Transportation Research Part A 147 (2021) 320–338

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Empirical analysis of commercial vehicle dwell times around freight-attracting urban buildings in downtown Seattle

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ARTICLE INFO

Keywords:
Urban freight
Delivery
Logistics
Parking
Commercial vehicle

ABSTRACT

Dwell time is defined as the time that delivery workers spend performing out-of-vehicle activities while their vehicle is parked. Restricting vehicle dwell time is widely used to manage commercial vehicle parking behavior. However, there is insufficient data to help assess the effectiveness of these restrictions. This makes it difficult for policymakers to account for the complexity of commercial vehicle parking behavior. The current study aims to identify factors correlated with dwell time for commercial vehicles. This is accomplished by using generalized linear models with data collected from five buildings that are known to include commercial vehicle activities in the downtown area of Seattle, Washington, USA. Our models showed that dwell times for buildings with concierge services tended to be shorter. Deliveries of documents also tended to have shorter dwell times than oversized supplies deliveries. Passenger vehicle deliveries had shorter dwell times than deliveries made with vehicles with roll-up doors or swing doors (e.g., vans and trucks). When there were deliveries made to multiple locations within a building, the dwell times were significantly longer than dwell times made to one location in a building. The findings from the presented models demonstrate the potential for improving future parking policies for commercial vehicles by considering data collected from different building types, delivered goods, and vehicle types.

1. Introduction

With rapid growth and evolution in supply chain practices, cities around the world are experiencing an influx of goods pickup and delivery activities. The additional related traffic has added pressure to already congested urban roads. A popular method for managing commercial vehicle parking behaviors is to restrict vehicle dwell time, which is defined as the time delivery workers spend performing out-of-vehicle activities while the truck is parked. However, there are challenges in managing dwell time restrictions. The high number of commercial parking fines issued in New York City (NYC) is an example of the challenges in managing the current dwell time restrictions. In 2018, the total amount of commercial parking fines in NYC was $181.5 million, with major delivery companies such as FedEx and UPS responsible for 20 to 30 percent of them (Baker, 2019).

Understanding urban freight parking behaviors is particularly difficult because several underlying factors influence vehicle dwell time. Data on such factors are often proprietary to independent private companies, and are therefore, not shared with researchers and city planners. For this reason, most current parking policies overlook the complexity of urban freight parking behaviors. This paper

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https://doi.org/10.1016/j.tra.2021.02.019
Received 1 January 2020; Received in revised form 5 December 2020; Accepted 21 February 2021
Available online 31 March 2021
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aims to provide insights on factors that influence dwell time for commercial vehicles and estimate the magnitude of their influences. Parking characteristics for urban freight deliveries are fundamentally different from commuter parking (Amer and Chow, 2017). Urban freight delivery needs close proximity to destinations and requires more space and time to load and unload goods and to maneuver and park the commercial vehicles (Amer and Chow, 2017). Lengthy dwell time at limited curbside spaces could negatively affect the travel times of other commercial vehicles, searching for parking spaces. Rhodes et al. (2012) noted that quantifying and addressing both horizontal and vertical "last mile" inefficiencies are important from a planning perspective (Rhodes et al., 2012). Kim et al. (2018) introduced a process flow for delivery and pick-up activities inside a building in the Seattle central business district and noted that many factors may affect vehicle dwell time, emphasizing the importance of accounting for the vertical movement in understanding the fundamental aspects of urban goods movement (Kim et al., 2018). The goal of this paper is to identify the factors correlated with commercial vehicle dwell times and quantifying their impacts. This goal was achieved by using a generalized linear regression approach with data collected at five different buildings in downtown Seattle: a residential tower, a hotel, a historical building, an office tower, and a shopping mall. Insights gained from our analysis can be used in the decision making process for urban freight policies in many cities.

2. Literature review

Commercial vehicle dwell time can be examined in terms of the challenges created by the current commercial vehicle parking systems, factors related to dwell time, and ways to improve commercial vehicle parking systems.

2.1. Challenges created by the current commercial vehicle parking systems

With the explosion of the e-commerce market, demands for dedicated delivery services to the end customer have increased rapidly (Morganti et al., 2014). This has resulted in high frequencies of urban freight deliveries in many cities, aggravating the fragmentation of freight flows (Kin et al., 2017). When there are not enough legal parking spaces for commercial vehicles, delivery workers are left with options such as cruising until finding other parking spaces or double-parking in unauthorized areas. A study conducted at a busy commercial street in Istanbul with a high parking occupancy rate showed that a vehicle parked for an hour can cause 3.6 other vehicles to cruise for parking. The authors pointed out that the current calculation for congestion costs does not account for the costs of cruising for parking. The external cruising cost for parking can be estimated as approximately equal to the external congestion cost in one trip, which is a significant contributor to congestion (Inci et al., 2017). Unauthorized parking behavior is another growing issue that is caused by a scarcity of commercial parking spaces in many cities. Parking fines in Toronto have been increased 70 percent between 2006 and 2009, with an estimated $ 2.5 million CAD paid by FedEx, United Parcel Service, and Purolator in 2009 (Nourinejad et al., 2014). In 2018 in NYC, where parking spaces are extremely limited, FedEx and UPS incurred $ 14.9 million and $ 33.8 million respectively in parking fines (Baker, 2019). Studies have shown that the delivery vehicles pay $ 500 to $ 1000 per truck per month for parking fines in New York City (Holguín-Veras et al., 2011). Although parking fines are imposed to discourage unauthorized parking, many delivery companies allocate costs for parking fines as a part of doing businesses in urban areas (Wenneman et al., 2015). In 2013, data collected at over 60 locations in Chicago showed that trucks parked illegally 28.7 percent of the time, far more than 3 percent of illegal parking rate for passenger vehicles (Kawamura and Sriraj, 2016). In 2018, commercial vehicle parking observations in downtown Seattle showed that 40 percent of commercial vehicles (with delivery vehicles constituting the biggest share) parked in unauthorized locations including passenger vehicle loading zones (PLZs), the middle of the road, tow-away zones, and no-parking zones (Girón-Valderrama et al., 2019). With increasing challenges created by commercial vehicle parking systems in cities, it is important to understand the factors correlated with dwell time in order to explore possible improvements to the current parking policies.

2.2. Factors related to commercial vehicle dwell time

Dwell time for commercial vehicles (also referred as parking duration or service time) is not determined by parking management or enforcement policy, but rather by operational constraints (Jaller et al., 2013). It is challenging to obtain detailed data and to account for variations in influencing factors. To better understand the urban freight system, researchers have gathered empirical data on dwell time. Morris (2004) conducted a time and motion study at loading docks at six commercial office buildings in the central business district of New York City (Morris, 2004). Sixty percent of observed deliveries were made in the morning, and the average truck dwell time was found to be 31.5 min, ranging between 22 min and 48 min. Kim et al. (2018) observed an office building in the Seattle central business district that had an average truck dwell time of 20 min, ranging between 9 min and 43 min. The authors further broke down the total truck dwell time into time spent for entering, delivering and exiting, which represented 35 percent (7 min), 40 percent (8 min), 25 percent (5 min), respectively, of the average total truck dwell time (Kim et al., 2018). Cherrett et al. (2012) collected studies in United Kingdom (UK) that studied dwell time for loading and unloading. The mean lengths of dwell time were suggested based on the types of commercial vehicles: 30 min for the average articulated heavy goods vehicle (HGV) delivery, 20 min for rigid HGV delivery, and 10 min for vans and cars (Cherrett et al., 2012).

Allen et al. (2000) identified several factors that influence dwell time, including proximity between the delivery vehicle and final customer, parked location (off-street vs. on-street), type and size of the product, the number of people performing the delivery, and a requirement to receive a signature from the recipient (Allen et al., 2000). Schmid et al. (2018) categorized factors influencing dwell time as intrinsic and extrinsic factors. They defined intrinsic factors as delivery-specific characteristics such as weight, volume, and value of delivered goods; the number of delivery workers; and the number of businesses served (Schmid et al., 2018). Extrinsic factors included environment-dependent characteristics such as parking capacity, accessibility of parking sites, and parking enforcement (Schmid et al., 2018). The authors addressed the difficulties of obtaining intrinsic factors and used only extrinsic factors in their delivery vehicle parking duration study.

Many factors have been shown to affect the dwell time of commercial vehicles. Zou et al. (2016) used the Cox proportional-hazard model to show that arrival time, commodity types, vehicle types, and parking location all affected the on-street parking duration of commercial vehicles in New York City (Zou et al., 2016). Dalla Chiara and Cheah (2017) used the log-normal regression for dwell times in the loading bays of two retail malls in Singapore. Factors that were correlated with dwell time included the percentage of vehicle capacity filled with goods prior to any pick-up/delivery, pick-up activity, the ratio of goods volume to the number of workers, time spent waiting for parking, and delivery vehicle type (Dalla Chiara and Cheah, 2017). Schmid et al. (2018) used a parametric survival model to predict parking duration for commercial vehicles using explanatory variables such as types of vehicles, types of items delivered, legal or illegal parking, and observation locations. Different lengths of dwell times were related to different types of items delivered and types of parking. For example, illegal parking occurred for only a short period of time (Schmid et al., 2018). Based on the past literature, our study included factors that are known to be related to commercial vehicle dwell time as the explanatory variables in the analysis.

2.3. *Efforts to improve commercial vehicle parking*

Cities worldwide have applied various parking policies to improve commercial vehicle parking systems. We explored those policies that involve three major areas of the systems; parking time, spaces, and operations.

2.3.1. *Parking time*

While most commercial vehicle parking limits are between 15 and 30 min (Muñuzuri et al., 2005), dwell times are varied based on individual delivery characteristics. Cities like Seattle and San Francisco are making efforts to measure vehicle dwell times using real-time sensor technology and to improve visibility of available parking spaces through mobile applications (Calvert, 2019). In some cities, commercial parking is restricted to a certain time of day. The New York City Department of Transportation (NYCDOT) is implementing delivery windows in the morning, as 65 percent of deliveries occur before 12:00 PM(Nourinejad et al., 2014). In Philadelphia, Pennsylvania, loading zones along the Walnut Street retail corridor require businesses to receive deliveries before 10:00 AM (Zalewski et al., 2011). The American Transportation Research Institute's 2016 parking survey revealed that 61.6 percent of drivers reported that time of day affects truck parking availability (American Transportation Research Institute, 2016). Holguín-Veras et al. (2011) introduced off-hour deliveries in the New York City metropolitan area. Using commercial vehicle dwell time (i.e., service time) as a performance measure, the study demonstrated that shifting 20 percent of freight traffic to night time would minimize the number of inefficient parking locations (Holguín-Veras et al., 2008). Commercial vehicle dwell time has been considered to be crucial information to provide insights into the delays associated with making deliveries (Holguín-Veras and Bromm, 2008; Cherrett et al., 2012). Jaller et al. (2013) also pointed out that parking availability during certain periods of time will depend on turnover, which will ultimately be affected by average commercial vehicle dwell time (Jaller et al., 2013).

2.3.2. *Parking spaces*

Cities are making efforts to improve physical spaces for commercial vehicles by increasing and relocating commercial parking spaces. Philadelphia is reserving 80 to 100 feet as all-day loading zone in busy downtown (Calvert, 2019). In Washington, D.C., USA, the District Department of Transportation (DDOT) partnered with the Downtown Business Improvement District to create a 'Downtown Curb-space Management Plan' to improve commercial vehicle loading zones (CVLZs) (Jones et al., 2009). As a part of the plan, CVLZs were relocated to the end of each block face wherever possible to make parking easier for commercial vehicles and the length of loading zones on K Street was extended from 40 feet to 100 feet to increase commercial parking capacity (Jones et al., 2009). However, Campbell et al. (2018) found that despite the ease of parking maneuvers, locating the parking at the end of the block can increase parking time by about 4%, as the parking is farther away from the delivery locations (Campbell et al., 2018). New York City's 'Commercial Vehicle Parking Plan' recommended providing additional curbside spaces for commercial vehicles (U.S. Department of Transportation, 2009). In Midtown Manhattan, where commercial activities are concentrated, CVLZs were added on the streets between 43rd and 59th and Fifth Avenue and Seventh Avenue and were later expanded to cover the additional streets between Second and Ninth avenues (U.S. Department of Transportation, 2009). Spatial limitations on loading and unloading goods could potentially lengthen dwell time as delivery workers may face conflicts with other roadway users (e.g., pedestrians, bicyclists, and other vehicles). Cities' efforts to relocate and expand the lengths of CVLZs could help reduce dwell time, in addition to increase parking capacity.

2.3.3. *Parking operations*

Cities are also implementing 'Shared Spaces' or 'Flex Zones' to accommodate commercial vehicle parking. The concept of 'Flex Zones' allows the areas within the public rights-of-way to be used by different permitted users according to the time of day. In limited city spaces, flex spaces can be shared with multiple roadway users based on their activities. As a part of 'Curb Management Strategies', Washington D.C. has 28 dedicated pick-up/drop-off zones for ride-sharing cars and commercial vehicles, expected to be added more throughout the city (Calvert, 2019). In Barcelona, Spain, variable message signs (i.e. electronic traffic sign that shows different messages based on times) were implemented to allow 700 loading zones between 8:00 AM and 2:00 PM (Perkins+Will Consultant Team, 2011). Despite the high capital costs required, the system gained popularity among residents, as it reduced travel time at study areas by 12 to 15 percent (Perkins+Will Consultant Team, 2011). The city of Seattle implemented 'Flex Zones' at areas where passengers loaded and unloaded from transit and ride share services, or delivery goods were being loaded or unloaded to/from commercial vehicles. The Flex Zone functions (e.g., mobility, access for people or commerce) were categorized and prioritized on the basis of surrounding land uses (e.g., residential, commercial & mixed use, industrial) to "safely and efficiently connect and move people and goods to their destinations while creating inviting spaces within the right-of-way" (City of Seattle, 2019).

In these examples, assigning shared space on the basis of the needs of different roadway users improved the management of limited curbside spaces. This paper aims to contribute to a more data-driven approach before such dynamic parking policies are implemented. By identifying explanatory variables correlated with dwell times for commercial vehicles, policymakers can better allocate parking space and time on the basis of users' needs.

3. Data collection

Data collection occurred in five different building types in downtown Seattle, Washington, USA. We carefully selected different types of buildings to capture the full range of delivery and vehicle characteristics. The selected buildings included a residential tower, a hotel, a historical building, an office tower, and a shopping mall. Table 1 describes key features of the observed buildings: mixed building types, number of floors, total floor area, and presence of a receptionist. In the building selection process, observing various types of freight activities at each building was important to collect sufficient data regarding explanatory variables (e.g., different types of goods, parked locations, vehicle types, etc.) to examine their effects on commercial vehicle dwell time. Therefore, the selected buildings were naturally considered to be large with the total floor area between 31 k - 92 k m^2. These types of buildings are often known as 'large urban freight traffic generators (LTGs)' as specific facilities housing businesses that individually or collectively produce and attract a large number of daily truck trips (Jaller et al., 2015).

Prior to data collection, the researchers conducted site visits to assess each building's configuration and freight activities. This helped identify the proper placement and number of researchers for data collection (see Fig. 1). Only the office building closed during weekends, however, we learned that relatively small numbers of freight activities are performed during weekends for other buildings based on the interviews with building managers. Therefore, the weekends were not observed in our data collection.

For each building, the data collection process occurred over five business days from Monday to Friday between the hours of 6:30 AM and 3:30 PM. Data collection occurred between the months of January to March 2017. The data collection team consisted of two or four people depending on the size of the building. They were trained to observe and collect data using a customized tablet application (Kim et al., 2018). They waited until a commercial vehicle was parked in either the loading bay or the street curbs near the building. They would then approach the delivery worker and ask permission to shadow and observe his or her delivery process. A sufficient number of deliveries were observed at each building type to estimate the impacts of key variables on dwell time.

4. Summary of data

There were 157 observations from the five buildings (see Table 1). Fig. 2 shows the histogram of the dwell times in minutes. Most commercial vehicle parking in this area are limited to 30 min or less. Most of the observed vehicles (90%) had dwell times less than 30 min. Only 16 observations (about 10%) had dwell times longer than 30 min. Although the parking fines were not monitored (as it was out of the scope for this study), we did note the number of vehicles that exceeded the parking time limit in order to meet their delivery schedules. Long dwell times can have a negative impact on parking capacity in the neighborhood (Schmid et al., 2018). Providing a good estimate of dwell times can assist the city to more effectively allocate parking facilities with solutions that are tailored for vehicles based on their expected dwell times.

Table 1
Description of observed buildings

Building ID	Building types	No. of floors	Total floor area	Receptionist present	Observations (n)
A	Residential (98%) Retail (2%)	41	89,000 m^2	Y	35
B	Hotel (78%) Residential (19%) Spa (2%) Dining (1%)	21	38,000 m^2	Y	29
C	Historical Office (93%) Retail (5%) Coffee shops (2%)	15	31,000 m^2	N	29
D	Office (97%) Retail (2%) Dining (1%)	62	92,000 m^2	N	30
E	Office (76%) Shopping mall (20%) Dining (4%)	25	45,000 m^2	N	34
Total					157

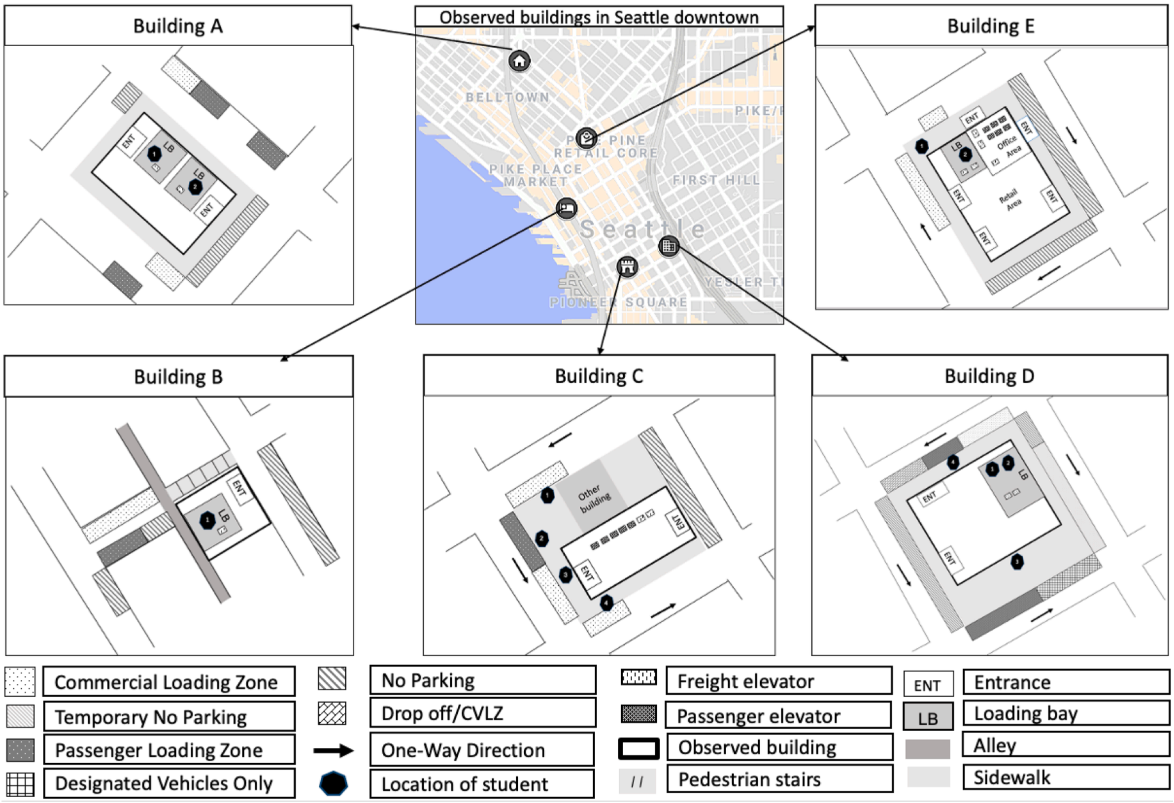

Fig. 1. Observed buildings location and configuration.

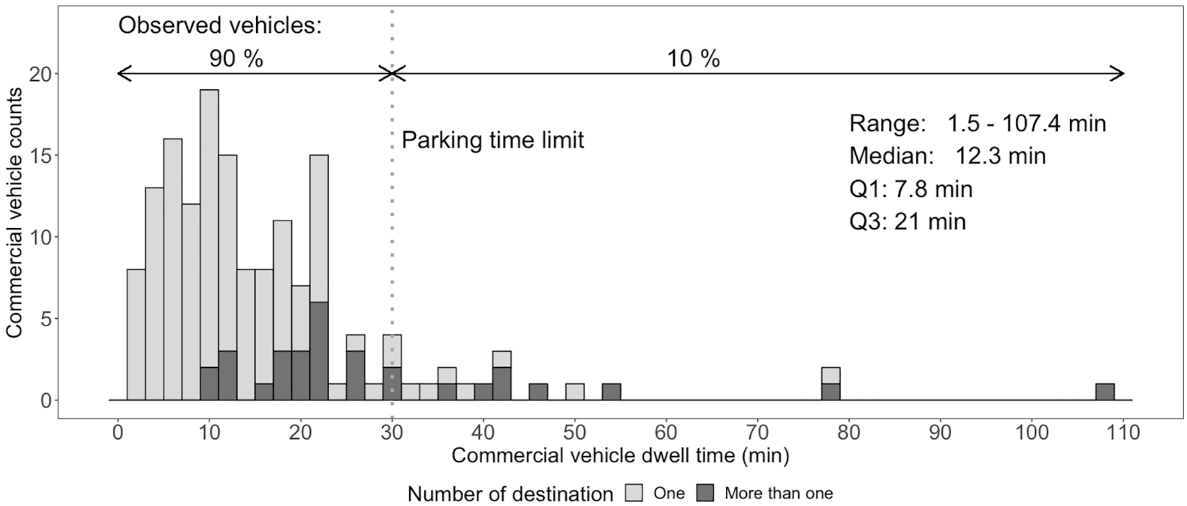

Fig. 2. Commercial vehicle dwell times for all five buildings combined.

The observed dwell times used in the analysis ranged from 1.5 min to 107.4 min. Several past empirical studies showed similar ranges between 1 min and 90 min for the on-street parking study by Schmid et al. (2018) (Schmid et al., 2018) and from 1.5 min to 180 min for the off-street parking study by Dalla Chiara and Cheah (2017). Campbell et al. (2018) used the estimated dwell times between 30 min and 90 min in calculating the number of on-street parking spaces (Campbell et al., 2018).

The distribution of observed dwell times was right-skewed with a mean of 16.4 min and a median of 12.3 min (1st quartile: 7.8 min and 3rd quartile: 21.1 min). The distribution of dwell times by each building also showed right-skewed trends (see Fig. 3). This right-skewness was expected as past models also showed right-skewed trends in dwell time distributions (Dalla Chiara and Cheah, 2017;

Schmid et al., 2018). Our data showed a peak dwell time around 10 min including both on and off-street parking spaces while past studies showed peaks at 5 min for on-street parking (Schmid et al., 2018) and 15 min for off-street parking (Dalla Chiara and Cheah, 2017).

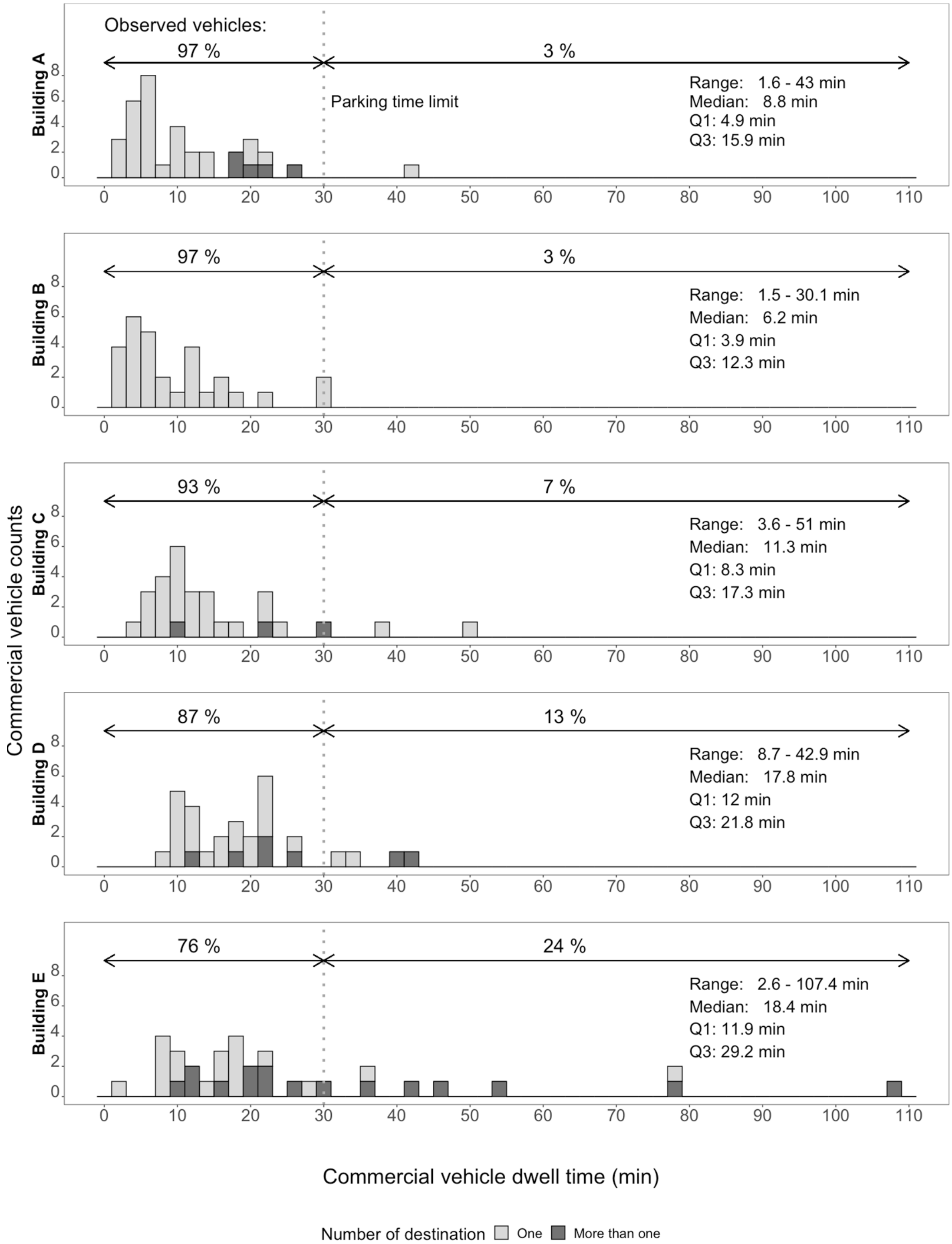

Fig. 3. Commercial vehicle dwell times for each building.

4.1. Data observations

On the basis of past commercial vehicle studies, the researchers identified potential factors that may influence dwell time (Morris, 2004; Cherrett et al., 2012; Allen et al., 2000; Schmid et al., 2018; Zou et al., 2016). Factors that were included in our study were the delivery day of the week, arrival time, total floor area, receptionist presence at lobby, parking location, delivery vehicle type, type of goods being delivered, number of delivery workers, and number of destinations within each building. The summary statistics of observed variables are shown in Table 2.

4.1.1. Day of the week

In this study, the delivery day of the week included only Mondays through Fridays (excluded Saturdays and Sundays). Through interviews with building managers, we learned that the office and historical buildings were closed and the other buildings had minimal freight activities on Saturdays and Sundays. Therefore, we limited our data collection to Mondays through Fridays. Mondays had the longest dwell times (mean = 25.6 min). The majority of our Monday observations were from Building E which showed the longest mean dwell times of 26.1 min. This may be pulled the average dwell times for Monday to the highest while the average dwell time for the other weekdays was 15 min. The longest dwell time (107.4 min) was observed on a Thursday. To account for the imbalanced size of observations from each building for Monday, the days of the week were categorized into two levels in our dwell time models: 1) Monday and Tuesday (early week- Group mean:19.7 min, Group SD: 17.4 min), 2) Wednesday, Thursday, and Friday (late week- Group mean: 14.7 min, Group SD: 12.7 min). As can be seen in Table 2, the percentage of deliveries was the lowest on Mondays (8.3 percent) and highest on Fridays (28.7 percent). A similar trend was observed in other studies. Cherrett et al. (2012) showed that freight activity was busiest on Fridays and quietest on Mondays (Cherrett et al., 2012). Han et al. (2005) showed that Thursdays and Fridays had the most pick-ups and deliveries, whereas Mondays and Tuesdays had the lowest numbers of deliveries (Han et al., 2005). Some studies showed that weekends or the middle of the week can also be popular days for deliveries. In the UK, deliveries of wholesale produce were concentrated on Saturdays, and Tuesdays and Wednesdays were shown to be popular for freight deliveries (Cherrett et al., 2009).

4.1.2. Vehicle arrival time

Fig. 4 shows the histogram of the commercial vehicle arrival time for all five buildings combined. 25% of observed vehicles arrived before 9:39 AM while 90% of them arrived before 12:25 PM. The distributions of arrival times for each building type are shown in Fig. 5. As shown in Fig. 5, Building B and Building E showed 25% of commercial vehicles to be arrived before 9:00 AM, earlier than other buildings. Presence of restaurants in these buildings may have contributed to the early arrival time as the delivered goods in the morning at Building B and E were mostly food and oversized materials (e.g., construction or utility materials, etc.). 25% of deliveries at

Table 2
Summary statistics (n = 157), dependent variable: dwell time.

No.	Variable	Categories	Total sample (%)	Group mean duration (in minutes)	Group SD duration (in minutes)
1	Day	Mon	13 (8.3)	25.6	19.5
2		Tues	39 (24.8)	17.7	16.5
3		Wed	23 (14.6)	13.6	9.1
4		Thurs	37 (23.6)	16.4	17.3
5		Fri	45 (28.7)	13.9	9.4
6	Vehicle arrival time	6:30–9:30	33 (21)	17.2	18.1
7		9:30–11:30	79 (50.3)	17.5	13.5
8		11:30–15:00	45 (28.7)	13.8	13.5
9	Total floor area	31,000 m^2	29 (18.5)	15.1	10.4
10		38,000 m^2	29 (18.5)	9.7	7.7
11		45,000 m^2	34 (21.7)	26.1	23.1
12		89,000 m^2	35 (22.3)	11.0	8.8
13		92,000 m^2	30 (19.1)	19.2	9.0
14	Receptionist presence	No	93 (59.2)	20.4	16.5
15	at lobby	Yes	64 (40.8)	10.4	8.3
16	Parking location	Off-street	82 (52.2)	19.1	17.5
17		On-street	75 (47.8)	13.4	9.8
18	Vehicle type	Roll-up door	89 (56.7)	18.4	16.9
19		Swing doors	53 (33.8)	15.2	10.8
20		Passenger	15 (9.6)	8.2	5.2
21	Type of goods	Oversized supplies	18 (11.5)	20.5	10.6
22		Office supplies	34 (21.7)	17.9	10.7
23		Parcels	39 (24.8)	17.4	22.4
24		Documents	12 (7.6)	14.3	11.1
25		Food	54 (34.4)	13.7	10.7
26	No. of workers	One	135 (86)	15.8	14.9
27		Two or more	22 (14)	19.7	11.8
28	No. of destinations	One	126 (80.3)	13.2	10.7
29		Two or more	31 (19.7)	29.1	20.5

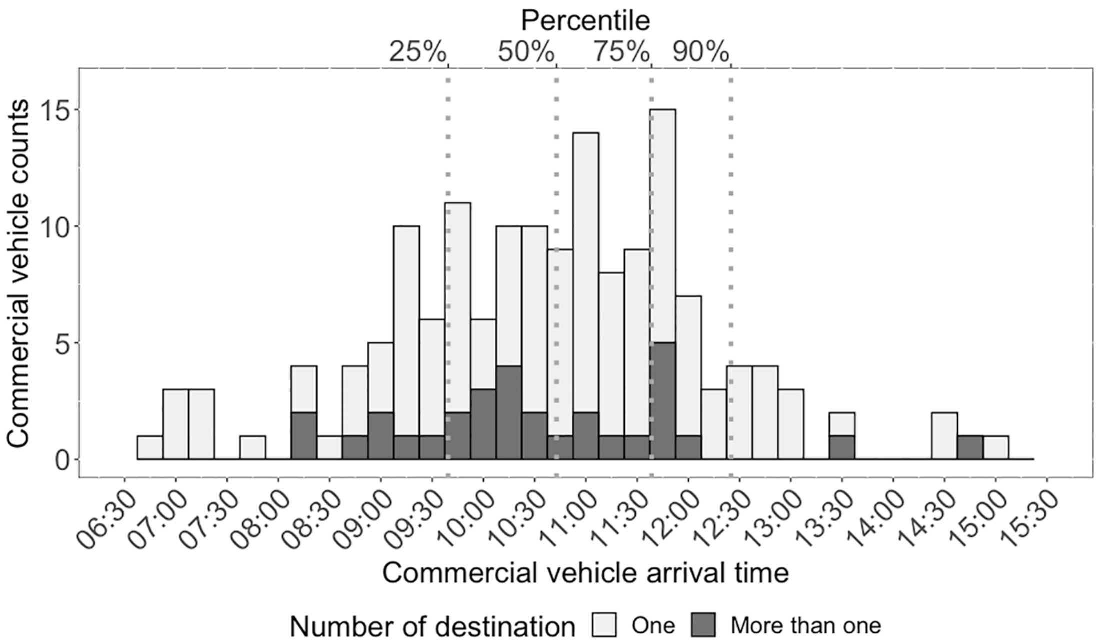

Fig. 4. Arrival times for all five buildings combined.

Building C and D were arrived at the buildings before 10 AM. 90th percentile of vehicle arrival time for Building C and D were around 12:00 PM and 1:00 PM respectively. The goods delivered at Building C after 12:00 PM were mostly food (e.g., lunch, catering) for the offices whereas the delivered goods after 1:00 PM at Building D were mostly parcels and documents. Among the five buildings, the Building A (which had residential units) showed that 25% of deliveries (mixed types of food, parcels and oversized goods) arrived at the building before 11:00 AM, the latest 25th percentile compared to other buildings. In our models, vehicle arrival time was grouped into three levels: 1) 6:30–9:30, 2) 9:30–11:30, 3) 11:30–15:00. The average dwell time for the first group of 6:30–9:30 (17.2 min) and the second group of 9:30–11:30 (17.5 min) were longer than those for deliveries made in the third group of 11:30–15:00 (13.8 min). The observed deliveries were concentrated in the AM period, sharing a similar trend with other studies. According to an extensive analysis of 30 UK surveys over 15 years (1996–2009) by Allen et al. (2012), most urban delivery activities were concentrated in the morning between 6:00 AM and 12:00 PM (Allen et al., 2012). A study conducted by Morris and Kornhauser (2000) that observed delivery activities in New York City's central business district (which was defined as south of 59th street to the tip of Manhattan from the river to river) showed a delivery peak in the morning, with an average dwell time of 33 min or more (Morris and Kornhauser, 2000). In 1999, McKinnon observed a large number of food deliveries in the early time period between 5:00 and 9:00 AM (McKinnon, 1999). However, Winchester study in 2008 argued that there is no significant difference in delivery arrival time among business categories, as that study found that 26 percent of businesses had no scheduled delivery arrival time (Cherrett et al., 2012). The study suggested that the commercial vehicle arrival time was more likely determined by suppliers or carriers more than by the receiving businesses (Cherrett et al., 2012).

4.1.3. Total floor area

Total floor areas for the observed building differed between 31,000 and 92,000 m^2. The total floor area of the building was assumed to be a good indicator to estimate commercial vehicle dwell time as a bigger sized building may attract larger sizes and quantities of goods which require additional time for navigating and handling inside of buildings. However, the number of floors and total floor area did not follow a linear trend with overall dwell time. For example, the mean dwell time at Building A with 89,000 m^2 and 41 floors - 11 min - was less than that at Building E with 45,000 m^2 and 25 floors - 26 min. This could be due to different building configurations and delivery policies, such as having a concierge service or building configurations that were difficult to maneuver around and inside. Although Building C had the smallest number of floors (15) and 31,000 m^2, both mean and median dwell times were longer than those at Building A and B where concierge services were offered.

4.1.4. Receptionist presence at lobby

Building A and B had concierge services that allowed delivery workers to drop off their goods at a designated location close to the entrance of the building and loading bay. In this way, delivery workers could avoid vertical activities (e.g., taking freight elevators, navigating inside of the building). Some deliveries at Building A still required travel inside of the building in case the goods could not be dropped off (e.g., lunch or dinner food deliveries and deliveries that required a signature from the receiver directly). As expected, the buildings with receptionists at the lobby showed 10 min lower mean dwell time than the buildings without receptionists at the

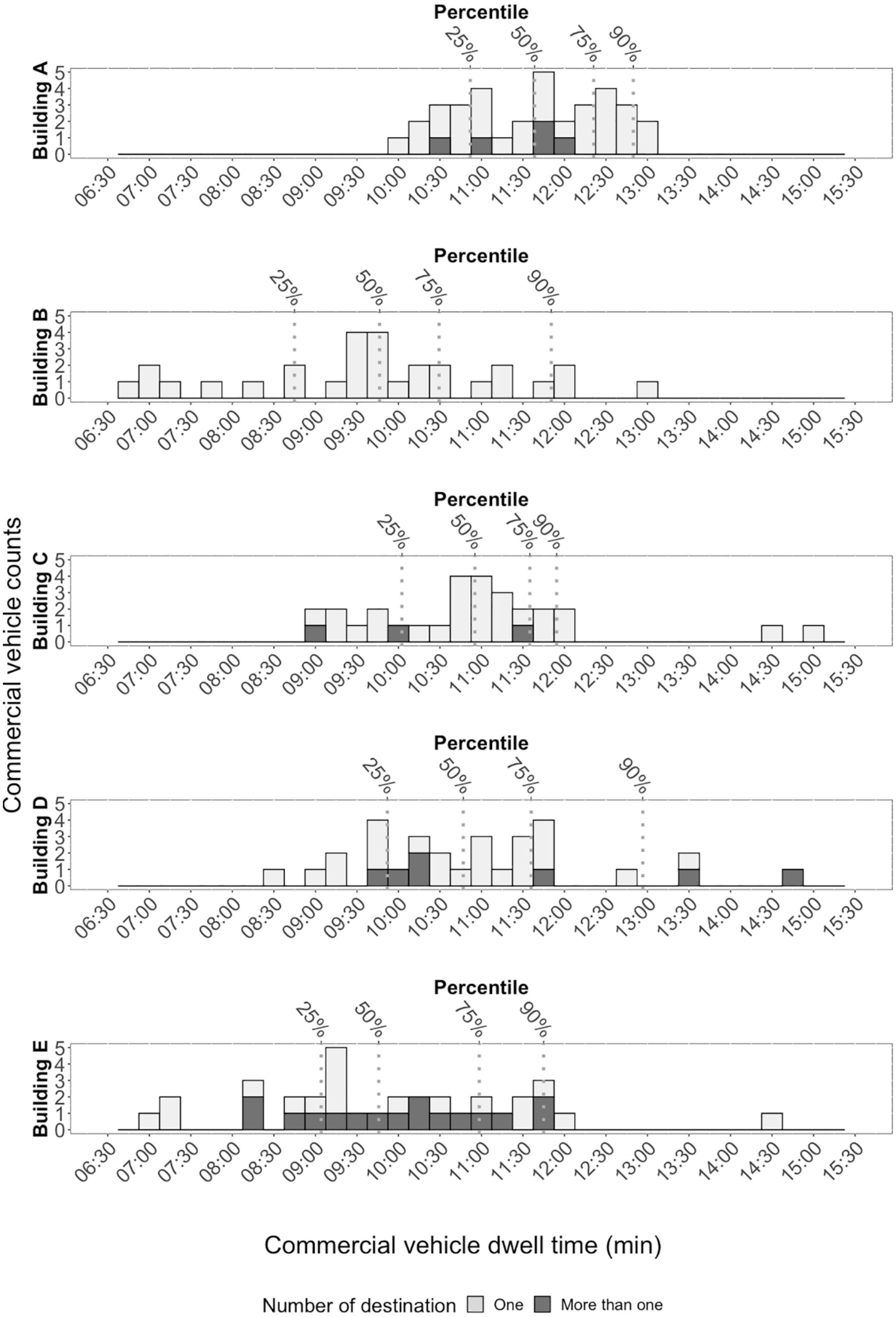

Fig. 5. Arrival times for each building.

lobby. This intuitively makes sense because the extra time to travel to the final destination could be minimized by consolidating goods at the concierge location. Because the delivery workers had to navigate inside the building, longer dwell times were expected for other buildings in comparison to deliveries at buildings with concierge services.

4.1.5. Parking location

Parking location can affect the length of dwell time. Our observed parking options included on-street and off-street parking. Alternatively, unauthorized parking such as double parking could have occurred. However, our observations did not distinguish the unauthorized parking option, as our focus was on the dwell times either on the street curbs (on-street parking) or at loading bays (off-street parking). While observed proportions between off-street and on-street parking were similar, off-street parking showed a longer mean dwell time - 19 min - than on-street parking with an average of 13.4 min. Given the parking location, delivery workers will leave their cargo compartments open or closed. At loading bays, most delivery workers left their doors open, as a security guard or a surveillance camera was present. On the other hand, on the street, some delivery workers kept the cargo compartment closed or locked when they left their vehicles for deliveries. Closing or locking mechanisms could add extra time to dwell time. The levels of conflict with other roadway users (e.g., pedestrians, bicyclists, and other vehicles) would also vary depending on parking location, which could potentially add extra dwell time. Campbell et al. (2018) studied the impact of on-street parking locations on dwell times and found that the middle of the block is an optimal location for parking needs, minimizing walking time (Campbell et al., 2018). Butrina et al. (2017) stated that the decision of parking location could be influenced by package size and weight, as well as the distance to the recipient's location (Butrina et al., 2017). Depending on the types of locations served, the number of parking facilities might differ (Cherrett et al., 2012). According to Cherrett et al.'s review of recent UK urban freight studies, shopping centers had a higher percentage of off-street parking facilities whereas local shops tended to have more on-street parking (Cherrett et al., 2012).

4.1.6. Vehicle type

While most of the commercial vehicles were vans or trucks with either swing doors or roll-up doors, about 10 percent of the observed vehicles were passenger vehicles with commercial vehicle logos or vehicles performing crowd-sourced delivery services (e.g., 'Uber eats', 'Amazon Flex'). The average dwell time for passenger vehicles was around 8 min, lower than that for trucks or vans with roll-up and swing doors (around 17 min on average). Delivery vehicles such as trucks and vans were categorized on the basis of the types of cargo compartments; roll-up doors and swing doors. Roll-up doors are often found on trucks (e.g., trailer trucks, single-unit trucks, box trucks) while swing doors are often found on vans. When parking, delivery workers had to consider extra space for loading and unloading, especially for swing doors or liftgates. Some trucks had a hydraulic or electric powered liftgate at the rear of the vehicle that moved up and down to assist in unloading and loading heavy cargo. When swing doors were blocked by a loading bay wall or parked vehicles behind, delivery workers had to adjust parking to allow extra space. Additional time required for operating the lift-gate or adjusting parking could be added to the total delivery vehicle dwell time.

4.1.7. Type of goods

The types of goods - including oversized supplies, office supplies, parcels, documents, and food - were studied. The average dwell time for oversized supplies was 20 min, which was much longer than times for other delivered goods, which ranged between 14 min and 18 min. Oversized supplies included furniture and construction materials that required special moving equipment. Parcels represented the deliveries that were packaged in cardboard boxes and for which data collectors could not identify the type of items inside. Office supplies included papers, toilet papers, electronics such as computers, and monitors identified by data collectors. Deliveries of documents accounted for mail and small documents that were more likely to require a signature from a recipient. Food deliveries included both large quantities for restaurants or catering services and small quantities for individuals, such as grocery deliveries and lunch/dinner deliveries. Differences in the quantity of food deliveries could be accounted for by the vehicle type because small food deliveries tended to be performed by passenger vehicles. Because of their similar delivery process characteristics, office supplies, and parcels were grouped into one category in the model for simplicity.

4.1.8. Number of workers

Typically, one delivery worker performed deliveries (approximately 86 percent) with an average dwell time of 16 min. When two or more delivery workers were involved in deliveries, the goods were more likely to be large and numerous in quantity, which may increase the overall dwell times due to longer handling times (e.g., loading and unloading, navigating). Since we do not have a volume-controlled variable in our models, the number of workers was used as a proxy to a large volume of goods. As expected, the mean dwell time for the deliveries with two or more delivery workers (20 min) was higher than deliveries performed by one worker.

4.1.9. Number of destinations

Most of the deliveries (80 percent) went to one location within the building. As expected, multiple deliveries with two or more destinations within one building had a much larger mean dwell time (13 min vs. 29 min). When visiting multiple locations within a single building, delivery workers may be required to maneuver through unfamiliar floor plans and to cope with different delivery policies between departments and floors. Also, certain building types may naturally have a large number of destinations and attract large volumes of goods to be delivered. For example, Building E has a large shopping mall area with several restaurants where goods are being delivered in large quantities to multiple locations within the building. Even when there is only one destination, the delivery may require multiple trips from a vehicle to the same destination due to a large quantity being delivered. This had led some deliveries at Building E to have dwell times longer than 50 min.

5. Method

The study objectives were to identify factors correlated with dwell time for commercial vehicles and measure their level of impact on dwell times. We hypothesized that dwell time is a function of independent variables such as day of a week, vehicle arrival time, building type, parking location, vehicle type, type of goods, number of workers and number of destinations within a building. We used two main modeling approaches. The first approach estimated models with combined data from all of five building types. The second approach further analyzed the effects of the independent variables on dwell time in different building types by applying five separate models.

As was shown in Fig. 2, the distribution of dwell times was right-skewed. Hence, right-skewed distributions (log-normal and gamma) were examined in comparison to the normal distribution. Fig. 6 shows the distribution fit for the data sets. The Shapiro–Wilk test (Table 3) confirmed that the gamma distribution would be a good fit for the observed dwell times, as almost all the data sets failed to reject the null hypothesis that the observed data would follow theoretical densities.

Hence, a general linear model with a gamma-distributed dependent variable was created by using the 'GLM' function in the R statistical software package (version 4.0.2). The probability density function of gamma-distributed data y_i, given scale parameter (θ_i) and shape parameter (κ) is:

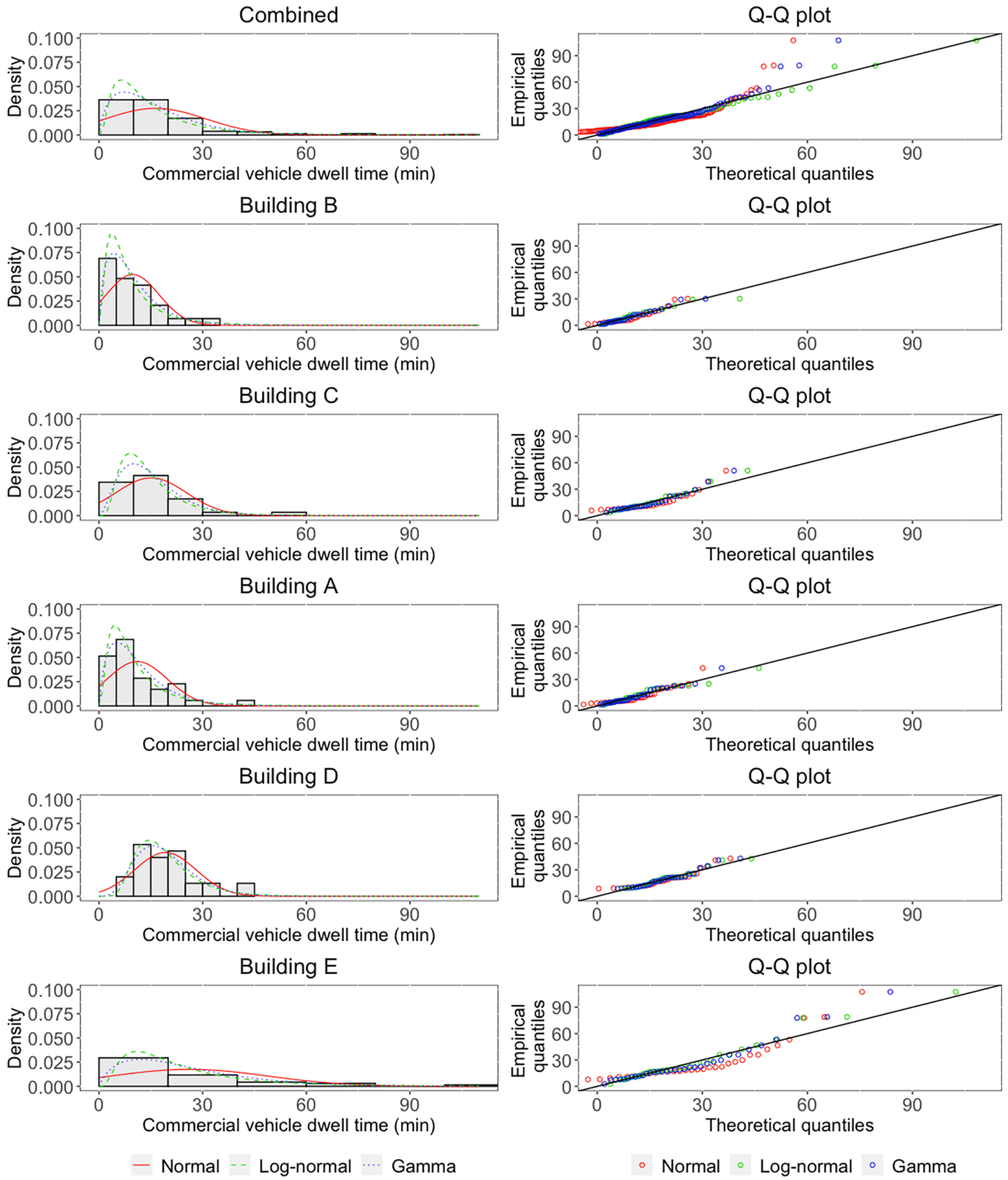

Fig. 6. Histogram with fitted distributions.

Table 3
Shapiro–Wilk test p-value.

Distribution	Combined	Building A	Building B	Building C	Building D	Building E
Normal	2.66e-15	1.42e-04	1.47e-03	7.81e-05	4.23e-03	4.67e-06
Log-Normal	0.1555	0.6864	0.5121	0.796	0.2977	0.7127
Gamma	0	0.35	0.44	0.1	0.14	0.07
Total observations	157	35	29	29	30	34

Null hypothesis: True cumulative distribution function equals the tested distribution.

$$f(y_i) = \frac{y_i^{\kappa-1} e^{-y_i/\theta_i}}{\theta_i^{\kappa}\Gamma(\kappa)} \text{where} y_i, \theta, \kappa > 0$$

$$\Gamma(\kappa) = \int_0^{\infty} y^{\kappa-1} e^{-y} dy$$

The multivariate gamma-distributed variable can be presented by y_i and the vector size, p, which is a function of independent variables $x_1, x_2, \ldots, x_\alpha$. Assuming that the link function of "log" that was used in our dwell time models (g(μ) = log(μ)) and the shape parameter α was constant throughout the process, then each element in y can be expressed as:

$$y_i \sim GAMMA(shape = \kappa, scale = [\beta_0 + \beta_1 {}^* x_1 + \beta_2 {}^* x_2 + \ldots \beta_\kappa {}^* x_\kappa]/\kappa])$$

for $i = 1, \ldots, p$. The mean and standard deviation for the gamma distribution are then:

$$\begin{aligned} \mu = E(y_i) = & \quad \kappa^*\theta = g^-1(\beta^* x_i') = exp(\beta^* x_i') \\ Var(y_i) = & \quad \kappa^*\theta^2 \end{aligned}$$

5.1. Correlation analysis

A correlation analysis was conducted to ensure there were no issues with multicollinearity. Since the variables are categorical, chi-square tests of independence and Cramer's V values were calculated to test the correlations and strength of these associations. Fig. 7 shows the Cramer's V values with p-values of the chi-square test (in shades of grey).

The correlation analysis shows high correlations in total floor area and parking location with other variables. Especially, the

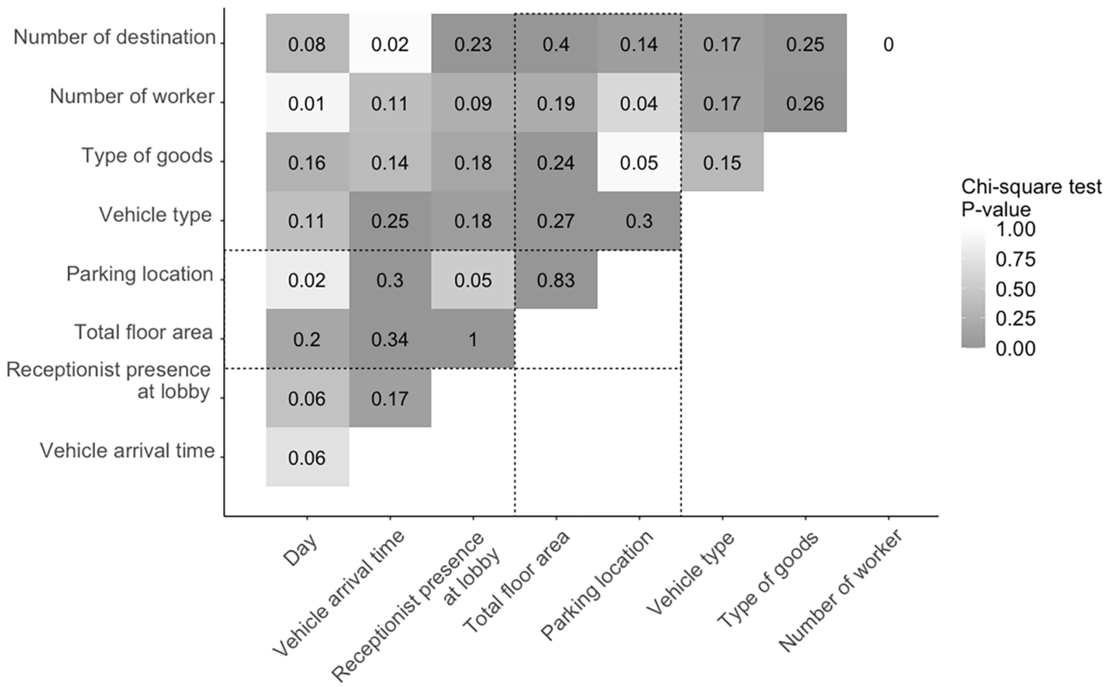

Fig. 7. Correlation between explanatory variables.

correlation between total floor area (building specific) and parking location variables was significant showing a high Cramer's V value of 0.83. This is anticipated because parking location availability was highly dependent on different buildings. For example, Building C was built in 1924 and did not have any off-street parking facility (e.g., loading bay). On the other hand, Building B had a full-time staff member who received goods at the loading bay, deliveries always went to that off-street parking locations. Both the total floor area and parking location variables had strong correlations with the vehicle type and vehicle arrival time variables.

As a result, we removed the total floor area and parking locations from our models and ensured that the association does not exceed the Cramer's V value of 0.3 among explanatory variables (Akoglu, 2018; Cohen, 1988).

6. Results

The full models contained days of the week, vehicle arrival time, receptionist presence at lobby, vehicle type, type of goods, number of workers, and number of destinations within a building as independent variables. Using a stepwise algorithm ('stepAIC' function with both directions in MASS package) for feature selection, the full models were further refined into the refined models that include valuable variables that are significantly or marginally correlated with dwell times (Ripley, 2020). To examine the model assumptions for the final models, the 'simulateResiduals' function in the DHARMa package was used to plot residual diagnostics (Hartig, 2020).

Different types of models (i.e. Linear, Log-linear, Gamma regressions) were generated for model comparison. For all of our dwell time models, the linear and log-linear models showed the worse fit than the Gamma model. The Gamma model showed the least negative log-likelihood value, indicating the best fit in estimating coefficients with minimal errors.

6.1. *Combined dwell time models - using data from all five buildings*

The combined data ($n = 157$) from the five buildings was used for the models in this section and referred as 'combined dwell time models' throughout the paper. The results are summarized in Table 4. The days of the week, vehicle arrival time, and number of workers were not significant in explaining dwell times for commercial vehicles. However, receptionist presence at lobby, vehicle type, type of goods, and number of destinations within a building were significantly associated ($p < 0.05$) with dwell times. Residual diagnostics plots (shown in Fig. 8) and Nagelkerke pseudo-R-squared values showed strong goodness of fit for both full and refined dwell time models. The refined model showed lower Alkaike Information Criterian (AIC) value, indicating a better fit. Therefore, the refined model was chosen as the final model, and results were analyzed based on the refined model.

The estimates from the refined model (see Table 4) showed that deliveries to the buildings with receptionist presence at the lobby were significantly correlated with a 44% shorter dwell time than deliveries to buildings without a receptionist. Deliveries made by

Table 4
Results of the combined dwell time models.

Variables	Categories	Full model			Refined model		
		Exp(β)	95% CI	p-value	Exp(β)	95% CI	p-value
Intercept		25.13	16.59–38.94	<0.001	22.14	17.38–28.51	<0.001
Day	Mon, Tues (Ref)						
	Weds, Thurs, Fri	0.80	0.64–1.01	0.068	0.80	0.64–1.01	0.063
Vehicle arrival time	9:30–11:30 AM (Ref)						
	6:30–9:30 AM	0.90	0.68–1.20	0.465			
	11:30 AM–15:00 PM	0.89	0.69–1.17	0.410			
Receptionist presence at lobby	No (Ref)						
	Yes	**0.57**	**0.46–0.72**	**<0.001**	**0.56**	**0.45–0.70**	**<0.001**
Vehicle type	Roll-Up doors (Ref)						
	Swing doors	0.86	0.67–1.10	0.214	0.83	0.66–1.04	0.109
	Passenger vehicle	**0.58**	**0.40–0.88**	**0.011**	**0.56**	**0.39–0.82**	**0.003**
Type of goods	Oversized (Ref)						
	Office S.&Parcels	0.87	0.59–1.27	0.471			
	Documents	**0.58**	**0.34–0.99**	**0.039**	**0.64**	**0.43–0.99**	**0.035**
	Food	0.86	0.57–1.25	0.420			
Number of workers	One (Ref)						
	Two or more	1.14	0.83–1.61	0.419			
Number of destinations	One (Ref)						
	Two or more	**1.87**	**1.40–2.52**	**<0.001**	**1.83**	**1.40–2.44**	**<0.001**
Nagelkerke Pseudo R^2		0.459			0.444		
Deviance		59.08			60.53		
Log-Likelihood		−541.71			−543.72		
Akaike information criterion (*AIC*)		1109.4			1103.4		
Sample size (N)		157			157		

Note: Generalized linear model (using a gamma distribution with log link). Results are in antilogarithms of the regression coefficients and their 95% confidence intervals (CI) and p-values. Coefficients of less than 1 denote shorter dwell times for commercial vehicles relative to the reference category (Ref).

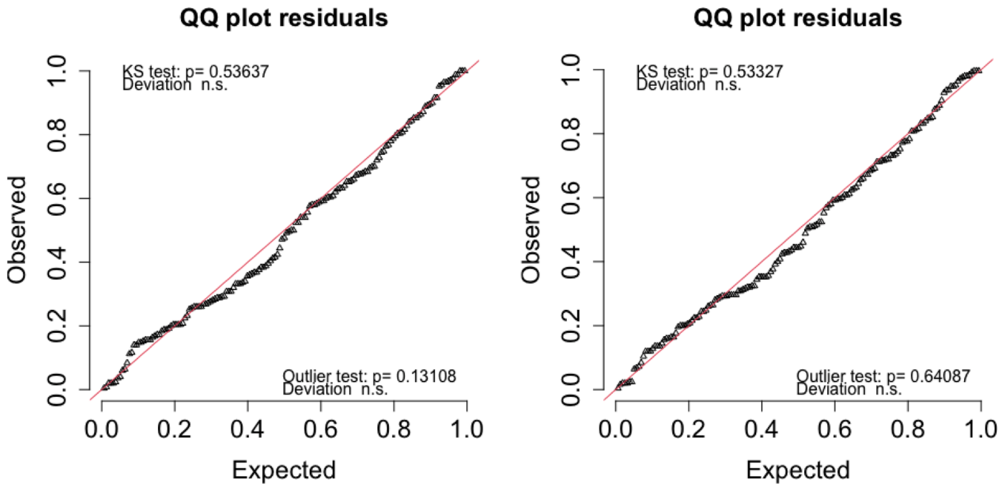

Fig. 8. Residual diagnostics QQplots for the combined dwell time models - left (full model), right (refined model).

passenger vehicles had 44% shorter dwell times than deliveries made by vehicles with roll-up doors (e.g., trucks). Deliveries of documents were correlated with shorter dwell times (36 percent shorter) than deliveries of oversized goods. Deliveries that were delivered to multiple (two or more) destinations within a building had longer dwell times (1.83 times) than deliveries to one destination.

Table 5 shows the log-likelihood values for different types of dwell time models with the variables used in the final refined model.

6.2. Dwell time models for each building type

The findings from dwell time models for each building type are summarized in Table 6. Apart from the combined dwell time models from the previous section, dwell time models in this section were built for each building type to separately investigate the relationship between independent variables and dwell times for the individual building types. The final dwell time models were selected using a stepwise algorithm. Residual diagnostics plots (shown in Fig. 9) and Nagelkerke pseudo-R-squared values showed strong goodness of fit for the models.

Because of differences in building configurations and operations, a few independent variables were not controlled for particular building types. For example, at Building B, all deliveries were conducted by one delivery worker and vehicles with swing doors or roll-up doors at the off-street loading bay. Because a full-time staff member received goods at the Building B's loading bay, the number of destinations was always one, as deliveries always went to that single location. Therefore, variables such as vehicle types: passenger vehicle, number of workers, and number of destinations were eliminated for Building B. The vehicle type: passenger vehicle was not included in the model for Building E because no deliveries were observed to be made by passenger vehicles. Nevertheless, although a few variables were not controlled for in some models, significant variables correlated with dwell times were still identified, consistent with the combined dwell time models.

Vehicle type: In the full and refined models from the combined dwell time models, vehicles with swing doors, as opposed to vehicles with roll-up doors, were not significantly but only marginally correlated with dwell times. However, they showed significant associations at Building E and D, respectively. At Building E, dwell times for vehicles with swing doors (e.g., vans) were significantly shorter (55 percent) than those for vehicles with roll-up doors (e.g., trucks). On the other hand, the vehicles with swing doors were significantly correlated with longer dwell times (1.45 times) at Building D. Passenger vehicles in combined dwell time models showed more significant association with shorter dwell times than vehicles with roll-up doors. Passenger vehicles at Building A showed similar but marginal associations with shorter dwell times.

Type of goods: In the full and refined models, deliveries of documents were significantly correlated with shorter dwell times than deliveries of oversized supplies such as furniture and construction materials. Deliveries of documents were significantly and marginally correlated with shorter dwell times for Building C and D respectively. Although the full and refined models showed deliveries for food had no significant association with dwell time, food deliveries at Building E showed a significant association with shorter dwell times than oversized supplies.

Table 5
Combined dwell time model comparison.

Model	Log-Likelihood
Linear	−614.38
Log-linear	−614.03
Gamma	−543.72

Table 6
Results of the dwell time models for each building type.

Variables	Categories	Building A			Building B			Building C		
		Exp(β)	95% CI	p-value	Exp(β)	95% CI	p-value	Exp(β)	95% CI	p-value
(Intercept)		**10.69**	**7.94–14.78**	**<0.001**	**11.05**	**5.79–23.72**	**<0.001**	**16.84**	**12.79–22.80**	**<0.001**
Day	Weds, Thurs, Fri				0.58	0.27–1.16	0.123			
Vehicle arrival time	11:30 AM–15:00 PM	0.71	0.47–1.06	0.111	0.49	0.20–1.30	0.109			
Vehicle types	Passenger vehicle	0.61	0.39–0.99	0.052						
Type of goods	Office S.&Parcels							0.65	0.39–1.12	0.118
	Documents							**0.38**	**0.18–0.87**	**0.023**
	Food				1.73	1.01–2.94	0.058			
Number of workers	**Two or more**	**2.10**	**1.27–3.71**	**0.011**						
Number of destinations	**Two or more**	**2.13**	**1.26–3.84**	**0.012**				**2.62**	**1.14–6.57**	**0.039**
Nagelkerke Pseudo R^2		0.554			0.240			0.281		
Log-Likelihood		−103.57			−89.44			−96.33		
AIC		219.13			188.89			202.66		
N		35			29			29		

Variables	Categories	Building D			Building E		
		Exp(β)	95% CI	p-value	Exp(β)	95% CI	p-value
(Intercept)		**16.73**	**12.16–23.47**	**<0.001**	**29.77**	**20.57–44.61**	**<0.001**
Day	Weds, Thurs, Fri	0.83	0.60–1.15	0.304			
Vehicle types	**Swing doors**	**1.45**	**1.09–1.93**	**0.020**	**0.45**	**0.30–0.69**	**<0.001**
Type of goods	Documents	0.76	0.50–1.18	0.221			
	Food				**0.57**	**0.37–0.88**	**0.018**
Number of destination	Two or more	**1.48**	**1.07–2.07**	**0.030**	**1.64**	**1.08–2.49**	**0.027**
Nagelkerke Pseudo R^2		0.471			0.554		
Log-Likelihood		−95.07			−129.89		
AIC		202.15			269.80		
N		30			34		

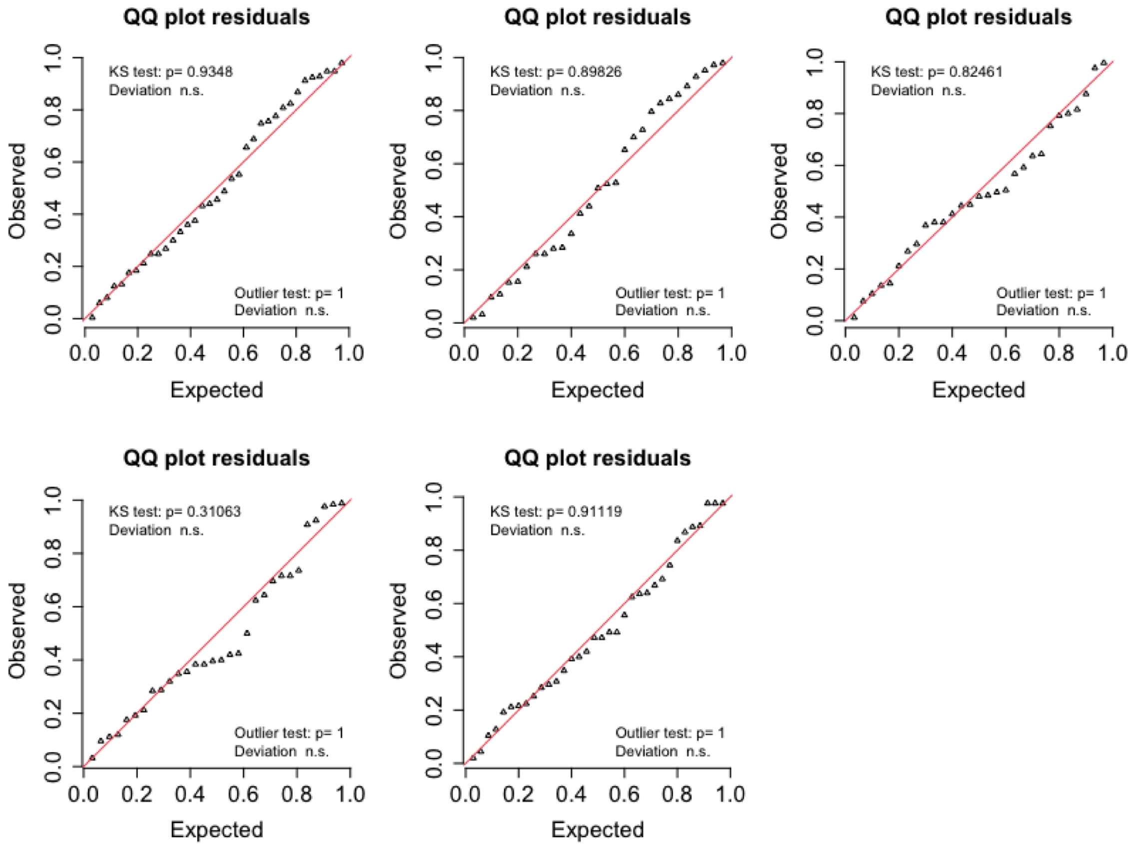

Fig. 9. Residual diagnostics QQ plots for the five separate dwell time models by different building type (Building A,B,C (top rows from left to right) and Building D,E (bottom rows from left to right)).

Number of destinations: For all buildings except Building B, deliveries with two or more delivery destinations showed significant associations with longer dwell times (range between 1.48 and 2.62 times) as compared to deliveries that go to a single destination. These findings aligned with the combined dwell time model results, which showed significant associations with a longer dwell times (1.83 times).

Both the combined dwell time models and dwell time models for each building type revealed that the significant variables related to dwell times were vehicle type, type of goods, and number of destinations, which are discussed further in the following section.

Table 7 shows the log-likelihood and AIC values for different types of models with the variables used in the final refined models.

7. Discussion

The aim of this study was to examine if there are correlations between commercial vehicle dwell times and characteristics of buildings and deliveries and identify the strength of the correlations. Our analysis showed that there are significant factors that are correlated with shorter or longer dwell times for commercial vehicles. Using data collected at a residential building, a hotel, a historical building, an office building, and a shopping mall in downtown Seattle, we built generalized linear models with attributes that were known to be correlated with dwell times (Kim et al., 2018; Morris, 2004; Cherrett et al., 2012; Allen et al., 2000; Schmid et al., 2018; Zou et al., 2016; Dalla Chiara and Cheah, 2017). Factors such as a receptionist presence at lobby, number of destinations, vehicle type, and type of goods were significantly correlated with dwell times for commercial vehicles. The study shed new light on the effects of these important factors on commercial vehicle dwell time.

Table 7
Model comparison - five separate dwell time models by different building type.

	Log-Likelihood (AIC)				
Model	Building A	Building B	Building C	Building D	Building E
Linear	−113.6 (239.3)	−96.8 (203.6)	−106.9 (221.8)	−99.2 (208.5)	−146.9 (303.9)
Log-Normal	−114.4 (238.9)	−96.5 (203.0)	−106.9 (221.8)	−96.7 (203.4)	−145.9 (301.9)
Gamma	−103.6 (219.1)	−89.4 (188.9)	−96.3 (202.7)	−95.1 (202.1)	−129.9 (269.8)

7.1. Building operations and number of destinations

Dwell times at the buildings with a receptionist presence at lobby were significantly correlated with shorter dwell times as compared to those without. Allen et al. (2000) indicated that the distance from the goods vehicle to the premises being served can influence dwell times (Allen et al., 2000). Although there have been several dwell time studies related to commercial vehicles, each study focused on a particular building type (e.g., office buildings (Morris, 2004), shopping malls (Dalla Chiara and Cheah, 2017)) or parking location type (on-street parking in New York City (Zou et al., 2016; Schmid et al., 2018)). Cherrett et al. (2012) examined the relationship between dwell times and floor areas of different store types (e.g., jewelers, mobile phone stores, food and drink retail) but found no correlations (Cherrett et al., 2012). This motivated us to observe the relationship between dwell times and different building types, rather than business types.

Shorter dwell times were expected for the buildings with a receptionist presence at the lobby, as the physical location for receiving goods was close to the parked vehicles. At Building B, the same loading bay area was used as both a parking location and the drop-off location where full-time concierge staff received goods. Also, dwell times for deliveries to a single destination within a building was significantly correlated with shorter dwell times than deliveries to multiple destinations within a building. The key finding from this result was that not only the physical building characteristics (e.g., location of loading bays, freight elevators) but also delivery operations within buildings can strongly influence dwell times for commercial vehicles. When parking policies are implemented, it is important to consider their relationship with building operations for handling deliveries, as building operations within different buildings can greatly influence dwell time for commercial vehicles.

7.2. Vehicle type

Consistent with previous dwell time studies (Zou et al., 2016; Dalla Chiara and Cheah, 2017; Schmid et al., 2018), vehicles with swing doors (e.g., vans) were correlated with shorter dwell times (significance showed only at Building E) than were vehicles with roll-up doors (e.g., trucks). As we expected, deliveries made by passenger vehicles were significantly correlated with shorter dwell times than were vehicles with roll-up doors, which had not been reported in previous studies. Currently in Seattle, passenger vehicles can be registered as commercial vehicles as company fleets can comprise passenger vehicles. In addition, in recent years, more deliveries have been made by individuals using their own passenger vehicles for deliveries. Documentation of dwell times for deliveries made by passenger vehicles is especially limited. With crowd-sourcing delivery platforms, deliveries by passenger vehicles are certainly growing in number without regulation. The varying levels of influence of different vehicle types on dwell times should be further investigated as more samples are collected.

7.3. Type of goods

Deliveries of documents were correlated with shorter dwell times than oversized supplies, as expected. The dwell time model for Building E showed a significant correlation between food deliveries and shorter dwell times. The dwell time model developed by Schmid et al. (2018) using data of on-street parking dwell times in New York City found that deliveries of parcels and food were involved with shorter parking durations than service vehicles and other deliveries. With New York City on-street parking data, Zou et al. (2016) consistently found that food deliveries were correlated with shorter dwell times than other types of deliveries such as furniture.

The knowledge gained from this study can be extended to other cities that have similar types of buildings that attract urban freight activities. In this study, we clearly identified factors that are correlated with dwell times for commercial vehicles and presented detailed data analysis results, along with comparisons with factors found in previous studies.

7.4. Parking strategies

Our dwell time models identified factors that can provide good estimates of commercial vehicle dwell times. Being able to estimate commercial vehicle dwell times provides for better predictions of commercial parking needs. Our models provide insights that can enhance parking policies by tailoring time limits and locations based on commercial vehicle needs. Our analysis suggests the following recommendations for the future parking policies; 1) allow passenger load zone use for short commercial deliveries, 2) implement standardized delivery receipt policies aimed to reduce dwell time, 3) consider context-specific commercial vehicle parking time limits. With additional dwell-time studies, cities can develop locally-specific policies that reduce unauthorized parking and its consequences, while best utilizing commercial parking spaces.

1. Allow passenger load zone use for short commercial deliveries

The model results showed that the dwell times were greatly affected by the types of delivery vehicles and goods, and that dwell times for smaller vehicles (e.g., passenger car) were significantly shorter (44% less) than larger vehicles with roll-up and swing doors (e.g., vans, trucks). Deliveries of documents were correlated with shorter dwell times (36% less) than deliveries of oversized goods. Because dwell times for short deliveries are similar to that of passenger drop-offs, allowing passenger load zones for these types of deliveries will allow maximizing the use of passenger load zones, while reserving the limited commercial load zones for longer deliveries.

2. Implement standardized delivery receipt policies aimed to reduce dwell time

Our dwell time models showed that having a receptionist in the lobby is associated with 44% shorter commercial vehicle dwell times. Our models also found that the number of destinations that are two or more locations within a building can result in 1.83 times longer dwell times. Introducing standardized delivery policies such as providing a designated consolidation location (e.g., reception desks, common carrier locker installation at entrances) will reduce the time required to navigate and operate floor-to-floor deliveries inside of buildings. Currently, delivery policies are mostly determined by individual building managers alone. In many cases, different floors or offices in one building may have several different delivery policies for their convenience. Even when there are consolidation areas, they are often haphazardly located. For example, a reception desk can be located on a high floor (e.g., 15th floor) without any consequences from the city. This will lead to high costs for both carriers and cities because carriers are required to learn the specific building configuration to find the location of the reception desk and travel longer routes within the building. Meanwhile, the cities need to manage limited parking facilities for these carriers. In contrast, the locations of mailboxes inside of the urban buildings have been thoroughly considered to be placed conveniently for the United States Postal Service carriers, even before the building construction. With the rapid growth in urban goods movements, consolidation locations such as reception desks or common carrier lockers can be suggested to be designated near main entrances as a standardized delivery policy. With the standardized delivery policies, dwell times can be reduced, as well as more accurately predicted, which will allow planners to better allocate and utilize commercial parking capacity.

3. Consider context-specific commercial vehicle parking time limits

Our five separate dwell time models for each building type showed that significant variables that influence the dwell times can vary by different buildings. Different building types may require longer or shorter dwell times based on the type of goods, vehicle types, number of destinations. This shed new light on the use case for context-specific commercial vehicle parking time limits for commercial vehicle parking. With the current fixed time limits of 30 min, we observed Building E had more vehicles that exceeded the parking limits (24%) as compared to Building A (3%). The commercial vehicles may run out of time and have to re-enter the CVLZs because the deliveries at Building E may require more time than those at Building A. This can also be translated into Building A may not require a full parking limit of 30 min. Accurate dwell time models like the ones described in this paper can be used for developing context-specific commercial vehicle parking time limits for commercial vehicle parking. The information gained from our dwell time models can enable the cities to develop and apply context-specific commercial vehicle parking time limits. This can also further developed into new parking pricing structures for various types of deliveries or delivery vehicles. This could improve the current one-size-fits-all approach to a more data-driven approach to commercial vehicle parking management.

8. Conclusion

Delivery activities in downtown Seattle were observed at five freight-attracting buildings that include the residential building, the hotel, the historical building, the office building, and the shopping mall. This paper identifies factors correlated with dwell time for commercial vehicles. Generalized linear models with gamma distribution were developed, with commercial dwell time as the dependent variable and several explanatory variables. Dwell times correlated with buildings with concierge services tended to be shorter. As expected, deliveries of oversized supplies tended to have longer dwell times. Deliveries by passenger cars had shorter dwell times. When there were deliveries made to multiple locations within the building, the dwell times significantly increased in comparison to one consolidated delivery.

Our dwell time models provide valuable insights into the correlations between commercial vehicle dwell time and other explanatory variables. Valuable information on factors affecting commercial vehicle dwell time can help in developing future parking strategies. The dwell time model can provide estimated commercial vehicle dwell time with a known delivery day, types of vehicles and goods, whether single or multiple deliveries. Under different policy scenarios, our models can be applied to estimate the percent changes of commercial vehicle dwell time to better understand the effects of the policies on commercial vehicle dwell time. A future goal is to observe these changes based on different policy scenarios using establishment data in a city. Additionally, we plan to apply our dwell time models for optimizing parking operations and building resource allocations. For example, with the estimated dwell times, the number of on and off-street parking lots and the number of receptionists can be optimized based on the number of deliveries made to buildings. At the same time, many logistics and delivery companies can also benefit from estimated dwell time to optimize their delivery routes and the number of deliveries for each delivery worker.

Future improvements can be achieved by expanding the data set by collecting observations around more buildings and for a longer period of time. With a larger data set, the accuracy of the estimates can be enhanced, and specific characteristics could be well-defined. Also, data collection for a long period of time can allow discovering possible temporal differences with respect to seasons, holidays, and weekends vs weekdays. In the future, different types of models (e.g., duration models, etc.) can be developed with the same data set and compared with this generalized linear model results to compare the model performances.

CRediT authorship contribution statement

Haena Kim: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration. **Anne Goodchild:** Conceptualization, Methodology, Investigation, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Linda Ng Boyle:** Conceptualization, Methodology, Investigation, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition.

Acknowledgments

This work was conducted in conjunction with a project for the Seattle Department of Transportation (SDOT). Any opinions, findings, conclusions or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of SDOT.

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