Analyzing the impact of the built environment on the bike sharing usage: the case of Lyon city

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Abstract

This paper aims to analyze the bike sharing usage in Lyon city using the real bike sharing trips data collected in 2011. A typology of bike sharing stations was determined by using the method of clustering k-means. This typology shows that bike sharing usage at station level is different according to the observation periods in a working day. The variables of built environment are then estimated in order to explain the difference of bike sharing usage between groups of bike sharing stations. A principal component analysis of built environment variables was done to explain the bike sharing usage at station level. The results of this study can be helpful for bike sharing operators to improve the quality of service and for bike sharing planners to better positioning and dimensioning a new bike sharing system.

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1. Introduction

During the last 10 years, there was a steady development of bike sharing systems around the world. Bike sharing is considered as an alternative and complementary mode of transportation which has traffic and health benefits such as flexible mobility, physical activity benefits and supports for multimodal transport connections (Shaheen et al, 2010). Bike sharing can provide an alternative to traditional modes of transport or a complementary service for solving the "last mile problem" of getting from a public transportation stop to the final destination (Bargar et al, 2014). Currently, the bike sharing scheme is present in 49 countries with more than 500 systems and about 700 000 bikes (Earth Policy Institute, 2014).

In France, the bike sharing system is implemented in more than 35 cities to improve soft mode transportation and encourage the sustainable development. Vélo'v, the bike sharing system of Lyon, installed in 2005, is recognized as a success of bike sharing. Today, Vélo'v has 345 stations with more than 4,000 bicycles. Operated by JC Decaux, the system has 58,000 long-term subscribers in 2014 with an average of 23,000 rentals per day (Lyon Capitale, 2014). Although bikesharing is becoming popular in France and around the world, there are relatively few quantitative studies exploring the influence of built environment on the bikesharing usage.

To ensure the success of bike sharing schemes, it is important to understand the influence of built environment on the bike sharing usage. Vélo'v in Lyon city is mature and successful bike sharing system that offers a unique opportunity for understanding the factors influencing its flows and usage.

In this paper, we use bike sharing trips data from minute-by-minute readings of bicycle flows at all 341 stations Vélo'v in 2011 given by JC Decaux - operator of bike sharing system of Lyon - to determine a typology of bike sharing stations. The built environment attributes around station are then determined in order to understand the influence of these factors on bicycle sharing demand.

The rest of the paper is organized as follows. Section 2 provides a literature review of earlier researches and positions our research. Section 3 explains the data used in the modeling and the socio-economic variables around bike sharing stations. The typology of bike sharing stations and the results of the principal component analysis are discussed in section 4. Finally, section 5 concludes the paper with recommendations for future researches.

2. Literature review

There have been four generations of bike sharing since the introduction of the first bike sharing system in the 1960s in the Netherlands (De Maio, 2009 and Shaheen, 2010). Bike sharing has become more popular since the introduction of the 3rd generation. The third generation of bike sharing can be described by the automatic transaction kiosk at each station and identified bike sharing users. These systems have become relatively successful around the world. There are some bike sharing systems of fourth generation installed in Copenhagen and Madrid with improving docking stations, bike redistribution, integration with other transport modes (De Maio, 2009 and Shaheen, 2010) and electrical bikes.

Vélo'v belongs to the 3rd generation of bike sharing systems. The Vélo'v system aggregated more than 6.2 million trips in the 2011 and more than 50,000 long term subscribers (Tran et al, 2014). Vélo'v bike sharing system of Lyon city is installed in the city of Lyon and Villeurbanne which cover an area of 60 kilometer square. In 2014, there were 8.3 million bike sharing trips recorded with more than 59,000 long term subscribers (Lyon Capitale, 2014).

In recent years, many researches have used traditional surveys in order to determine the factors that may promote the adoptions of bike sharing by urban populations (LDA Consulting, 2013 and Melbourne BSS survey, 2015). The automated data collected from docking stations constitutes a precious source of information to better understand the usage of bike sharing in the city.

There have been several studies conducted using data from the Vélo'v system. These studies use actual bike sharing flow data obtained from stations to determine the typology of bike sharing users or to analyze the characteristics of bike sharing usage. They contribute to the literature by studying user behavior in response to bike sharing system and examining the characteristics of this system. The average speed of bike sharing is 14 km per hour (Jensen et al, 2010) and the average duration of bike sharing trip is about 15 minutes.

There are also several researches that determine a typology of bike sharing stations using the real bike sharing data trips (Froehlich, 2009; Lathia, 2012; Kaltenbrunner, 2010). They have determined that there are different groups of bike sharing stations according to their operation during a working day. However, it lacks a clear explanation for the difference between groups of bike sharing station.

The current paper contributes to literature by determining a typology of bike sharing stations using hourly bike sharing data. The typology is then explained by the built environment attributes around the bike sharing stations in each group of bike sharing stations. The results can be useful for better understand the bike sharing usage and for modeling the bike sharing demand at station level.

3. Data

The main objective of the study is to measure the influence of various factors (such as: socio-economic factors, public transport station, urban amenities, etc.) on bike sharing usage at station level. First, we use the method k-means to determine different clusters of bike sharing stations using the trips data in 2011. The principal component analysis is used then to explain the influence of built environment on different clusters of bike sharing station. The data used in this study consists of all bike sharing trips in 2011: over 6 million trips and the built environment data geo-computed by the GIS-transport modeling platform MOSART developed by the researcher from Transport Economics Laboratory.

There are 3 types of bike sharing users: long term subscribers who have annual bike sharing subscriptions and short term subscribers who have 7 day or 1 bike sharing day subscriptions. In this study the data were calculated from the bike sharing trips data of long term subscribers which represent about 80% of bike sharing data trips in 2011 according to our calculation.

3.1 Bike sharing trips data

In this study, we used the bike sharing trips data obtained from JC Decaux – operator of Lyon bike sharing system, for all stations during the year of 2011. Each trip gives us information about the departure and arrival station, the date and hour of check in and check out and the type of subscribers.

In order to calculate the flows of bike sharing, we aggregated the bike sharing trips per hour. All non-valid trips were eliminated. A non-valid trip is a trip less than 3 minutes or more than 3 hours. The data aggregated were calculated only for working days (from Monday to Friday and not during vacations). We eliminated also the bike sharing trips made during July and August because they are the months of vacations in France. Finally, 173 working days were counted for calculating bike sharing flows. The bike sharing flows are then divided by 173 and multiplied by 100 before using for the calculations in the models.

In order to estimate the flows of bike sharing, we divided a working day in eight different periods: 12 am to 3 am; 3 am to 7 am; 7 am to 9 am; 9

am to 12 pm; 12 pm to 2 pm; 2 pm to 5 pm; 5 pm to 8 pm and 8 pm to 12 am. For each period, we calculated the relation between inbound flow and total flow for all bike sharing stations. This relation shows us how the bike sharing flow is distributed during a day. We also took into account the absolute value of inbound and outbound flow of each bike sharing station in order to keep the variety of bike sharing usage between stations.

3.2 Built environment variables

In order to analyze the influence of built environment, we determined built environment variables around each station. The explicative variables used in our analysis can be categorized in five groups: public transport variable, socio-economic variable, topographic variable, bike sharing network variable and leisure variable. A 300 meter buffer zone was chosen because it was found to be an appropriate walking distance between Vélo’v stations (BSS Lyon survey, 2008).

In terms of public transit variables, the number of metro, tramway and railway stations near a Vélo’v station were generated to examine the influence of public transit on bike sharing flows. The variables of public transit were normalized by the number of passengers of each station per day or per year.

Table 1. Built environment around bike sharing stations

Variable	Min	Max	Mean	Std. Dev.
Population	4	10977	4707	2481
Job	148	11828	2332	2114
Students in campus	0	25788	780	2892
Student residence	0	10	1.33	1.98
Railway station	0	20	0.26	2.02
Metro station	0	12	1.51	2.71
Tramway station	0	27	1.69	4.33
Altitude	164	289	180.84	28.04
Bicycle infrastructure	0	2835	1024.95	650.50
Station capacity	10	40	19.37	5.89
Network density	45	277	238	58
Cinema	0	4	0.25	0.68
Restaurant	0	28	3.06	5.34
Night club	0	10	0.61	1.52

The socio-economic variables included four factors: (1) population, (2) number of jobs, (3) number of students in campus and (4) number of student residences near a bike sharing station. The altitude of each station was calculated to examine the influence of topographic variable on bike sharing usage.

The length of bicycle facilities in the buffer zone was also calculated to capture the impact of placing Vélo'v stations near bicycle facilities on the usage of the bike sharing system. The number of bike sharing stations in a 3,500 meter buffer zone around a Vélo'v station and the capacity of each Vélo'v station were computed to capture the effect of bike sharing network. Leisure variables are also considered in our analysis. We also considered three types of points of interest near each station: (1) number of restaurants, (2) number of cinema, and (3) number of night clubs.

4. Results and discussions

In this session, we are going to present, discuss and visualize the results of bike sharing stations clustering and of the principal component analysis. The clustering k-means allows us to determine the different groups of bike sharing stations according to the flows and the distribution of flows during a working day. A principal component analysis is performed then in order to understand the influence of built environment on the bike sharing usage of each group of bike sharing stations. A visualization of bike sharing stations can be useful to better understand the localization of the bike sharing station groups in the city.

4.1 Typology of bike sharing stations

In order to find out a typology of bike sharing stations using the bike sharing trips data, we have firstly determine the optimal number of clusters before using the k-means method to determine the different clusters of bike sharing stations.

Determination of number of clusters

In this study, we choose the method of elbow determination for calculating the number of clusters of bike sharing stations. The principle of this method is to analyze the percentage of variance explained as a function of the number of clusters. We all know that the more clusters we add, the modeling of the data gets better. This method aims to choose a number of clusters so that adding another cluster doesn't give much better information about the data. The "optimal" number of clusters is chosen at this point. The right choice of number of clusters is 7 where the value of subtraction level 2 is maximal.

Table 2. Determination of the number of clusters

K – number of clusters	1	2	3	4	5	6	7	8	9	10
R^2	0	0.273	0.430	0.530	0.582	0.614	0.649	0.661	0.680	0.694
Subtraction level 1	-0.273	-0.157	-0.100	-0.052	-0.032	-0.035	-0.012	-0.019	-0.014	-0.011
Subtraction level 2	-0.116	-0.057	-0.048	-0.020	-0.003	-0.023	0.007	-0.005	-0.003	-0.001

The typology of bike sharing stations

The results of clustering give us seven groups of bike sharing stations. In general, we can see that bike sharing usage is very different during the periods from 12 pm to 3 am, from 3 am to 7 am, from 7 am to 9 am and from 5 pm to 8 pm. The periods *7 am - 9 am* and *5 pm - 8 pm* correspond to the peak period on a working day while the period from *12 pm - 3 am* is just after the stop of public transportation. We could see in the Fig. 1 that the difference of usage between bike sharing station groups is principally during AM and PM peak periods.

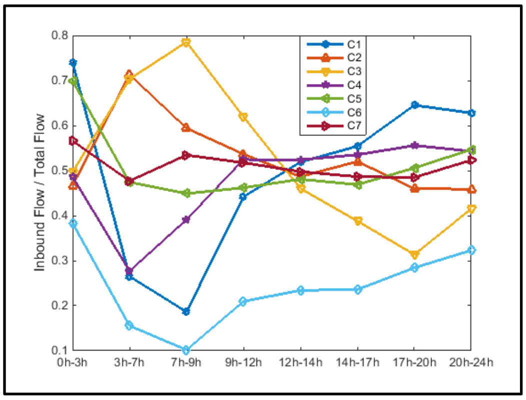
The difference between clusters of bike sharing stations can be described by the relation between inbound and total bike sharing flows during a working day and the daily bike sharing flows (daily inbound flow and outbound flow). The relation between inbound flows and total flows of bike sharing allows us to understand the balance of a bike sharing station during a working day while the daily bike sharing flows allow us to know how many trips were made at a bike sharing station.

First, by looking at the daily inbound and outbound bike sharing flows, we can see that the cluster C2 is the cluster with the most important bike sharing flows while the cluster C6 is the cluster with the less important bike sharing flows. In terms of balance between daily inbound and daily outbound flows, the cluster C6 is the only cluster who presents an unbalance.

Let's now have look at the distribution of percentage of inbound flows compared to total flows during different period of a working day. The clusters C7 and C5 are the two groups of bike sharing stations with a good balance of flows during a working day except from 12 pm to 3 am. The distribution of flows of the cluster C1 and the clusters C3 are symmetrical during the day. The distribution of bike sharing flows of the cluster C2 and the cluster C4 are also symmetrical.

Table 3. Clusters of bike sharing stations

Clusters	0h – 3h	3h – 7h	7h – 9h	9h – 12h	12h – 14h	14h – 17h	17h – 20h	20h – 24h	Daily in flow by station	Daily out flow by station	Size
C1	0.74	0.27	0.19	0.44	0.52	0.55	0.65	0.63	20	20	49
C2	0.47	0.71	0.59	0.54	0.49	0.52	0.46	0.46	155	158	12
C3	0.5	0.7	0.79	0.62	0.46	0.39	0.31	0.42	24	24	40
C4	0.49	0.28	0.39	0.52	0.52	0.54	0.56	0.54	50	52	78
C5	0.7	0.47	0.45	0.46	0.48	0.47	0.51	0.55	22	21	67
C6	0.38	0.16	0.1	0.21	0.23	0.24	0.28	0.32	16	5	31
C7	0.57	0.48	0.53	0.52	0.5	0.49	0.48	0.52	75	77	64



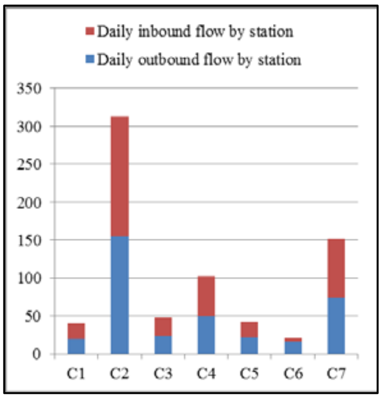


Fig. 1. Profile of clusters of bike sharing stations

The difference of bike sharing flow distribution during the different periods of a weekday shows that the difference between inbound flow and outbound flows is clearer in the evening and during peak periods than during off-peak periods.

4.2 Principal component analysis of built environment

Determination of built environment variables

The built environment variables for each cluster of bike sharing stations represented the average of the built environment variables of all bike sharing stations in the cluster.

Table 4. Built environment of groups of bike sharing stations

Variable	C1	C2	C3	C4	C5	C6	C7	Unit
Population	4453	4667	1777	6528	3798	4429	5653	person
Job	924	7232	2063	2782	1413	940	3829	job
Student	32	237	913	537	476	409	2259	student
Student residence	81	45	27	94	102	90	230	residence
Railway	0.0	5.5	0.0	0.2	0.0	0.0	0.2	x (5000 passengers per day)
Metro	0.4	7.7	0.3	2.3	0.9	0.4	2.2	x (1,000,000 passengers per year)
Tramway	0.3	10.8	0.9	1.3	1.0	0.0	3.6	x (200,000 passengers per year)
Altitude	175	169	178	169	178	257	169	meter
Bike infrastructure	769	1266	987	1385	768	565	1257	meter
Capacity	18	26	24	17	19	18	21	number of places
Cinema	0.0	1.3	0.1	0.6	0.0	0.1	0.2	number of cinemas

Night club	0.2	0.5	0.1	1.7	0.2	0.1	0.6	number of night clubs
Restaurant	0.9	5.9	1.0	6.8	0.6	1.5	4.3	number of restaurants
Density network	156	257	136	227	151	168	233	number of bike sharing stations

The choice of number of axis

Looking at the scree plot, we can see that there are 4 eigenvalues over 1.00, and together these explain more than 97% of the total variability in the data. This leads us to the conclusion that a four factor solution will probably be adequate.

Table 5. Variation of Eigenvalue

Component	Before Varimax rotation				After Varimax rotation			
	F1	F2	F3	F4	D1	D2	D3	D4
Variance explained (%)	54.351	23.032	11.466	7.934	44.108	25.056	14.612	13.007
Variance cumulated (%)	54.351	77.383	88.849	96.784	44.108	69.164	83.776	96.784

Above, is the table showing the percentage of variance explained before and after using Varimax rotation. The middle part of the table shows the percentage of variance explained for just the four factors of the initial solution that are regarded as important. Clearly the first factor of the initial solution is much more important than the other factors. Let's have a look at the rotated factors in the right hand part of the table, the percentage of variance explained for the four rotated factors are displayed. Whilst, taken together, the four rotated factors explain just the same amount of variance as the four factors of the initial solution, the division of importance between the four rotated factors is very different. The effect of Varimax rotation is to spread the importance more equally between the rotated factors.

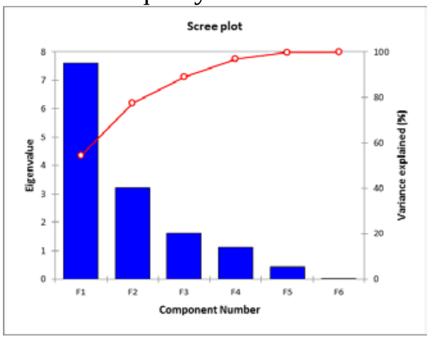


Fig. 2. Variation of Eigenvalue and variance explained

We used the rotation Varimax in the principal component analysis. The purpose of Varimax rotation is to facilitate the interpretation of the principal component analysis results.

Explication of Varimax rotation

Varimax rotation is an orthogonal rotation of the factor axes to maximize the variance of the squared loadings of a factor (column) on all the variables (rows) in a factor matrix, which has the effect of differentiating the original variables by extracted factor. Each factor will tend to have either large or small loadings of any particular variable. Varimax rotation makes it as easy as possible to identify each variable with a single factor.

These four rotated factors are just as good as the initial factors in explaining and reproducing the observed correlation matrix. In the rotated factors, *Job*, *Railway*, *Metro* and *Tramway* all have high positive loadings on the first factor (and low loadings on the other factors), whereas *Population* has high positive loadings on the second factor (and low loadings on the first). *Student* and *Student Residence* all have high positive loadings on the third factor. And the fourth factor is negatively influenced by the variable *Altitude*.

Table 6. Unrotated factor loadings (before Varimax) - Rotated factor loadings (after Varimax)

Parameters	Unrotated axes				Rotated axes			
	F1	F2	F3	F4	D1	D2	D3	D4
Population	0.166	0.417	-0.280	0.243	0.086	0.937	0.254	-0.100
Job	0.349	-0.106	0.138	0.078	0.942	0.184	0.113	0.256
Student	0.039	0.301	0.627	0.097	-0.020	-0.015	0.940	0.246
Student Residence	0.011	0.432	0.373	0.342	-0.157	0.313	0.910	-0.077
Railway	0.302	-0.283	-0.057	0.163	0.967	0.049	-0.224	0.024
Metro	0.344	-0.140	-0.042	0.140	0.946	0.268	-0.071	0.118
Tramway	0.329	-0.190	0.111	0.159	0.980	0.079	0.032	0.134
Altitude	-0.180	-0.080	-0.235	0.668	-0.198	-0.105	-0.088	-0.890
Bike Infrastructure	0.300	0.207	0.105	-0.349	0.451	0.520	0.222	0.672
Capacity	0.212	-0.364	0.349	-0.104	0.805	-0.465	-0.024	0.333
Cinema	0.340	-0.138	-0.170	0.048	0.890	0.352	-0.227	0.153
Night Club	0.193	0.352	-0.329	-0.326	0.026	0.888	-0.062	0.426
Restaurant	0.318	0.217	-0.166	-0.017	0.539	0.768	0.096	0.275
Density Network	0.333	0.174	-0.026	0.223	0.701	0.646	0.280	0.105

Naming the factors

The naming of the factors is based on their loading on each factor. It seems reasonable to tentatively identify the first rotated factor as *Jobs and Public Transit*, because Job, Railway, Metro and Tramway all have high loadings on it but low loadings on other factors. The second rotated factor can be called *Population*, as Population has high loadings on it. The third rotated factor can be named *Student Activities* because of the high loadings of the variables Student and Student Residence on it. The fourth rotated factor should be named *Altitude* because the variable Altitude has a high loading on it.

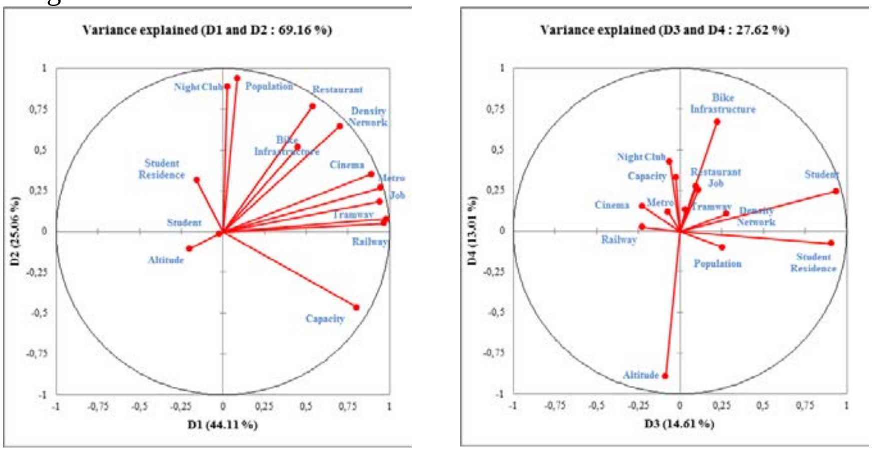


Fig. 3. The principal components after Varimax rotation

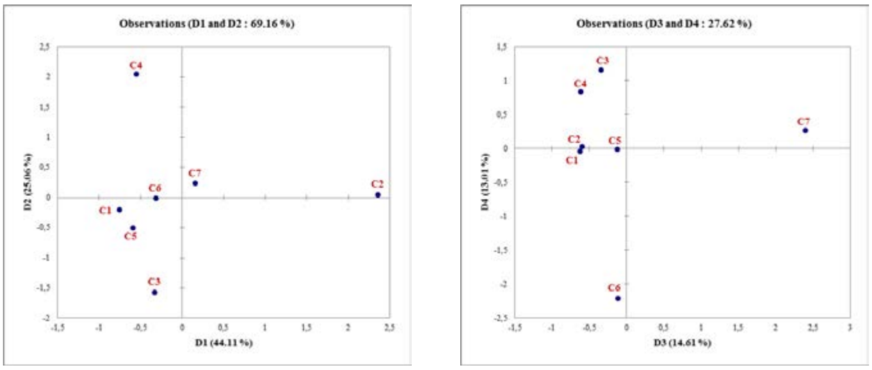


Fig. 4. The repartition of bike sharing clusters according to principal components

4.3 Influence of built environment on bike sharing usage

We are going to explain the daily inbound and outbound bike sharing flows of each clusters and the distribution of flows during different periods of day by the built environment variables that we have presented above.

Let's have look at the cluster C2. By analyzing the position of C2 to the axis D1 *Job and Public Transit* and to the axis D2 *Population,* we see that C2 is located in the areas where there is a high density of jobs and an important offer of public transit. The population around the bike sharing stations of cluster C2 is also averagely important. That explains why the inbound flows of the stations in the cluster C2 are more important in the morning and less important in the afternoon than outbound flows. An important offer of public transit, especially the railway station, can certainly contribute to increase the bike sharing usage. The cluster C4 is located in the areas with a high density of *population* (axis D2) and an average density of *jobs* and *offers of public transit* (axis D1). That's why the distribution of inbound flows during a working day of this cluster is symmetrical to the distribution of inbound flows of the cluster C2.

The cluster C7 is located in the areas with a high density of *students* and *student residences* (axis D3) and an average density of population and an average density of jobs and public transits offers. In this cluster, the bike sharing flows are well balanced during a working day. The cluster C6 is located in the hilly areas of the city (axis D4). That explains why the inbound flows in this cluster is always less important than the outbound flows. The bike sharing stations in this group have to be regulated in order to ensure the availability of bike for the users.

The cluster C1 is located in the areas with a low density of jobs and public transit and a medium density of population. The operation of the bike sharing stations in this cluster is dominated by the influence of population. People take bike sharing from these stations to go to work in the morning and they come home in the afternoon after returning their bike to these bike sharing stations. That's why we can see that the inbound flows are less important than the outbound flows in the morning and the inbound flows are more important than the outbound flows in the afternoon.

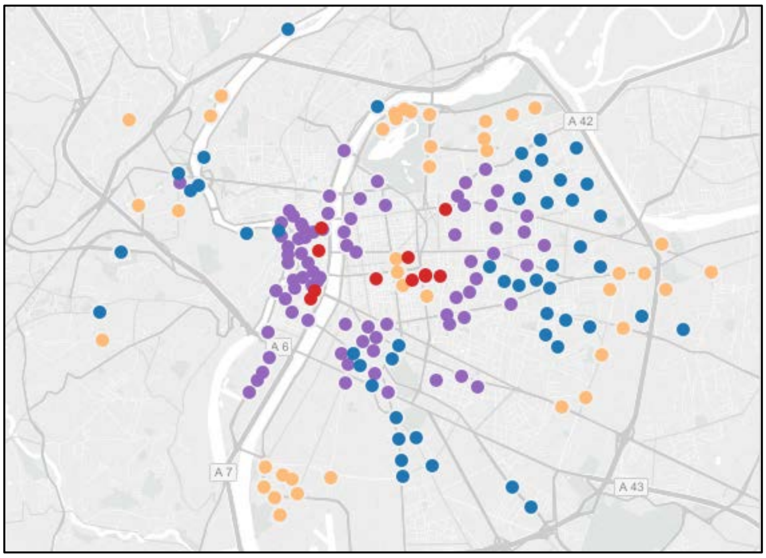


Fig 5. The clusters of bike sharing stations (C1: navy blue, C2: red, C3: orange, C4: magenta)

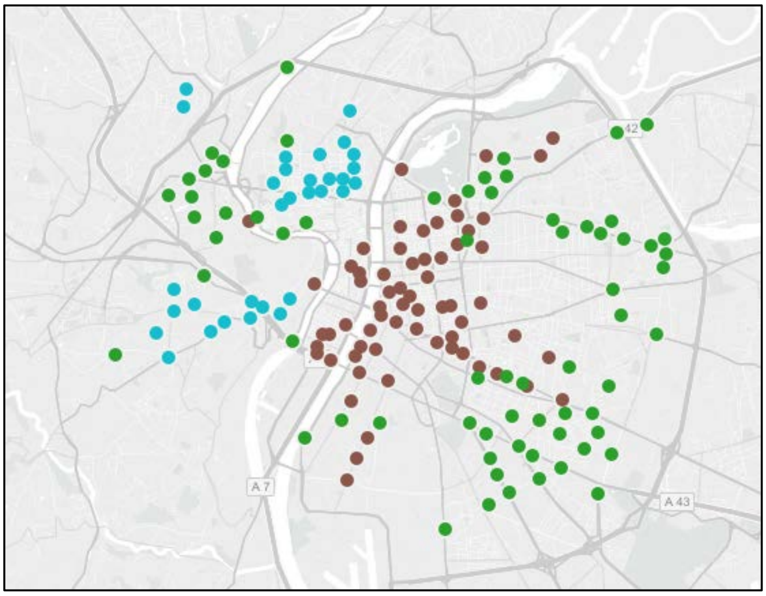


Fig 6. The cluster of bike sharing stations (C5: green, C6: cyan; C7: brown)

The cluster C5 is located in the areas with a low density of population and a low density of jobs and public transit. That's why the bike sharing stations in this group (Fig. 1) are well balanced but the daily flows of the station are not very important.

The cluster C3 (*orange*) is located in the areas with a low density of population and a medium density of jobs and public transit. The operation of the bike sharing stations in this cluster is dominated by the influence of jobs and public transit. People use bike sharing to go to the stations to work in the morning; in the afternoon, they take bike sharing from these stations to come home. That's why we can see that the inbound flows are more important than the outbound flows in the morning and the inbound flows are less important than the outbound flows in the afternoon.

4.4 Limits

In this paper, we use the method of clustering k-means in order to find the clusters of bike sharing stations. This method is non-deterministic. In terms of analyzing the built environment around bike sharing stations, we have used the average variables for each cluster of bike sharing stations. This can hide the difference of built environment between bike sharing stations' built environment. The number of explicative variables that we used is limited. We hope that the explicative variables we used are all the important variables for the bike sharing usage.

4.5 Propositions

The method utilized for analysing bike sharing station

The bike sharing system of Lyon is a stable and successful BSS not only in France but also in the world. The typology of bike sharing stations and the method using to determine the typology of bike sharing stations can be useful for other bike sharing system in order to understand the usage of bike sharing. The method k-means is good method for clustering the bike sharing stations in order to have a good strategy of rebalancing the BSS station. The method of clustering can be useful for analyzing not only the big data of bike sharing but also for other types of big data.

The built-environment and the position of bike sharing stations

The built-environment analysis give us an explanation for the clustering of bike sharing station, we can understand the influence of built-environment factors on bike sharing usage. This can help us to choose a good position for a new BSS station or for building a new BSS.

The important socio-economic variables that we have cited is *population* and *employment & public transport* for positioning the bike sharing stations and also for understanding the bike sharing station functionality. We can see that the stations in the group with a mixed of socio-economic variable will have a higher flow comparing to the stations in other group.

Strategy for rebalancing bike sharing stations

For bike sharing operator, it is important to determine the stations having a high risk of saturation (full or empty). The saturation of bike sharing station depends not only on the station's position but also on the moment in the day and on the day of week. The typology of bike sharing station allows creating a time of day demand profiles for each bike sharing station on which bike sharing operator can base in order to apply a suitable strategy of rebalancing.

For example:

- During the morning peak period (from 7 AM to 9 AM), the bike sharing stations in the group C2 and C3 are risky to be full while the stations in the group C1 and C4 are risky to be empty during the morning peak period
- During the afternoon peak (from 5 PM to 8 PM), the bike sharing stations in the group C2 and C3 become risky to be empty while the stations in the group C1 and C4 are risky to be full
- The stations in the group C6, situated in the hilly zones of the city, need to be supplied during all day

5. Conclusion

This study aims to determine a typology of bike sharing stations using the bike sharing trips data. After determining the typology of bike sharing stations, we try to explain the bike sharing usage at station level by the built environment around each station. The findings in this paper can be useful for policy-makers and bike sharing operator to improve the quality of bike sharing service. It can be a basic for building a model to explain and predict bike sharing demand at station level.

The results show that bike sharing seems to become a mode of transportation in the urban mobility. The main usage of bike sharing is for commuting purposes. In this paper, we also found that built environment have influenced on the bike sharing usage at station level. The population and job seems to be very important to explain the rhythm of bike sharing usage during a weekday while during a weekend. The four elements the most important to bike sharing usage are population, job, student and topography. It seems that there are more than four explicative elements for bike sharing usage, but these four factors are the most important factors.

The bike sharing stations work better in the areas where the density of population and the number of jobs are important. The relation between number of population and number of jobs is very important to the distribution of bike sharing flows during a day. The bike sharing stations located in the areas with high density of population and jobs are more balanced than the others bike sharing stations. In the areas where the built environment is principally represented by a high density of population or a high density of jobs, the bike sharing stations are exposed to a saturation of bike: the station can be empty in the morning and full in the afternoon or inversely.

In conclusion, the approach used in this study can be useful for analyzing the relation between bikesharing and the built environment in order to build a model predicting bike sharing demand at station level. The results of this research can be useful both for improving the quality of an existent bike sharing system and for better positioning and dimensioning a new bike sharing system. The approach used in this study can be applicable on carsharing data in order to better understand how carsharing stations work.

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