proposed a control scheme in which platoon speed is set according to the surrounding traffic conditions to minimize congestion. Haas and Friedrich (2021) found that increasing the platoon number can decrease waiting time but increase intersection delay.

Studies have also been done on human factors in truck platooning. Neubauer et. al. (2020) examined the issue of driver acceptance and found hesitancy with regards to Level 1 platooning. Similarly, Castritius et. al. (2020) investigated truck platooning acceptance among German commercial drivers and found a clear increase in acceptance after they had experienced platooning on the Autobahn. Castritius et. al. (2021) found that sleepiness of drivers did not increase under semi-automated platoon driving. These studies show that researchers still consider the human factors surrounding truck platoons, namely with respect to the human drivers that lead the platoon. However, this investigation examines the behavior of external drivers interacting with platoons. Truck drivers are commercially licensed and trained; their behavior may not compare with drivers of passenger vehicles.

3.1.3 Motivation for Research

In fact, only two sources had a remote connection with the present research. Duret et. al. (2020) investigated a truck platoon splitting algorithm near discontinuities. The scenario they address could apply to work zones as lane closures are common. Zhang et. al. (2018a) investigated the issue of following trucks being heavily blocked in their front view because of short headways in a truck platoon following scenario. The authors found positive effects of a see-through display where the lead truck projects its front view to its rear. However, neither of these studies address work zones explicitly.

Of 426 sources, only two had limited connection with the subject of this research. This demonstrates the uniqueness of the project and the need for these issues to be studied. Previous research has not addressed the issues of driver education on truck platoons, truck platoon signage, and the effect of the number of platooned trucks on nearby drivers. Such original questions are important when formulating policies and guidelines for the operation of truck platoons near work zones. From the literature on efficiency and freight transport, truck platooning has the potential to increase food delivery between urban farms and other suppliers to underserved communities with insufficient access to healthy food. As this technology continues to develop and immerge, questions regarding atypical driving environments such as work zones must be addressed.

3.2 Methodology

The simulator study utilizes the ZouSim driving simulator. ZouSim is a suite of networked transportation simulators that allow for safe and efficient investigation of transportation modes, as well as the interaction between multiple modes within the same virtual environment. Driving and trucking simulators are both medium-fidelity simulators, built around a half-cab Toyota sedan and a full-cab Volvo heavy truck, respectively. The ZouSim simulators have been used for various projects sponsored by agencies such as the FHWA, MoDOT, FAA, and City of Columbia, Missouri. Several work zone related projects have been performed using the ZouSim simulators. Examples include the use of green lights on truck-mounted attenuators (Zhang et. al., 2019) and automated flaggers (Qing et. al., 2018). Further, other simulator studies have been performed in the ZouSim lab on topics like geometric design (Sun et. al., 2017), bicycle signage and markings (Sun and Qing, 2018), autonomous vehicle interactions with pedestrians (Qing et. al., 2019), wheelchair accessibility in airports (Qing et. al., 2019), and e-scooter safety and education.

The virtual road and work zone designed for this simulator study is a two-way four-lane divided highway with a closure on the right-most lane. The work zone follows MUTCD Typical Application 33 (FHWA, 2009), which is a standard lane closure on a divided highway. The road is intentionally designed straight as not to let road curvature influence driver behavior. The road is also designed to appear like a typical Missouri highway but does not replicate an actual section of road. This is done so that test subjects are not influenced by their own memory of existing roads.

Figure 3.1 Example of a vehicle approaching a truck platoon

Ten scenarios are presented to each participant. Scenarios, shown in Table 3.1, include different combinations of education, number of platooned trucks, and signage on the backs of trucks. The order of scenarios are partially randomized to avoid sequence bias, also known as learning bias (Perreault, 1975).

Table 3.1 Simulator Scenarios

Scenario	Education	Number of Trucks	Sign	Order
1	No	2	No	Randomized
2	No	4	No	
3	No	2	Truck Platoon	Randomized
4	No	4	Truck Platoon	
5	No	2	2 Trucks	
6	No	4	4 Trucks	
7	Yes	2	Truck Platoon	Randomized
8	Yes	4	Truck Platoon	
9	Yes	2	2 Trucks	
10	Yes	4	4 Trucks	

Education refers to the experiment host explaining to the human subject what a truck platoon is and the meanings of the signage. Signage refers to the sign displays on the back of the truck platoon. Signs may either read only the phrase “Truck Platoon” or display the number of platooned trucks (either two or four). It is important to note that all pre-education scenarios must be presented first before post-education. Also, the two scenarios with no signs are always presented first. The researchers were concerned that after subjects had seen the signage, they may retain the mental picture of the signs moving onward in the test. Further, no-sign scenarios were eliminated from post-education scenarios for two reasons. First, it would be difficult to ascertain what portion of behavior was resultant from education versus the signage. Second, the number of scenarios was kept at a reasonable level for participant comfort.

Figure 3.2 Example of truck platoons with no signage and “Truck Platoon” signage

In each scenario, the human subject starts in the right lane with the lead platoon truck driven by a research assistant, using the federated truck ZouSim simulator. As they approach the lane closure, the human subjects must then decide when to merge into the open lane, whether they should overtake the truck platoon, and whether they should merge in the middle of the platoon. In addition to the simulator readout, that displayed the speed of the participant’s vehicle and their distances relative to the truck platoon and work zone, eye-tracking data and biofeedback data were also collected. An eye-tracker tracked the movement of the participant’s gaze and attention, capturing the frequency they look at specific spots, such as signage on the road or the platoon, and when such glances occurred. Biofeedback data was gathered using the Empatica E4 device: a wrist-mounted psychophysiological sensor that measured the participants’ heart rate, skin conductivity, and temperature (Empatica, 2020). Eye-tracking data provided a general validation that subjects did glance at the signage on the back of trucks and along the road.

The psychophysiological sensor data was discarded during the data analysis due to frequent issues of poor data quality, which may have been due to the device not being properly secured to the subjects’ wrists or being shaken excessively.

Participants were also given a post-simulator survey to be completed immediately following the test. The purpose of the survey to gather written information and opinions on the subjects’ preferences toward scenarios during the simulator study, and to elaborate on their driving behavior. The survey asked participants to describe the effectiveness of education and understandability of the platoon signage. Simulator fidelity and simulator sickness were also examined during the survey.

Participants of the study were all licensed drivers. They were recruited through flyers, word-of-mouth, and individual invitation. Thirty-two human subjects participated in the study. None of the participants required their test to end early. However, two scenarios across two different participants were unable to be completed due to technical malfunction. Eye-tracking data were unavailable for 29 scenarios across four different participants. Driving data could not be collected from five different scenarios from one participant. Eye-tracking data and/or driving data that could still be collected from incomplete scenarios were kept and analyzed, as were post-simulator surveys from these participants. All data from one participant was excluded following their test due to poor playback quality, but the test itself had no issues and their survey was kept. Despite the challenges of human subject recruitment due to COVID-19, participants represented a fairly diverse population with respect to age and gender. 28% of participants were age 18 to 25, 44% were ages 26 to 40, 9% were ages 41 to 55, and 19% were ages 56 to 70. The age distribution is skewed towards a younger population. Approximately 53% of participants were female. 84% of participants claimed they were unfamiliar with truck platoons before the study.

3.3 Simulator Results

In this section, results will be presented as a description of the data; the practical significance of the results will be discussed in the following Discussion section. The simulator results will be presented first, followed by the post-simulator survey results. Table 3.2 shows the total number of times participants chose to either overtake or follow the truck platoon. The Table is sorted between two independent variables: level of education and number of trucks. There is no significant difference between the number of follows and overtakes between treatments. However, in all cases, participants followed the truck platoon more often than overtake.

Table 3.2 Number of Follows and Overtakes (Education and Number of Trucks)

		2 Truck		4 Truck	
		Count	%	Count	%
No Education	Follow	56	65.9%	58	64.4%
	Overtake	29	34.1%	32	35.6%
Education	Follow	39	67.2%	43	71.7%
	Overtake	19	32.8%	17	28.3%

Simulator results for measurements of car speed and distance between the car and truck platoon, taken as the car passed the work zone, are shown in Tables 3.3a and 3.3b. A negative value in car-truck distance indicates that the car is ahead of the truck platoon. Participants could freely choose to follow or overtake between scenarios, and there were more no-education scenarios than education. Therefore, the data was analyzed with unpaired t-tests assuming unequal variances. Table 3.3a shows a comparison between no-education and education on these data. With no education, the average following speed was 39.27 mph and average distance was 933.71 feet for scenarios with two trucks.

Education resulted in a 12.90% (p=0.000) increase in speed and a 30.06% (p=0.002) decrease in distance in the two-truck platoon scenarios. For scenarios with four trucks, the average following speed was 39.26 mph. In the four-truck scenarios, post-education car speed also increased by 8.58% (p=0.038).

Similar results are seen for cases where the driver overtook the two-truck platoon, in an 8.27% (p=0.074) increase in speed and 28.77% (p=0.103) decrease in distance between the car and trucks. For the four-truck platoon, speed increased by 5.52% (p=0.116) after education. In overtaking cases, the confidence interval for these three values is not as narrow as in the follower cases stated previously. This may be due to smaller sample sizes for overtaking cases.

Table 3.3b compares two-truck platoon scenarios against four-truck platoon scenarios. There was no significant difference for followers with no education between two- and four-truck scenarios. With education, the average following distance was 653.08 feet in the two-truck scenario. Four trucks resulted in a 36.52% (p=0.020) increase in the distance participants followed. For scenarios with no education and two-trucks, the average speed and distance of overtaking participants are 47.10 mph and -611.45 feet, respectively. Four trucks resulted in a 19.42% (p=0.001) increase in speed and a 48.37% (p=0.038) decrease in distance. For scenarios with education and two trucks, the average speed and distance of overtaking participants are 51.00 mph and -435.35 feet. Similarly, four trucks resulted in a 16.38% (p=0.001) increase in speed and a 35.80% (p=0.032) decrease in distance.

Table 3.3a Level of Education Results Comparison

			2 Truck		4 Truck	
			Car Speed (mph)	Distance (ft.)	Car Speed (mph)	Distance (ft.)
No Education	Follow	Mean	39.27	933.71	39.26	943.02
	Overtake	Mean	47.10	-611.45	56.25	-315.69
Education	Follow	Mean	**44.33**	**653.08**	**42.63**	891.60
		% Difference	**12.90%**	**-30.06%**	**8.58%**	-5.45%
		p-value	**0.000**	**0.002**	**0.038**	0.343
	Overtake	Mean	51.00	-435.53	59.35	-279.59
		% Difference	8.27%	-28.77%	5.52%	-11.44%
		p-value	0.074	0.103	0.116	0.383

Note: bold values indicate statistical significance at the 95% confidence interval

Table 3.3b Number of Trucks Results Comparison

			2 Truck		4 Truck	
			Car Speed (mph)	Distance (ft.)	Car Speed (mph)	Distance (ft.)
No Education	Follow	Mean	39.27	933.71	39.26	943.02
		% Difference			-0.02%	1.00%
		p-value			0.498	0.467
	Overtake	Mean	47.10	-611.45	**56.25**	**-315.69**
		% Difference			**19.42%**	**-48.37%**
		p-value			**0.001**	**0.038**
Education	Follow	Mean	44.33	653.08	42.63	**891.60**
		% Difference			-3.85%	**36.52%**
		p-value			0.142	**0.020**
	Overtake	Mean	51.00	-435.53	**59.35**	**-279.59**
		% Difference			**16.38%**	**-35.80%**
		p-value			**0.001**	**0.032**

Note: bold values indicate statistical significance at the 95% confidence interval

Table 3.4a shows the number of follows and overtakes sorted against type of signage and level of education. The results show with at least 90% confidence that signage of either type resulted in an increase in the percentage of participants that chose to overtake the truck platoon. There is no significant difference between the two types of signs, as well as between levels of education. Table 3.4b shows the distribution with respect to the number of platooned trucks. Within the two-truck scenarios, the results show with at least 90% confidence that signage resulted in more overtakes. However, within the four-truck scenarios, there was no significant difference between the proportions of follows versus overtakes between “No Sign” and either type of signage. There was also no significant difference between two- and four-truck scenarios within each signage category.

Table 3.4a Number of Follows and Overtakes (Education and Signage)

		No Sign		Truck Platoon		# of Trucks	
		Count	%	Count	%	Count	%
No Education	Follow	43	75.4%	34	57.6%	34	58.6%
	Overtake	14	24.6%	25	42.4%	24	41.4%
Education	Follow	-	-	39	65.0%	40	69.0%
	Overtake	-	-	21	35.0%	18	31.0%

Table 3.4b Number of Follows and Overtakes (Number of Trucks and Signage)

		No Sign		Truck Platoon		# of Trucks	
		Count	%	Count	%	Count	%
2 Trucks	Follow	23	82.1%	36	61.0%	36	64.3%
	Overtake	5	17.9%	23	39.0%	20	35.7%
4 Trucks	Follow	20	69.0%	37	61.7%	38	63.3%
	Overtake	9	31.0%	23	38.3%	22	36.7%

Table 3.5 compares the results of car speed and car-truck distance for the three types of signage and two levels of education. Values in Table 3.5 are also measured when the participant car passed the work zone, as in Table 3.3a and 3.3b. The mean speed of followers was 38.30 mph with no signage and no education. “Truck Platoon” signage resulted in an 8.66% (p=0.035) increase in speed. Similarly, “# of Trucks” signage resulted in a 6.74% (p=0.081) increase in speed. The mean speed of no-education followers was 41.62 mph with “Truck Platoon” signage and 40.88 mph with “# of Trucks” signage. Education resulted in an 7.57% (p=0.033) and 6.22% (p=0.080) increase these values, respectively. The mean distances of this same group are 901.24 feet with “Truck Platoon” signage and 898.59 feet with “# of Trucks” signage. The follow distances decreased by 16.47% (p=0.085) for “Truck Platoon” signage and 21.20% (p=0.033) for “# of Trucks” signage, after education. In the overtaking case, the

mean speed was 47.75 mph with “# of Trucks” signage and no education. Education resulted in a 10.99% (p=0.028) increase in this value. There was no significant difference between results for the two signs: “Truck Platoon” and “# of Trucks”.

Table 3.6 compares the results of car speed and car-truck distance with respect to signage and number of trucks. The mean speed of following cars was 36.87 mph with no sign and two trucks. The “Truck Platoon” sign resulted in an 17.76% (p=0.003) increase in speed and the “# of Trucks” sign resulted in a 14.29% (p=0.010) increase in speed. The mean speed of followers in the four-truck scenarios was 39.95 mph, with no sign, and also increased by 8.11% (p=0.028) with the “Truck Platoon” sign and 6.05% (p=0.090) with the “# of Trucks” sign. There was no significant difference between speed results for overtaking cases. The mean distance for followers in the two-truck scenarios with no sign was 1037.22 feet. The “Truck Platoon” and “# of Trucks” signage both resulted in a decrease in distance of 24.85% (p=0.048) and 30.79% (p=0.017), respectively. There was no statistically significant difference between the two signs, nor between two- and four-truck results within each signage category.

Table 3.5 Type of Signage and Level of Education Results Comparison

			No Sign		Truck Platoon		# of Trucks	
			Car Speed (mph)	Distance (ft.)	Car Speed (mph)	Distance (ft.)	Car Speed (mph)	Distance (ft.)
No Education	Follow	Mean	38.30	1034.42	41.62	901.24	40.88	898.59
	Overtake	Mean	47.43	-670.79	48.36	-556.24	47.75	-497.42
Education	Follow	Mean	-	-	44.77	752.77	43.43	708.10
	Overtake	Mean	-	-	49.38	-462.86	53.00	-456.33

Comparing signs against no sign			No Sign		Truck Platoon		# of Trucks	
			Car Speed (mph)	Distance (ft.)	Car Speed (mph)	Distance (ft.)	Car Speed (mph)	Distance (ft.)
No Edu	Follow	% Diff	baseline	baseline	**8.66%**	-12.88%	6.74%	-13.13%
		p-value			**0.035**	0.140	0.081	0.113
	Overtake	% Diff	baseline	baseline	1.96%	-17.08%	0.68%	-25.85%
		p-value			0.407	0.355	0.465	0.269
Edu	Follow	% Diff	-	-	-	-	-	-
		p-value	-	-	-	-	-	-
	Overtake	% Diff	-	-	-	-	-	-
		p-value	-	-	-	-	-	-

Comparing "truck platoon" vs. "# of trucks"			No Sign		Truck Platoon		# of Trucks	
			Car Speed (mph)	Distance (ft.)	Car Speed (mph)	Distance (ft.)	Car Speed (mph)	Distance (ft.)
No Edu	Follow	% Diff	-	-	baseline	baseline	-1.77%	-0.29%
		p-value	-	-			0.357	0.491
	Overtake	% Diff	-	-	baseline	baseline	-1.26%	-10.58%
		p-value	-	-			0.416	0.350
Edu	Follow	% Diff	-	-	baseline	baseline	-3.00%	-5.93%
		p-value	-	-			0.176	0.312
	Overtake	% Diff	-	-	baseline	baseline	7.33%	-1.41%
		p-value	-	-			0.085	0.463

No Education vs. Education			No Sign		Truck Platoon		# of Trucks	
			Car Speed (mph)	Distance (ft.)	Car Speed (mph)	Distance (ft.)	Car Speed (mph)	Distance (ft.)
No Edu	Follow	% Diff	-	-	baseline	baseline	baseline	baseline
		p-value	-	-				
	Overtake	% Diff	-	-	baseline	baseline	baseline	baseline
		p-value	-	-				
Edu	Follow	% Diff	-	-	**7.57%**	-16.47%	6.22%	**-21.20%**
		p-value	-	-	**0.033**	0.085	0.080	**0.033**
	Overtake	% Diff	-	-	2.11%	-16.79%	**10.99%**	-8.26%
		p-value	-	-	0.358	0.267	**0.028**	0.295

Note: bold values indicate statistical significance at the 95% confidence interval

Table 3.6 Type of Signage and Number of Trucks Results Comparison

			No Sign		Truck Platoon		# of Trucks	
			Car Speed (mph)	Distance (ft.)	Car Speed (mph)	Distance (ft.)	Car Speed (mph)	Distance (ft.)
2 Trucks	Follow	Mean	36.87	1037.22	43.42	779.44	42.14	717.83
	Overtake	Mean	51.20	-644.60	47.57	-558.61	49.25	-496.80
4 Trucks	Follow	Mean	39.95	1031.20	43.19	863.24	42.37	869.32
	Overtake	Mean	45.33	-685.33	50.09	-468.61	50.68	-464.36

Comparing signs against no sign			No Sign		Truck Platoon		# of Trucks	
			Car Speed (mph)	Distance (ft.)	Car Speed (mph)	Distance (ft.)	Car Speed (mph)	Distance (ft.)
2 Trucks	Follow	% Diff	baseline	baseline	**17.76%**	-24.85%	**14.29%**	**-30.79%**
		p-value			**0.003**	0.048	**0.010**	**0.017**
	Overtake	% Diff	baseline	baseline	-7.10%	-13.34%	-3.81%	-22.93%
		p-value			0.246	0.401	0.353	0.321
4 Trucks	Follow	% Diff	baseline	baseline	**8.11%**	-16.29%	6.05%	-15.70%
		p-value			**0.028**	0.093	0.090	0.111
	Overtake	% Diff	baseline	baseline	10.49%	-31.62%	11.80%	-32.24%
		p-value			0.168	0.303	0.140	0.300

Comparing "truck platoon" vs. "# of trucks"			No Sign		Truck Platoon		# of Trucks	
			Car Speed (mph)	Distance (ft.)	Car Speed (mph)	Distance (ft.)	Car Speed (mph)	Distance (ft.)
2 Trucks	Follow	% Diff	-	-	baseline	baseline	-2.94%	-7.90%
		p-value	-	-			0.202	0.288
	Overtake	% Diff	-	-	baseline	baseline	3.54%	-11.06%
		p-value	-	-			0.280	0.353
4 Trucks	Follow	% Diff	-	-	baseline	baseline	-1.90%	0.70%
		p-value	-	-			0.334	0.475
	Overtake	% Diff	-	-	baseline	baseline	1.19%	-0.91%
		p-value	-	-			0.415	0.476

No Education vs. Education			No Sign		Truck Platoon		# of Trucks	
			Car Speed (mph)	Distance (ft.)	Car Speed (mph)	Distance (ft.)	Car Speed (mph)	Distance (ft.)
2 Trucks	Follow	% Diff	baseline	baseline	baseline	baseline	baseline	baseline
		p-value						
	Overtake	% Diff	baseline	baseline	baseline	baseline	baseline	baseline
		p-value						
4 Trucks	Follow	% Diff	8.35%	-0.58%	-0.52%	10.75%	0.54%	21.10%
		p-value	0.083	0.486	0.447	0.214	0.448	0.073
	Overtake	% Diff	-11.46%	6.32%	5.30%	-16.11%	2.91%	-6.53%
		p-value	0.185	0.468	0.192	0.289	0.302	0.336

Note: bold values indicate statistical significance at the 95% confidence interval

3.4 Post-Simulator Survey Results

In the post-simulator survey, participants answered questions regarding effectiveness and clarity of education, their understanding of truck platoon signage, and driving behavior when encountering truck platoons. Table 3.7 shows most participants agree that education clarifies the meaning of signage and how to react to truck platoons. 94% of participants believe the safest reaction to truck platoons is to follow. However, when asked which reaction the participant would perform, only 63% claimed they would follow and 34% claimed they would overtake the platoon. Regarding preference to truck platoon size, most participants preferred fewer trucks in the platoon and 56% felt pressure when more trucks are present. Table 3.7 compares the results of questions regarding understanding of signage. Given pictures of the two types of signage, most participants were able to correctly identify the meaning of each sign. 78% of participants preferred the “# of Trucks” sign. There was no statistically significant difference between the understandability of either sign. With regards to simulator fidelity, at least 62% of participants felt like they were on a highway and could drive freely. The most reported issue was difficulty controlling the simulator and the steering wheel.

Table 3.7 Post-Simulator Survey Results

<table>
<tr><th colspan="2">User feedback*</th><th>n</th><th>Mean</th><th>Median</th><th></th></tr>
<tr><td colspan="2">Education was helpful to understand the platoon sign on the truck.</td><td>30</td><td>4.23</td><td>5</td><td></td></tr>
<tr><td colspan="2">Education clarified how to react with the truck platoon.</td><td>32</td><td>4.75</td><td>5</td><td></td></tr>
<tr><td colspan="2">More pressure was felt when there were more platooned trucks.</td><td>32</td><td>3.59</td><td>4</td><td></td></tr>
<tr><th colspan="2">Reactions to truck platoons</th><th>n</th><th>Fewer trucks</th><th>More trucks</th><th></th></tr>
<tr><td colspan="2">User’s preference</td><td>32</td><td>93.75%</td><td>6.25%</td><td></td></tr>
<tr><th colspan="2"></th><th>n</th><th>Follow</th><th>Overtake</th><th>Merge between</th></tr>
<tr><td colspan="2">Safest option</td><td>32</td><td>90.63%</td><td>9.38%</td><td>0.00%</td></tr>
<tr><td colspan="2">Would perform</td><td>32</td><td>62.50%</td><td>34.38%</td><td>0.00%</td></tr>
<tr><td colspan="2">From simulator data</td><td>293</td><td>66.89%</td><td>33.11%</td><td>0.00%</td></tr>
<tr><th colspan="2">Preference for type of sign</th><th>n</th><th>No Sign</th><th>Truck Platoon</th><th>“# of Trucks”</th></tr>
<tr><td colspan="2">Identified correct meaning</td><td>32</td><td>-</td><td>100.00%</td><td>93.75%</td></tr>
<tr><td colspan="2">Most preferred</td><td>32</td><td>6.25%</td><td>15.63%</td><td>78.13%</td></tr>
<tr><td rowspan="4">Easily understandable*</td><td>Mean</td><td>32</td><td>-</td><td>3.81</td><td>4.06</td></tr>
<tr><td>Median</td><td>32</td><td>-</td><td>5</td><td>5</td></tr>
<tr><td>Diff</td><td>32</td><td></td><td colspan="2">0.25</td></tr>
<tr><td>p-value</td><td>32</td><td></td><td colspan="2">0.159</td></tr>
</table>

*The values in these rows follow a Likert scale (*Vogt, 1999)*, with 1 = in least agreement with the statement and 5 = in most agreement

3.5 Discussion

The simulator experiments showed that education on truck platoons may affect driver behavior when interacting with these platoons around work zones. The simulator results showed that education reduced the distance (headway) between car and platoon. Furthermore, education resulted in an increase in the drivers' speed when passing the work zone for drivers that both followed and passed the platoon. Car speed results after education were closer to the posted speed limit for the simulated work zone: 50 mph. A reduction in headway and increase in speed could mean that education on truck platoons increases driver efficiency when merging before and passing through work zones. Operating speeds close to the posted speed limit of the road could also mean low speed variance within the work zone. In all cases, more human subjects chose to follow the platoon instead of passing it. The highest percentage of cases where the driver chose to follow the platoon came from the four-truck platoon post-education. This result is intuitive as drivers who are aware of platoons may choose not to overtake a longer platoon before reaching the work zone. This is the safer option. Post-simulator surveys also showed that drivers strongly agreed that education is helpful in clarifying how to react to a truck platoon.

The number of trucks in the platoon may also influence driver behavior. Simulator results showed that more platooned trucks resulted in higher car speed when passing the platoon and a decrease in headway after merging ahead of the front truck. This may be due to drivers feeling urgency to speed up when overtaking a longer platoon, to ensure they are able to safely merge before the lane closure. Notably, average speed when passing the work zone in the four truck overtaking case is above the speed limit of the road. 90% of drivers indicated on the post-simulator survey that it would be safer to slow down and follow when encountering a platoon, yet only 62% of drivers indicated this is how they themselves would react. Similarly, only about 67% of human subjects chose to follow the platoon in the simulator experiment.

Results show that there is a statistically significant difference in car speed and following distance between no signage and signage scenarios. With signage, drivers increased their speed by at least 14% and decreased their following distance by 24%. Similar to the effects of education, drivers drove more efficiently when there is signage on the back of platooned trucks. Drivers may prefer more information about the length of truck platoons when it comes to signage. While there was no statistically significant difference in the simulator data between the two types of signs, or a difference in the survey on the understandability of those signs, more human subjects preferred the signage that displayed the number of platooned trucks. On average, human subjects felt more pressure with longer platoons and almost all human subjects indicated they would prefer shorter platoons. Signage with information on the number of platooned trucks may assist drivers in making informed decisions when interacting with a truck platoon near work zones.

CHAPTER 4: CONCLUSION

In summary, these two studies investigated different transportation innovations that may be applicable to food delivery for underserved communities. The first section focused on the topic of food deserts and evaluated tradeoffs between emerging technologies that can be directly applied to delivering food, as well as existing food delivery services. The second section covered autonomous truck platooning technologies and previously uninvestigated interactions between drivers and truck platoons that must share the road. Truck platooning technology can potentially be applied to food delivery and the transport of food across greater distances, outside of urban environments.

As shown in the quantitative comparison between modes of food delivery, trucks were found to be the most expensive option but were optimal for the longest form of trips (e.g. between a farm and the market). The second-best option was delivery via car, which would still take several hours when factoring in the limited capacity of a car. Delivery via car would be possible if a food producer allows for multiple small deliveries over a longer period, but is not feasible if a single efficient delivery is desired. In the case that trucks are used, it may be possible for these delivery trucks to sync up with a truck platoon and experience the benefits. There is also work done on integrating aerial drone technology with delivery trucks (Ackerman, 2015). For example, a truck carrying both packages and drones could use the drone to cover the last mile of the delivery and hand-off to the customer.

Regardless, these emerging technologies should be researched to provide DOTs and other policy makers comprehensive information to formulate regulations. The study of truck platoons revealed driver tendencies after learning about truck platoons and the importance of education. The knowledge that drivers speed up and reduce their headways after being educated on truck platoons could influence how DOTs develop their education messages. A DOT may need to balance explicit recommendations to lower speeds when approaching platoons with promoting efficient but safe driver behavior for work zone congestion relief. As truck platooning technology is adopted, this research on work zone scenarios presents a unique quandary. Work zone scenarios raises some potential issues that could impact safety and efficiency of truck platoons, including how to break up platoons while approaching work zones, how early should this occur to not negatively impact traffic, and how best to formulate display messages on the backs of trucks. A proactive investigation of various factors that affect driver behavior could result in smoother deployment of autonomous truck platooning.

Similarly, uptake of e-scooters for food delivery requires robust and comprehensive policies on safe and proper usage. Currently, there is inconsistency surrounding e-scooter policies across the country. As of January 2021, e-scooters are street-legal in 38 US states and illegal on streets in 10 states (Parker Waichman LLP, 2021). Among the 38 states, some allow scooters on sidewalks while others do not allow them or do not specify. Most regulations on e-scooters are handled on the local level, and in 2017 following the deployment of e-scooters from companies Bird and Lime (Dias et. al., 2021), cities had no well-developed regulations and temporary bans on e-scooters were issued in several major American cities (Zarif et. al., 2019). Safety concerns from e-scooters sharing the sidewalk with pedestrians and obstructing sidewalks led to public frustration regarding e-scooters (Trivedi, 2019; Namiri et. al., 2020; Brown, 2018; and Levin, 2018). To get a full picture of this emerging technology, the benefits of e-scooters and their viability towards food delivery should be contrasted with the need for robust policies and research on riders' interactions with other modes of transportation in the shared space.

The innovations discussed in this thesis all have the potential to impact transportation; food delivery and food accessibility for underserved communities is specifically discussed. Study into these transportation innovations can provide DOTs or local governments information to formulate robust policies that integrate the technologies into the greater transportation system.

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