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

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Abstract

Road autonomous mobile robots have attracted the attention of delivery companies and policy makers owing to their potential to reduce costs and increase urban freight efficiency. Established delivery companies and new startups are investing in technologies that reduce delivery times, increase delivery drivers' productivity, or both. 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 U.S. 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.

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*). Autonomous delivery robots (ADRs) are equipped with sensors and navigation technology which allows them to travel on roads and sidewalks without a driver or on-site delivery staff.

Some researchers such as Fagnant and Kockelman have extensively studied the potential of autonomous vehicles for passenger transportation (*2*). In comparison, significantly less studies have focused 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 discussed the effect of long-haul autonomous trucks on hours-of-service, safety, driver shortage and driver retention, truck parking, driver health and wellness, and the economy (*3*). Aboulkacem and Combes studied the effect of long-haul autonomous trucks utilizing an economic model and scenarios with and without full automation, and found that full automation is likely to produce more truck volumes and a decrease in shipment sizes (*4*).

Flämig presented a history of automation in the freight sector by analyzing four cases of automation in the freight industry and the potential applications (*5*). With regards to urban deliveries, Flämig 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 (*5*). Kristoffersson et al. discussed 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 (*6*). For urban areas, Kristoffersson et al. 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 (*6*). Slowik and Sharpe studied the potential of autonomous technology to reduce fuel use and emissions for heavy-duty freight vehicles (*7*). The work of Viscelli analyzed the effect of ADRs on the U.S. labor market (*8*).

There are significantly less studies focusing on urban deliveries or short-haul freight trips. Jennings and Figliozzi recently studied the potential of sidewalk

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autonomous delivery robots (SADRs) (*9*). Given the relatively short range of SADRs, these small robots are usually complemented by a "mothership" van that can transport SADRs close to the delivery zone or service area. Vleeshouwer et al. utilized simulations to study a small bakery robot delivery service in the Netherlands (*10*). Other researches have analyzed the shortcomings of current regulations for delivery robots (*11*). Another line of research has focused on the optimal wayfinding of ADRs or optimizing the joint scheduling of both trucks and ADRs; some of the research in this field has been conducted by Boysen et al., Baldi et al., Sonneberg et al., Deng et al., and Moeini et al. (*12–16*).

The key contributions of this research are: (a) an analysis of the characteristics and regulation of RADRs in the U.S.; 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 on-road autonomous delivery robot (RADR) regulations and characteristics is limited to the U.S. 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

As 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 on. The U.S. federal government has only outlined suggested legislation for 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 U.S. were Nevada, California, Florida, and Washington D.C. (*18*). All of the regulations for these states' 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' (NCSL) Autonomous Vehicles State Bill Tracking Database has the most up-to-date information on legislation for each state (*19*). According to the NCSL, as of March 2019, ten additional states had pending legislation in 2014 and have already enacted legislation with regards to 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 U.S. 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, it cannot use freeways, but can use city streets, and will be able to carry up to 20 grocery bags (*23*). Nuro claims that the robot weighs 680 kg and can carry 110 kg 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 ft wide (*24*). 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 mi from the store (*25*). Using the same assumptions made in Jennings and Figliozzi, we assume that 20 grocery bags equates to 40 parcels, and in turn, the Nuro vehicle could deliver to 40 customers (*9, 20*).

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 (*21*), with a range of 60 mi before recharging, and a carrying capacity of 1,300 lb (*26*). 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 (*27*). 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,

Figure 1. Road autonomous delivery robots: (*from top to bottom*) Nuro (*20*), Udelv (*21*), and AutoX (22).

where customers can select from a choice of items to take, in addition to their order (*22*). These three vehicles' specifications are provided in Table 1.

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, by utilizing a smartphone, that they can meet the vehicle at a specific location in a similar way to how 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., these types of analytical approximations are "particularly well suited to address big picture questions" because they are parsimonious and tractable, yet realistic if the main tradeoffs are included (*28*). This type of modeling approach has been successfully used in the past by many authors to model urban deliveries and the 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, in which 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 owing 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, driver, or both 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 the time, distance, and cost for each

Table 1. RADRs in the U.S. Market as of June 2019

RADR and 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	1,300 (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)

Note: RADR = on-road autonomous delivery robots; Max. = maximum; mi = miles.

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:

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

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 in which customers are located is represented by a. The number of parcels or stops is represented by n. The average area (mi^2) of the SA in which 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 and the second term represents the distance traveled within the service area between customers. This equation based on continuous approximations has been validated empirically and continuous approximations have been used in numerous freight and logistics research efforts and publications (*29, 30*).

Another important number to consider if 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 if the available time is T. The resulting equation for the maximum number of customers that a conventional van can deliver is:

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

Equation 3 provides the maximum number of customers n that can be served with one conventional van if any parameter changes (for example when t, d, and a change). Therefore, 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, may also change. The conventional van's capacity, range, and constraints (Equation 4) are as follows:

$$m_C \geqslant \left\lceil \frac{n}{Q_C} \right\rceil \qquad 2d + k_l\sqrt{an} \leqslant R_C \tag{4}$$

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 the 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 (Equation 5):

Minimum m_R subject to these constraints

$$\frac{k_l\sqrt{an}}{\sqrt{m_R}} + 2d > R_R$$
$$\frac{2d}{s_h} + \frac{k_l\sqrt{an}}{s\sqrt{m_R}} + (t_0 + t_u)\frac{n}{m_R} > T_R \text{ , and} \tag{5}$$
$$m_R \geqslant \left\lceil \frac{n}{Q_R} \right\rceil \text{ and } m_R \in \mathbb{N}$$

Delivery Costs

The cost per delivery for any delivery method is calculated by taking two aspects into account—the cost of time for 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 ($\tau_i \leqslant T$) 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 the RADRs with conventional vans. The total time the vehicle is idle (or not traveling) owing 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 with regards to 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; as parcels are compartmentalized, people can only take parcels intended to be delivered to them. The Udelv vehicle has the capability to travel on highways, but 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 as the carrying capacity is known.

Table 2 below provides the assumptions for variables used in this case study analysis for both the Udelv and conventional vans. This table contains several assumptions about the 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 a capacity limit of 200.

The range and capacity of the Udelv van were taken from an article discussing the latest revision of the Udelv vehicle (*21*), which claims that the vehicle has a range of 60 mi and has capacity to make 32 deliveries.

Vehicle Costs

Although autonomous vehicles are beginning to be tested across the United States, the costs associated with manufacturing autonomous vehicles 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 required 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 to between \$25,000 and \$50,000 per vehicle. Once the market share of autonomous vehicles becomes at least 10%, the cost of automation equipment could reduce to \$10,000 per vehicle. The price of implementing

Table 2. Default Values for Variables Used in Calculations

Variable	Description of variable	Units	Udelv van	Conventional van
T	shift time (max.)	hours	10[a]	10[a]
R_i	range of vehicle (max.)	miles (km)	60 (96.6)[c]	695 (1118)[a]
Q_i	capacity (max.)	unitless	32[c]	200[a]
$c_{h,i}$	cost per hour of operation	USD	30[d]	40[d]
s'	full unlimited vehicle speed in service area	mph (km/h)	30 (48.3)[a]	30 (48.3)[a]
s'_h	full unlimited vehicle speed between DC and SA	mph (km/h)	60 (96.6)[a]	60 (96.6)[a]
s	vehicle speed in service area	mph (km/h)	21 (33.8)[b]	21 (33.8)[b]
s_h	vehicle speed on between DC and SA	mph (km/h)	42 (67.6)[b]	42 (67.6)[b]
k_l	routing constraints	unitless	0.7[e]	0.7[e]
ϕ	stopping because of traffic/signals	unitless	0.3[a]	0.3[a]

Note: DC = distribution center; SA = service or delivery area; Max. = maximum.
[a]Value approximated by authors utilizing average consumption and fuel tank size.
[b]Calculated value.
[c]From ref. (*21*).
[d]From ref. (*32*).
[e]From ref. (*9*).

automation about 20–22 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 estimate that Level 3 of automation for long-haul trucks may cost around $30,000 (*3*). In this research, it is assumed that RADRs are operating at Level 5. According to the National Highway Traffic Safety Administration (NHTS), 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 (*17*). Level 5 is called "Full Automation" and in this case, the autonomous system can handle all roadway conditions and environments, that is, drivers are not needed.

Outwater and Kitchen indicate that trucking values of time may range from $25 to $73/hour and they utilize a value of $40/hour for small trucks (*32*). 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 was obtained from the cost given by Outwater and Kitchen, but without labor costs and then adding a 15% increase for the more expensive autonomous vehicle technology (*32*). This percentage is approximately the additional cost of autonomous vehicles given by Fagnant and Kockelman (*2*).

Results

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

The results of varying the 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 the 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 if RADRs are utilized close to the depot (i.e., if 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 if 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 customers per km^2) the number of miles driven by RADRs have increased threefold. However, the cost per delivery is lower in all cases if RADRs are utilized.

The results of varying the 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 with regards to vehicle-miles are larger, for example with the highest distance of 24 mi (38.8 km) the number of miles driven by RADRs increases more

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

Note: cust = customer; mi = miles; Convent. = conventional van; $n =$ Total number of customers served; $\delta = n/a$ customer density; $t = t_0 + t_u =$ Total time vehicle is idle (i.e., not traveling) during a delivery.

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

Note: cust = customer; Convent. = conventional van; mi = miles; n = total number of customers served; a = area (units length squared) of the service area, in which n customers reside; $\delta = n/a$ customer density.

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

Note: cust = customer; Convent. = conventional van; mi = miles; n = total number of customers served; $\delta = n/a$ customer density; d = distance between the depot and the geometric center of the service area.

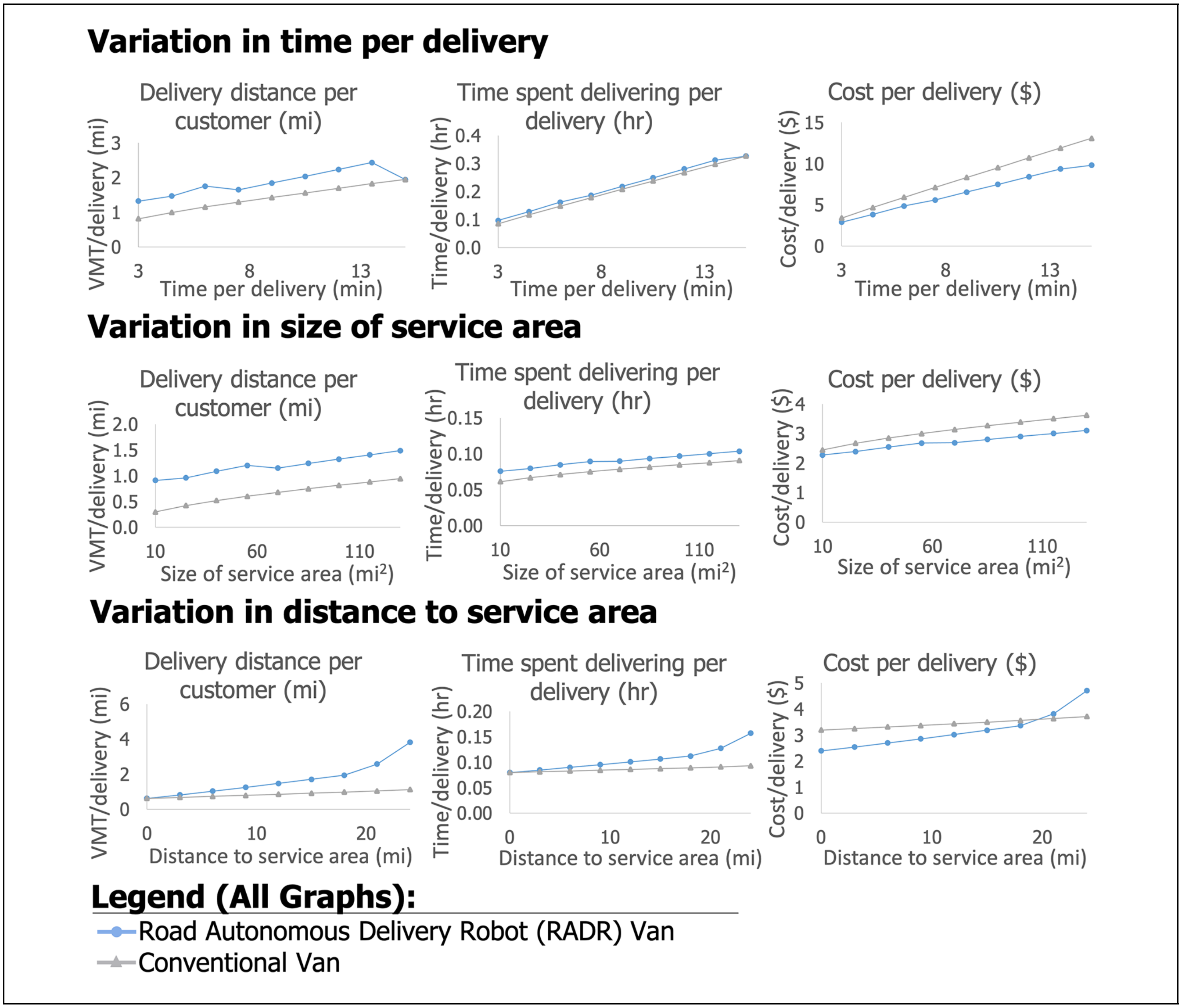

Figure 2. Graphical representation of the results from Tables 3 to 5.
Note: VMT = vehicle miles traveled; mi = miles; min = minutes; hr = hours; $ = United States Dollars.

han threefold. Unlike previous tables, the cost per delivery is not always lower if RADRs are utilized. There is a breakeven point when the distance d is around 12–15 mi. For RADRs the 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 and that urban areas are complex environments with many deliveries/stops and interactions with pedestrians and cyclists (*5,6*). Therefore, 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, cyclists, or both.

Figure 2 plots Tables 3–5 utilizing the varying variable on the x-axis of each graph and the vehicle miles traveled (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 variables and the resulting metric.

To illustrate the importance of an additional time penalty for delivery, Table 6 shows the results if the conventional van delivers in t minutes, but the RADR delivers in $t + 3$ (min). Vehicle-miles are significantly lowered if a conventional van is utilized. Unlike Table 3, the RADR does not dominate with regards to cost per delivery. In Table 6, the conventional van is more economical up to

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

Note: cust = customer; Convent. = conventional van; mi = miles; $n =$ total number of customers served; $\delta = n/a$ customer density; $t = t_0 + t_u =$ total time vehicle is idle (i.e., not traveling) during a delivery.

the point when $t = 9$ minutes for the conventional van and $t = 12$ minutes for the Udelv.

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. Although 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 lb in weight (*36*). If larger packages are considered, then RADR vans may not be a feasible option as 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 the efficiency of autonomous vehicles can be reduced if delivery time windows are narrow (*37*).

The large-scale introduction of RADRs can also bring about new business and service models that are made possible by 24-h operations as autonomous delivery robots are not subject to limitations such as 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 with regards to vehicle-miles per customer visited.

As RADRs deliver freight, they can prioritize the safety of pedestrians and other road users over the safety of the freight being carried by the RADR. Therefore, RADRs are not faced with the potential ethical issues that passenger autonomous vehicles are likely to face with regards to tradeoffs between the safety of passengers and other vulnerable road users, such as pedestrians, cyclists, or both. Owing to 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 with 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 the economic appeal of RADRs as shown in the previous section.

Conclusion

Assuming current RADR characteristics, this research has shown that road automated delivery robots have the potential to reduce delivery costs in many scenarios. Therefore, it is likely that delivery companies will try to implement this cost-saving technology to meet growing E-commerce demands. Given the relatively limited range of RADRs and the limited number of individual storage compartments, these automated vehicles are less competitive if the route distances are long or there are many customers. A potentially noteworthy drawback for the cost competitiveness of RADRs is longer delivery times per customer owing to safety concerns and numerous interactions with traffic, pedestrians, and 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 the large-scale introduction of RADRs may further increase the already high growth of E-commerce. The combination of higher vehicle-miles per delivery plus the growth of E-commerce 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 with regards to future RADR costs and regulations. As many companies are moving toward same day and even shorter delivery windows, future researchers should consider the performance of RADRs in scenarios with narrower delivery windows (1 or 2 h). Additionally, more extensive sensitivity analyses including other parameters such as costs, speed, range, and capacity would be necessary as this data becomes available. Second order effects such as additional or induced demand owing to reductions in delivery costs is another area that should be considered in future research efforts. In particular with regards to the potential externalities of automated deliveries, but also the potential benefits, such as the reduction of VMT figures associated with grocery/shopping trips.

Author Contributions

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.

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