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The role of walking in last-mile urban deliveries

Giacomo Dalla Chiara[1] · **Anne Goodchild**[1]

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Abstract
Most of a delivery driver's time is spent outside the vehicle, walking the last-50-feet to reach the delivery customers while the vehicle is stationary. However, little is known about the walking component of delivery routes, while most models and algorithms used for scheduling and planning urban freight vehicles focus solely on the driving component. This study fills this research gap by providing an empirical analysis of the role of walking in last-mile deliveries. The study aims to empirically quantify delivery drivers' walking distances and shed light on the interrelation between walking and the overall efficiency and sustainability of delivery routes. Two data samples were obtained that recorded more than 1,800 real deliveries performed by a parcel carrier and a beverage carrier in Seattle, WA. Data on both vehicle routes and drivers' walking sub-routes were obtained and analyzed. Dwell time regression analyses and simulations were performed to understand the impact of walking on last-mile routes. The results highlighted the importance of walking across different types of deliveries. Both carriers either walked longer distances to find better parking or to serve multiple delivery customers from a single stop. The parcel carrier also showed large economies of scale in performing multiple deliveries per stop. An increase in willingness to walk showed a general reduction in the number of stops per route and in total vehicle miles traveled. The paper concludes with a discussion on the importance of walking in scheduling and planning for delivery vehicles in urban areas.

Keywords Urban freight · Walking behavior · Last-mile · Freight simulation · Freight parking

✉ Giacomo Dalla Chiara
giacomod@uw.edu

Anne Goodchild
annegood@uw.edu

[1] Department of Civil and Environmental Engineering, University of Washington, Seattle, WA 98195, USA

Introduction

Last-mile urban deliveries are often depicted as in the left picture in Fig. 1—a delivery van or a truck driving through an urban neighborhood. However, an observer is much more likely to see something closer to the picture on the right—a parked delivery vehicle and a driver walking to reach a delivery customer. In fact, a delivery driver spends most of their time outside the vehicle, loading–unloading and walking the last-50-feet of a delivery. Dalla Chiara et al. (2021) documented the delivery journey of six drivers, performing from parcel to heavy goods and mail deliveries, and found that about 80 percent of a delivery driver's time is spent parked, walking to reach the final delivery destinations, while the vehicle is stationary. Other authors reported similar behaviors. Allen et al. (2017) performed 25 ride-alongs in London, UK, and found that drivers spent, on average, 62 percent of their time parked. However, despite most of the delivery journey taking place outside the vehicle, little is known about the walking behavior of delivery drivers and how walking impacts the overall efficiency and sustainability of delivery routes in urban areas.

Instead, most urban freight modeling and empirical analysis focused on the driving component of a delivery route, trying to route vehicles to minimize traffic congestion and total distance traveled, often ignoring what, according to the current work, is the most important component of the delivery route: walking. With the current work, we want to recognize the essential role walking plays in the daily job of urban delivery workers and empirically quantify what we will generally refer to as delivery drivers' walking behavior.

The journey of a delivery driver starts with a delivery manifest—a pre-planned list of delivery customers associated with respective addresses to which a delivery/pick-up or a service activity is performed. The driver then performs the assigned tour as quickly and safely as possible, often under strict time window constraints, facing a complex urban environment. While sophisticated routing technologies were developed to support drivers in this effort (Schiller et al. 2016), even in the most advanced and largest carriers, it is still entirely up to the driver to choose where and how far to park the vehicle from the delivery customers, which and how many customers to serve from the chosen parking stop location, and how long to be parked for. However, in this paper, we argue that these decisions significantly impact the overall performance and impact of an urban logistics system. With 60–80

Fig. 1 Despite urban deliveries being associated with the picture on the left depicting a van driving, for most of the delivery route time, delivery vehicles are parked while drivers walk the last-50-feet (right)

percent of a delivery driver's time spent outside the vehicle, more data, methods, and tools must be paid to understand and optimize this component of urban deliveries.

We generally refer to these choices as the *walking behavior* of delivery drivers. The current study objective is to empirically observe and analyze delivery drivers' walking behavior and understand how walking affects a delivery route's efficiency and environmental impact, including the time it takes to complete all deliveries, the total vehicle miles traveled, and related vehicle emissions. In particular, the current paper addresses three main research questions:

1. How far do delivery drivers walk to reach the delivery customers?
2. How does walking behavior impact vehicle dwell times?
3. How does walking behavior impact the time it takes to complete a delivery route and the total vehicle miles traveled?

Understanding delivery drivers' walking behavior is paramount for carriers to incorporate walking in the planning and scheduling of delivery routes and for urban planners to integrate walking into urban logistics policy and infrastructure planning. The empirical results and methods developed in this study have direct implications for many decisions in urban logistics optimization, modeling, and planning, including curb management and allocation of commercial vehicle load zones, routing, and scheduling of commercial vehicles in urban areas, as well as strategies in reducing delivery vehicle miles traveled, hence promoting multimodal freight, including cargo bikes and portering.

To address the first research question, data samples were obtained from a parcel delivery carrier and a beverage delivery carrier that performed deliveries in Seattle, WA. For each sample, two data sources were combined to empirically analyze walking behaviors: one GPS tracking the delivery vehicle routes and parking locations, and one tracking the delivery drivers walking and delivery sub-routes. By combining these two data sources, it was possible to derive the empirical distributions of the walking distance, number of delivery customers served per parking stop, number of buildings visited, and delivery dwell times. Then, the second research question was addressed by performing a regression analysis of the vehicle parking dwell times on the observed walking behaviors. Finally, a simulation framework was developed to address the third research question. A delivery route was divided into space and time segments representing three main actions: driving, cruising for parking, and walking. Different walking behavior scenarios were tested to understand the impact of walking on the performance of a delivery route, including the total vehicle miles traveled and the time it takes to perform a route.

This empirical analysis of drivers' walking behavior is a first step towards a more general understanding of drivers' delivery behaviors, which is necessary to formulate and estimate better urban freight models and simulations. Current urban freight models assume a fixed demand of delivery stops without distinguishing between stop (where the vehicle parks) and delivery (where the delivery request is met). Moreover, dwell time modeling efforts often disregarded walking distances and time. The current work provides an empirical framework to study walking behavior and its impact on delivery routes.

In the next section, the relevant literature is described, and the contributions of this work with respect to the literature are highlighted. 3 introduces the data sources used, the sample data, regression model formulations, and the simulation framework. Empirical descriptive results are presented in Sect. "Descriptive results", while regression model estimates and simulation results are reported in Sect. "Modeling results". The paper concludes with Sect. "Conclusion and discussion", which summarizes the key results and discusses the implications of the research results from the private and public sector perspectives.

Relevant literature

Walking is the oldest, the most universal, and the most common mode of transportation in urban areas worldwide (Volvo Research and Educational Foundations 2022). Considerable research efforts in the past decades focused on studying walking as a means of transport to access destinations and activities in urban areas (Calvert et al. 2019; Zapata-Diomedi 2017). Given the documented benefit of walking, many researchers, urban planners, and public jurisdictions have started asking themself how to make cities more walkable, studying the relationship between the built environment and walkability, and integrating walking in urban planning and design (D'Orso and Migliore 2020; Koo et al. 2022).

Walking also represents a key component to accessing other modes of transportation. In this regard, several studies have analyzed the role of walking in public transit, private vehicle transportation, biking, and shared micromobility. Walking plays a key role in determining the structure of a public transit network and its utilization, being the main mode used to access bus stops, subway, and rail stations (Durand et al. 2016; van Soest et al. 2019; Louf et al. 2014)). Walking was also analyzed in the context of shared micromobility. Especially in a fixed station bike share network, understanding the willingness to walk is a key component in designing an efficient micromobility network (Mix et al. 2022). Walking has been identified as a major factor influencing the passenger vehicle choice of parking location, parking type (whether on-street or off-street), and cruising for parking time. Gillen (1978) formulated one of the first disaggregate models of passenger vehicle parking location choice. He modeled this choice as a trade-off between parking fees and walking time (which he referred to as "egress time") and derived elasticities for changes in price, time, and full cost (cost of parking fee and walking time) for different walking distances. Axhausen and Polak (1991) developed a model of passenger vehicle choice between on-street and off-street parking as a function of four main variables: access time (driving time from origin to destination), search time (cruising for parking time), egress time (walking time) and parking cost (fees or expected parking tickets if double parked). Millard-Ball et al. (2019) further decouple parking search and cruising (defined as excess travel beyond search time) and derive the interplay with a driver's willingness to walk. The authors showed that drivers facing parking scarcity are more willing to accept less optimal parking locations, trading it off with longer walking time.

Despite its importance in many modes of travel, walking has been rarely analyzed in the context of freight transportation and logistics, which is the focus of the current study. Previous research focused on demonstrating and analyzing walking delivery routes, known as on-foot porters or portering. Allen et al. (2021) documented a one-day pilot of using porters to perform deliveries in central London, UK. The researchers collaborated with a parcel delivery company and tested a two-echelon system in which a driver transported pre-loaded bags using a van and met with porters at pre-determined locations, where the porters performed walking routes. The paper documented operational reductions in total parking dwell times, vehicle use, and distance traveled but worsened the total labor required. McLeod et al. (2020) simulated different operational scenarios, including porters with wheeled bags, trolleys, and cargo bikes, documenting substantial environmental and financial savings potentials. Several papers contributed to practical optimization literature formally defining two-echelon routing problems and proposing automated solutions integrating walking and driving routes (Nguyen et al. 2019; Martinez-Sykora et al. 2020). Similar models were developed assuming, instead of porters, drones, or automated ground vehicles (Luo et al. 1144; Simoni et al. 2019).

While these works analyzed walking as an alternative mode of transporting goods in urban areas, a handful of research papers recognized the importance of walking in delivery routes traditionally performed with motorized trucks and vans. Table 1 summarizes the reported walking distances and times obtained by reviewed studies, described below.

Allen et al. (2017) performed 25 ridealongs with a carrier delivering parcels in London, UK, and identified both driving and walking segments of the delivery process. They found that of the average total route time of 7.3 h, drivers spent 62 percent of their time parked, walking to perform the deliveries and pickups. They also measured the total walking distance, estimated at 7.94 km per route, representing 40 percent of the total distance covered by driving and walking.

Similarly, Dalla Chiara et al. (2021) also used ridealongs to observe delivery drivers' behaviors. The authors performed six ridealongs with different carriers performing parcel, heavy goods, and medical deliveries in Seattle, WA. The authors found that drivers spent, on average, 80 percent of their time parked, walking to the final delivery destinations, except for one ridealong, which showed a reversed ratio of 20 percent walking and 80 percent driving, which only had overnight deliveries to rural communities.

Holguin-Veras et al. (2016) performed a delivery driver intercept and online surveys to inform a behavioral microsimulation of commercial vehicle parking in a study area in New York City. They collected 16 responses and documented an average walking time for delivery customers of 10 min, ranging from 0 min in Brooklyn to a maximum of 45 min in Queens.

Nourinejad et al. (2014) developed a simulation framework that included a parking choice model and a traffic simulation model for freight vehicles in urban areas and applied it to the Toronto Central Business District to evaluate potential closures to freight vehicle traffic of selected road segments. The authors included walking distance and time of deliv-

Table 1 Summary of delivery drivers' walking distances and times reported in the literature

Study	Location	Walking distance	Walking time	Method
Allen et al. (2017)	London, UK	107.6 meters[1]	–	Ride-along
Holguin-Veras et al. (2016)	New York, US	–	10 min	Survey
Nourinejad et al. (2014)	Toronto, CA	65.5 meters[2]	2.2 min[2]	Simulation
Holguin-Veras et al. (2013)	New York, US	–	7 min[3]	Survey
Dezi et al. (2010)	Bologna, IT	70 m	–	Survey
Aiura and Taniguchi (2005)	Kyoto, JP	25.5 meters[4]	–	Survey

[1]Average per stop, one way

[2]Averaged across simulated scenarios

[3]A further reduction in walking time to 5.3 min was reported for off-peak deliveries

[4]Averaged across maximum distances drivers reported being willing to walk

ery drivers as a key output metric of the framework and obtained average walking distances for delivery drivers per stop between 37 and 88 m across different scenarios.

Holguin-Veras et al. (2013), as part of a larger study to evaluate the impact of incentivizing truck drivers and receivers to shift deliveries to off-peak in New York City, surveyed 11 drivers and documented, among other variables, how their walking behavior changed by shifting deliveries overnight. They found that drivers walk from their parking location to a delivery destination on average 7 min during daytime and 5.4 min during nighttime. They also found that 40 and 60 percent of drivers park within one block of the receiver during daytime and nighttime, respectively.

Dezi et al. (2010) used circles of a 70-m radius to optimally allocate commercial vehicle loading zones in Bologna, Italy, after performing a survey among delivery drivers.

Allen et al. (2008) reviewed 30 empirical urban freight studies performed in the U.K. and reported their findings regarding several freight behaviors, including parking dwell time and walking. The authors analyzed the locations where the drivers met the receivers, but no quantitative analysis of the distance of these locations from the stop location was carried out. All studies found that most drivers walked to the retailer location, and only a few performed the delivery at the stop location. Moreover, they identified walking distance and the number of deliveries performed per stop among key factors explaining parking dwell times.

Aiura and Taniguchi (2005) surveyed delivery drivers in Kyoto, Japan, and asked their maximum willingness to walk. They found a range between 10 m (29 percent of drivers) and 50 m (17 percent of drivers), with 6 percent reporting not caring about how far the parking location was.

Given the importance and prevalence of walking in urban delivery routes, it is paramount to include it in the analysis of urban deliveries. While several studies have assumed that walking distance is a key variable affecting dwell times (Holguín-Veras et al. 2016, 2015), none of the empirical studies that analyzed urban commercial vehicle dwell time distribution looked at the impact of walking distance. Schmid et al. (2016) modeled commercial vehicle dwell times based on field observations collected in New York City. The empirical model estimate contained information only on the vehicle type, type of delivery, and parking choice. Zou et al. (2016) analyzed stop dwell time and the number of stops per tour for commercial vehicles delivering in New York City. Their dwell time model used only vehicle type, type of delivery, and time of day. They also found that a vehicle performed an average of 14 stops per tour. Dalla Chiara and Cheah (2017) analyzed the dwell time of commercial vehicles delivering to urban retail malls in Singapore and found that the volume of goods transported, the vehicle loading, and the presence of pick-up activities increased dwell time. Kim et al. (2018) collected detailed data on the delivery operations inside an office building in Seattle by following the drivers as they performed the deliveries. They found that 26% of the drivers performed more than one delivery. However, drivers might have performed more deliveries outside the building, which were not observed. They also observed that delivery operations at the receiver took one to two minutes, and the remaining dwell time was spent performing other operations such as loading/unloading and walking to the receiver locations. No statistical modeling of the effect of walking distance and number of deliveries on stop dwell time was carried out.

Contributions to the literature

To summarize, while walking has been increasingly recognized as a mode of transport in its own right and as a key component of many modes of transportation, a considerably smaller number of studies considered walking within urban freight transport. Urban last-mile deliveries have mostly been associated with the action of driving trucks and delivery vans, with the consequence that most research works analyzed and modeled urban freight transport only focusing on its driving component, ignoring walking. Few research works documented walking within last-mile delivery operations, reporting walking distances ranging from 26 to 108 m and walking times ranging between 2 and 10 min per delivery. The current study expands on the previous literature by developing a novel empirical methodology to document and analyze walking in last-mile deliveries and further delve into understanding the relationship between walking and the performance of delivery routes in urban areas. This work fills the research gap by considering walking as a key component of last-mile urban deliveries and exploring the effect of walking on routing, parking, dwell time, and urban delivery routes' overall efficiency and sustainability.

Research methodology

Study area

The data used in this study was obtained from two logistics carriers delivering in the Seattle downtown core, which refers to the ten neighborhoods highlighted in Fig. 2.

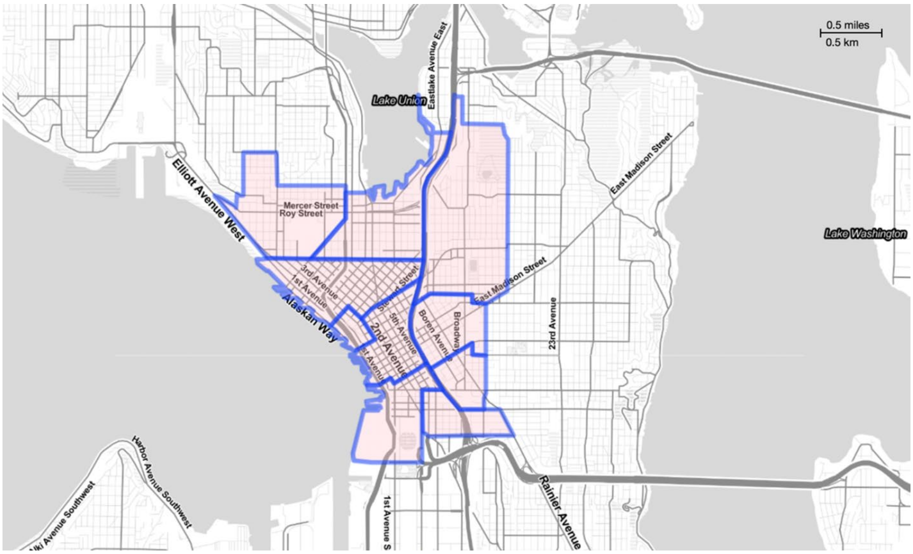


Fig. 2 The study area, highlighted in the map, is formed by ten neighborhoods of Seattle, WA. From top-left to bottom-right: Lower Queen Anne, South Lake Union, Broadway, Belltown, Pike-Market, Central Business District, First Hill, Pioneer Square, Yesler Terrace, and International District

The study area measures 11.4 square km (4.4 square miles), and it comprises primarily mixed-used high-density developments, including offices, apartment buildings, commercial establishments, and tourist and sports venues such as the Space Needle, the Pike Place Market, and the Lumen Field Stadium.

As reported by the carriers, the study area is generally characterized by a lack of off-street loading/unloading bays, with the consequence that delivery vehicle drivers rely, for the most part, on the curb lane to park and load/unload the vehicles. Approximately 10 percent of the curb allocated to vehicle parking in the study area is designated as Commercial Vehicle Load Zones (CVLZs) and Passenger Load Zones (PLZs). These two types of curb space are the most frequently used authorized stopping locations for delivery vehicles (Dalla Chiara et al. 2021).

Data sources: stop and delivery data

The current study used *stop data* and *delivery data* collected from real-world deliveries from two carriers operating in the study area.

Stop data describes the delivery vehicles' activities, recording the start and end timestamps of each vehicle parking stop and the corresponding latitude/longitude coordinates of the parking location. Stop data was obtained from the Global Positioning System (GPS) tracking devices deployed in the vehicles by the carriers. Stop times and geolocation were identified by the carriers using a multitude of sensors embedded in the vehicles, including engine, seatbelt, and door sensors.

Delivery data contains activities performed by the delivery drivers outside the vehicle, including loading/unloading, walking from the vehicle stop locations to the delivery destinations, and completing deliveries to customers. Each delivery location's latitude/longitude coordinates and a timestamp of when the delivery occurred were recorded. Delivery data was obtained from drivers' mobile delivery devices at the points of delivery, when the consignee needed to sign the proof of delivery, or when the driver took a picture of where the shipment was dropped.

In addition to the geolocations and timestamps of stops and deliveries, the dates and anonymized drivers' identifiers were reported.

Data processing: merging stop and delivery data

For each delivery, the corresponding vehicle stop from which the delivered item was unloaded was identified (Fig. 3). A delivery was matched to a stop whenever both events (i) were associated with the same driver unique identifier, (ii) were performed during the same day, and (iii) the delivery timestamp was contained within the stop time window. In the

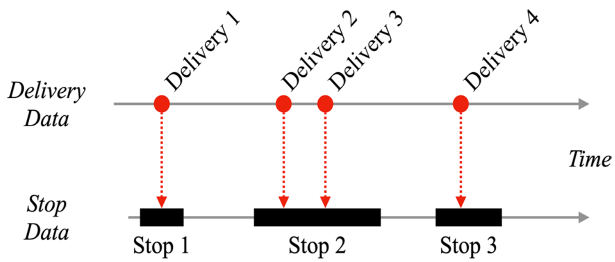


Fig. 3 Matching of delivery events to respective parking stops

example in Fig. 3 , the first delivery event was matched with Stop 1, the second and third were matched with Stop 2, and the fourth was matched with Stop 3.

The following variables of interest were computed after matching delivery and stop data.

- The *walking distance*s were computed as the Euclidean distance between a delivery location and its associated vehicle stop location. No data was available on the actual walking tour performed by the driver to reach the delivery destination. Therefore, the Euclidean distance was used to proxy how far away a driver parked. Figure 4 shows an example of a stop matched with four deliveries and their respective walking distances. The walking distance can be seen as a lower bound to the actual walking distance, as the latter often includes navigating physical barriers such as finding a building's entrance, taking elevators, etc.
- The number of *deliveries per stop* consists of the number of deliveries performed by a driver for each vehicle stop event; in other words, the number of delivery customers visited each time the driver parked the vehicle.
- Finally, delivery locations were matched with the building shapes GIS layer (City of Seattle 2020) to compute the number of buildings visited per stop. For instance, in Fig. 4, the four deliveries associated with a single stop occurred within three buildings. Hypothetically, it takes more effort to perform multiple deliveries across multiple buildings than to perform multiple deliveries within the same building.

Sample data description

Delivery and stop data samples were obtained from two logistics carriers: a parcel delivery company (thereafter named *Carrier P*) and a beverage carrier (thereafter named *Carrier B*).

Carrier P used delivery vans (approximately 26 ft—8 m long) to deliver and pick up parcels in downtown Seattle's residential buildings, offices, and retailers. Carrier B used larger box trucks (approximately 33 ft—10 m long) to deliver beverages and non-perishable food to retailers in downtown Seattle.

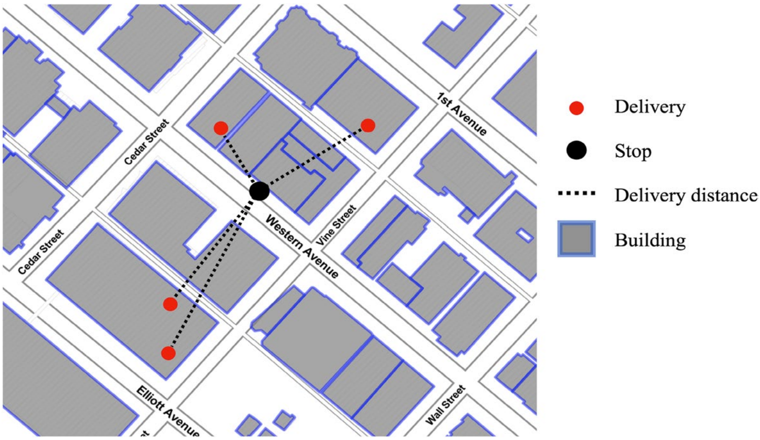


Fig. 4 Map showing four delivery locations (smaller red dots) that were served by a single stop location (larger black dot) and the respective walking distances (dashed lines)

Table 2 reports the main summary statistics for each carrier's stop and delivery data. Carrier P recorded 284 stops and 972 deliveries, while carrier B recorded 668 stops and 897 deliveries. For sample P, only one driver was observed for 24 days between October 3 and November 9, right before peak e-commerce sales starting in mid-November. Sample B records data from 13 drivers over 125 days spread across 12 months, from March 2019 to March 2020. While carrier B data includes peak sales time, we do not expect carrier B to be affected by high demand fluctuations. Moreover, carrier B was mostly recorded before COVID-19 lockdown, which took place in Seattle at the end of February 2020.

Carrier P made a similar number of deliveries/pick-ups throughout the day, mostly starting at 9 a.m., and only a few deliveries were made earlier than 9 a.m. Deliveries are evenly distributed throughout the week. Carrier B makes most deliveries early in the morning, and the number of deliveries decreases throughout the day. Most deliveries are made on Monday, Tuesday, and Thursday.

Dwell time modeling

A regression analysis was performed to better understand the impact of the number of deliveries per stop and walking distance on stop dwell times. The logarithm of dwell time was regressed over the variables of interest, and their marginal effect was estimated separately for carriers P and B, obtaining two sets of estimated regression coefficients.

Table 2 Summary statistics of variables obtained for two samples

Statistic	Data sample	
	Parcel carrier (P)	Beverage carrier (B)
No. stops	284 stops	668 stops
No. deliveries	972 deliveries	897 deliveries
Delivery density	40 deliveries/km^2	3 deliveries/km^2
Date range	October 3 to November 9, 2018	March 27, 2019 to March 10, 2020
No. days	24 days	125 days
No. tours	24 tours	152 tours
No. drivers	1 driver	13 drivers
Time of day		
8	3.9%	18.4%
9	13.6%	17.3%
10	10.0%	17.7%
11	17.5%	12.5%
12	11.1%	13.5%
13	6.1%	10.6%
14	10.0%	7.4%
15	16.8%	2.2%
16	11.1%	0.4%
Day of week		
Mon	20.0%	19.2%
Tue	19.3%	32.1%
Wed	26.8%	14.7%
Thu	17.1%	21.8%
Fri	16.8%	12.2%

Different model specifications were tested using different functional forms to capture possible non-linearities and other temporal variables. The final model specification was selected such that the resulting adjusted R squared was smaller than simpler model specifications, the p-values of the relevant parameters showed significance for the key parameters, and the models were interpretable. The final dwell time model specification is as follows:

$$\log(T) = \beta_0 + \beta_1 ndel + \beta_2 ndel^2 + \beta_3 \frac{ndel}{nbuild} + \beta_4 maxdist + \beta_5 1_{[morning]} + \beta_6 weight + \varepsilon$$

where:

- $\log(T)$ is the natural logarithm of the stop dwell time T(minutes);
- $ndel$ is the number of deliveries per stop;
- $nbuild$ is the number of buildings per stop;
- the fraction $ndel/nbuild$ is referred to as delivery density and can be interpreted as the number of deliveries per building served;
- $maxdist$ is the largest walking distance between a stop and the associated deliveries (km);
- $1_{[morning]}$ is a dummy variable = 1 whenever the delivery was performed before noon;
- $weight$ is the total weight of the goods delivered (kg), available only for company B;
- $\{\beta_i\}_{i=1,\dots,6}$ are the unknown regression parameters to be estimated;
- ε is a zero-mean normally distributed random error.

The dwell time model coefficients for carrier P were estimated using 284 observations from a single driver, while the parameters for the dwell time model for carrier B were estimated using 668 observations recorded from 13 drivers.

For carrier P data, regression coefficients were estimated using Ordinary Least Squares (OLS). For carrier B data, a mixed-effect model with a random effect accounting for variation caused by different driver unique identifiers was used to capture possible dependencies between stops performed by the same driver (Bates et al. 2015). For the latter model, the regression coefficients were estimated using Restricted Maximum Likelihood (REML) using the Lme4 package (Bates et al. 2015) coded in the R language (R Core Team 2017).

Tour simulation modeling

A tour simulation model was developed to understand the impact of delivery drivers' walking behavior on the performance of delivery routes. Figure 5 provides a general overview of the model framework. The model consists of a set of inputs, outputs, and three sub-models: the stop formation, dwell time, and driving and cruising sub-models.

The model inputs consist of a set of real tours performed by parcel carrier P and beverage carrier B and a given maximum walking distance, measured in meters, representing the approximate maximum distance a driver is willing to walk from a parking location to a delivery destination. The stop formation model then aggregates the deliveries in each tour into stops—assuming that a driver might be willing to perform multiple deliveries from the same stop—and, for each stop, identifies the vehicle parking location. Once the stops are simulated, two additional models simulate the total time the driver takes to perform all

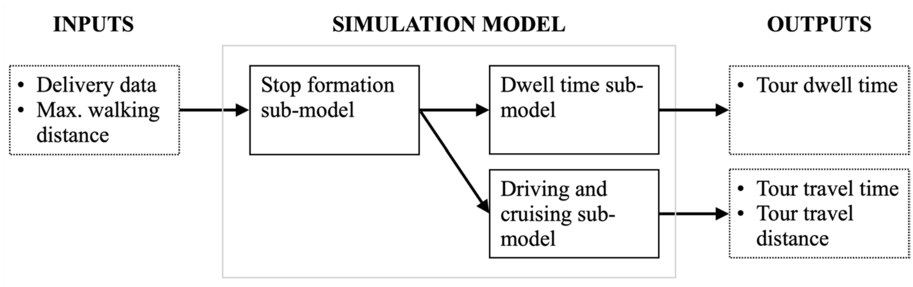


Fig. 5 Simulation model framework: dotted boxes represent inputs/outputs, solid-line boxes represent sub-models

deliveries at a given stop and the total travel and cruising time between stops and between the depot and the first and last stop of a given route. The model outputs the total tour time, i.e., the total time it takes to perform all deliveries in a tour and the total distance driven. The total tour time is defined as the sum of the driving time, the cruising for parking time, and the stop dwell times. The following three subsections provide more details for each sub-model.

Inputs The simulation model has two main inputs: a set of real delivery tours and a maximum walking distance parameter. A total of 176 tours, comprising 1869 deliveries performed by carriers P and B in Seattle between October 2018 and March 2020 were used as input to the model. For each performed delivery, a time and date, a GPS location, and a unique anonymous driver identifier were recorded. To simulate different walking behaviors, a maximum walking distance, defined as the maximum Euclidean distance between a stop location and any delivery served, is given as an input parameter to the simulation. By varying the maximum walking distance, the number of stops in a given tour is also affected: the shorter the maximum walking distance, the fewer deliveries are performed per stop, and consequently, the larger the number of stops in a tour.

Stop formation sub-model In the stop formation sub-model, the deliveries performed by a driver in a given tour are assigned to stops. Each stop represents a parking event from which the deliveries assigned to that stop are performed. The deliveries are assigned to each stop so that all deliveries are not farther than the assumed maximum walking distance. Moreover, the model maintains the observed delivery sequence, i.e., the original order in which the drivers performed the recorded deliveries. The sequence in which a driver performs deliveries depends not only on their geographical location (deliveries that are nearby are more likely to be served from the same stop) but also on other variables that were not recorded in the data, such as delivery time windows and delivery priority level, among others. Therefore, while the deliveries to stop aggregation is re-computed, the original time sequence of deliveries in a tour is not changed from the one observed in reality.

The stop formation sub-model consists of three steps: (1) clustering, (2) feasible stop search, and (3) stop location. In the clustering step, deliveries are grouped into disjoint clusters, each representing a potential stop. A hierarchical clustering algorithm is applied to each tour to generate a hierarchy of nested clustering solutions. At the highest level of the hierarchy, all deliveries are clustered into a single stop; at the lowest level of the hierarchy, each delivery is a stop on its own; at any intermediate level, two clusters generated at a lower level are merged into a single cluster. The clustering algorithm requires a distance matrix T with elements t_{ij} measuring the dissimilarity between any two elements i and j. In this model, each t_{ij} is defined as the time distance between any two deliveries i and j. In such a way, deliveries that were performed consecutively are clustered together, maintaining the observed delivery sequence.

Once the hierarchy of clustering solutions is found, a feasible stop search is performed. For each candidate stop in the hierarchy, the maximum geographical distance between any two deliveries belonging to the same stop is computed. If this distance is less than or equal to twice the given maximum walking distance (we assumed that the vehicle stops in the middle of the cluster), then the stop is feasible. The feasible stop search starts from the top of the hierarchy (all deliveries are assigned to the same stop) and iteratively searches for feasible stops going down to lower levels. The feasible stop search ends once all deliveries are assigned to stops. The output of this algorithm consists of finding the largest clusters of deliveries that were performed consecutively in time so that any two deliveries belonging to the same stop are not farther apart than the assumed maximum walking distance. Figure 6 shows the result of the stop formation algorithm for an artificial set of delivery locations and varying levels of maximum walking distance. Note that the number of stops decreases as the maximum walking distance increases.

Once all stops are determined, the vehicle stop location is found by averaging the latitude/longitude coordinates of all deliveries belonging to the same stop, assuming that the vehicle stops at the cluster's center. The final output of the stop formation model consists of a set of stops for each observed tour, each stop characterized by a given number of deliveries, their geographical distribution, and a vehicle stop location from which deliveries are performed.

Dwell time sub-model The set of stops generated from the previous sub-model is then used as input to a dwell time sub-model, which predicts the total dwell time of each stop using the dwell time regression formulas developed in the previous section. Carriers P and B data were used to estimate two different dwell time models (see estimated parameters in Table S4). The model takes as input the number of deliveries at a stop, the maximum distance between the vehicle stop location and the delivery destinations served, and the number of buildings that contain all the deliveries assigned to that stop. Each variable is then multiplied by the respective value of the estimated regression coefficient. Moreover, a random number picked from a normal distribution with mean zero and standard deviation

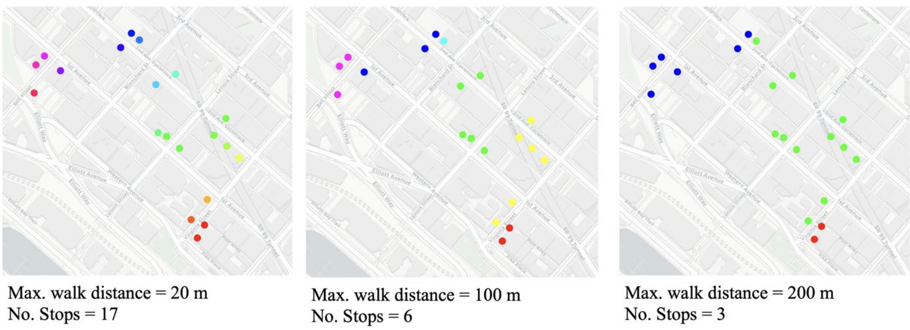


Fig. 6 Results of the stop formation sub-model for an artificial tour of 20 deliveries for varying levels of maximum walking distance

equal to the observed standard deviation of the estimated regression residuals is added to the predicted stop dwell time.

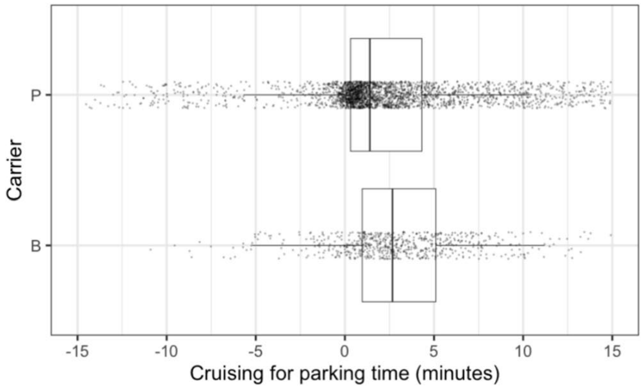
Driving and cruising sub-model. The driving model takes as input each tour's vehicle stop location and time sequence in which the stops are performed and outputs the driving distance and time between each pair of consecutive stops and between the first/last stop and the depot. The shortest path between each pair of destinations is computed using the Open Source Routing Machine (OSRM) package in R (Giraud 2020). To each trip time between stops, cruising for parking time was added by randomly picking from a normal distribution with mean and standard deviation equal to the empirical mean and standard deviation of the empirical distribution of cruising for parking times observed for carriers P and B. Figure 7 shows the empirical distributions of estimated cruising for parking times obtained from the two carriers' data. These estimates were obtained by benchmarking each trip time performed by the carriers with the forecasted time using the Google Maps Distance Matrix API (Platform and "Distance Matrix API", Developer Guide 2021). ld (2020), and Dalla Chiara et al. (2022) for more details on the methodology used to estimate cruising for parking times.

Outputs The above steps are performed for each observed tour and each given value of maximum walking distance. Moreover, for each stop, the respective dwell time and trip time are predicted 100 times; each time, a different random error and cruising time are picked at random from the respective probability distributions. Two sets of output metrics are obtained for each given value of maximum walking distance: stop- and tour-level metrics. Stop-level output metrics include the following.

- *Stop dwell time* Vehicle stop dwell time is averaged over all
- *Trip travel and cruising time* Sum of travel time between any two stops and cruising for parking time, averaged over all tours (minutes).

Tour-level output metrics include the following.

- *Number of stops per tour* Mean number of stops per tour, averaged over all tours.
- *Tour travel distance* Mean total travel distance per tour, averaged over all tours (km).
- *Tour travel and cruising time* Total time spent traveling between stops and between the



	Carrier	
	P	B
Min	-14.5	-10.9
1st Qu.	0.3	1.0
Median	1.4	2.7
Mean	2.3	3.0
3rd Qu.	4.3	5.1
Max	14.9	14.9
St. Dev.	4.8	3.7

Fig. 7 Empirical distributions of estimated cruising for parking times for carriers P and B

depot and the first/last stop and spent cruising for parking in a tour, averaged over all tours (hours).

- *Tour dwell time* Sum of all dwell times in a tour, averaged over all tours (hours).
- *Tour total time* Sum of tour dwell time and tour travel and cruising time, averaged over all tours (hours).

Descriptive results

Four main variables of interest are obtained after processing and merging delivery and stop data:

- *Deliveries per stop* The number of delivery locations served from a given stop; each delivery is characterized by a unique pair of latitude/longitude coordinates.
- *Buildings per stop* Number of buildings that contain all deliveries performed from a stop.
- *Walking distance* Euclidean distance between a delivery and its respective stop location.
- *Dwell time* Total time a vehicle is parked while the driver performs the delivery requests.

Table 3 reports the main summary statistics of these variables. The following subsections discuss each variable's observed empirical distribution, and results from the two data samples are compared.

Number of deliveries and buildings served per stop

Figure 8 shows the percentage of stops by number of deliveries for each carrier. For both carriers, most stops are characterized by only one or a few deliveries, and this share decreases as the number of deliveries per stop increases. However, while 81 percent of stops performed by carrier B are characterized by one delivery, only 33 percent of stops of carrier P served one delivery location. Table 2 shows that carrier P's median number of deliveries performed per stop is two, while carrier B performed a median number of one delivery per stop. The mean number of deliveries per stop is 3.4 and 1.3 deliveries per stop for P and B, respectively.

The number of buildings per stop shows similar distributions to Fig. 8; hence, they are not reported here. The median numbers of buildings visited per stop are 2 and 1 for carriers P and B, and the means are 2.7 and 1.3. Of course, the number of buildings served per stop is lower or equal to the number of deliveries per stop, as two or more deliveries can be located within the same building.

Several factors can explain the different behaviors. The parcel carrier generally performed more frequent deliveries (higher delivery density) of smaller and lighted items than the beverage delivery carrier. Moreover, the parcel carrier P delivered mostly in the Belltown district of Seattle, one of the city's busiest neighborhoods, and therefore, drivers might have experienced a high cost of re-parking the vehicle. The beverage carrier's drivers also operated in other neighborhoods where the cost of re-parking the vehicle might have been smaller.

Table 3 Summary statistics of main variables of interest

Statistic	Data sample	
	Parcel carrier (P)	Beverage carrier (B)
No. deliveries per stop		
Min	1.0	1.0
Median	2.0	1.0
Mean	3.4	1.3
Max	16.0	11.0
No. buildings per stop		
Min	1.0	1.0
Median	2.0	1.0
Mean	2.7	1.3
Max	12.0	9.0
Walking distance (meters)		
Min	3.1	2.4
Median	38.4	104.5
Mean	53.3	148.8
Max	417.7	499.5
Dwell time (minutes)		
Min	0.9	3.8
Median	17.5	33.4
Mean	26.2	43.0
Max	148.9	290.0

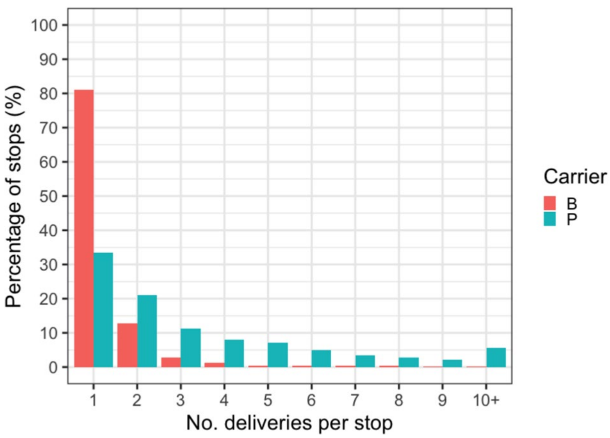


Fig. 8 Empirical distributions of the number of deliveries per stop for beverage carrier B and parcel carrier P

Walking distance

Figure 9 shows the empirical distributions of the observed walking distances for each carrier, defined as the Euclidean distance between the parking stop location and the customer delivery location, for each delivery performed. The median walking distance for carrier P is 38.4 m (126 feet), while for carrier B is 104.5 m (343 feet), almost three times longer. The larger median walking distance can be explained by the fact that the vehicles used by carrier B are larger than those used by carrier P, and they might not be able to find a large enough parking location close to the delivery location and, therefore, are forced to park farther away. The beverage carrier B also shows a wider variation in walking distance, which might have been caused by the larger number of drivers observed and data obtained.

Parking dwell time

Figure 10 shows the empirical distributions of parking dwell times for carriers P and B. On average, carrier B's dwell times are longer than carrier P's, with median dwell times of 33.4 min and 17.5 min, respectively. The variation in dwell times is also larger for carrier B.

Longer carrier B dwell times might be caused by several factors, including (*i*) the larger volumes and weight of deliveries, (*ii*) the fact that carrier B mostly delivers to retailers, while carrier P mostly delivers to households and offices, and (*iii*) the longer walking distances.

Modeling results

Effect of walking on dwell time

Table 4 reports the estimated regression coefficients for the two dwell time models estimated using data from companies P and B, for which we provide an interpretation in the following paragraphs.

As expected, the estimated value for β_1 is positive for both carriers, indicating that the larger the number of deliveries performed in a stop ($ndel$), the longer the dwell time. The negative sign of the estimated β_2 indicates a decreasing marginal effect of the number of deliveries per stop on dwell time.

The number of deliveries per stop interacts with the number of buildings where the deliveries are located. The sign of the estimated regression coefficient β_3 multiplying the delivery density is negative for both carriers: for a given number of delivery customers, the more deliveries are within the same building(s), instead of being spread across different buildings, the shorter the parking dwell time. Whereas, spreading deliveries across different buildings will have the opposite effect of increasing dwell time, for a given number of deliveries.

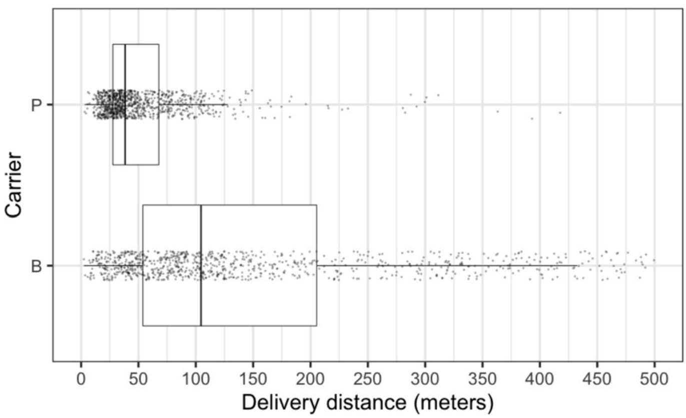


Fig. 9 Boxplots showing the empirical distributions of walking distance for carriers B and P

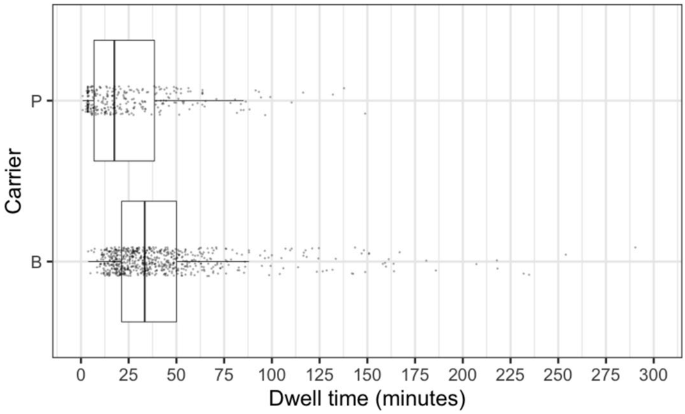


Fig. 10 Boxplots of the empirical distributions of parking dwell times for carriers B and P

Table 4 Regression estimation results

Variable		Parcel carrier (P)		Beverage carrier (B)	
		Estimate[(A)]	S.E	Estimate[(A)]	S.E
β_0	Intercept	2.044 (***)	0.167	2.497 (***)	0.127
β_1	No. deliveries	0.396 (***)	0.047	0.661 (***)	0.059
β_2	(No. deliveries)^2	−0.013 (***)	0.003	−0.043 (***)	0.007
β_3	Delivery density	−0.309 (**)	0.130	−0.069	0.113
β_4	Max. walking distance (km)	1.311 (*)	0.768	0.104	0.183
β_5	Morning time	−0.119	0.087	0.344 (***)	0.046
β_6	Weight (kg)	–	–	6.767×10^{-6} (·)	4.549×10^{-6}
Random effects					
σ_{driver}		–		0.138	
Summary statistics					
Sample size		284		708	
Adjusted R^2		0.510		0.308	
Log likelihood		−307.907		−482.598	

(A): p value < 0.15; *p value < 0.1; **p value < 0.05; ***p value < 0.01

The effect of maximum walking distance ($maxdist$) on dwell time is positive for both carriers, although not statistically significant for carrier B. For carrier P, an additional 100 m (328 ft) of maximum walking distance increases dwell time by 13 percent. For carrier B, an additional 100 m will increase dwell time by 1 percent. Considering the average dwell time for each carrier, an increase of 100 m for the maximum walking distance would increase the average dwell time by 2.3 min for carrier P and by a third of a minute for carrier B. The smaller percentage change for carrier B can be explained by the fact that the time spent walking to reach a delivery location occupied a smaller share of the total dwell time, while a larger share of time spent in other activities, such as loading/unloading at the delivery destination.

The effect of the temporal binary variable *morning* shows different modality of performing deliveries across the two companies. For parcel carrier P, higher priority express deliveries have to be delivered by noon, and therefore we expect the driver to be more in rush compared with afternoon deliveries. For beverage carrier B instead, most of the deliveries are done early in the morning to avoid peak hour road traffic and parking congestion; hence, company B drivers seem to prioritize longer deliveries in the morning, leaving a few shorter deliveries in the afternoon.

Finally, the total weight (in kg) of the deliveries performed per stop was available only for carrier B, showing a positive effect of an increase in weight on total parking dwell time.

To better understand how parking dwell time is affected by walking distance and related variables, the estimated models are used to forecast dwell time across different scenarios with varying maximum walking distance, number of deliveries, and number of buildings served per stop. The results of this forecasting exercise are shown in Fig. 11 (carrier P forecast) and Fig. 12 (carrier B forecast). The figure shows the percentage change in dwell time across changes in the three input variables, with respect to a reference scenario of a carrier P and carrier B driver performing a single delivery in a single building with a maximum distance equal to one block in Seattle (assumed 122 m or 400 ft). We observe that the effect of walking distance is much stronger in carrier P: when the driver has to walk one additional block to deliver, the parking dwell time increases by 46 percent. On the contrary, a carrier B driver's dwell time increases only 5 percent. If, instead, we increase the number of deliveries from 1 to 2, keeping the delivery density unchanged (both deliveries are within the same building), carrier P's dwell time increases only by 10 percent, while carrier B's dwell time increases by a staggering 59 percent. Because carrier B's deliveries are much heavier than carrier P's, it is reasonable that adding one more customer served by the same stop increases dwell time more for carrier B than P. In general, carrier P seems more efficient in taking advantage of its delivery density to serve more customers within the same building without impacting too much dwell time, while carrier B does not have an efficient economy of scale in increasing delivery density. However, when the second delivery is in a different building, dwell time increases by 46 and 71 percent for carriers P and B, respectively. Adding one delivery to a different building is costly (in terms of total parking dwell time) for both carriers.

Effect of walking on tour performance

A simulation model was developed to better understand the role of walking on a delivery tour performance—defined as the amount of time it takes to travel and perform all deliveries assigned to a given route. The simulation took as inputs the real delivery schedules of drivers from carriers P and B and a set of simulated maximum walking distances. The latter is defined as the maximum Euclidean distance between the vehicle parking location and delivery customers' locations a driver is willing to cover. The simulation model was run for all tours, and all simulated maximum walking distances ranged from 10 to 200 m.

Figures 13, 14 and 15 and Table 5 show the simulation output metrics for varying maximum walking distances. Each metric's mean value is reported across all simulated tours, separately for carriers P and B.

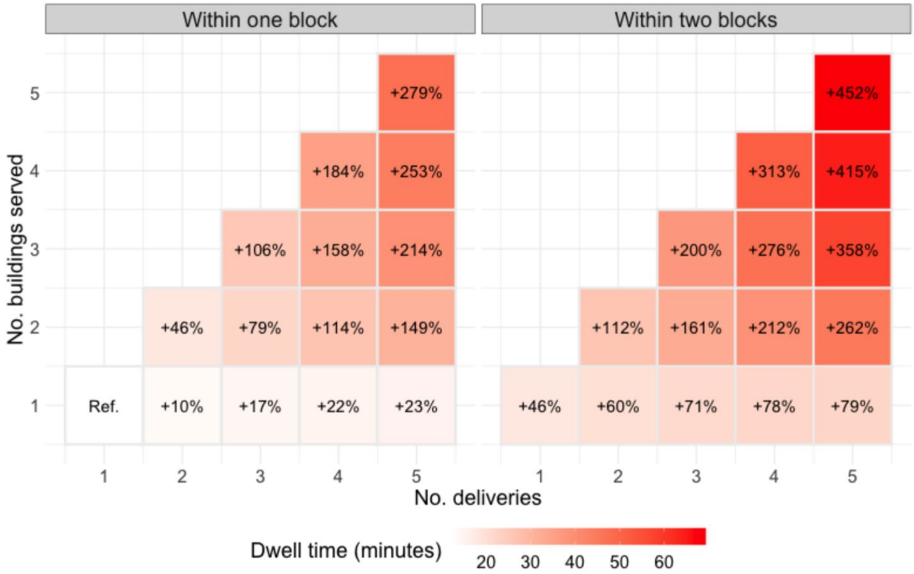


Fig. 11 Parcel carrier (P) dwell time prediction for varying numbers of buildings visited, deliveries, and maximum walking distance. Percentage changes are reported with respect to the reference scenario (one delivery in one building)

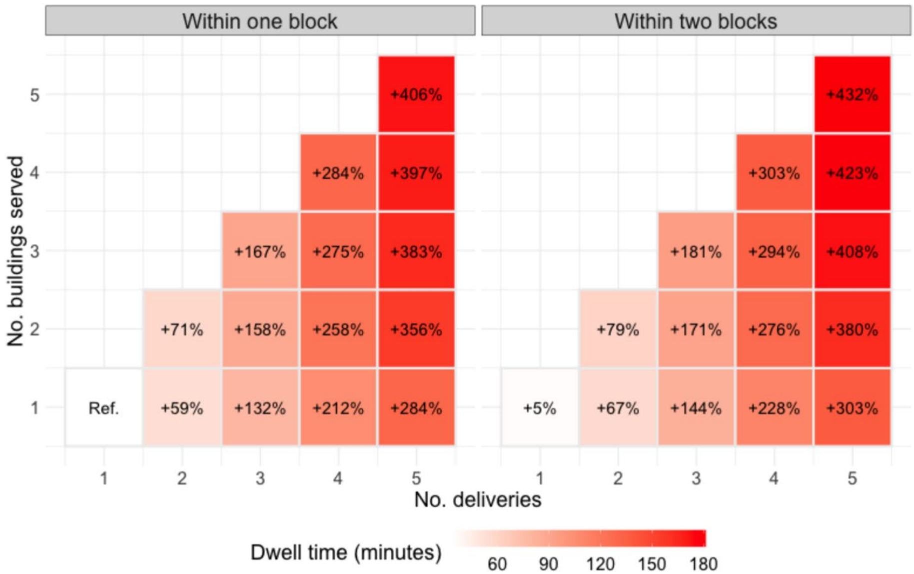


Fig. 12 Beverage carrier (B) dwell time prediction for varying numbers of buildings visited, deliveries, and maximum walking distance. Percentage changes are reported with respect to the reference scenario (one delivery in one building)

Figure 12-left reports the *mean stop dwell time* for varying maximum walking distances, showing the average dwell time across all stops and tours. The more a driver is willing to walk (larger maximum walking distances), the more deliveries they perform from a single vehicle stop location, and consequently, the longer the individual stop dwell time. While there is an increasing trend for both carriers, carrier P's increase in dwell time with an increase in maximum walking distance is higher in magnitude than carrier B's: from 10 to 100 m change in maximum walking distance, the mean dwell time for carrier P more than double, while carrier B's increases less than 5 percent. This is because carrier B's delivery density is much more sparse than carrier P's, and therefore, increasing the driver's willingness to walk does not result in more deliveries being served from the same stop that frequently, except for certain segments of carrier B's tours that show a higher concentration of deliveries in a smaller area. We also note that at 10 m of walking distance, where most deliveries are served from an individual stop location, carrier B's mean dwell time is higher than carrier P's since individual parcel deliveries are usually performed faster than beverage deliveries. Even if the walking distance is reduced to the smallest possible value (10 m), the stop dwell time is still approximately 10 and 15 min for carriers P and B, respectively.

A similar trend is shown in Fig. 13-right, where the *mean trip travel time* increases with maximum walking distance, although at a much lower rate than with stop dwell times. The more deliveries are aggregated within fewer stops, the fewer *stops per tour* a driver performs, as shown in Fig. 14-left, and therefore the longer the trips between stops. We note again that the mean trip travel time is generally higher for carrier B than P because its delivery customers are located farther apart from each other.

Figure 14-right shows the total *tour travel distance*, measured in km. The larger the driver's willingness to walk, the longer delivery trips between stops are on average, but the fewer trips are performed, since the fewer times a driver stops per tour. The overall effect is a decrease in the total distance traveled. For carrier P, increasing the willingness to walk from 10 to 200 m (which reduced the mean number of stops per tour from 36 to 4) reduced total tour travel distance by 25 percent (5 km) per delivery tour. For carrier B the same

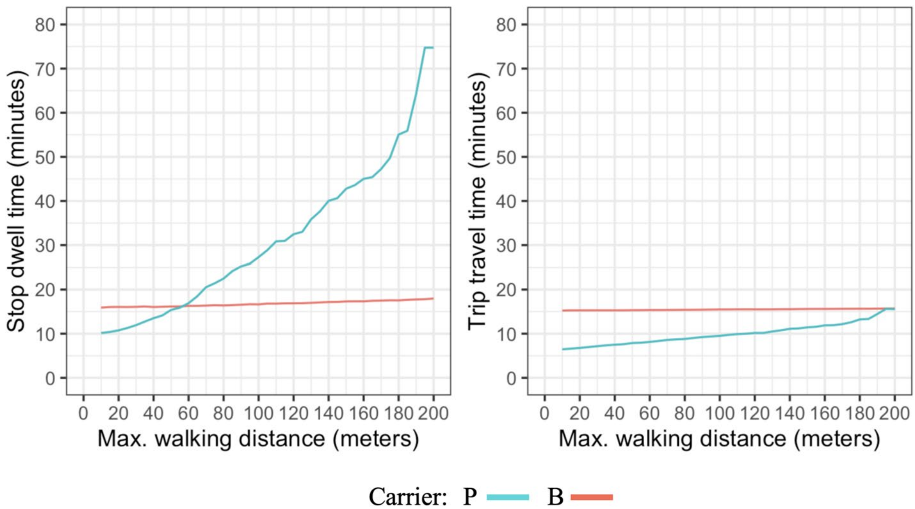


Fig. 13 Changes in simulation outputs over maximum walking distances, averaged across all tours by carrier. (left) Mean stop dwell times; (right) mean trip travel time, including cruising for parking

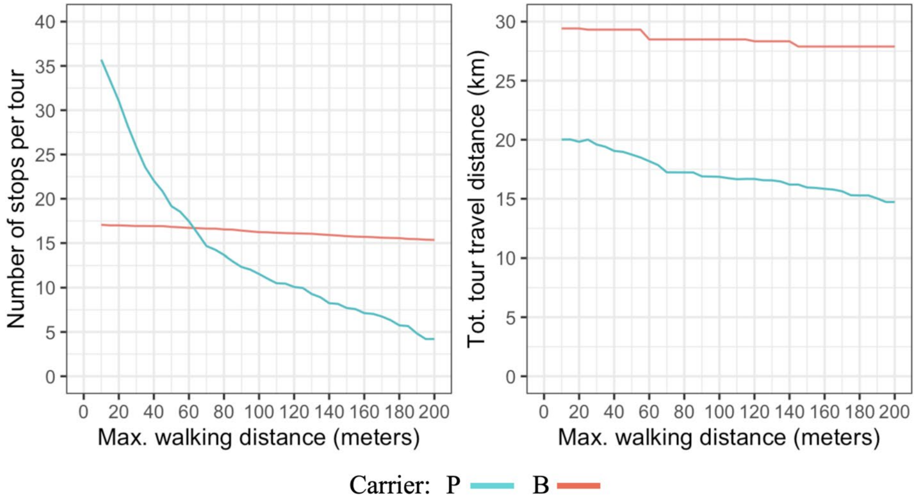


Fig. 14 Changes in simulation outputs over maximum walking distances, averaged across all tours by carrier. (left) Mean number of stops in a tour; (right) mean total tour travel distance

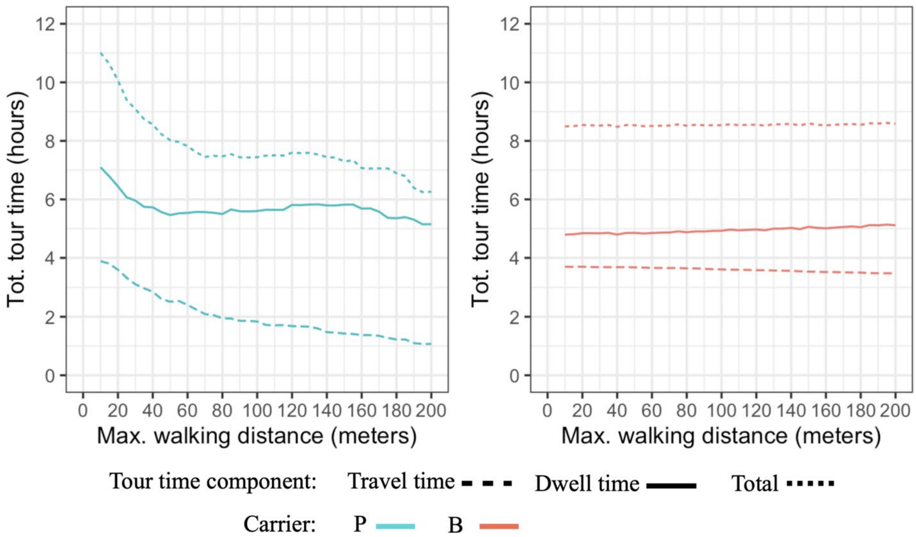


Fig. 15 Total tour travel time, dwell time, and total tour time for parcel delivery carrier P (left), and for beverage carrier B (right), over maximum walking distances

increase in willingness to walk (which reduced the mean number of stops per tour from 17 to 15) reduced total tour travel distance by 4 percent (2 km) per delivery tour.

Combining the output metrics described above, the total tour travel time, total tour dwell time, and the total tour time (defined as the sum of tour travel and dwell times) are obtained. All three metrics are reported in Fig. 15.

Table 5 Changes in key simulation output metrics over varying maximum walking distances allowed, for parcel carrier P and beverage carrier B

Output metric	Max. walking distance (meters)	Carrier	
		P	B
Stop dwell time (min)	10*	10.2	15.9
	100	27.3 (+168.6%)	16.6 (+4.6%)
	200	74.7 (+635.9%)	18.0 (+12.9%)
Trip time (min)	10	6.5	15.2
	100	9.5 (+47.0%)	15.5 (+1.6%)
	200	15.6 (+140.7%)	15.7 (+3.0%)
Number of stops per tour	10	35.7	17.1
	100	11.5 (−67.7%)	16.2 (−4.8%)
	200	4.2 (−88.2%)	15.4 (−10.0%)
Total tour travel distance (km)	10	20.1	31.9
	100	17.3 (−14.0%)	31.6 (−1.1%)
	200	15.2 (−24.7%)	30.8 (−3.6%)
Total tour dwell time (hour)	10	7.1	4.8
	100	5.6 (−21.1%)	4.9 (+2.7%)
	200	5.2 (−27.4%)	5.1 (+6.7%)
Total tour travel time (hour)	10	3.9	3.7
	100	1.8 (−52.7%)	3.6 (−2.4%)
	200	1.1 (−72.4%)	3.5 (−6.2%)
Total tour time (hour)	10	11.0	8.5
	100	7.4 (−32.4%)	8.5 (+0.5%)
	200	6.3 (−43.2%)	8.6 (+1.1%)

*Maximum walking distance of 10 m is used as reference points to compute the percentage changes for each output metric and carrier

The *total tour travel time* shows a similar trend to the total tour travel distance. While the average trip time increases with a driver's willingness to walk, fewer trips are needed in a tour, and the total amount of time spent driving decreases. The total tour time includes cruising for parking times, and the fewer stops performed also implies a decrease in total cruising for parking time.

The total tour dwell time shows a more complex behavior. For carrier P, an increase in walking results in an initial sharp decrease in total dwell time as fewer stops are performed. However, at around 50 m (164 feet, approximately the average length of a blockface in Seattle downtown) of maximum walking distance, the total tour dwell time starts increasing again as the mean stop dwell time starts increasing almost exponentially, as more delivery customers are being served from each stop. Carrier B shows an opposite trend: an increase in willingness to walk increases total dwell time. In this case, the reduction in the total number of stops is not enough to offset the increase in mean dwell time for each stop. This is mainly because carrier B's delivery stops are generally longer and located farther apart; therefore, aggregating multiple deliveries within a single stop worsens total tour dwell time.

The *total tour time* is computed as the sum of tour travel and dwell times. For carrier P, an increase in willingness to walk has an initial positive effect of reducing the total amount of time it takes to perform a delivery tour up to 50 m, after which the rate of change in total tour time is close to zero. We note a decrease in total tour time beyond 160 m. However, this might be due to the reduced performance of the dwell time simulation algorithm in predicting dwell times at higher walking distances than those observed. For carrier B, an increase in willingness to walk has an overall small effect on total tour time, with approximately a 1 percent increase. In this case, the increase in tour dwell time is offset by the decrease in tour travel time, resulting in only a small increase in total time. In particular, we note that, while for carrier P, the tour travel time represents only a small fraction of the total tour time, for carrier B, travel represents an almost equal share of total tour time.

Conclusion and discussion

Key results

Several authors have shown that most urban delivery drivers' time is spent not in the vehicle driving but outside the vehicle, walking to perform the last-50-feet of urban deliveries. While it is logical to focus on analyzing and optimizing this portion of a delivery route, most technologies and research efforts focus on the driving component of urban delivery routes, while little is known about the walking component. This study took the first step in identifying a novel empirical method to analyze the role of walking in last-mile deliveries and understanding how delivery drivers' walking behavior affects the efficiency and sustainability of urban delivery routes.

The paper uses two datasets of more than 1,800 real deliveries performed in Seattle, WA, by a parcel carrier (P) and a beverage carrier (B) as a case study. GPS data from the vehicles and drivers' movements were obtained and matched to identify vehicle stop locations, customer delivery destinations, and related walking behaviors between stops and delivery locations, including willingness to walk, number of delivery customers drivers walked to from each vehicle parking stop, number of buildings visited from each stop, and resulting stop dwell time. First, descriptive results were obtained, describing the summary statistics of the empirical distributions of the key variables obtained: walking distance, number of delivery customers served per stop, number of buildings visited per stop, and stop dwell time. Then, two behavioral models were estimated: a regression analysis of the impact of walking on stop dwell time and a simulation analysis to understand the impact of walking on total route performance and vehicle miles traveled. Table 6 summarizes the key empirical results obtained.

Results 1 to 3 report the main summary statistics from the two data samples. It shows that the two carriers have fundamentally different walking behaviors. Parcel carrier's drivers, given the much higher density of deliveries per square mile faced and the use of more agile smaller delivery vans, park their vehicles closer to the delivery customers (hence walking shorter distances between the parking location and the delivery destinations), while serving multiple customers from a single stop. The beverage carrier drivers instead walk longer distances while serving mostly one customer per vehicle stop, with fewer than 20 percent of the stops serving more than one customer. We note that the walking distance reported in Table 6 is defined as the maximum Euclidean distance between the vehicle parking locations and the customer delivery locations served from that stop. Therefore, it shows how far the drivers parked from the delivery destinations, and not the actual length of the path walked by a driver (the latter variable would be an interesting extension of the current work, to analyze in a more detailed way actual walking paths). While a parcel delivery driver parked closer to their customers, they might have walked longer distances, given the larger number of customers served from each stop. In general, given the higher number of customers served

Table 6 Summary of results obtained from the observed data samples

Result metric	Carrier	
	 Parcel carrier (P)	 Beverage carrier (B)
(1) Walking distance	Carrier P parked on average 53.3 m (175 ft.) away from their delivery destination	Carrier B parked 148.5 m (487 ft.) away from their delivery destination
(2) Deliveries per stop	In *67 percent* of carrier P's stops drivers walked to 2 + customers	In *19 percent* of carrier P's stops drivers walked to 2 + customers, most stops served only 1 customer
(3) Stop dwell time	Carrier P's drivers stops were on average 26.2 min long	Carrier B's drivers stops were on average 43 min long
(4) Impact of no. deliveries per stop on dwell time	*Strong economies of scale* in serving multiple customers from the same stop	*Weak economies of scale* in serving multiple customers from the same stop (possibly due to larger average delivery size)
(5) Impact of walking on dwell time	Walking an additional 100 m *increases dwell time by 17 percent*	Walking an additional 100 m *increases dwell time by 1 percent*
(6) Impact of walking on total route dwell time	Increase in walking *reduces total route dwell time* (longer but fewer stops)	Increase in walking *increases total route dwell time* by a small amount (the reduction in number of stops does not offset longer dwell times)
(7) Impact of walking on total route drive and cruising time	Increase in walking from 10 to 200 m (656 ft.) *reduces vehicle miles traveled by 25 percent and driving time by 72 percent*	Increase in walking from 10 to 200 m (656 ft.) *reduces vehicle miles traveled by 4 percent and driving time by 6.2 percent*
(8) Impact of walking on total route time	*Reduces total time* drivers take in performing delivery routes	*Small increase in total time* drivers take in performing delivery routes

per stop for carrier P and the longer distances from the parking location for carrier B, both data samples show that delivery drivers walked a significant amount to perform the deliveries, and that walking is an important—if not the most important—activity in their daily job.

Results 4 and 5 delve deeper into the impact of delivery drivers' walking behavior on stop dwell times, defined as the amount of time vehicles are parked. Formulating and estimating a regression model for each carrier, it was found that the parcel carrier showed strong economies of scale in serving multiple customers from a single delivery stop, while parking far away from delivery customers increased dwell time by a significant 17 percent. On the other hand, carrier B showed the opposite effects: longer walking distances increased dwell time by only 1 percent, while serving multiple customers from a single stop resulted in a significant increase in dwell times.

Results 6–8 report the impact of walking on the routes performed by the carriers. The observed routes were divided into three components: driving, cruising for parking, and walking. Similar effects of walking were observed on the two carriers but with different magnitudes. An increased willingness to walk implies that drivers serve more delivery customers per stop, and therefore, the total number of stops decreases while the dwell time for each stop increases. The total effect of walking on the total time spent parking is then determined as to whether the reduction in the number of stops is large enough to counterbalance the increase in dwell time per stop. In the case of the parcel carrier, longer walking distances reduce the total route dwell time and the total time to perform the whole route. However, in the beverage carrier, longer walking distances increase dwell times without significantly reducing the total number of stops per route, with the consequence that increasing walking does not improve the route performance. However, the simulation also showed another important effect of walking: an overall reduction in total vehicle miles traveled and, consequently, a reduction in vehicle emissions.

Implications for policy and practice

The results above highlight the importance of walking in delivery route performance and sustainability in urban areas. Consequently, this paper emphasizes the need to consider walking in infrastructure planning, urban freight policy design, and the routing and scheduling of delivery vehicles.

From a public sector perspective, the key question is how to design and manage freight infrastructure and policies that best support delivery carriers' performance while minimizing negative externalities. Rephrasing this objective using key route performance metrics discussed in this study: how can we preserve carriers' ability to perform delivery routes in the shortest time possible while reducing vehicle miles traveled and its byproducts, including emissions, pollution, congestion, and safety externalities? One approach several cities in North America have taken is to allocate curb space to commercial vehicle parking, often referred to as Commercial Vehicle Load Zones (CVLZs). Assuming a certain level of parking enforcement, by dedicating curb space to delivery vehicles, their cruising for parking time is reduced, as well as the likelihood for these vehicles to double park or to park too far away from their delivery destinations, hence guaranteeing carriers and businesses a certain level of delivery efficiency, especially in urban congested areas. The current study has also shown that encouraging delivery drivers to stop frequently (e.g., providing several CVLZs every blockface) might not represent the best strategy, as a decreased cost of re-parking the vehicles and hence a reduced willingness to walk increases total vehicle miles traveled. This reasoning is, in a way, obvious, as providing more parking encourages vehicles to park more often, reducing the average stop dwell times and increasing the number of stops in a tour. Instead, this study has shown that some walking is desirable, both from the perspective of efficiency and sustainability. Using empirical data from Seattle, it was demonstrated that encouraging a delivery driver to walk up to approximately one blockface length of Seattle downtown, decreased the total time a driver takes to perform a tour as well as reduced vehicle miles traveled. However, further increasing the total walking time, without a systemic change in how deliveries are conducted, would risk deteriorating delivery performance; hence, the time it takes drivers to perform delivery tours to a level in which the drivers will be forced to double park or the carriers to increase the number of vehicles serving a given area. In designing a CVLZ program, cities should consider that many delivery drivers are willing to walk for a block or two and aggregate multiple deliveries within a single vehicle stop. Allowing drivers longer dwell times at CVLZs, providing them with suitable infrastructure for walking, including curb ramps and wide sidewalks, and enforcing CVLZs such that drivers are more likely to find them available when needed are equally important efforts to expanding the network of CVLZs. Empirical results from the current study have also shown that the cost of walking (measured as impact to total stop dwell time) differs between the observed carriers. Longer walking distances have a more significant impact on the parcel carrier, than the beverage carrier, percentagewise. Consequently, their infrastructure needs differ, with smaller but more geographically prominent CVLZs supporting the parcel carrier's operations, while fewer, but better enforced and larger CVLZs supporting the beverage carrier's operations.

From a carrier perspective, ignoring walking in scheduling and routing delivery vehicles implies ignoring the largest share of a delivery driver's time. While drivers naturally try to minimize the amount of walking to perform last-mile deliveries, given the complexity of the urban environment, the high rates of paring occupancies and road traffic, and the higher delivery identities many carriers are currently facing, it implies that walking is a natural and needed activity. Drivers do not always find parking right in front of delivery customer addresses, and drivers are neither able nor willing to double park due to often potential safety concerns. Therefore, walking is an important component of any delivery route. More data, methods, and tools should be invested in supporting delivery drivers in understanding the optimal amount of walking needed to perform their delivery routes efficiently while minimizing negative externalities.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no competing interests.

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Giacomo Dalla Chiara is a Research Scientist at the University of Washington and an investigative lead at the Urban Freight Lab. His research focuses on urban freight behavior modeling, urban data science, and transport policy.

Anne Goodchild is a Professor of Civil and Environmental Engineering at the University of Washington and founding director of the Urban Freight Lab. Her expertise is in urban freight transportation, border and port operations, and freight equity.