Technical University of Munich

Where to allocate mobility hubs? Identifying common built environment factors associated with the usage of multiple shared mobility options in Chicago

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Hereby, I confirm that this document, corresponding to the report of the study project for the MSc. Environmental Engineering program, is my own work and I have documented all sources and material used.

Munich, July 5, 2022

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Abstract: City planners have the challenge of steering people away from the usage of private passenger cars to reduce its environment drawbacks. In this context, mobility hubs may constitute a physical and digital space to group different mobility options and services. However, there is a lack of research about common spatial variables that affect the ridership of multiple shared mobility options. Therefore, this study examines the relationship between the built environment, specifically points of interest (POIs), in the city of Chicago and the ridership of three shared mobility options: bike sharing, e-scooter sharing and taxis. Negative binomial regression was used to identify the statistically relevant built environment that is associated with the usage of each mode. The categories restaurant and residential buildings were identified as the common categories associated with the usage of bike sharing and e-scooter sharing. Only arrival trips for each mode were used as a target variable, further improvement can be done by adding the departure trips, hence understanding the departure-arrival flow. Economical and social variables can also be added to better explain the overall usage of these modes.

Keywords: bike-sharing; e-scooter sharing; taxis; mobility hubs; sustainable mobility; built environment

1. Introduction

The transport sector is facing the challenge of major reduction in CO_2 emissions to reach the ambitious goal of climate neutrality by 2050 [1]. In fact, around one fifth of the global CO_2 emissions are accounted for the transport sector in 2018 [2]. In particular, passenger road vehicles account for the highest proportion of the overall transport emissions, which makes the main challenge of city planners and policy makers is to decrease the attractiveness of the private passenger car and elevate the one its counter part shared mobility modes [3]. Improving public and shared transportation systems and transit options is maybe a way to incite its usage [4].

Mobility hubs are relatively a new concept that can be defined as a physical space where different shared mobility options and services that benefit the traveler are offered [5]. The goal of mobility hubs would be to increase the usage shared and sustainable modes of transport, hence reduce the private car usage [5]. Nevertheless, due to the infancy of the concept of mobility hubs, researchers and urban planners are still developing definitions and guidelines to enable their sustainability and inclusively [6]. Yet cities are moving quickly in the direction of planning and implementing these hubs. For instance, the city of Munich, Germany is planning 200 "mobility points" for 2026, where bike sharing, e-scooter and car sharing are made available [7]. Therefore, choosing the location for mobility hubs is a crucial step to ensure their successful integration and usability. To do so, there are different characteristics which are considered important when choosing potential locations, one of which is the built environment surrounding the mobility hub [6].

The relationship between the built environment and multiple shared mobility options is yet to be comprehensively examined. Although separately, there have been research on the relationship between the built environment and bike sharing (e.g [8,9]), e-scooters (e.g [10,11]) and taxis (e.g [12,13]), there is thus far no research that combines them all.

To fill in this gap, I examine the common built environment factors, specifically points of interest (POIs), that are associated with the usage of bike sharing, e-scooter sharing and taxis using open source data of the city of Chicago. Negative binomial regression is used to better understand this relationship. The paper comprises seven sections. Following the introduction, the literature review section presents some previous studies that explored the relationship between the built environment and bike sharing, e-scooter sharing, taxis and the built environment, separately. Then, the third section contains the methodology, its application is found in section 4. Section 5 outlines the results from the regression analysis. Section 6 is dedicated for the discussion of the results and its limitations. Finally, the last section concludes with the study's contribution and suggestions for future research.

2. Literature review

Research about the effect of the built environment on multiple shared mobility options is limited. Nevertheless, bike sharing systems and taxis have been more studied than e-scooters, which have only been around since 2017 in the US and 2018 in Europe [14].

2.1. Bike sharing and the built environment

Tran *et al.*[9] examined the effect of built environment on bike sharing system in Lyon. They used a robust linear regression model to predict flow rates of each bike station. A buffer of 300 meters around each station was used, that contained the the built environment factors. Public transportation variables were the most significant variables in all their models. In addition, leisure variables, such as restaurants and cinemas, were found to be significant for short term users but not for long term ones.

In New York City, a spatio-temporal case study for the CitiBike system was conducted to better understand the factors that contribute to the bike sharing demand [15]. Built environment attributes, such as population density, presence of subway station in buffer and number of restaurants in buffer, were used to estimate the arrivals and departures. The buffer used in this case is equal to 250 meters. It was found that subway stations have a positive impact both on arrivals and departures for both members and daily customers. The same positive impact on both types of flows is seen when the number of restaurants is higher within the buffer. As for job density, it showed a clear relationship with population density and demonstrated a commute pattern to work and back to home. The same result about employment density was found in El-Assi *et al.*'station [16] based analysis of commercial bike sharing in Toronto, using a distributed lag model.

2.2. Taxis and the built environment

Ordinary least squares (OLS) and Geographically Weighted Regression (GWR) have been used to determine the influence of the built environment on taxi ridership. The ridership was found to positively correlate with residential areas, employment density, hotels and bus stops [13]. The same authors examined the effects of built environment on taxi in New York City using a geographically and temporally weighted regression (GTWR) model [17]. They found that higher numbers of different transport POIs, such as bicycles, buses, and subways correlate with higher numbers of taxi ridership. However, the main outcome was that the relationship between the built environment and taxi ridership vary over space and time in New York City.

Furthermore, Wu and Zhuo's [12] study about the impact of built environment on urban short distance taxi travel in Shanghai, using multi factor linear regression model, identified a competition relationship between metro systems and taxis. In fact, the metro had a significant negative impact on the taxi travel density [12].

2.3. *E-scooter sharing and the built environment*

The impact of the built environment has been scarcely studied for e-scooters, since it is a relatively new system. Espinoza *et al.* [10] examined the e-scooter system "Bird" in Atlanta in the attempt of determining the purpose of the trips, from business to pleasure to transit. They clustered POIs, resulting in categories such as business, food, parking and residential, and investigated the trips done between these categories. Business to business had the highest count. Recreation and food were also found to be dominant categories, especially evenings and at night.

Jiao and Bai [11] used a negative binomial regression model to investigate the relationship between the built environment and e-scooter usage using the data of city Austin in Texas. The results of the model showed that mixed land use, educational, commercial and transit facility are all positively correlated with e-scooter trips. In fact, mixed land use was found to be the most relevant variable amongst the surrounding urban environment variables, as a 1% increase could generate 50% or more increase in e-scooter usage. Similar findings were established when studying the e-scooter ridership in Chicago, mixed land use appeared to be an important variables as it was associated with 23% cent of increased demand. Bus stops, on the other hand, were found to be negatively correlated with the departure model [18].

2.4. *Identified built environment from the literature*

Table 1 presents the identified built environment from the literature review. Residential or population density is a variable that was identified across every research. Some of the variables that are commonly used are public transport options such as bus, metro and subway stations. Educational, entertainment and food facilities are also present throughout the examined papers.

Table 1. Identified built environment from the literature review.

Built environment					**Sources**				
	[9]	[15]	[16]	[13]	[17]	[12]	[10]	[11]	[18]
Bus stops	✓	✓		✓	✓	✓			✓
Bicycle infrastructure	✓	✓	✓		✓	✓			
Metro stations	✓		✓		✓				
Subway stations		✓	✓			✓			
Road length/density				✓		✓			
Student residence	✓								
University			✓					✓	
Cinema	✓								
Restaurant	✓	✓							
Residential	✓	✓	✓	✓	✓	✓	✓	✓	✓
Employment	✓	✓	✓	✓					
Tourist attraction				✓					
Hotel				✓		✓			
Park		✓				✓	✓	✓	✓
Mixed land use	✓							✓	✓
Entertainment facilities						✓	✓		
Business							✓		
Shopping							✓		
Parking rate									✓
Parking for cars							✓		
Public service				✓					
Commercial				✓	✓			✓	
Health and fitness							✓		

3. Methodology

Figure 1 shows the proposed methodology. First the docked bike station location is collected. Second, the ridership data of the docked bike sharing system, e-scooters sharing system and taxis is collected. These are the dependent variables. Then the built environment data, which is the independent variable, is collected. A buffer zone surrounding each bike station is set. After the data analysis and processing, the number of arrival trips and POIs is counted for the buffer zone of each station. Pearson correlation test is performed to eliminate collinear variables, then regression analysis is used to identify the common built environment factors.

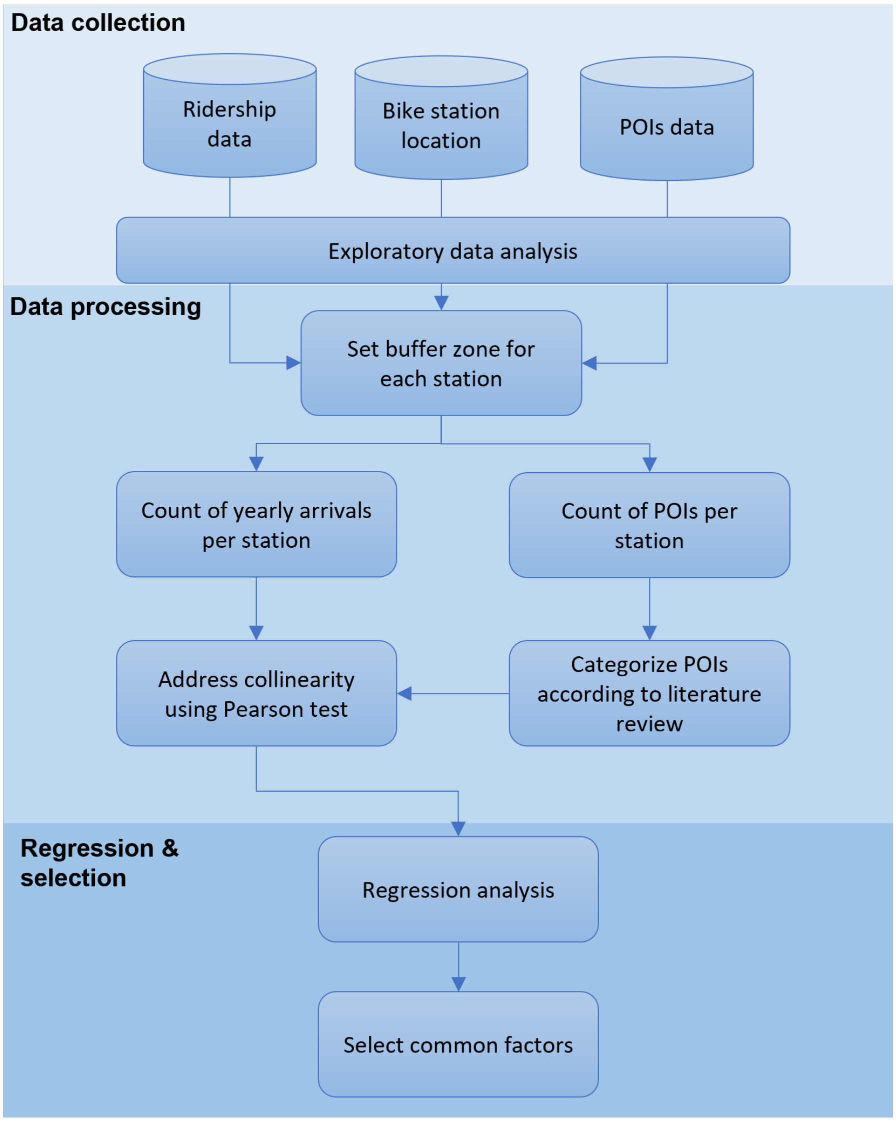

Figure 1. Methodology.

3.1. Data collection and processing

The ridership data is downloaded from an open source database. First the docked bike station's locations are identified. A buffer zone equal to 300 meter is set around each station. The buffer zone was chosen based on previous research, where this value is between 250 and 400 meters [8,9,15], as it is an acceptable distance to be walked from or to a station. The arrival trips that fall into the buffer zone are then counted and assigned to each docked bike station. For e-scooter and taxis, only stations that get assigned a total of ridership bigger than 0 are considered.

The built environment data is download from an open source database. The nature of the built environment to be explored is points of interest (POIs) such as restaurants, schools and bus stops. The collected POIs are then counted and assigned to each station. Thereafter, the POIs are categorized based on the findings of subsection 2.4. Finally, Pearson correlation test is performed and collinear variables are removed.

3.2. Regression and factor selection

Regression methods is one of the most used ways to study correlations between dependent and independent variables. Linear and logistic regression are some of the commonly used regression models [19].

3.2.1. Ordinary Least Square regression

Ordinary Least Square regression (OLS) is a regression technique that was used in previous research to explore the relationship between ridership and the built environment [8,16,20]. It is one of the most used techniques in multivariate analysis [21]. OLS is a useful tool when the relationship between the dependent and the independent variable is the hypothesis to be tested but the parameters are unknown. The relationship is modeled as follows [21]:

$$Y = \beta_0 + \beta_1 X + \epsilon \tag{1}$$

where Y is the dependent variable, β_0 is the intercept, β_1 is the slope, X the independent variable and ϵ is the random error [21].

3.2.2. Negative binomial regression

Negative binomial regression is a modelling technique also used in previous research and primarily for count data [11,18,20,22]. In negative binomial regression, the probability that the dependent variable y is equal to m, a non-negative integer, conditioning on the linear combination of x_1,x_2,.. and a parameterλ is calculated as follows [23]:

$$P(y = m|x_1, x_2, ...) = \frac{\lambda^m e^{-\lambda}}{m!} \tag{2}$$

where we assume that λ is the mean of y and the variance is equal to $\lambda(1 + \alpha\lambda^2)$. To estimate α and βs, the Maximum likelihood estimation (MLE) is used as follows [23]:

$$\ln \lambda = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + .. \tag{3}$$

3.2.3. Factor selection

After the regression analysis of each shared transportation mode, only the statistically relevant factors are considered. Finally, the common factors for the three modes can be identified.

4. Application

4.1. Data collection and processing

The ridership data for the bike-sharing system, the e-scooters pilot program and taxis were obtained from the data portal of the city of Chicago (https://data.cityofchicago.org/). The built environment data is obtained both from the server Geofabrik (http://download.geofabrik.de/north-america/us/illinois.html) and the above mentioned data portal of the city of Chicago.

4.1.1. Divvy bike-sharing system

Divvy is a public dock-based bike sharing system owned by the city of Chicago. The system started operating since 2013 and stations can be found all over the city of Chicago [18]. Recently, the Chicago Department of Transportation announced that in 2021 the system recorded 4 million trips, making it its all time high record. The city is planning more biking infrastructure and stations and making Divvy the largest bike-sharing system in North America by service area [24].

The data set used consists of 3,815,815 unique trips for the year 2019. Start, end time, bike ID, the specific location of the trips (latitude and longitude of the start and destination station), trip duration, user type and gender. Empty entries and trips lasting less than 90 seconds were eliminated, making the total number of trips for the year 2019 equal to 2,484,619.

Although the Divvy stations are spread out across the city, a concentration of trips is observed in what is considered downtown Chicago, compared to lower ridership in the city outskirts. For example the five best performing stations have an average of 36,918 trips in 2019, in contrast with the five least performing with an average of 4 trips.

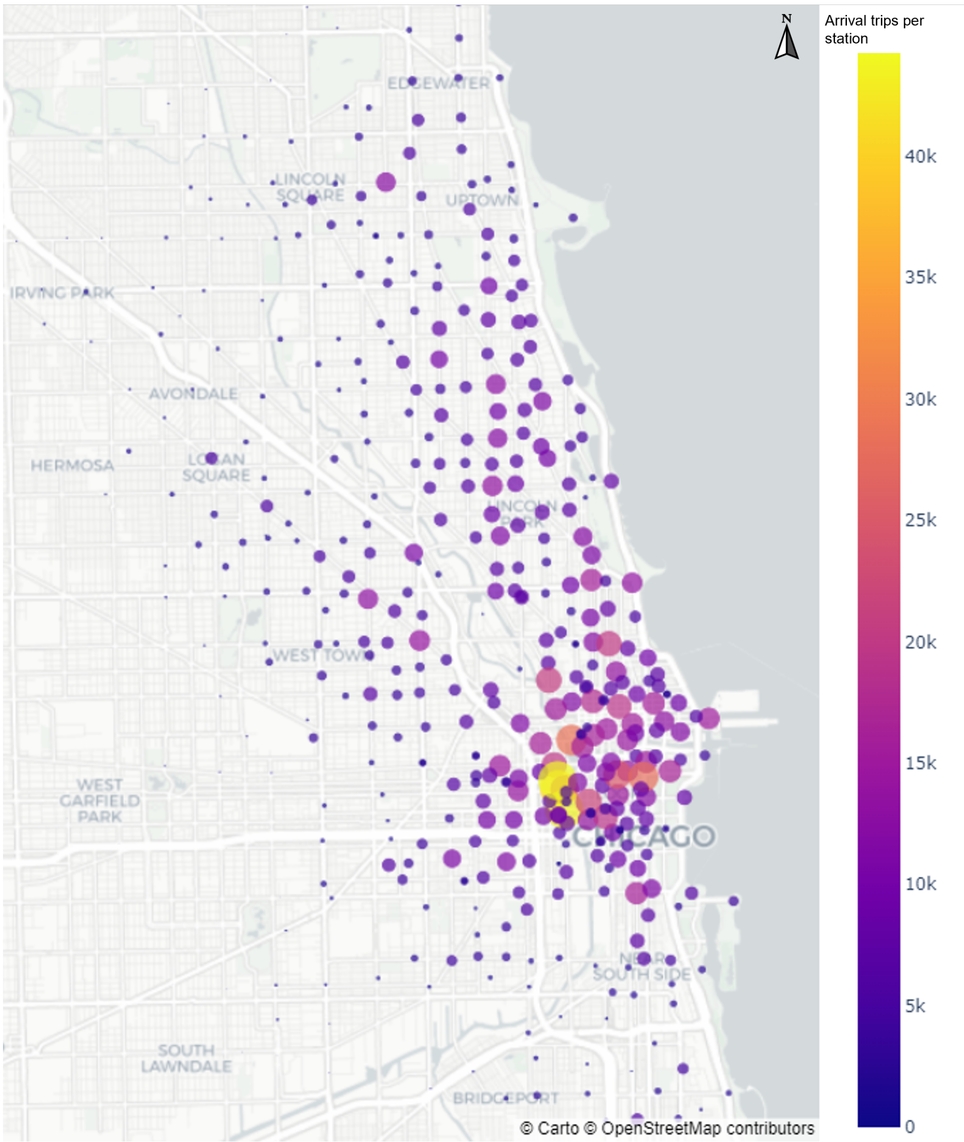

Figure 2. Bike arrivals per station in 2019.

4.1.2. E-scooter Pilot Program data

The 2020 e-scooter pilot is the second version program launched by the Chicago Department of Business Affairs and Consumer Protection (BACP) and the Chicago Department of Transportation (CDOT) to better understand the role of e-scooters in Chicago and whether it could yield to a better mobility and access for the people of Chicago [25]. What is unique about this program is the distribution of the e-scooters. An Equity Priority Area was determined, in which each e-scooter vendor had the requirement of deploying at least 50% of their fleet. This program operated from August 12 to December 12 of the year 2020. The total number of e-scooters is 10,000 [25]. It is important to state that the city center was not included in the 2020 e-scooter pilot program.

The dataset consisted of 630,816 unique trips. Start, end times, the specific location of the trips (the latitude and longitude of the centroids of both pickup and drop-off), trip duration, trip distance, as well as the vendor are provided. All empty trips or ones lasting less than 90 seconds were eliminated. This resulted in a total number of trips equal to 594,131.

As this study focused on the arrivals within the 300 meters buffer of the corresponding Divvy station, the total number of trips was equal to 481,550.

In figure 3, the spatial distribution of e-scooter arrival trips is plotted.

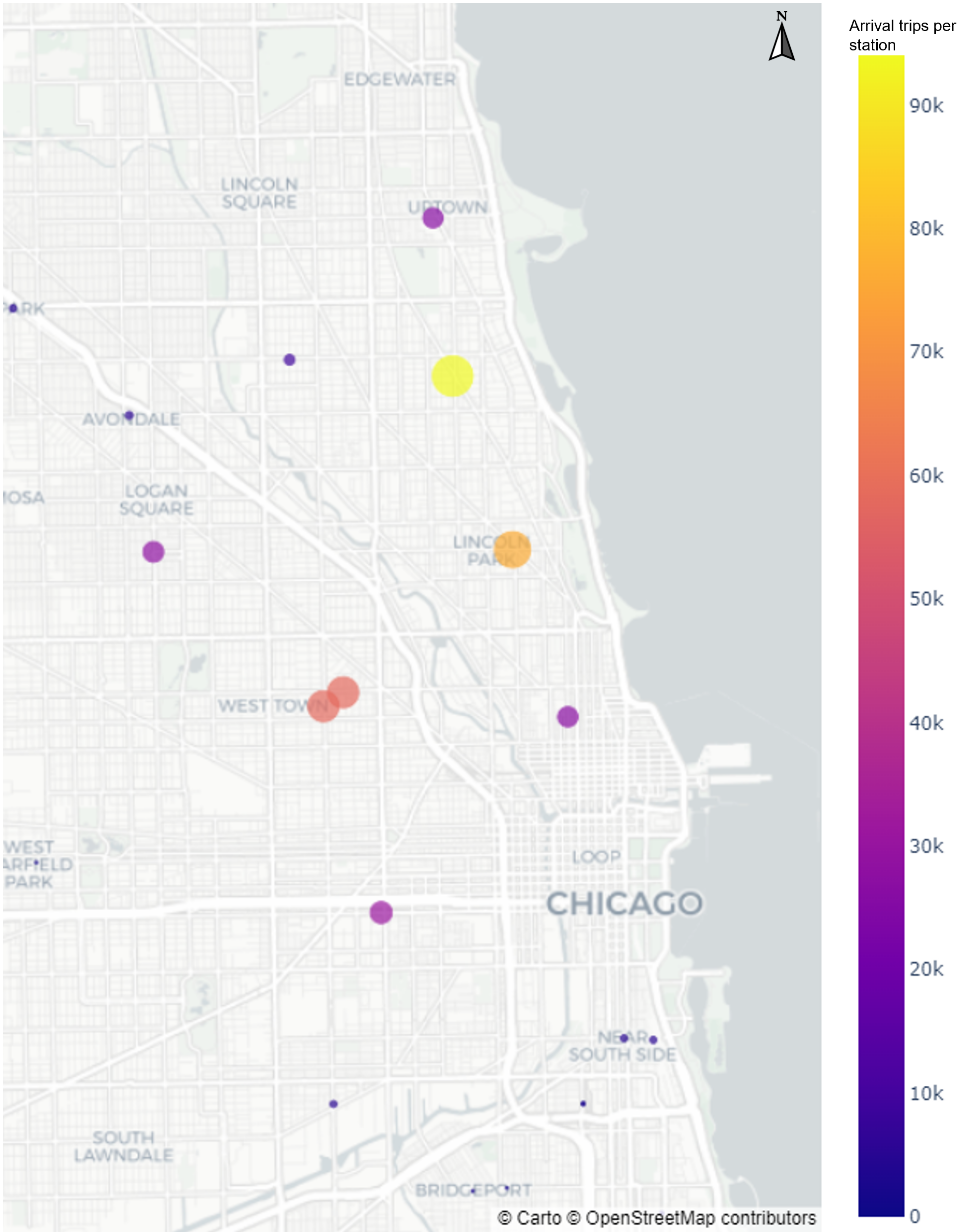

Figure 3. E-scooter arrivals per station in 2020.

4.1.3. Taxi data

The open-source data set consists of 16,477,365 unique trips. Due to downloading and storage issues, I could retrieve 1,000,000 for the year 2014. Start, end time, taxi ID, the specific location of the trips (latitude and longitude of the pickup and drop-off), trip duration, the cost of the trip and the payment method. After removing trips with missing latitudes and longitudes, I could retrieve 848,766 trips. In figure 4, the spatial distribution of taxi arrival is plotted.

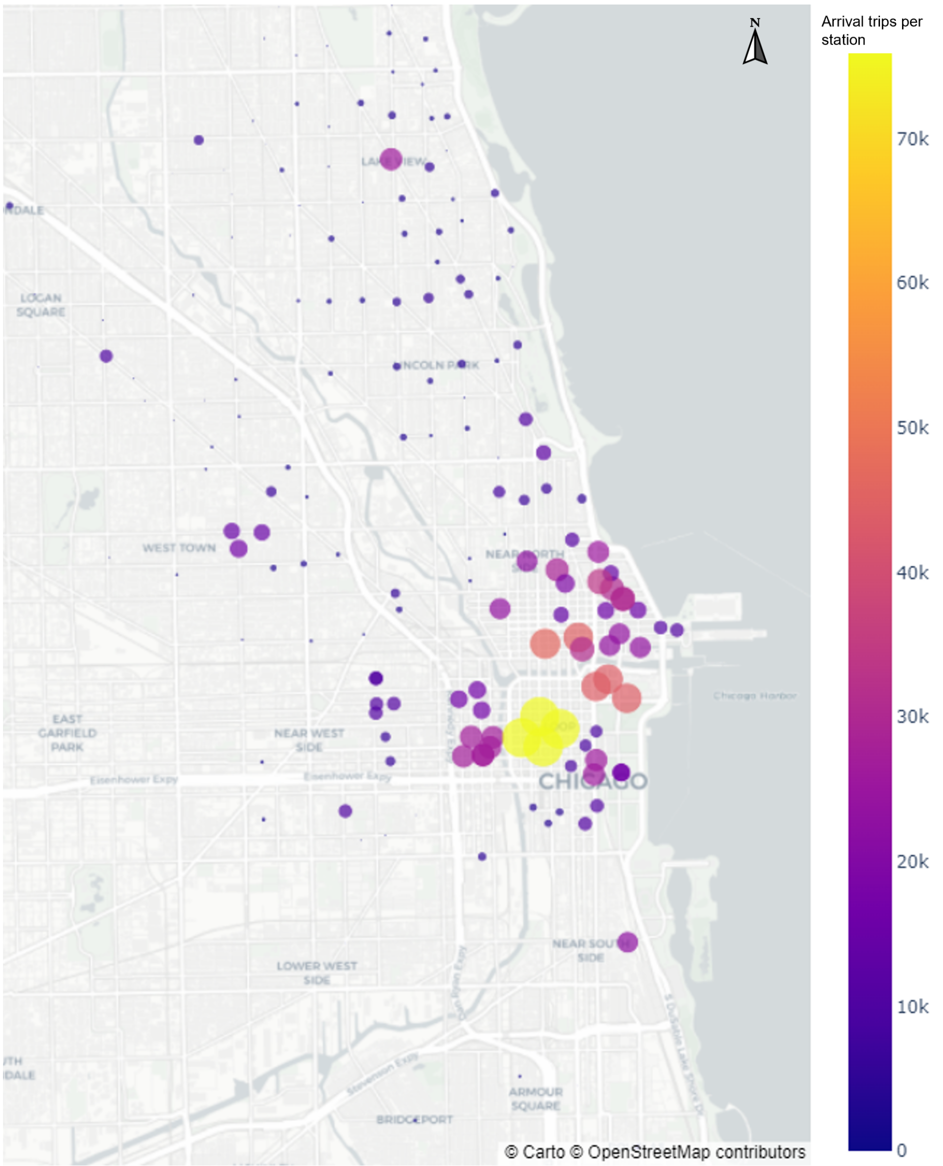

Figure 4. Taxi arrivals per station in 2014.

4.1.4. Built environment variables

The dataset of Geofabrik consisted of 133 different POIs. Bus stations, metro stations and residential buildings were separately collected from the open official data portal of the city of Chicago. The different POIs were clustered based on the commonly identified POIs found in the literature review 2.4.

The chosen categories are restaurant, education, grocery, entertainment, attraction, park, office, bus stations, metro stations and shops. Table 2 shows the different categories and their corresponding POIs.

Table 2. Points of interest used for the categories.

Category	POIs
Restaurant	Restaurants
Education	School University College
Grocery	Supermarket Convenience
Attraction	Museum Attractions for tourists
Entertainment	Cinema Theatre
Park	Parks
Metro stations	Chicago Transit Authority L-stations
Bus stations	Chicago Transit Authority bus stations
Residential	Residential buildings Houses Apartments
Office	Offices
Shops	Department stores/Shoe shops Book shops/Gift shops Clothing shops/Beauty shops

Since the spatial distribution of the three types of ridership is not the same, multicollinerity is considered separately for each mode.

Built environment and bike sharing ridership

For bike sharing, 633 stations and their corresponding POIs are considered. Table 3 presents a descriptive statistics of the bike sharing ridership the POIs .

Table 3. Descriptive statistics of dependent and independent variables.

Variable	Unit	Mean	Min	Max	Standard Deviation
Bike arrivals per station per year	Count	3925.14	2.00	44334.00	5310.26
Restaurant	Count	5.29	0.00	53.00	8.47
Education	Count	0.42	0.00	4.00	0.76
Grocery	Count	0.54	0.00	5.00	0.97
Shops	Count	1.19	0.00	35.00	3.45
Entertainment	Count	0.13	0.00	5.00	0.47
Attraction	Count	0.13	0.00	5.00	0.52
Parks	Count	0.01	0.00	3.00	0.18
Metro stations	Count	0.71	0.00	12.00	1.55
Bus stations	Count	8.94	0.00	27.00	4.93
Residential	Count	9.90	0.00	522.00	29.42
Employment	Count	2.29	0.00	54.00	7.07

To check for multicollinearity, Pearson correlation coefficient was calculated. Figure 5 shows the results of the pairwise correlation between the variables.

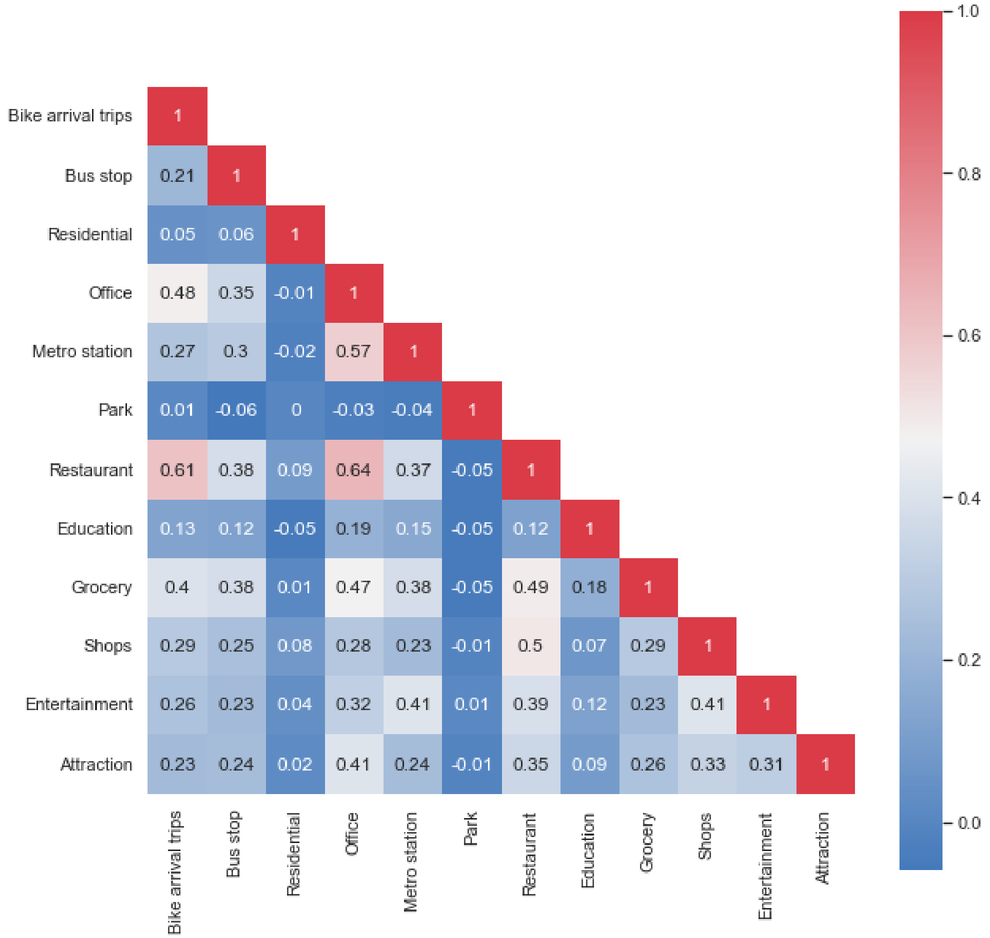

Figure 5. Pearson correlation matrix of bike sharing and the POIs.

The pairwise correlation between restaurant and office (0.64) and metro stations and office (0.57) is higher than 0.5, which implies the existence of collinearity. Since the variable restaurant has a higher correlation coefficient with the arrival trips, the variable office is excluded from the model.

Built environment and E-scooter sharing ridership

For e-scooter sharing, 34 stations and their corresponding POIs are considered. Table 4 presents descriptive statistics of the e-scooter sharing ridership and the POIs .

Table 4. Descriptive statistics of dependent and independent variables.

Variable	Unit	Mean	Min	Max	Standard Deviation
E-scooter arrivals per station per year	Count	760.91	261.00	93422.00	23195.94
Restaurant	Count	5.29	0.00	26.00	6.44
Education	Count	0.76	0.00	4.00	1.12
Grocery	Count	0.94	0.00	4.00	1.34
Shops	Count	1.58	0.00	14.00	2.73
Entertainment	Count	0.23	0.00	2.00	0.60
Attraction	Count	0.11	0.00	1.00	0.32
Parks	Count	0.02	0.00	1.00	0.17
Metro stations	Count	1.64	0.00	12.00	3.24
Bus stations	Count	9.58	0.00	17.00	4.45
Residential	Count	12.97	0.00	269.00	45.75
Employment	Count	3.79	0.00	39.00	8.98

To check for multicollinearity between the POIs, Pearson correlation coefficient was calculated. Figure 6 shows the results of the pairwise correlation between the variables.

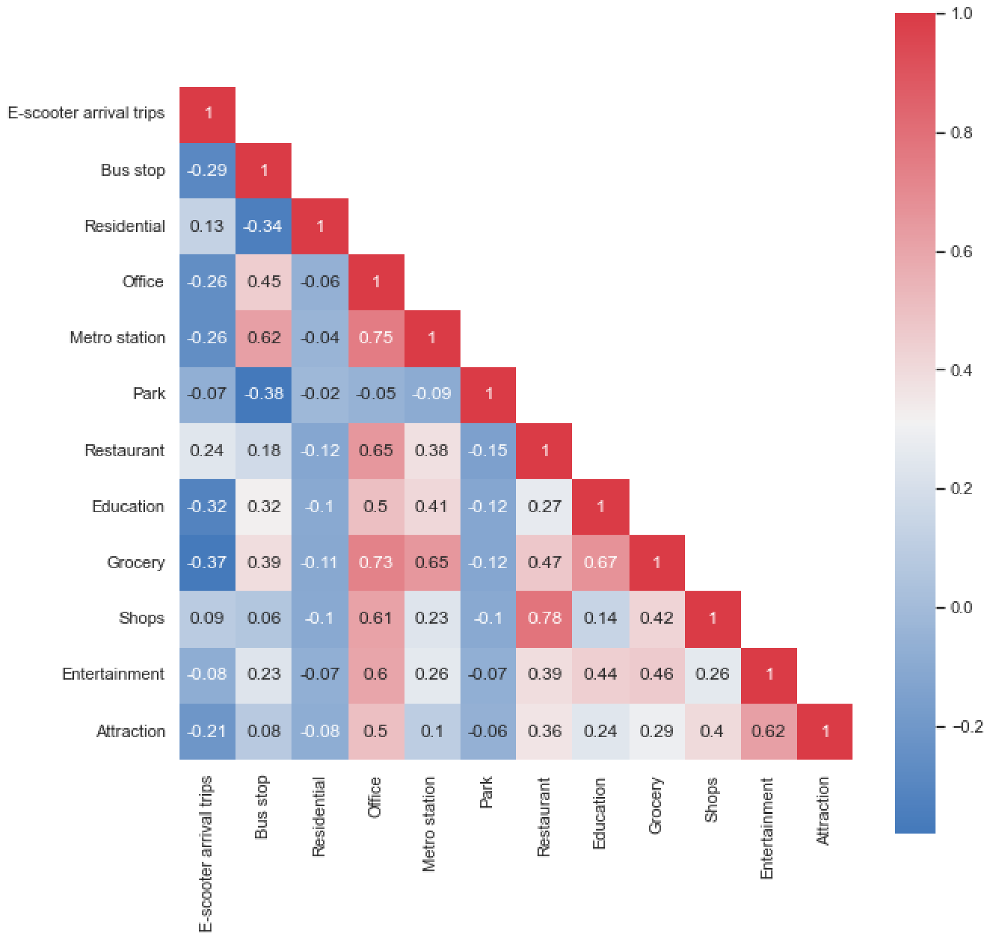

Figure 6. Pearson correlation matrix of e-scooter sharing and the POIs.

The pairwise correlation between office and almost all variables is higher than 0.5. The variable grocery correlates strongly with metro station (0.73) and education (0.67). Restaurant and shops have a correlation coefficient of 0.78. As a result, the variables office, grocery, attraction and bus station are removed from the model.

Built environment and taxi ridership

For taxis, 260 stations and their corresponding POIs are considered. Table 5 presents the descriptive statistics of the taxi ridership and the POIs .

Table 5. Descriptive statistics of dependent and independent variables.

Variable	Unit	Mean	Min	Max	Standard Deviation
Taxi arrivals per station per year	Count	6731.84	1.00	76090.00	12958.25
Restaurant	Count	6.58	0.00	53.00	8.41
Education	Count	0.46	0.00	4.00	0.79
Grocery	Count	0.62	0.00	5.00	1.09
Shops	Count	1.54	0.00	28.00	3.87
Entertainment	Count	0.15	0.00	2.00	0.42
Attraction	Count	0.17	0.00	4.00	0.56
Parks	Count	0.007	0.00	1.00	0.08
Metro stations	Count	0.60	0.00	8.00	1.28
Bus stations	Count	8.66	0.00	27.00	5.44
Residential	Count	13.43	0.00	522.00	40.98
Employment	Count	2.54	0.00	54.00	2.54

Pearson correlation coefficient was calculated to check for multicollinearity. Figure 7 shows the results of the pairwise correlation between the variables.

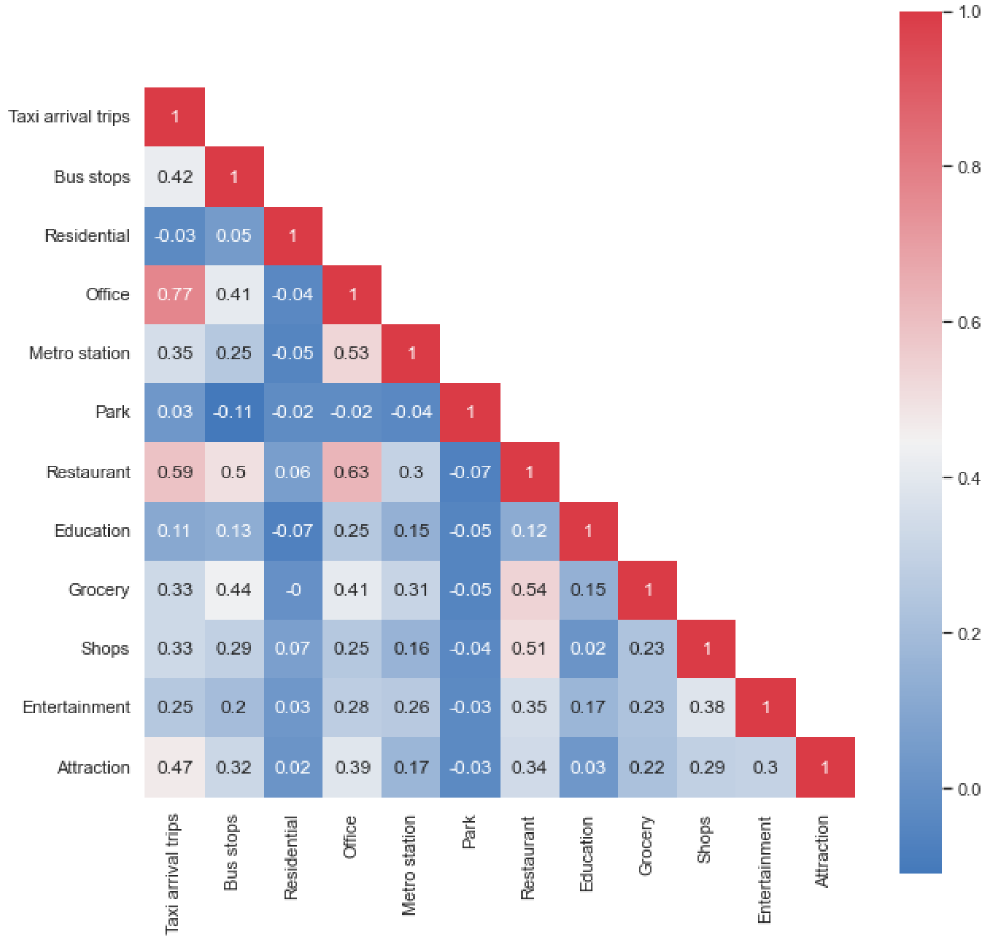

Figure 7. Pearson correlation matrix of taxis and the POIs.

The pairwise correlation between restaurant and office (0.63), restaurant and grocery (0.54) and restaurant and shops (0.51) is higher than 0.5, which implies the existence of collinearity. The variable restaurant has a weaker correlation coefficient with taxi arrivals than office, which lead to its exclusion from the model.

4.1.5. Model choice

Both Ordinary Least Square regression (OLS) and negative binomial regression (NB) were considered to identify the common built environment factors between the modes. However, the three dependant variables examined in this study do not have a normal distribution, as shown in figure 8. This lead to a non-normal distribution of the prediction error. Consequently, OLS should not be applied without a prior transformation of these variables. This resulted in the usage of negative binomial regression.

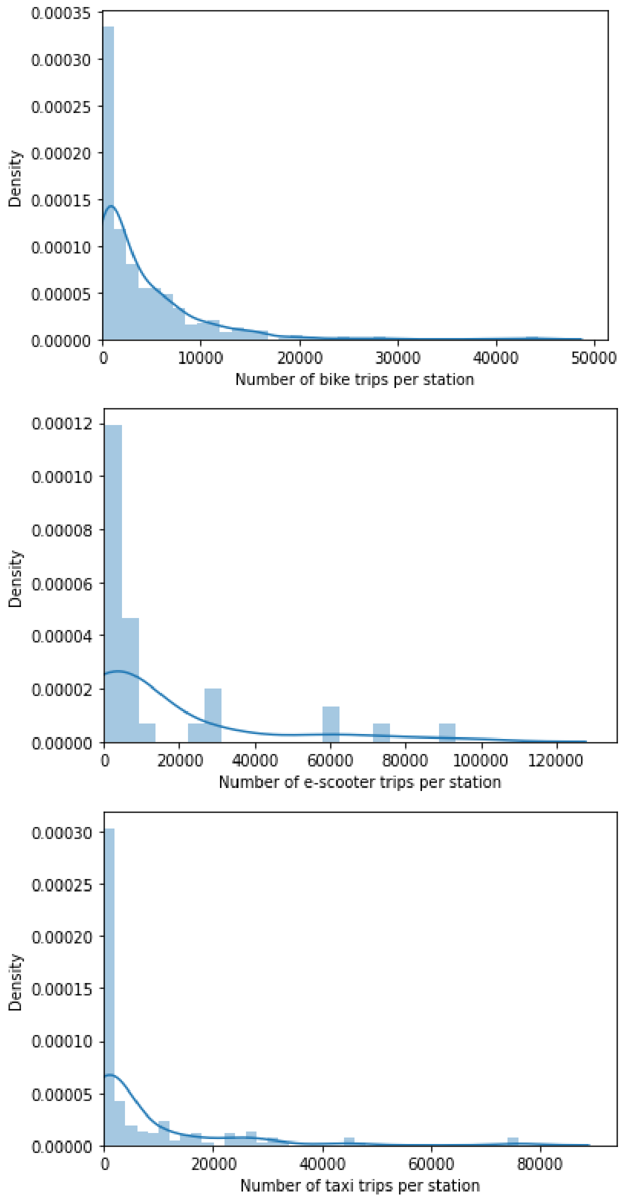

Figure 8. Histogram of the count trips of bikes, e-scooters and taxis per station.

5. Results

The results of the three regression models are shown in table 6. Three variables were found to be statistically significant for bike and e-scooter sharing and taxis.

Table 6. Negative binomial regression for each mode.

Dependent variables	Independent variables	Coefficients	Z value
Bike trips per station per year	Restaurant	0.0891	15.229
	Residential	0.0030	2.156
	Education	0.1158	2.019
Pseudo R^2		0.3798	
E-scooter trips per station per year	Restaurant	0.1332	3.505
	Metro stations	-0.3530	-5.957
	Residential	0.0077	1.988
Pseudo R^2		0.6562	
Taxi trips per station per year	Office	0.0968	8.798
	Bus stops	0.0210	1.446
	Attraction	0.3070	2.398
Pseudo R^2		0.6039	

The categories restaurant, education and residential buildings were found to be positively correlated with bike ridership. The variable restaurant is significant with a significance at the 0% level. Residential and education are significant at the 0.5%. Pseudo R^2 is equal to 0.3798. The regression model revealed that the variable education has a strong impact on ridership as it has the highest coefficient of 0.11.

E-scooter trips were found to be negatively correlated with metro stations, with a significance at the 0% level, and positively correlated with restaurants and residential buildings, with a significance at the 0% and 5% level, respectively. Restaurants have the highest coefficient, suggesting that a 1% increase in the number of the buildings will result in a 13% increase of the ridership.

Taxi trips were found to be positively correlated with office and attraction, with a significance at the 0% level. Bus stations also correlated positively with taxi ridership, but with a significance at the 5% level . The attraction variable has particularly a high coefficient, indicating that a 1% increase in the number of attractions might result in over 30% increase in taxi ridership. This makes attraction for tourists the most relevant variable for taxis.

6. Discussion

Negative binomial regression was used to explore the relationship between POIs in a buffer zone of 300 meters around docked bike stations and the ridership of three shared mobility modes: bike sharing, e-scooter sharing and taxis. The goal is to find the common POIs between these modes.

As expected residential buildings were found to have a positive impact on the bike and e-scooter ridership. These results coincides with previous research [22,25]. The category restaurant is a reoccurred variable with positive impact in research about both bike- and e-scooter sharing [8,25]. This can be explained by the fact that restaurants in urban areas are planned in dense and accessible areas [26], making their accessibility via bikes and e-scooters easier. Furthermore, education has the highest coefficient for bike sharing, which highlights the importance of students as a current user and possible one. This relationship is in line with Tran *et al.*'work [9].

As for the negative correlation between e-scooters and metro stations, it can be explained in this case by COVID-19 and its impact on transit mode choice as according to the E-scooter Pilot Evaluation "Approximately 22% of e-scooter riders surveyed said they “often” used an e-scooter to avoid using transit because of COVID-19 concerns" [24]. This result is also consistent with Espinoza *et al.*'s [10] work on e-scooters in Atlanta, where it was found that e-scooters were not usually used to reach a transit station.

Bus stops were found to positively correlate with taxi trips. This result is consistent with the findings from the literature review [13]. Although the correlation coefficient between the metro stations and taxis is positive according to the correlation results, it is worth mentioning that this relation tends to vary from study to study. For example Yang *et al.* [27] found a complementary relationship between metro stations and taxis in Washington DC but Wu and Zhuo [12] identified a competition relationship between them when taking Shanghai as a case study. In this study, the positive relationship between taxi ridership and public transportation modes can be explained by the usage of public transportation as a mile option.

Offices correlated positively with taxi arrivals, suggesting that some employees tend to use taxis as means of transport to get to their place of work. As for the attraction for tourists variable, it was found to be the most significant variable for taxis, this can be explained by the fact that tourist may tend to use taxis as they might not be familiar with the public transportation systems of a new city.

The discussed results do not come without limitations. The considerate E-scooter pilot program only ran for 4 months and during the warmer period of the year. In addition, the program only covered a specific area of Chicago that did not include the city center. The results for the e-scooter trips are very time and space specific and cannot be generalized. Furthermore, the park variable was used as a point and not as area, that might of affected its importance. Finally, any kind of ridership is affected by both space and time, therefore an aggregation of the trips by time can only make the results more precise.

7. Conclusion

This study aims to identify the common built environment factors between bike sharing, e-scooter sharing and taxis to get a idea where to allocate mobility hubs. The results from this study show that restaurant and residential buildings are the common factors between bike sharing and e-scooter sharing. For bike sharing, the category education had the strongest factor suggesting that students are a main user group. Furthermore, public transportation such as bus stops and metro stations do affect the usage of both e-scooters and taxis. For e-scooter users, metro stations do not seem to be a their destination or a transit point. On the other hand, the presence of bus stops means more arrival taxi trips.

These results can help urban planners and policy makers when deciding where could be the optimal location to place a mobility hub based on the built environment. For an optimal usage of bike sharing, e-scooter sharing and taxis as means of shared transportation present in a mobility hub, the presence of restaurants, educational institutions, public transportation and attractions should be checked when planning the mobility hub.

For further research, an improvement would be to take the departure trips and model the departure-arrival flow, as this model only considered the arrival trips as a target variable. Economical and social variables can also be added to better understand the overall usage of these modes. In addition, different cities need to be taken as case studies to better understand the importance of the mentioned factors.

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Lehrstuhl für Siedlungsstruktur und Verkehrsplanung
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Exposé- STUDY PROJECT

Study program M.Sc. Environmental Engineering

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Processing period: seven months, submitted 13.12.2021

Title: Where to allocate mobility hubs? Identifying common built environment factors associated with the usage of multiple shared mobility options in Chicago

Background:

The transport sector is facing the challenge of major reduction in CO_2 emissions to reach the ambitious goal of climate neutrality by 2050 [1]. In fact, 19% of the global final energy demand is accounted for the transport sector, which led to CO_2 emissions equal to 8260 $MtCO_2eq$ in 2015 [2]. However, passenger road vehicles account for the highest proportion of the overall transport emissions [3] . Therefore, a radical switch of the current modal split, in which daily car-orientated use constitutes the largest share [4], is much needed. That's why finding ways to incentivize the usage of non-private motorized vehicles eg: public transportation, biking, walking, and shared vehicles is key to reach this goal. In this context, a mobility hub can be a physical and digital integration of the above-mentioned modes. The concept of mobility hubs is gaining rapid interest, as it provides a potential way to seamlessly combine different shared mobility options and services [5]. There is not yet a standard definition used, therefore, I define a mobility hub as a place from which at least one public and two shared modes of transport e.g.: public transportation, bike-sharing, car-sharing are integrated. Mobility hubs can be potentially used to incentivize shared ridership, hence the importance of its potential location. However, the built environment as an influencing factor to use shared mobility options is yet to be fully explored [6] . Consequently, there is a need to study and understand this relationship. By exploring the connection between the built environment and the usage of different options of shared mobility, we can identify the relevant factors that is associated ridership and utilize the findings to increase it.

Goals:

The aim of this project is to explore the relationship between the built environment and the usage of different shared transportation modes, hence potentially identifying the recommended conditions of a mobility hub. [7]

To comply with this intention, the following research questions are defined:

- How to model the relationship between the built environment and the usage of different shared modes of transport?
- What are the common built environment factors between different shared modes of transport?

Methodology:

1. Literature review about built environment and travel, and mobility hubs.
2. Built environment and transport data collection.
3. Model the relationship between the built environment data and the ridership data.
4. Identify the common factors that are associated with the usage of different modes.

Supervision:

The candidate will present to his supervisor Dr.-Ing. David Duran a draft of the structure for his master thesis and a work plan two weeks after this approval. Other supervision meetings will be planned with the candidate when necessary. The Chair of Urban Structure and Transport Planning supports the candidate with the contact to relevant actors and or experts if needed. After two weeks of the submission of his thesis, the candidate must defend it by means of a presentation (20 minutes) and the following discussion. The results are responsibility of the author. The Chair does not take responsibility for those results.

M.Sc. Aaron James Nichols

Dr.-Ing. David Telmo Duran Rodas

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