2020

A Study of Road Autonomous Delivery Robots and Their Potential Impacts on Freight Efficiency and Travel

Dylan Jennings
Portland State University

Miguel A. Figliozzi
Portland State University, figliozzi@pdx.edu

A STUDY OF ROAD AUTONOMOUS DELIVERY ROBOTS AND THEIR POTENTIAL IMPACTS ON FREIGHT EFFICIENCY AND TRAVEL

Dylan Jennings
Student Researcher
Transportation Technology and People (TTP) Lab
Department of Civil and Environmental Engineering
Portland State University
PO Box 751—CEE
Portland, OR 97207-0751
Email: dwj@pdx.edu

Miguel Figliozzi
Director
Transportation Technology and People (TTP) Lab
Department of Civil and Environmental Engineering
Portland State University
PO Box 751—CEE
Portland, OR 97207-0751
Phone: 503-725-4282
Fax: 503-725-5950
Email: figliozzi@pdx.edu

PLEASE CITE AS

Jennings, D. and Figliozzi, M., 2020. Study of road autonomous delivery robots and their potential impacts on freight efficiency and travel. Forthcoming *Transportation Research Record.*

ABSTRACT

Road autonomous mobile robots have attracted the attention of delivery companies and policy makers for their potential to reduce costs and increase urban freight efficiency. Established delivery companies and new startups are investing in technologies that reduce delivery times and/or increase delivery drivers' productivity. In this context, the adoption of Road Automatic (or Autonomous) Delivery Robots (RADRs) has a growing appeal. Several RADRs are currently being tested in the United States. The key novel contributions of this research are: (a) an analysis of the characteristics and regulation of RADRs in the US and (b) a study of the relative travel, time, and cost efficiencies that RADRs can bring about when compared to traditional van deliveries. The results show that RADRs can provide substantial cost savings in many scenarios but in all cases, at the expense of substantially higher vehicle miles per customer served. Unlike sidewalk autonomous delivery robots (SADRs), it is possible the RADRs will contribute significantly to additional vehicle miles per customer served.

Keywords: Last mile, delivery, autonomous, robot, regulation, cost, time, vehicle miles

INTRODUCTION

Robots may soon deliver groceries and parcels to commercial and residential customers. Although most deployments are at the pilot level, on-Road Autonomous Delivery Robots (RADRs) might be able to meet the growing delivery demands generated by E-Commerce, which is growing at a double-digit annual rate (*1*). ADRs are equipped with sensors and navigation technology which allows them travel on roads and sidewalks without a driver or on-site delivery staff.

Some researchers like Fagnant and Kockelman (*2*) have extensively studied the potential of autonomous vehicles for passenger transportation. In comparison, significantly less studies focus on the potential of autonomous vehicles in the freight sector. Some researchers have studied the implications of autonomous vehicles for long-haul freight. Short and Murray (*3*) discuss the impact of long-haul autonomous trucks on hours-of-service, safety, driver shortage and driver retention, truck parking, driver health and wellness, and the economy. Aboulkacem and Combes (*4*) study the impact of long-haul autonomous trucks utilizing an economic model and scenarios with and without full automation; full automation is likely to produce more truck volumes and a decrease of shipment sizes.

Flämig (*5*) presented a history of automation in the freight sector by analyzing four cases of automation in the freight industry and potential applications. Regarding urban deliveries, Flämig (*5*) indicates that small ADRs may better navigate/access narrow urban centers but that delivering parcels may still require human involvement, even if the vehicle is automated, at the receiver side. Kristoffersson et al. (*6*) discusses scenarios for the development of ADRs based on the results of a workshop that included elicit insights from a group of vehicle manufacturers, transport agencies, carriers, and academics. Regarding urban areas, Kristoffersson et al. (*6*) adds that ADRs can facilitate flexible last mile deliveries but also recognizes that urban areas are complex environments with many deliveries/stops and interactions with pedestrians and cyclists. Slowik and Sharpe (*7*) studied the potential of autonomous technology to reduce fuel use and emissions for heavy-duty freight vehicles. The work of Viscelli (*8*) analyzes the impact of ADRs on the US labor market.

There are significantly less studies focusing on urban deliveries or short-haul freight trips. Jennings and Figliozzi (*9*) recently studied the potential of sidewalk autonomous delivery robots (SADRs). Given the relatively short range of SADRs, these small robots are usually complemented by a "mothership" van that can transport SADRs near the delivery zone or service area. Vleeshouwer et al. (*10*) utilized simulations to study a small bakery robot delivery service in the Netherlands. Other researches have analyzed the shortcomings of current regulations for delivery robots (*11*). Another line of research has focused on optimal wayfinding of ADRs or optimizing the joint scheduling of both trucks and ADRs; some of the research in this field includes Boysen et al. (*12*), Baldi et al. (*13*), Sonneberg et al. (*14*), Deng et al. (*15*), and Moeini et al. (*16*).

The key contributions of this research are: (a) an analysis of the characteristics and regulation of RADRs in the US and, (b) a study of the relative travel, time, and cost efficiencies that RADRs can bring about when compared to conventional vans. The analysis of RADR regulations and characteristics is limited to the US. A global review, though important, is outside the scope of this paper and left as a research task for future research efforts that focus mainly on the regulatory aspects of this new technology.

REGULATORY FRAMEWORK

Since RADR vehicles utilize state-of-the-art technology to navigate streets without human intervention, regulators have mainly focused on their safety implications. Regulation of autonomous vehicles and their testing and use is not yet fully agreed upon. The US federal government has only outlined suggested legislation regarding autonomous vehicles and has left it up to individual states to determine laws (*17*).

As of January 2014, early crafters of self-driving vehicle regulation in the US were Nevada, California, Florida, and Washington D.C. (*18*). All of these states' regulations required—the vehicle to be autonomous; the operator to have a driver's license (except Washington D.C.; not specified); manual override features; and insurance in the millions of dollars for testing purposes (except Washington D.C.; not specified). Some regulatory frameworks also included additional requirements—removal of liability from the original vehicle manufacturer when modified to be autonomous; a visual indicator to the operator when the vehicle is in autonomous mode; a system to alert the operator of malfunctions; a human operator present to monitor the vehicle's performance; and directions for the Department of Motor Vehicles of the state to create rules for testing.

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

VEHICLE CHARACTERISTICS

In the US market, there are three prominent companies currently developing RADRs. These companies are: Nuro, based in Mountain View, California; Udelv, based in Burlingame, California; and Ford's AutoX, based in San Jose, California. The vehicles each of these companies are prototyping are very different and are shown in Figure 1.

Nuro's vehicle is a driverless car-like vehicle, with two large main compartments with doors that swing upwards to release delivery items. Nuro advertises that its vehicles will soon be able to travel at up to 35 mph (*20*), it cannot use freeways, but can use city streets, and will be able to carry up to 20 grocery bags. Nuro claims that the robot weighs 680 kilograms and can carry 110 kilograms of products. The robot is about the same size as a small conventional American car, except for the width; it is about half of the width of a standard car, at about 3 feet wide (*21*). As of December 2018, Nuro's vehicle was being tested by a Kroger grocery store in Phoenix, Arizona, where the vehicle traveled up to 1 mile from the store (*22*). Using the same assumptions made in Jennings and Figliozzi (*9*), we assume that 20 grocery bags equate to 40 parcels, and in turn, the Nuro vehicle could deliver to 40 customers (*23*).

The Udelv vehicle is a modified Ford Transit Connect, which has 32 individual compartments to store delivery items. The Ford Transit Connect can travel at up to 60 mph (*24*), with a range of 60 miles before recharging, and a carrying capacity of 1,300 pounds (*25*). The Udelv team has modified this van to allow individual compartments to be opened one at a time, which would prevent theft of other delivery parcels.

Finally, Ford's AutoX RADR is based on a Lincoln MKZ hybrid vehicle, which can travel at up to 80 mph, weighs slightly less than the Udelv vehicle, and has a large range when using gasoline and electric lithium-ion batteries (*26*). Ford has outfitted these vehicles to use the trunk for carrying parcels, and the passenger side rear window has been modified to be a beverage dispensary, where customers can select from a choice of items to take, in addition to their order (*27*). These three vehicles' specifications are provided in Table 1.

TABLE 1 RADRs in the US market as of June 2019

RADR & Company	**Capacity, parcels/volume**	**Capacity, lb (kg)**	**Max Speed, mph (kph)**	**Dimensions L*W*H, in (m)**	**Vehicle Weight, lb (kg)**	**Range, mi (km)**
Nuro	40	243 (110)	35 (56)	120*36*84 (3.05*0.91*2.13)	1,499 (680)	2 (3.2)
Udelv	32	1300 (590)	60 (97)	174-190*72*72 (4.42-4.83*1.83*1.83)	4,167 (1890)	60 (97)
AutoX	11.1 ft^3 (0.31 m^3)	Unknown	80 (129)	194*73*58 (4.93*1.85*1.47)	3,900 (1769)	560 (901)

It is assumed that in all cases deliveries can be performed without a driver, for example, the RADR is only dispatched if the customers confirm utilizing a smartphone that they can meet the vehicle at a specific location in a similar way customers currently meet ridesharing services.

METHODOLOGY

In this section, the methodology used for comparing conventional (or standard) vans with Udelv's RADR is presented. The methodology is based on continuous approximations. As indicated by Daganzo et al. (*28*), these types of analytical approximations are "particularly well suited to address big picture questions" because they are parsimonious and tractable, yet realistic when the main tradeoffs are included. This type of modeling approach has been successfully used in the past by many authors to model urban deliveries and key tradeoffs of new technologies (*29*).

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

$n =$ Total number of customers served
$k_l =$ Routing constraint (constant value), representing non-Euclidean travel on sidewalks and roads
$a =$ Area (units length squared) of the service area, where n customers reside
$\delta = n/a$, customer density
d = Distance between the depot and the geometric center of the service area
$T =$ Maximum duration of shift or tour (same for all vehicle types)

$l_i(n) =$ Average distance a vehicle travels to serve n customers for vehicle type i
$m_i =$ Minimum number of vans for vehicle type i
$R_i =$ Range of a vehicle for vehicle type i
$Q_i =$ Capacity of a vehicle (number of parcels) for vehicle type i
$\tau_i =$ Total van time necessary to make n deliveries for vehicle type i

$\phi =$ Stop percentage (percent of the time a vehicle is stopped due to traffic control)
$s' =$ Average speed of the vehicle while delivering in the service area, not including ϕ
$s'_h =$ Average speed of the vehicle while traveling to and from the service area, not including ϕ
$s = s'(1-\phi) =$ Average speed of the vehicle while delivering in the service area
$s_h = s'_h(1-\phi) =$ Average speed of the vehicle while traveling to and from the service area
$t_0 =$ Time it takes to wait for the customer to pick up their order from the vehicle or delivery person
$t_u =$ Time it takes the vehicle and/or driver to unload the delivery
$t = t_0 + t_u =$ Total time vehicle is idle (i.e., not traveling) during a delivery

$c_{h,i} =$ Cost per hour of operating vehicle type i, including cost of a driver if applicable
$c_{d,i} =$ Cost per delivery for vehicle type i

To compare RADRs and conventional vans, we must be able to calculate time, distance, and cost for each vehicle, given the same delivery problem and the constraints inherent to each delivery technology. The average distance $l(n)$ to serve n customers can be estimated as a function of customer density, number of vehicles, network characteristics and route constraint coefficients, and the distance between the depot and the delivery area (*30*). In this paper, the equation used to calculate the distance traveled to visit n customers by a conventional van is:

$$l_i(n) = 2d + k_l\sqrt{an} \tag{1}$$

FIGURE 1 RADRs: Nuro (*23*), Udelv (*24*), and AutoX (*27*) (from top to bottom)

In equation (1), d represents the average distance from the depot or distribution center (DC) to the customer(s). The parameter d is multiplied by two, the number of times the vehicle goes to and from the service or delivery area (SA). The parameter k_l is a constant value representing network characteristics and routing constraints in the SA (*30*). The average area (mi^2) of the SA where customers are located is represented by a. The number of parcels or stops is represented by n. The average area (mi2) of the SA where customers are located is represented by a. The number of parcels or stops is represented by n.Therefore, the first term of Equation 1 represents the average distance traveled to and from the SA while the second term represents the distance traveled within the service area between customers. This equation based on continuous approximations has been validated empirically (30) and continuous approximations have been used in numerous freight and logistics research efforts and publications (29).

Another important number to consider when dealing with last mile deliveries is the time it takes to make n deliveries. A formula that can be used to calculate the route duration time accounting not only for driving time but also waiting for the customer and unloading the parcels is (*31*):

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

Conventional Vans

In equation (2), the first term represents the driving time and the second term represents the time it takes to park, wait for or go to the customer and unload the parcels. To determine the maximum number of deliveries that can be made by the conventional van within a shift of duration T, equation (1) is plugged into equation (2) and solved for n when the available time is T. The resulting equation for the maximum number of customers that a conventional van can deliver is:

$$n = \left\lfloor \frac{k_l^2 a + 2s^2Tt - \frac{4ds^2t}{s_h} - k_l^2\sqrt{\left(\frac{4ds^2t}{k_l^2 s_h} - \frac{2s^2Tt}{k_l^2} - a\right)^2 - \frac{4t^2s^2}{k_l^2}\left(\frac{s^2T^2}{k_l^2} + \frac{4d^2s^2}{k_l^2 s_h^2} - \frac{4s^2Td}{k_l^2 s_h}\right)}}{2s^2t^2} \right\rfloor \tag{3}$$

Equation 3 provides the maximum number of customers n that can be served with one conventional van when any parameter changes (for example when t, d, and a change). Hence, each value of n provided in the tables represent the maximum number of customers that can be served by one conventional van given a set of parameter values. The floor function is used in equation (3) to avoid a fractional number of customers. In turn, the customer density, δ, also may change. The conventional van's capacity, range, and constraints (4) are as follows:

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

$$2d + k_l\sqrt{an} \leq R_C \tag{4}$$

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

RADRs

To compare the performance of a RADR against a conventional van, it is necessary to estimate the minimum number of RADRs necessary to deliver to n customers while satisfying delivery constraints. Range constraints are important for RADRs because the range of the Udelv is considerably smaller than the range of a conventional van. Therefore, m_R, the optimum number of RADRs is given by the following optimization problem (5):

Min m_R subject to these constraints

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

$\frac{2d}{s_h} + \frac{k_l\sqrt{an}}{s\sqrt{m_R}} + (t_0 + t_u)\frac{n}{m_R} < T_R$, and

$m_R \geq \lceil\frac{n}{Q_R}\rceil$ and $m_R \in \mathbb{N}$ (5)

Delivery Costs

The cost per delivery for any delivery method is calculated taking two aspects into account—the cost of time of each vehicle (including driver if appropriate) and the number of vehicles that are required. The transportation cost per delivery is estimated by finding the total cost for all deliveries and dividing by the number of deliveries, as follows:

$$c_{d,i} = \frac{c_{h,i}\ \tau_i\ m_i}{n} \tag{6}$$

Note that τ_i ($\tau_i \leq T$) is the tour time and n is the total number of parcels delivered, as defined in equation (3).

DATA AND SCENARIO DESIGN

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

Vehicle Characteristics

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

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

Table 2 below provides the assumptions for variables used in this case study analysis for both Udelv and conventional vans. This table has several assumptions regarding vehicle characteristics and several sources for other characteristics. The following variables have assumed values for both vehicles: T, s', s_h',

k_l, and ϕ. Additionally, the conventional van is assumed to have no significant range limitations and capacity limit of 200.

The range and capacity of the Udelv van were taken from an article discussing the latest revision of the Udelv vehcile (*24*), which claims that the vehicle has a range of 60 miles and has capacity to make 32 deliveries.

TABLE 2 Default values for variables used in calculations

Variable	Description of Variable	Units	Udelv Van	Conventional Van
T	shift time (max)	hours	10[1]	10[1]
R_i	range of vehicle (max)	miles (km)	60 (96.6)[3]	n/a[1]
Q_i	capacity (max)	unitless	32[3]	200[1]
$c_{h,i}$	cost per hour of operation	USD	30[4]	40[4]
s'	full unlimited vehicle speed in service area	mph (kph)	30 (48.3)[1]	30 (48.3)[1]
s'_h	full unlimited vehicle speed between DC and SA	mph (kph)	60 (96.6)[1]	60 (96.6)[1]
s	vehicle speed in service area	mph (kph)	21 (33.8)[2]	21 (33.8)[2]
s_h	vehicle speed on between DC and SA	mph (kph)	42 (67.6)[2]	42 (67.6)[2]
k_l	routing constraints	unitless	0.7[5]	0.7[5]
ϕ	stopping b/c traffic/signals	unitless	0.3[1]	0.3[1]

[1] Value approximated by authors utilizing average consumption and fuel tank size.
[2] Calculated value, [3] from ref. (*24*), [4] from ref. (*32*), and [5] from ref. (*9*)

Vehicle Costs

While autonomous vehicles are beginning to be tested across the United States, the costs associated with manufacturing autonomous vehicle are still significantly higher than those of conventional vehicles.

Based on a 2015 estimate, the additional cost of including the Light Detection and Ranging (LIDAR) sensors to allow a vehicle to be fully autonomous (level 4+) is $30,000 to $85,000 per vehicle, and over $100,000 per vehicle for LIDAR and other sensors and software. The cost of automation equipment for mass-produced autonomous vehicles could eventually fall between $25,000 and $50,000 per vehicle. Once market share of autonomous vehicles becomes at least 10%, the cost of automation equipment could lower to $10,000 per vehicle. The price of implementing automation about 20 to 22 years after introduction is expected to be $3,000 per vehicle, eventually reaching a low of $1,000 to $1,500 per vehicle (*2*).

Short and Murray (*3*) estimate that Level 3 of automation for long-haul trucks may cost around $30,000. In this research, it is assumed that RADRs are operating at Level 5. According to the NHTS (*17*), Level 3 is also called "Condition Automation" when all tasks can be controlled by the autonomous system in some specific (easier) situations, but the human driver must be ready to take back control at any time. Level 5 is called "Full Automation" and in this case, the autonomous system can handle all roadway conditions and environments, i.e. drivers are not needed.

Outwater and Kitchen (*32*) indicate that trucking values of time may range from $25–$73/hour and they utilize a value of $40/hour for small trucks. We assumed a cost of $40/hour as the base cost for conventional vans because these require a human driver. It was not possible to find the cost of production of the Udelv vehicles. The $30/hr operating cost of a RADR is obtained from the cost given by Outwater and Kitchen (*32*) but without labor costs and then adding a 15% increase for the more expensive autonomous vehicle technology. This percentage is approximately the additional cost of autonomous vehicles given by Fagnant and Kockelman (*2*).

RESULTS

Multiple scenarios are created by varying three key variables—time per delivery, service area, and distance between the depot and the service areas. These parameters are denoted by t, a, and d respectively, and only one parameter is varied at a time. Results are reported in Tables 3 to 5. The default values for these parameters are 3 minutes, 100 mi^2 (259 km^2), and 10 miles (16.1 km) respectively.

The results of varying total delivery time t are shown in Table 3. As time t changes, there is a change in the number of customers served (utilizing equation (3)), as well as the delivery density and in some cases, a change in m_R—the RADR fleet size. There are some noteworthy trends: (i) more RADRs than conventional vans are required in most scenarios, (ii) conventional vans generate less vehicle miles per delivery, (iii) conventional vans spend less time per delivery and (iv) the cost per delivery is lower in all cases when RADRs are utilized near the depot (i.e. when the range constraint is not binding) or when conventional delivery times are relatively long.

The results of varying the area of service a are shown in Table 4. As a decreases, there is a rapid increase in the number of customers served (utilizing equation (3)) as well as the delivery density. The RADR fleet size is higher than in Table 4, as a higher number of customers can be served with a conventional van when the density is high. The trends (i) to (iv) observed in Table 3 are maintained but the differences between RADRs and conventional vans have increased. For example, with the highest density of 16.3 customers per $mile^2$ (6.9 cust/km^2) the number of miles driven by RADRs have increased threefold. However, the cost per delivery is lower in all cases when RADRs are utilized.

The results of varying depot–service area distance d are shown in Table 5. As d increases, there is also a rapid decrease in the number of customers served (utilizing equation (3)) as well as the delivery density. The RADR fleet size is also larger in Table 5 than in Table 3. The differences regarding vehicle-miles are larger, for example with the highest distance of 24 miles (38.8 km) the number of miles driven by RADRs increases more than threefold. Unlike previous tables, the cost per delivery is not always lower when RADRs are utilized. There is a breakeven point when the distance d is around 12–15 miles. For RADRs distance driven and fleet size increases rapidly for large values of d and this is caused by the relatively low RADR range.

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

Figure 2 below plots Tables 3, 4, and 5 utilizing the varying variable on the x-axis of each graph and the VMT, time, or cost per delivery on the y-axis. In all of these graphs, lower numbers on the y-axis can be interpreted as the better vehicle option for that combination of varying variable and resulting metric.

To illustrate the importance of an additional time penalty for delivery, Table 6 shows the results when the conventional van delivers on *t* minutes but the RADR delivers on $t + 3$ (min). Vehicle-miles are significantly lowered when a conventional van is utilized. Unlike Table 3, the RADR does not dominate in terms of cost per delivery. In Table 6, the conventional van is more economical up to the point when $t = 9$ minutes for the conventional van and $t = 12$ minutes for the Udelv.

TABLE 3 Results of Varying t

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

TABLE 4 Results of Varying a

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

TABLE 5 Results of Varying d

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

TABLE 6 Results of Varying t with +3 (min) penalty for Udelv

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

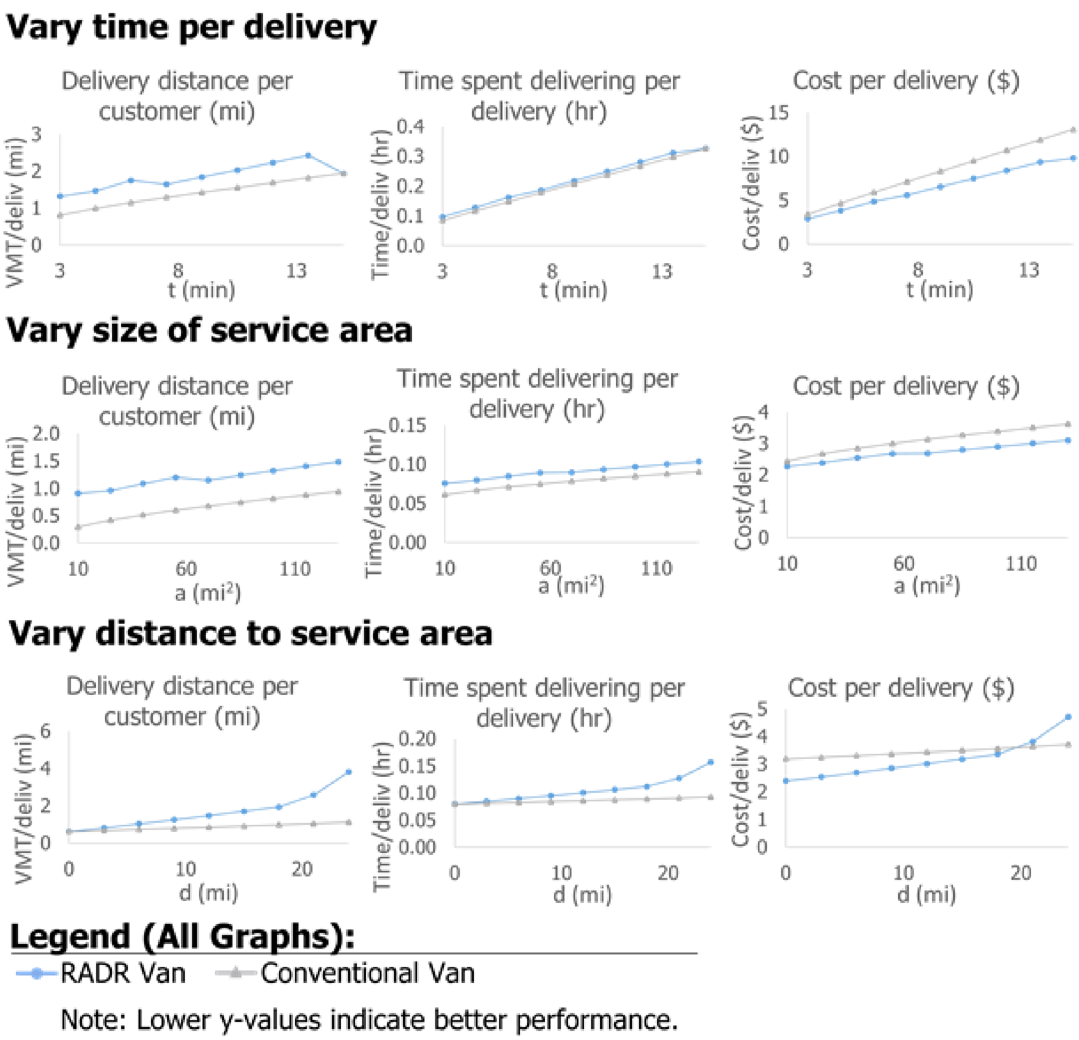

FIGURE 2 Graphical Representation of Results from Tables 3, 4, & 5

DISCUSSION

RADRs are more competitive than conventional vans but are mostly limited by their short range and limited storage capacity. The short range can be addressed by more and better batteries. Though this would be at the expense of additional vehicle weight and cost, batteries are one of the major barriers to the electrification of freight (*33*).

The largest uncertainties related to RADRs are perhaps the cost and regulatory barriers. The rate and speed of adoption of RADRs will greatly depend on the costs and ease of entry into the delivery market, as discussed by previous studies focusing on the adoption of autonomous trucks by freight organizations (*34; 35*). It is assumed that packages transported are small, as Amazon reported most packages delivered are less than 5 pounds (*36*). If larger packages are considered, then RADR vans may not be a feasible option since a driver or other type of equipment would be necessary for the delivery. This is an important limitation and indicates that full automation would not be easily achieved for special or more cumbersome deliveries and efficiency of autonomous vehicles can be reduced when delivery time windows are narrow (37).

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

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

CONCLUSIONS

Assuming current RADR characteristics, this research has shown that road automated delivery robots have the potential to reduce delivery costs in many scenarios. Hence, it is likely that delivery companies will try to implement this cost-saving technology to meet growing ecommerce demands. Given the relatively limited range of RADRs and the limited number of individual storage compartments, these automated vehicles are less competitive when route distances are long or with many customers. A potentially noteworthy drawback for RADRs' cost competitiveness is longer delivery times per customer due to safety concerns and/or numerous interactions with traffic, pedestrians, and/or cyclists.

From a public policy perspective, the utilization of RADRs may significantly increase the number of vehicle-miles related to package delivery. The scenarios analyzed indicate that RADRs generate more vehicle-miles per delivery than conventional vans (substantially more in many scenarios). As a secondary effect, new delivery/service models (anytime/anywhere) plus a reduction in delivery costs brought about by a large-scale introduction of RADRs may further increase the already high growth of ecommerce. The combination of higher vehicle-miles per delivery plus the growth of ecommerce can compound congestion and high curb utilization problems in many urban areas.

This research is the first step to understanding the key tradeoffs between road automated delivery robots and conventional vans. Although many scenarios have been studied there is still a lot of uncertainty regarding future RADR costs and regulations. As many companies are moving towards same day and even shorter delivery windows, future researchers should consider the performance of RADRs in scenarios with narrower delivery windows (one or two hours). Additionally, more extensive sensitivity analyses including other parameters such as costs, speed, range, and capacity would be necessary as data become available. Second order effects such as additional or induced demand due to reductions in delivery costs is another area that should be considered in future research efforts. In particular regarding potential externalities of automated deliveries, but also potential benefits such as the reduction of VMT figures associated to grocery/shopping trips.

ACKNOWLEDGEMENTS

This research project was funded by the Freight Mobility Research Institute (FMRI), a U.S. DOT University Transportation Center.

AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows:
Study conception and design: M. Figliozzi
Data collection: D. Jennings, M. Figliozzi
Analysis and interpretation of results: M. Figliozzi, D. Jennings
Draft manuscript preparation: D. Jennings, M. Figliozzi
All authors reviewed the results and approved the final version of the manuscript.
Sirisha Vegulla proofread the manuscript.

REFERENCES

1. U.S. Department of Commerce [Internet]. Quarterly E-Commerce Report 1st Quarter 2018. Publication CB18-74. Washington, D.C.: U.S. Department of Commerce; 2018 [cited 2019 Mar 1]. Available from: https://www2.census.gov/retail/releases/historical/ecomm/18q1.pdf
2. Fagnant DJ, Kockelman K. Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. Transportation Research Part A: Policy and Practice. 2015;77:167–181.
3. Short, J. and Murray, D. Identifying autonomous vehicle technology impacts on the trucking industry. American Transportation Research Institute [Internet]. Arlington, Virgina, USA: American Transport Research Institute. 2016 [cited 2019 Jul 1]. Available from: http://atri-online.org/wp-content/uploads/2016/11/ATRI-Autonomous-Vehicle-Impacts-11-2016.pdf
4. Aboulkacem E, Combes F. May autonomous vehicles transform freight and logistics. Presented at 99th Annual Meeting of the Transportation Research Board, Washington, D.C., 2020.
5. Flämig H. Autonomous vehicles and autonomous driving in freight transport. Autonomous Driving [Internet]. Berlin, Heidelberg: Springer. 2016:365-385 [cited 2020 May 9]. Available from: https://link.springer.com/chapter/10.1007/978-3-662-48847-8_18 DOI: https://doi.org/10.1007/978-3-662-48847-8_18
6. Kristoffersson I, Pernestål BA. Scenarios for the development of self-driving vehicles in freight transport. In Proceedings of 7th Transport Research Arena TRA 2018, April 16–19, 2018, Vienna, Austria. [Internet] Zenodo. 2018 [cited 2019 Jul 15]. Available from: http://www.diva-portal.se/smash/get/diva2:1269611/FULLTEXT01.pdf
7. Slowik P, Sharpe B. Automation in the long haul: Challenges and opportunities of autonomous heavy-duty trucking in the United States. The International Council of Clean Transportation [Internet]. 2018:1–30 [cited 2019 Jul 1]. Available from: https://theicct.org/sites/default/files/publications/Automation_long-haul_WorkingPaper-06_20180328.pdf
8. Viscelli S. Driverless? Autonomous trucks and the future of the American trucker. Berkeley, California: Center for Labor Research and Education, University of California, Berkeley, and Working Partnerships USA [Internet]. 2018 [cited 2019 Jun 20]. Available from: http://driverlessreport.org/files/driverless.pdf
9. Jennings D, Figliozzi M. Study of sidewalk autonomous delivery robots and their potential impacts on freight efficiency and travel. TRR: J of the TRB. 2019;2673(6):317-326.
10. Vleeshouwer T, van Duin J, Verbraeck A. Implementatie Van Autonome Bezorgrobots Voor Een Kleinschalige Thuisbenzorgdienst. ResearchGate, [Internet]. 2017 [cited 2018 Nov 1]. Available from: https://www.researchgate.net/publication/320451527_Implementatie_van_autonome_bezorgrobots_voor_een_kleinschalige_thuisbezorgdienst [cited 1 Nov. 2018]. Dutch.
11. Hoffmann T, Prause G. On the regulatory framework for last-mile delivery robots. Machines [Internet] 2018;6(3):33 [cited 2020 May 9]. Available from: https://www.mdpi.com/2075-1702/6/3/33 DOI: https://doi.org/10.3390/machines6030033
12. Boysen N, Schwerdfeger S, Weidinger F. Scheduling last-mile deliveries with truck-based autonomous robots. European Journal of Operational Research [Internet]. 2018;271(3):1085-1099 [cited 2020 May 9]. Available from: https://www.sciencedirect.com/science/article/abs/pii/S0377221718304776 DOI: https://doi.org/10.1016/j.ejor.2018.05.058

13. Baldi M, Manerba D, Perboli G, Tadei, R. A generalized bin packing problem for parcel delivery in last-mile logistics. European Journal of Operational Research [Internet]. 2019;274(3):990–999 [cited 2020 May 9]. Available from: https://www.sciencedirect.com/science/article/pii/S037722171830924X DOI: https://doi.org/10.1016/j.ejor.2018.10.056
14. Sonneberg MO, Leyerer M, Kleinschmidt A, Knigge F, Breitner M. Autonomous unmanned ground vehicles for urban logistics: optimization of last mile delivery operations. In Proceedings of the 52nd Hawaii International Conference on System Sciences [Internet]. Wailea, Hawaii, USA: IEEE. 2019:1538–1547 [cited 2019 Jul 1]. Available from: http://hdl.handle.net/10125/59594
15. Deng P, Amirjamshidi G, Roorda M. A vehicle routing problem with movement synchronization of drones, sidewalk robots, or foot-walkers. Proceedings XI International Conference on City Logistics, Dubrovnik, Croatia. 2019.
16. Moeini M, Salewski H. A genetic algorithm for solving the truck–drone–ATV routing problem. In Le Thi H., Pham Dinh T. (eds) Optimization of Complex Systems: Theory, Models, Algorithms and Applications [Internet]. WCGO 2019. Advances in Intelligent Systems and Computing. SpringerLink, Cham. 2020;991:1023–1032 [cited 2019 Jul 1]. Available from: https://link.springer.com/chapter/10.1007/978-3-030-21803-4_101.
17. National Highway Traffic Safety Administration. Automated vehicles for safety [Internet]. Washington, D.C., USA: U.S. Department of Transportation. 2019 [cited 2019 Jun 16]. Available from: https://www.nhtsa.gov/technology-innovation/automated-vehicles-safety
18. Anderson J, Kalra N, Stanley K, Sorensen P, Samaras C, Oluwatola T. Autonomous vehicle technology: a guide for policymakers. Santa Monica, California: RAND Corporation. 2016 [cited 2019 Jun 16]. Available from: https://www.rand.org/pubs/research_reports/RR443-2.html
19. National Conference of State Legislatures. Autonomous vehicles state bill tracking database [Internet]. Washington, D.C., USA: NCSL. 2019 [cited 2019 Jun 16]. Available from: http://www.ncsl.org/research/transportation/autonomous-vehicles-legislative-database.aspx
20. Lee T. Self-driving technology is going to change a lot more than cars. ArsTechnica [Internet]. 2018 [cited 2019 Jun 16]. Available from: https://arstechnica.com/cars/2018/05/self-driving-technology-is-going-to-change-a-lot-more-than-cars/3/
21. 2025AD Team. Driverless delivery: when a robot brings your pizza. 2025AD [Internet]. 2018 [cited 2019 Jun 16]. Available from: https://www.2025ad.com/latest/driverless-delivery-when-a-robot-brings-your-pizza/.
22. Bussewitz C. Driverless cars deliver from Kroger-owned store in Arizona. Transport Topics [Internet]. 2018 [cited 2019 Jun 16]. Available from: https://www.ttnews.com/articles/driverless-cars-deliver-kroger-owned-store-arizona
23. Davies A. Get yer bread and milk from Kroger's cute new delivery robot. Wired [Internet]. 2018 [cited 2019 Jun 16]. Available from: https://www.wired.com/story/nuro-grocery-delivery-robot/
24. Goodwin A. Udelv announces second-generation Newton autonomous delivery van at CES 2019. Road Show by CNET [Internet]. 2019 [cited 2019 Jun 16]. Available from: https://www.cnet.com/roadshow/news/udelv-announces-second-generation-newton-autonomous-delivery-van-ces-2019/.
25. Straight B. Udelv to begin autonomous last-mile delivery pilot in Houston. Freight Waves [Internet]. 2019 [cited 2019 Jun 16]. Available from: https://www.freightwaves.com/news/autonomous-trucking/udelv-truck-to-begin-pilot

26. AutoX Team. AutoX technical series 1: camera-first perception. AutoX [Internet]. 2018 [cited 2019 Jun 16]. Available from: https://medium.com/autox/autox-technical-series-1-camera-first-perception-f9d01acb8430
27. Kwoka-Coleman M. Using autonomous vehicles for grocery delivery. BusinessFleet [Internet]. 2019 [cited 2019 Jun 16]. Available from: https://www.businessfleet.com/323140/were-learning-very-quickly-using-autonomous-vehicles-for-grocery-delivery
28. Daganzo C, Gayah V, Gonzales E. The potential of parsimonious models for understanding large scale transportation systems and answering big picture questions. EURO Journal on Transportation and Logistics. 2012;1(1-2):47–65.
29. Ansari S, Başdere M, Li X, Ouyang Y, Smilowitz K. Advancements in continuous approximation models for logistics and transportation systems: 1996–2016. Transportation Research Part B: Methodological. 2018;107:229-252.
30. Figliozzi M. Analysis of the efficiency of urban commercial vehicle tours: data collection, methodology, and policy implications. Transportation Research Part B: Methodological. 2007;41(9)1014-1032.
31. Figliozzi M. The impacts of congestion on commercial vehicle tour characteristics and costs. Transportation Research Part E: Logistics and Transportation Review. 2010;46(4):496–506.
32. Outwater M, Kitchen M. Value of time for travel forecasting and benefit analysis. [memo]. 2008 [cited 2018 Jul 28]. Available from: https://www.psrc.org/sites/default/files/valueoftimememo-updated.pdf
33. Feng W, Figliozzi M. An economic and technological analysis of the key factors affecting the competitiveness of electric commercial vehicles: A case study from the USA market. Transportation Research Part C: Emerging Technologies. 2013;26:135–145.
34. Talebian A, Mishra S. Predicting the adoption of connected autonomous vehicles: A new approach based on the theory of diffusion of innovations. Transportation Research Part C: Emerging Technologies. 2018;95:363–380.
35. Simpson J, Mishra S, Talebian A, Golias M. An estimation of the future adoption rate of autonomous trucks by freight organizations. Forthcoming Research in Transportation Economics. 2019.
36. Pierce D. Delivery drones are coming: Jeff Bezos promises half-hour shipping with Amazon Prime Air. The Verge [Internet]. 2013 [cited 2018 Jul 22]. Available from: https://www.theverge.com/2013/12/1/5164340/delivery-drones-are-coming-jeff-bezos-previews-half-hour-shipping
37. Figliozzi MA. Analysis of the efficiency of urban commercial vehicle tours: Data collection, methodology, and policy implications. Transportation Research Part B: Methodological. 2007 Nov 1;41(9):1014-32.