MEMO TO THE INNOVATION MANAGEMENT TEAM
To: Office of Innovation and Technology, City of Philadelphia
From: Laura Frances & Emmy Park, Master of City Planning, University of Pennsylvania
Advisor: Dr. Jamaal Green, Assistant Professor, University of Pennsylvania
Subject: SmartLoadingZone Pilot Exploratory Data Analysis
Date: September 29, 2023

Dear [redacted],

An exploratory analysis of the 2022 SmartLoadingZone pilot's booking data shows that the leading variables to predict bookings are local economic context (specifically, the number of retail and health and social service jobs) and time of day. While the initial objective of this study was to quantify the supply and demand of curb space in Philadelphia to identify 'mismatch', the available data better supports a discussion about booking behavior rather than curb space allocation. Our analysis suggests that the SmartLoadingZone pilot demonstrates the following takeaways:

1. Cluster analysis's homogenous dataset failed to derive curb characteristic patterns to apply to a booking prediction model.
2. Local economic context is a decent determinant of booking demand.
3. Day of the week and time of day remain influential across our models.
4. Bookings can be digitized and adoption takes time.

To conduct this analysis, we employed a k-means cluster analysis and predictive machine learning demand models. All analysis was conducted in R and ArcGIS. *Refer to the appendix for technical notes.*

Cluster analysis's homogenous dataset failed to derive curb characteristic patterns to apply to a booking prediction model.

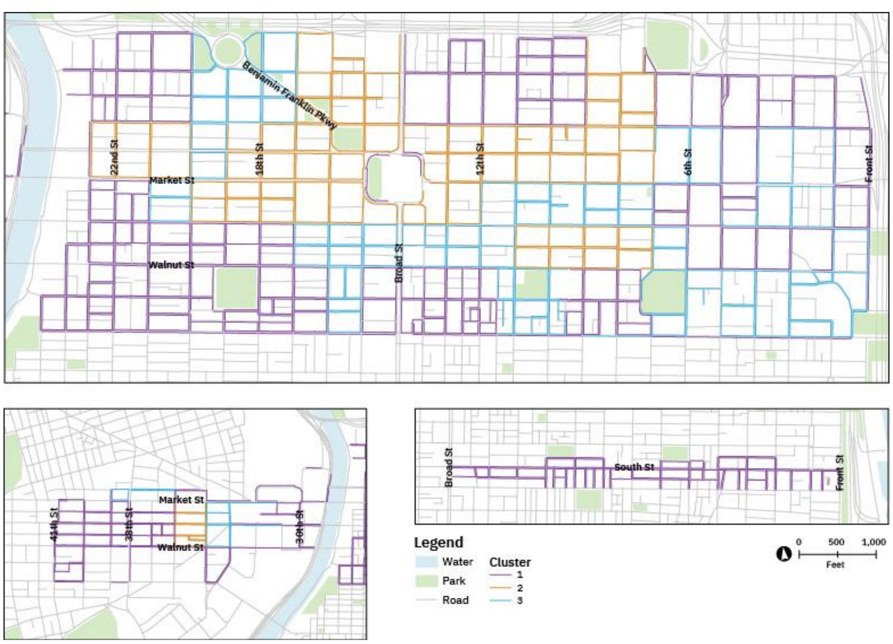

Figure 1: Map of curb clusters in the study area. Generally, Cluster 1 is residential, 2 commercial/municipal, and 3 institutional.

To generalize curbs across the study area, we ran an unsupervised k-means cluster analysis to group curbs by signage, number of jobs, and zoning. This analysis renders a predetermined number of distinct clusters of curbs. The goal is to unveil which variables distinguish the clusters from one another. Practically, clusters of curbs in this study are primarily distinguishable by land use: Cluster 1 is residential, Cluster 2 is commercial and municipal use, and Cluster 3 is institutional. However, statistically, these clusters are not significant predictors of any variables in our study because the curbs within the study area are arguably too homogenous to confidently provide a curb usage pattern to extrapolate across Philadelphia or use as a variable in our prediction models.

Local economic context is a decent determinant of booking demand.

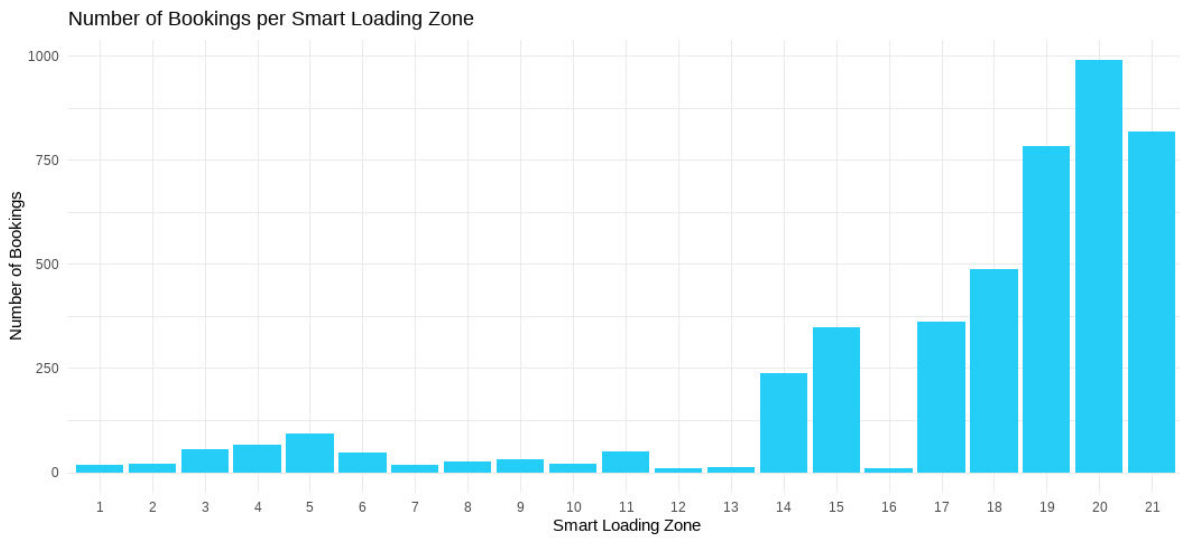

Figure 2: Total number of bookings per Smart Loading Zone. Zones 19, 20, and 21 had the most bookings during the pilot.

Machine learning predictive models yielded rankings of variable importance on predicting when a SLZ will be booked in the three busiest zones (19, 20, 21). Number of jobs, particularly retail jobs, was the most important. In order to proxy for surrounding land-uses we make use of 'ground-floor' job sectors including retail, restaurants, and healthcare. Compared to other studied variables such building density, zoning, or business permits, the number of jobs remains influential across our models. *For more details on the models, please refer to the technical notes in the appendix.*

Zone	**Address**	**Hours of Operation**	**Booking Count**	**Street Characteristics?**
19	1000 Chestnut Street	All vehicle; 24/7	783	1 Bus Only, 1 Traffic, 1 Parking Lane. Thomas Jefferson Hospital on the south side of the street. Low and high rise mixed-use. Retail and restaurants on ground level.
20	1200 Chestnut Street	All vehicle; 24/7	990	1 Bus Only, 1 Traffic, 1 Parking Lane. High-rise residential and mixed-use. UPS store. Retail and restaurants on ground level.
21	1300 Chestnut Street	All vehicle; 24/7	819	1 Bus Only, 1 Traffic, 1 Parking Lane. High-rise mixed use. Retail, restaurants, municipal, cultural buildings on ground level.

Booking frequency is a critical aspect of the booking data's usability. When there are more bookings, there are fewer 0s in the data, and therefore yield more significant results. Zones 19, 20, and 21 feature institutions such as Jefferson Hospital, as well as large hospitality businesses and mixed-use developments. In the following figures, the booking frequency of these three zones is clearly much higher than any other zones.

Day of the week and time of day remain influential across our models.

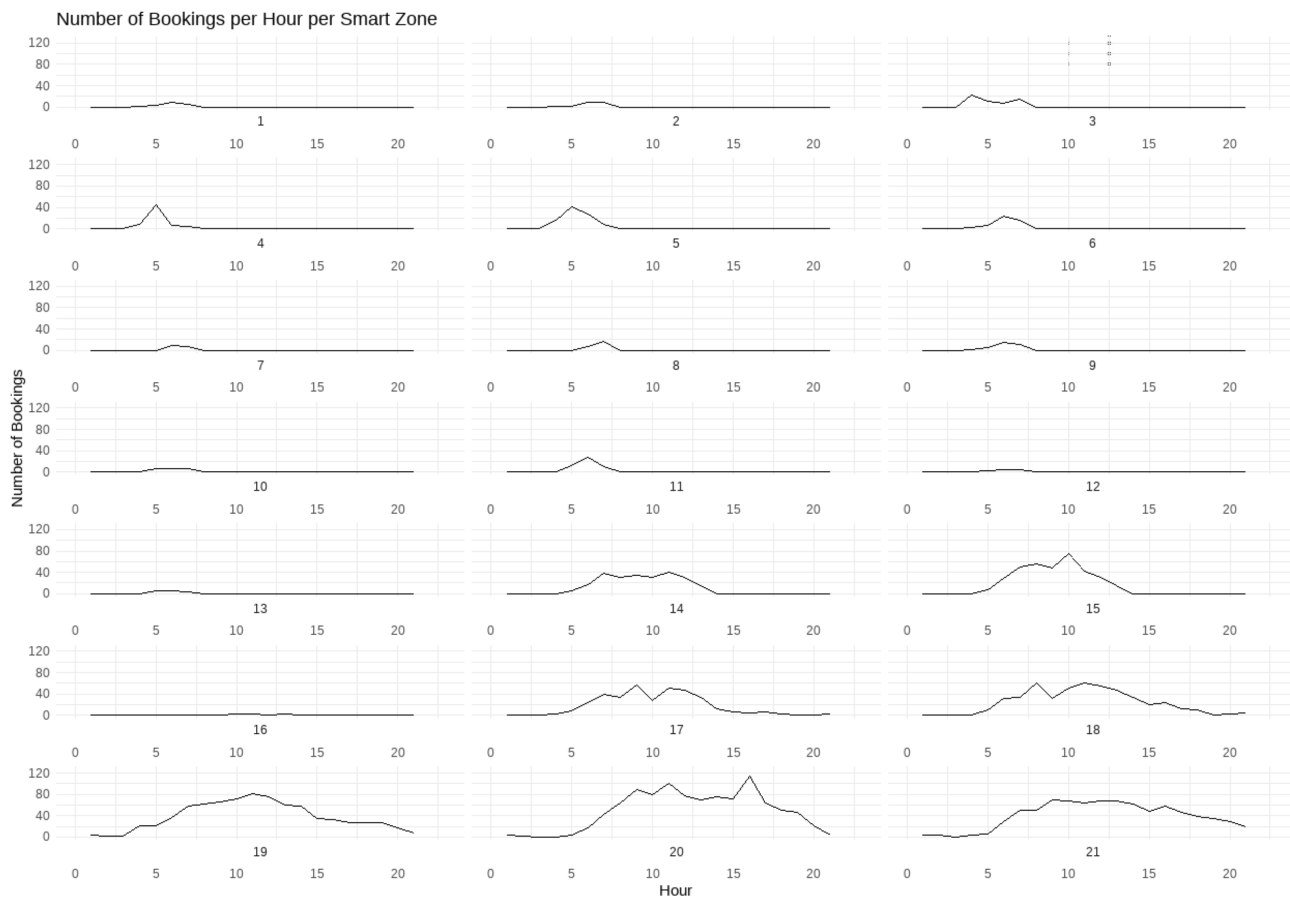

Figure 3: Total number of bookings per Smart Loading Zone by time of day. 11 AM - 4 PM tend to be the busiest hours.

Time of Day	Total Number of Bookings
Afternoon *11 AM - 4 PM*	2299
Evening *4 PM - 12 AM*	1153
Morning *6 AM - 10 AM*	1060
Night *12 AM - 6 AM*	21

Day of Week	Total Number of Bookings
Thursday	820
Wednesday	787
Tuesday	776
Friday	731
Monday	595
Saturday	499
Sunday	307

In addition to local economic context, the predictive models ranked time as an important variable in predicting bookings. 11AM to 4PM (afternoon) is the busiest time for bookings despite less than half of the zones being in operation during those hours. Considering the volume of bookings in Zones 19, 20, 21, it is reasonable to conclude that commercial activity, such as package, materials, and food deliveries, drive bookings. Furthermore, the lack of booking activity on the weekend also supports the conclusion that commercial deliveries drive bookings.

Bookings can be digitized and adoption takes time.

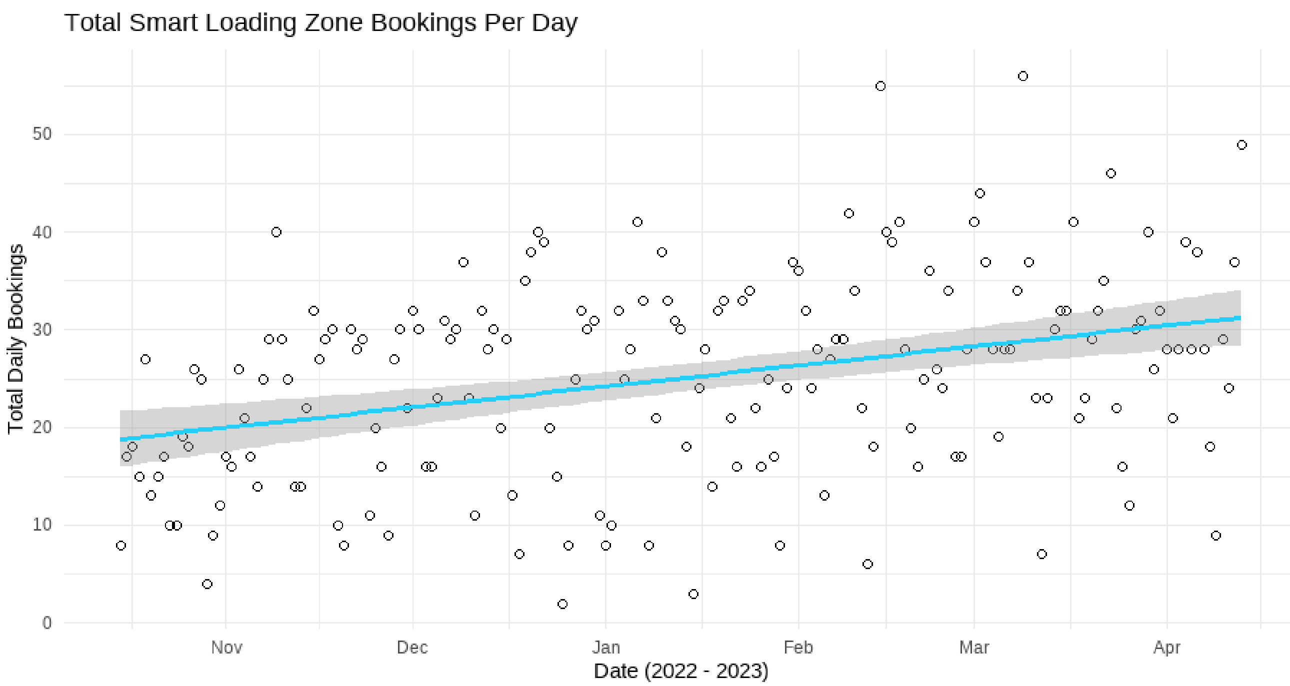

Figure 4: Distribution of bookings over the course of the pilot. Number of bookings trended upwards later in the study.[1]

While the number of bookings varied across the study period, there is a general upward trend. There is evidence to support the conclusion that, over time, users will adopt digital booking systems. Additionally, there are very few instances of users making a booking when the SLZ was not in operation, which is one indicator of the software's glitch rate.

Tangentially, it is worth noting an upside of adoption is reduced dwell time, and potentially less air pollution in some of the city's most congested areas. The Nelson\Nygaard pre- and mid-pilot analysis shows a 29% dwell time reduction in Zone 19 and a 77% reduction in Zone 21. Compared to Zone 2 (-3%) and Zones 8 (-4%), which are predominantly mixed use with small retail and large parking garages, booking systems adoption potentially stands to be part of the city's decongestion and decarbonization strategies.

[1] Increased bookings are not exclusively driven by Zones 19, 20, and 21. In general, the upward booking trend is driven by all zones.

Future Pilot Recommendations:

1. Choose a variety of types of streets and locations for future pilots. The majority of SLZs in the pilot were located on large, commercial corridors. If the goal of the study is to predict booking across all curbs in Philadelphia, the pilot needs to represent all types of streets and locations. If the goal is to manage truck loading, select zones with high levels of loading activity.
2. Procure establishment level data. Establishment level data can provide deeper insights into how local economic context is driving booking demand.
3. Disperse SLZ hours of operations and types of vehicles permitted across different streets. For example in this pilot, Chestnut Street only offered All Vehicles 24/7, while Walnut Street only offered Commercial vehicles on Weekdays. By segregating SLZ regulations by street, it is difficult to determine if higher activity on Chestnut is attributable to being open longer or its curb characteristics.
4. Reduce systematic zeros in the study. Select SLZs with existing or predicted loading activity, such as areas with mixed-use development or institutions such as hospitals and hospitality.

Appendix: Technical Notes

1. **Clean and Process Curb Inventory Dataset**
   Dataset: Curb Inventory
   Description: Cleaned and processed 2021 curb inventory data. This dataset provides spatial as well as categorical data about every street sign for Center City and University City. Analysis required mapping each curb and identifying SLZs.

2. **Run Unsupervised, Exploratory Cluster Analysis about Curb Signage**
   Datasets: Curb Inventory, LEHD LODES Data[2], Center City Business District Boundary, 5-Y American Community Survey 2021
   Description: Ran an unsupervised k-means cluster analysis to try and categorize each curb in the study areas based on the types of signs on the curb, number of signs per length of curb, whether or not the curb was located in the Center City Business District, and the share of zero vehicle households on the curb.

3. **Process Consultant's Survey Data of Select Zones**
   Dataset: Nelson\Nygaard Pre- and Mid-Pilot NN Collection
   Description: Conducted exploratory analysis on this survey of 5 zones (2, 8, 15, 19, 21) before and during the pilot provides some insight into behavior at the curb. Unfortunately, critical metrics, such as double parking, did not have any baseline data.

4. **Process SLZ Booking Data**
   Dataset: Booking Data for all zones
   Description: Analyzed the count and duration of booking for all 21 zones. The data is largely analyzed hour by hour. The data also is categorized into night (12am - 6am), morning (6am - 10am), afternoon (10pm - 4pm), and evening (4pm to 12am) to understand the impact of SLZs operating hours on bookings.

5. **Prepare data for predictive models**
   Dataset: Booking Data (Zone 1 -21), Curb Characteristic and Uses Data
   Description: Established the goal - can we predict if at a certain time and day a certain Smart Loading Zone will be booked or not? Executed parameter tuning of Curb Characteristic and Uses Data and Booking Data to explore the most statistically relevant variables. Developed and executed Random Forest and XGBoost predictive models.

6. **Run predictive model: Random Forest**
   Dataset: Booking Data (Zone 1 - 21), Curb Characteristic and Uses Data
   Description: The Random Forest model is a machine learning method to predict the number of bookings in a given zone on a given day and time. In this case, we used a regression. In short,

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[2] LEHD LODES Data was added to our analysis in August 2023. The attached cluster analysis is updated from the one that was shared mid July 2023.

the model creates a series of decision trees based on a random subset of the booking and curb datasets. Each decision tree outputs a number of bookings, and prediction is based on a mean of the decision trees' outputs.
Output: R^2 = 0.122, RMSE = 1.63[3] Overall, the model produced weak results because 3 of the 21 zones had the most booking activity which means that the model is often going to predict when there will be no bookings. It is important to note, that despite this general characterization of the model's output, the results previously discussed in the memo are statistically significant.

7. **Run predictive model: XGBoost**
   Dataset: Booking Data, Curb Characteristic and Uses Data
   Description: Extreme gradient boosting (XGBoost) is a machine learning method which attempts to accurately predict a variable by combining the estimates of a set of simpler models. The model is created through a series of iterative decision trees, predicting the errors of previous trees, which are then combined with previous trees to make the final prediction.
   Output: R^2 = 0.138, RMSE = 1.64 Notes from Random Forest apply here, too.

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[3] R-squared (R^2) is a statistical measure of the variance that is accounted for by the model. R-squared ranges from 0 to 1, with 0 indicating no relationship and 1 indicating that all variance can be accounted for by the model.
The root mean square error (RMSE) measures the average difference between a statistical model's predicted values and the actual values. The lower the RMSE, the better the model's predictions.