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Technical Section

A visual tool for the analysis of usage trends of small and medium bicycle sharing systems[☆]

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ABSTRACT

The last two decades have exhibited a profound transformation of traditional urban mobility patterns partly due to the exponential growth in both number and popularity of public bicycle sharing systems (BSS). Analysis and visualization of the data generated by BSSs have become of special interest to municipalities to evaluate the effect of their mobility programs and offer integrated urban mobility solutions. In this paper, we present a visualization system that aims to assist city officials from small and medium cities in their decision-making process with an intuitive representation of BSS' data. It has been developed, tested, and evaluated together with officials and domain experts from the city of Logroño (Spain). Our tool presents usage information with different time granularities (yearly, monthly, weekly, or seasonally), shows traffic flows between stations, and provides an in-depth breakdown of users' data such as their registered address, traveled distance, or gender-based patterns.

1. Introduction

According to Meddin [1], there are currently more than 1700 public bicycle sharing systems (BSS) of different types (public, private, dockless ...) around the world. Of those, more than 1000 have less than 700 bicycles, which a dimension suitable for medium and small cities (e.g., Murcia, with a population of 450K citizens, has 600 bicycles and 53 docking stations). Public BSSs are commonly created by a political entity (e.g., city governance) and commissioned to a private company, which is responsible for setting it up and for its management. This includes bike refurbishing, moving bicycles from one docking station to another, and ensuring that docks and bikes are working properly. Usually, its deployment includes the development of a web page and sometimes also an application to help customers handle the system. Frequently, such applications provide information on the stations' locations, their capacity levels, and free docks. Other applications may provide extra details such as distances between stations, planning routes, etc. Local governments need to supervise and monitor the deployed system. To this end, contractors give them information on the usage. Unfortunately, the information is usually highly aggregated. Thus, it is difficult to extract detailed information that helps them to perform concrete actions. Since maintenance contracts are not linked to performance metrics (according to the political officials we have talked to), contractors have little to no incentives to provide such detailed information. Therefore, although usage information can be obtained by local governments, it is either in the form of such highly aggregated reports or in the form of raw data (i.e., individual trips, that can be obtained on demand, as CSV files or SQL databases), which cannot be analyzed easily. Our collaborators in the Logroño City Hall, (from now on called *users*) wanted to get a detailed understanding of the service level of all stations along the year, to analyze their utilization, as well as other data such as the traveled distance, usage by gender, or most used stations. In this scenario, we created a visual exploration application (see Fig. 1) that facilitates getting insights on high-level questions such as how a certain station is used along a month, a week, or the whole year, the relationship between station's usage, and where the citizens registered in the system (henceforth called *customers*) live, or what is the difference of use (e.g., traveled distance) within genders.

The contributions of our paper are twofold:

- A web-based exploratory analysis tool for detailed usage analysis of Logroño's BSS, BiciLog, that includes trip information, use by gender, etc.
- A configurable "report mode" that enables the generation of data-based detailed reports based on the users' selections.

The application has been evaluated by domain experts from Logroño's government (called *users*) through an informal user

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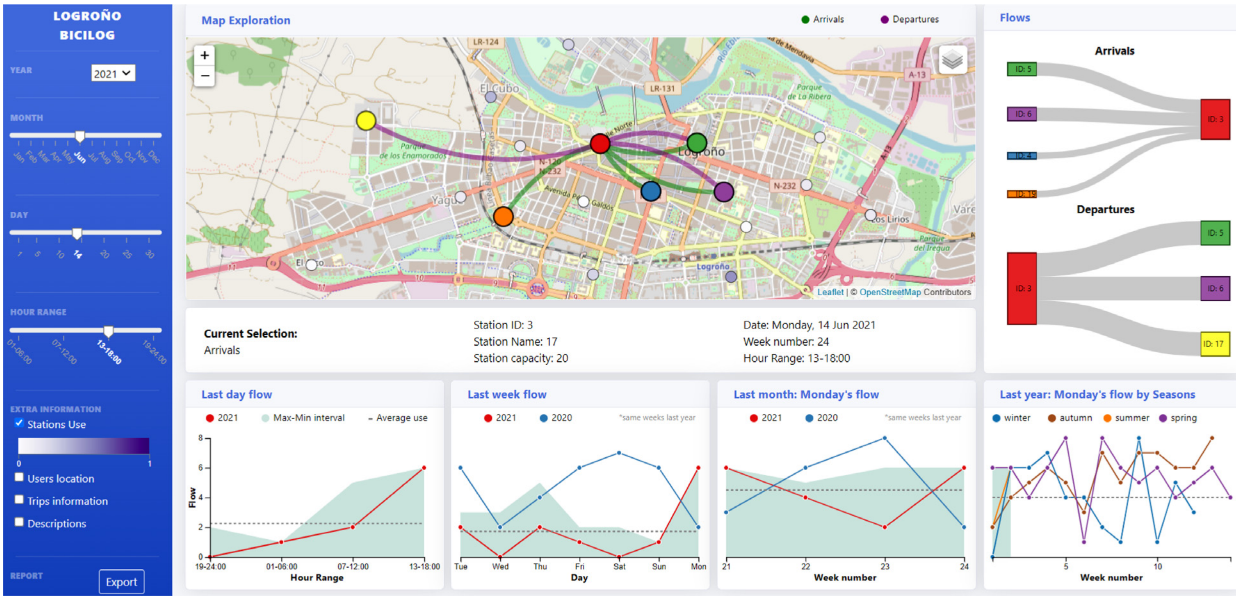

Fig. 1. Overview of our BSS analysis system when one station is selected. The application has multiple views: on the center the *Map View* shows the locations of the docking stations and usage flows directly over the map when a station is selected (highlighted in red color). On the left, the *Control Panel* lets the user define different parameters. This information is updated interactively in the *Details View*, just below the map. Flows (both arrivals and departures) are shown on the right in the *Flows View*. The usage details are provided on the bottom, in the *Analysis View*.

study, with high acceptance. As a result, the city officials are considering its installation in their computers as a governance tool. They are also interested in an extension that can handle real-time data.

The rest of the paper is organized as follows: Section 2 describes related work, Section 3 specifies the main needs of our collaborators in Logroño City Hall. Implementation details, an overview of our tool and its features are provided in Section 4. Section 5 shows several application scenarios. In Section 6 we describe the evaluation process. Section 7 contains a discussion about limitations of our tool. Finally, we conclude our paper with a discussion of the achieved goals, as well as pointing some lines for future research in Section 8.

2. Previous work

Bike Sharing Systems have become an important and dynamic research area in the latest years. Many cities across the world are adopting public and private BSS due to their associated benefits, such as pollution reduction, improvement of citizens' health, new means of transportation, etc. [2]. However, BSS adoption has also several challenges especially related to civic behavior (e.g., vandalism), the special characteristics of a city (e.g., elevation) [3], or how to achieve access equity [2]. From different previous contributions, two areas are relevant to our work: the BSS usage analysis, and visualization systems for BSSs.

2.1. Usage analysis

The analysis of how the BSS systems are being used has been addressed in different ways. For example, analyzing the trips, focusing on the redistribution of bikes through the network, trying to model the users' behavior, etc.

Many authors have studied bike traffic patterns [4,5] and how bicycle flows and destination preferences are impacted by urban configuration [6]. For instance, Kim et al. [7] analyze how the elevation of stations may affect the trips. Frade and Ribeiro [8] also consider the elevation of the neighborhoods in Coimbra to propose a demand model. Others analyze the characteristics of trips [9], and how pickups and drop-off trends could be affected by important events [4]. The effect of weather [10,11] and calendar events [12] have also been investigated. These studies mainly aim to identify potential factors which influence bike sharing flows (demographic, meteorological, population, etc.), but we are interested in being able to query the usage data to analyze system characteristics and utilization patterns of individual stations.

Taking advantage of the massive data generated by large BSSs, several studies focus on rebalancing operations, to generate efficient vehicle routes [13,14] or different possibilities of smart traffic control [15]. Likewise, some authors try to model and predict the pickup and drop-off events using different machine learning models, such as spatial generalized ordered response [16], regression [17], Graph Convolutional Neural Network [18], Gradient Boosting Regression Tree [19], or Multiple Additive Regression Trees [20], among others. Some investigations compare the results between different algorithms and select the more efficient one [21,22]. These studies usually explain their findings using tables and static charts, but their focus is not the development of an interactive visual tool. Moreover, they use highly complex mathematical tools to explain, predict and optimize BSS utilization at an aggregated level. These are useful for large systems, but in medium and small systems, these massive amounts of data are not available, and rebalancing operations are much less needed. Therefore, their utility to solve problems like the ones depicted here is arguable. In our case, political officials have an interest in being able to drill down the data and gather more profound insights about it. Towards this goal, we have created different metrics to analyze the information, and we developed a visualization tool to help users to gain understanding of the utilization of BSSs.

2.2. Visualization tools

In visualization, numerous tools have been presented to perform exploratory analysis of BSS data. The information commonly available in most of these systems consists of an availability state similar to the one already provided in official visualization systems [1,23]. Unfortunately, those do not typically save historical data. Therefore, temporal comparisons are not possible, such as comparing the current week usage to a previous one. As a result, limited information can be extracted unless a monitoring tool is built on top of them. Other systems study usage behavior patterns. For example, Froehlich et al. [24] produce a set of static views with Barcelona's BSS data. However, these cannot be easily compared to each other. Moreover, no detailed information about the trips is available. Talavera-Garcia et al. also produce a set of static views using data of the Madrid BSS system [5]. The static views contain aggregated information. Though the data is partitioned between working days and weekends, and frequent and occasional users, the level of aggregation makes it difficult to extract actionable information at an individual docking station grade. Dai et al. [25] fuse bicycle and taxi information to obtain patterns of usage. Again, the result is a set of charts with highly aggregated information. These charts are not useful for our problems, where officials need to make sense of the individual features of the desired individual docking stations. More similar to our data source is the one used by Wood et al. [26], where they focus on a visual design study model involving producers and consumers of the data when analyzing transportation systems. They also present data with gender and individual trips. Nevertheless, they do not analyze the behavior of a BSS system as a whole, with the goal of monitoring it. Another similar approach was done by Oliveira et al. [27]. In this study, they use New York City's data to create a very sophisticated and powerful exploratory analysis tool. The application has been designed with a large BSS system in mind and includes many features, including trips. Many of their visualizations could be used up to a certain extent for our scenario, however immediate comparison of different periods with the accuracy required is difficult to achieve. Moreover, most of their views include many stations at once, which is different from the focus needed by our users, who desired a tool that facilitates the individual analysis of docking stations.

Beecham et al. study the commuting behaviors of users by analyzing the journey data to gain insights on the people using those services, and the geography of commuters' workplaces [28]. Opperman et al. [23] scale this up, to focus on the visual analysis of multiple bicycle sharing systems. They provide an interactive visualization tool, but information can only be grouped by fill levels (ranging from empty to full). When going down to a single system, they also provide very interesting tools, such as a route planner. Similarly, O'Brien et al. analyze data from 38 bicycle sharing systems from different parts of the world [29]. However, they only analyzed the data on an aggregated level. Therefore, insights on a single system, to the detail required by managers or policymakers, cannot be extracted from their system. The previous system has evolved to the *Meddin Bike-sharing World Map* [1] that tracks the status of 174 systems around the world. It shows the numbers of available bikes for several previous years, but no visual exploration of the docking stations is available. Finally, Cortez and Vázquez created a visual tool for the analysis of Barcelona's BSS [30]. The system facilitates analyzing clusters of docking stations with similar behavior along the day. They also included information and filters based on the station's height, a relevant variable in the case of Barcelona. However, like in many of the previous cases, the system has been designed to analyze groups of stations all at once. And, even when some drill-down is possible, making sense of the behavior of a single station, or comparing its activity with other periods, is difficult.

When the number of stations is big (in the hundreds) it makes sense to create clusters and analyze them collectively. This is the case of Froehlich et al. [24], who cluster the stations based on a measure called *activity score*, which evaluates how the number of bicycles in a station changes in a time interval. Shi et al. cluster the stations based on similar behavior of trips [31]. Noussan et al. also show information on bike sharing, but they only group per day of the week or month [32]. Cortez and Vázquez [30] also cluster the stations. In this case, based on station availability levels' behavior. We did not perform a cluster analysis as we are focusing on a more concrete and limited scenario. In this case, users want to be able to analyze the behavior of a single docking station along the time. Thus, data-based decisions can be taken on an individual basis.

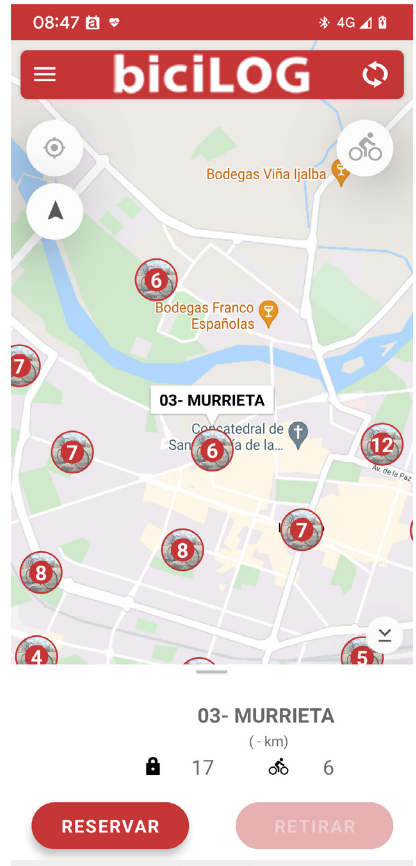

Fig. 2. Aspect of the mobile version of BiciLog system that customers use to rent a bike. The available slots and bikes are visible when clicking on a station.

3. Analysis of requirements

During our investigation, we analyzed several public bicycle sharing web services to understand their offered services and limitations. Moreover, we had several conversations with people with responsibilities for monitoring and managing the BSS in Girona (Girocleta) and Logroño (BiciLog). In general, the applications available to the customers are highly limited, providing only information about the number of bicycles and slots in each docking station. We can see an example in Fig. 2 from the BiciLog service. Note that only the number of available bikes is visible. If the station is selected with a tap, then the number of total slots is also shown.

However, with the logged data that these services have, a larger amount of additional information could be provided. For instance, predictions or availability of closer stations [30]. To make these data more useful, there are aspects of different nature to study:

- The BSS structure.
- How the BSS is governed/monitored.

Regarding the BSS structure, several relevant variables can be considered such as the size of the system (small, medium, large), the type of user (citizen, system operator, city planner, policymakers), or the quality of data. For instance, in the case of Spain, there are around forty BSS systems. The size of them mostly varies between small to medium, with less than 60–70 docking stations. Only five Spanish BSS are larger, with more than 70 docking stations. Considering the second aspect, BSS systems are commonly operated by a third-party company, as in the case of Logroño, or by a publicly company owned by the same city, like Girona's system. In both cases, from the developed tools, only little information is extracted as basic reports. This limits the analysis and the actions to improve the system. In Logroño, policymakers typically receive highly aggregated information or get the whole system logged data in CSV files, upon inquiry. On the other hand, in Girona, the publicly owned company has all mobility services under its responsibilities and may dedicate just small amounts of time for monitoring the BSS system. Therefore, they only produce a small set of basic charts when requested by the political authorities.

After the initial analysis, we focused on Logroño's BSS, called BiciLog and on its users who are responsible for policymaking, city planning, and system operation. As mentioned before, citizens who use the BSS are named *customers*. To get more details on how users are currently using the system and what information they lack, we performed several semi-structured interviews with officials from Logroño's City Hall.

Throughout our initial meetings, we got access to the data, analyzed in depth the requirements they had and the limitations they found in their current reports, and defined what usage flows means for them:

> *Usage flows.* The total sum of arrivals or departures between each pair of stations during a certain day and time range. It is derived from the frequency of pickups and drop-offs.

We also understood how useful it could be to provide a visual system that allows users to analyze and synthesize information easily and efficiently. However,users were not involved in the design decisions of the visual system and they only evaluated the final results. This visual system could be used as a tool to make decisions about mobility policies, such as creating new stations, increasing the size of the existing ones, or complementing the bicycle sharing service with other public transportation means. In particular, the system should help users to gain insights in the following aspects:

R1: Daily docking station usage by hour.

R2: Yearly comparison of usage flows by time period (months, weather seasons).

R3: Relationship between customers' addresses and docking stations.

R4: Usage flows employing customers' information.

Some of those requirements are oriented to analyze and compare flows during different periods. For example, users would like to check which stations are frequently used every day in the same time intervals and if this pattern is constant or changes based on factors such as holidays, weekends, and others **[R1]**. Similarly, they want to understand if bikes usage is increasing or decreasing, or how Covid-19 situation affected mobility by comparing usage flows in different years **[R2]**. By providing a map with all docking stations where it is possible to select the one of interest and a set of different charts (described in next section) to provide usage details, users will be able to analyze and compare flows during different periods. For instance, whether there are stations used mainly in the mornings/afternoons, and if this pattern changes during the weekends.

Additionally, Logroño City Hall officials are interested in studying customers' behavior. For instance, which gender uses more the BSS or has longer rides **[R4]**. The main reason behind that was to determine whether they considered promoting the usage among certain groups (e.g., males beyond 40). In previous literature, the gender gap (BSS systems'usage is clearly dominated by males [33]) has been analyzed to determine its environmental reasons, such as the lack of dedicated bike lanes. Therefore, visualizations that show gender differences are significant for our users. The connection between the most frequently used stations and the quantity of customers living around **[R3]** is also a key point to understand usage flow patterns. The views in our system will also allow users to inspect how citizens are using docking stations. This will enable them to understand, for example, whether the customers' behavior changes when any particular mobility policy is applied.

Through our meetings, we also detected and discussed on the fact that policymakers were lacking a method to obtain regular information on the detailed usage of the system. This way, they could elaborate reports based on the information they consider more relevant. Therefore, we considered that we could add the features that facilitate generating this information at any time. As a result, our visual tool will help users to take screenshots of the system based on their selections and share them with different stakeholders to analyze the information and make more informed decisions.

4. Exploratory analysis of usage data

4.1. Data processing and implementation

Since the information for BiciLog is not publicly available, approvals from Logroño's City Hall were needed to access and use it, respecting data protection laws (GDPR). Customers' information as well as real-time trips data, which includes information about arrivals and departures in each station, were made available from October 10th 2019 through a private website that is maintained by the ITCL (Instituto Tecnológico de Castilla *y* León). The selected period of analysis for this study is from October 10th 2019 to December 31st 2021. Logroño's BSS has a total of 20 docking stations distributed across the city. Three new stations were added to the system in the last quarter of 2021, but they are not considered since there is not enough historical information to perform a temporal analysis.

Trips' data. It is first cleaned to exclude these 3 new docking stations (about 0.11% of the total data set) and to remove information about temporal non-working stations and columns that are not used in this analysis. We have also removed garbled data such as bikes' loans that do not have an ending time frame or an end station registered (about 0.68% of the total data set). Then, usage flows were calculated for the following hour intervals:

- night: from 01:00 to 06:59
- morning: from 07:00 to 12:59
- afternoon: from 13:00 to 18:59
- evening: from 19:00 to 00:59

Additional variables necessary for the deployment of the visual interface were added, such as the day of the week, weather season (spring, summer, autumn, and winter) and the GPS position of the docking stations. Finally, two new metrics were calculated: traveled distance and usage ratio.

Traveled distance. It corresponds to the shortest path between two stations. It is an estimation of the real traveled distance as with the available information it is not possible to know the real trajectory for each single trip. For each pair of docking stations, the arc distance is calculated using the Haversine formula available in the *fossil* package in R. Traveled distance is calculated in kilometers (km).

Usage ratio. Similar to *Usage Flows* it is derived from the frequency of pickups and drop-offs. This ratio helps us to easily check which stations are more frequently used. It is the key attribute for coloring the stations using the *Stations Use* checkbox in the *Control Panel* as is described in the next section. It is calculated as follows:

$$use_{ijk} = \sum arrivals_{ijk} + \sum departures_{ijk}$$

Where i = StationID, j = day, k= hour interval

For a better interpretation, we re-scaled the ratio to make all the elements lie between 0 and 1, having a common scale:

$$UsageRatio_{ijk} = \frac{(use_{ijk} - MinUse_{jk})}{MaxUse_{jk} - MinUse_{jk}}$$

Where i = StationID, j = day, k= hour interval

This ratio will be equal to 0 if: *(i)* the usage is equal to 0, *(ii)* the usage is equal to MinUse. Similarly, the Usage Ratio will be equal to 1 if the usage is equal to MaxUse.

Customers' data. It comes from each citizen's profile. The gender, age, and contact details (address, phone number, etc.) is part of the information customers provide when registering in the system. Personal data is not considered for this work as it is not under the scope of GDPR. Customers' data has a structured format and, similar to trips' data, it also needs to be processed. Maintenance customers (about 0.5%) and others that miss key information such as the date of birth, gender, or address (about 4.41%) were removed. Those customers whose registered address is located in another region or country were not considered because we are interested in the analysis of long-term regular customers rather than those clients who only used the system for a short stay in the city. This last removal represents approximately the 16.6% of the customers' data. Finally, their equivalent geolocation information (latitude and longitude) was obtained using OpenStreetMap library.

Customers and trips' data were merged to calculate aggregated information by age group or gender and show results that help to explain customers behavior and docking stations' activity.

All the initial data processing, cleaning, and preparation procedures were performed in R. Data management was implemented in Python. Flask has been used to manage HTTP calls and render templates. The visual interface was built in D3 *(d3js.org)* using Leaflet *(leafletjs.com)* to deploy the maps.

4.2. Overview

Our application follows Schneiderman's visualization mantra: Overview, zoom and filter, details on demand. Our **Overview** of the transportation system consists of an interactive map with all BiciLog docking stations. By default, the system shows the average use of all stations for the current selected day. Upon station selection, the trips starting and ending on the selected station are shown on the right, together with the usage data (bottom), as shown in Fig. 1. On the left, we have the Control Panel that lets the user perform diverse queries to get details on demand. The remainder views provide information interactively. **Details** are provided in two flavors: the analysis view (on the bottom) and the flow view (on the right). Additional information such as plots' descriptions or information by customers can be displayed using the Control Panel. The contents of each view are described next.

Map view. It shows a map of Logroño city, with the docking stations on it. Interactive exploration lets users pan and zoom, as well as select stations, or hover, as described below. Besides the location of the stations, it also shows the usage flows of each station and the reported addresses of the customers through interaction.

Control panel. It is placed on the left and provides filter operations. It offers a wide range of configuration modes that enable fine-grain selection, so detailed insights can be obtained interactively. For instance, it is possible to select different periods (year, month, day, and hour intervals) or display the color of the stations based on their usage ratio.

Details view. Below the map (Fig. 3-bottom), we have another interactive view that provides information on the parameters and the selected docking station. This is useful to reduce the distance the eyes need to move when exploring the map to check the configuration (e.g., which month, day, hour interval or docking station has been defined), as well as for the *reporting mode* (arrivals or departures). This way, all the important data is shown through the application.

Flow view. This view is on the right of the map (Fig. 4), and it is populated with the flows reaching and leaving the station of interest, which was previously selected on the map. It is designed as two juxtaposed Sankey charts with arrivals (top), and departures (bottom) that depict the stations of origin and destination (labeled inside the colored rectangle), together with the values of these flows (showed when hovering). The color coding of the stations is the same as the one used in the map to facilitate reading.

Analysis view. It is composed of four different charts (see Fig. 8) placed on the bottom. They depict the traffic (arrivals or departures) of a docking station at different granularities using line charts. These charts are overlaid with different reference values, such as: *(i)* previous year traffic, *(ii)* usage average for the selected station, *(iii)* max–min usage of all stations in the selected period. From left to right, the description of the charts is presented as follows:

- Last day flow: it contains the usage information for the selected station in the last 24 h by hour intervals.
- Last week flow: it shows the traffic in the last 7 days, for the selected station and hour interval, and for the same week number in the previous year.
- Last month flow: it depicts the information about the last month's usage for the selected station, hour interval and day of the week (Monday to Sunday) and for the same weeks' number in the previous year.
- Last year flow: it displays the information about the last year's flow by weather seasons.

These charts are designed to satisfy requirements **R1** and **R2**. Throughout the charts, we used an area chart to encode maximum and minimum usage flows for the selected period to facilitate usage comparison between the selected station and the others. It is shown with less opacity, so it can be easily perceived, but does not interfere with the line charts. Values for the selected year are depicted in red while blue lines represent last year values. The usage average for the selected station is represented with a dashed line. Only the last chart has a different line color-code which represents the weather seasons. This way users can easily compare how a station's use is changing between years or seasons, and compare it with other stations.

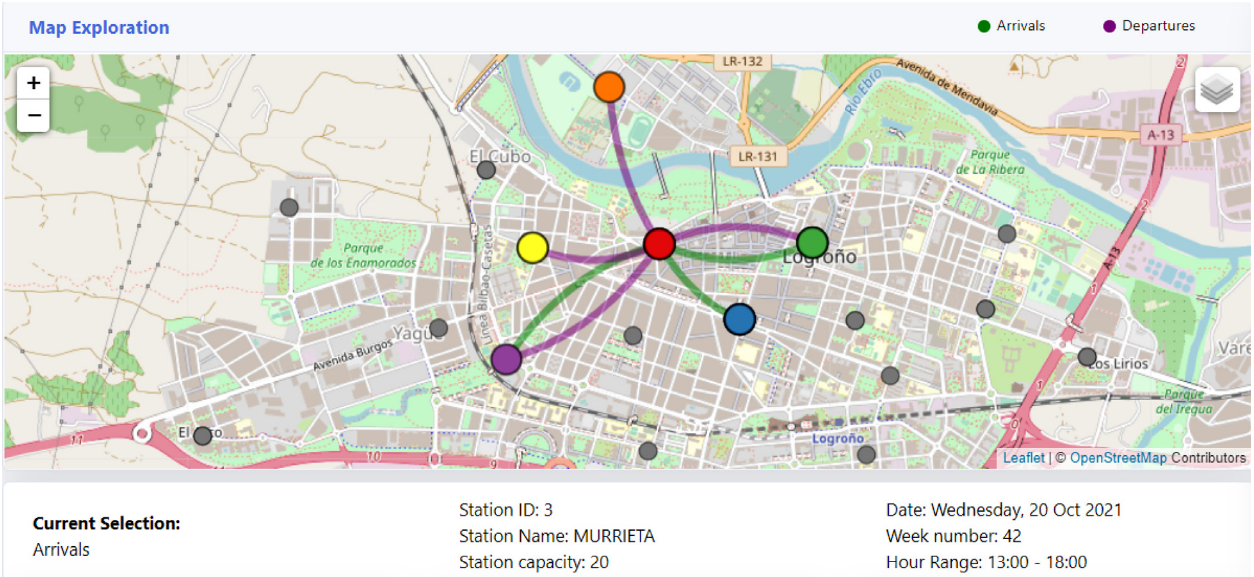

Fig. 3. Map and information of the station and the parameters that have been selected. The chosen station always appears in red and shows from which stations bikes are arriving (green link) and to which stations bikes are departing (purple link). Same color code for the stations is used in the Sankey chart to facilitate reading.

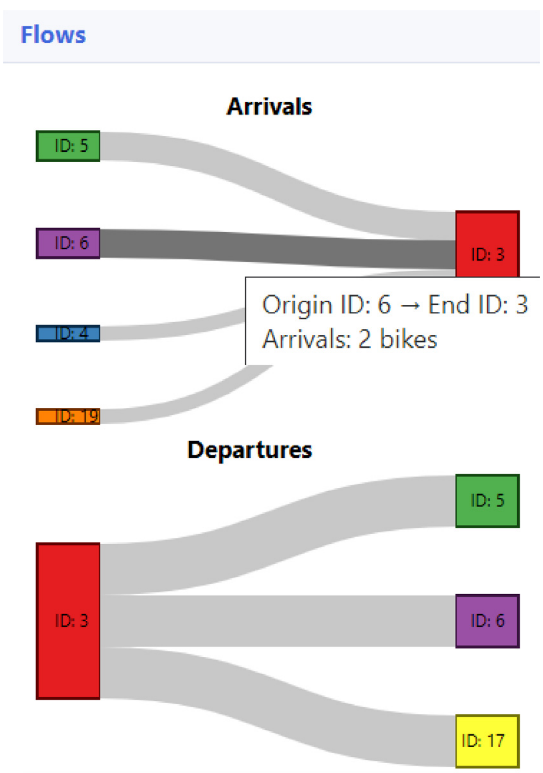

Fig. 4. Flows chart: It is designed as a pair of Sankey charts. The top view shows the arrivals to the station of interest, while the bottom one shows the departures. The positions of the stations can be modified by dragging. Besides, the size of flows is shown with the relative width of the connection, but also by hovering over the flow.

Extended analysis view. Besides regular station usage, users are also interested in the demographics of the customers (ages, distances covered...). When the button *Trips information*, in the *Control Panel* is toggled on, a new array of charts appears (see Fig. 7). These charts show information regarding the

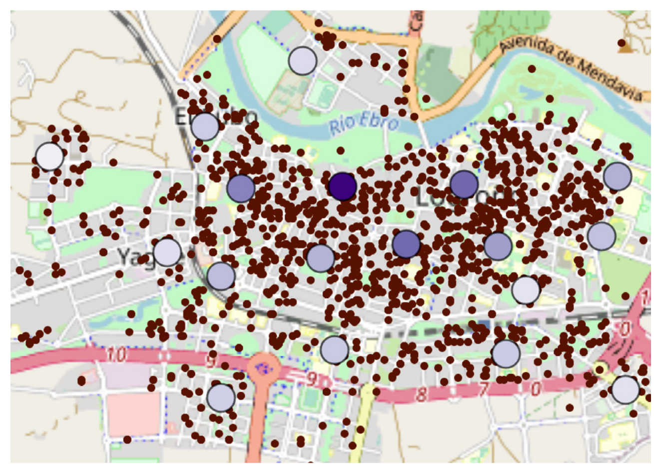

Fig. 5. Station Usage: This view shows the information regarding the addresses of the anonymized registered citizens of the system. Besides, we also color code the usage of the stations: the darker their color, the higher their usage. This way, officials can get a sense of whether the registration of customers is somewhat correlated with the fact that a docking station is near their homes.

demographics of the customers: age ranges and traveled distances by gender as a pyramid chart (the most common chart to compare population distributions). The most frequently used stations and their daily use was designed as a paired bar chart. We chose this design to facilitate comparison, because paired bar charts make use of the most effective encoding: position on a common scale [34]. In this case, the categories shown are most used stations (third chart) and time ranges defined in our application (last chart). Fig. 6 shows the *Extended analysis view*. Each chart is described as follows:

- Users by age: it shows the distribution of customers by age group and gender.
- Traveled distance: it displays the information about the average traveled distance by age group and gender.

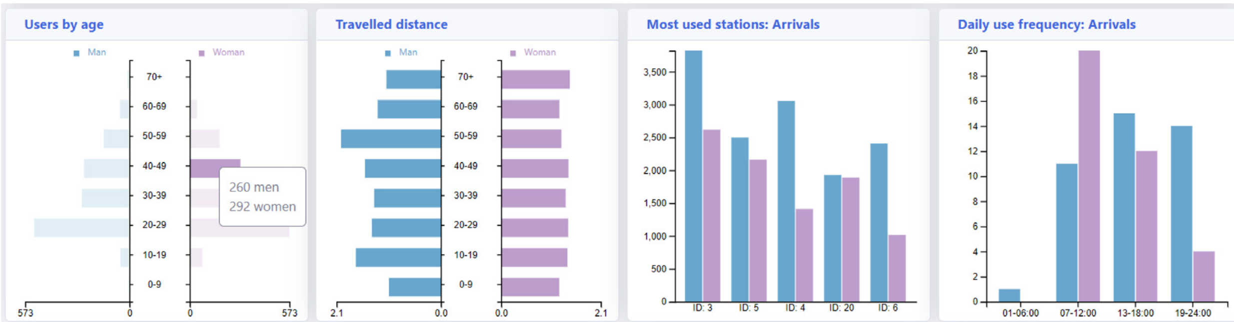

Fig. 6. Customers' information: these charts facilitate information on the demographics of system's customers, as well as information per gender. On the left, we can see an age pyramid. The second left chart lets us know the traveled distances (km) per age range. We can see a spike in usage among men 50–59 years old. The third chart provides information on the most used stations. We can see that certain stations are more used by men (3, 4, and 6) than women. Finally, the rightmost chart shows men usually use more of the BSS in any time frame.

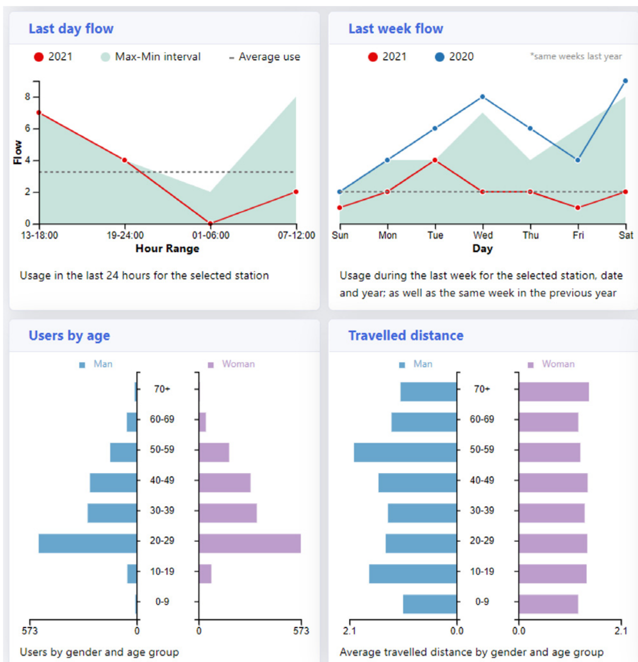

Fig. 7. Information of the selected docking station usage and the trips in report mode, with verbose descriptions.

- Most used stations: it represents the gender distribution of the traffic (arrivals or departures) for the most used docking stations in the system.
- Daily use frequency: It shows the average usage by hour interval and gender.

Report mode. Finally, we also included an *Export button* in the *Control Panel* to facilitate the generation of reports that can be shared among officials and managers. By default, this includes all charts in the regular layout that can be easily exported to PDF or printed. Moreover, if the *Descriptions* button, in the *Control Panel* is activated, it adds verbose descriptions of the charts to facilitate document understanding (see Fig. 7). This is a very valuable component since one of the complaints they have is the lack of detailed information obtained from the company managing their BSS. The fact that this mode can also be configured through the *Control Panel* facilitates obtaining, not only monthly or yearly data, but also hourly reports if necessary. The rationale behind this design was to provide a flexible feature that does not anchor the design of the exporting module to a certain report design.

By providing the charts description on the charts themselves, besides printing the whole UI to PDF, users can also choose to export a single view, or big portions of the interface with simple screenshot tools such as the ones directly incorporated by browsers such as Firefox. In this case, for example, the screenshot tool automatically adapts to the individual views (or groups of views) contained in the page, thus facilitating extracting each component with ease.

4.3. Interaction

Our application satisfies the above-mentioned requirements through a combination of in-situ direct manipulations on the map, and a set of linked interactions among the views. Here, we describe the different techniques that we have implemented:

Map interactions. Besides the common drag and zoom, we also provide other mouse-triggered actions. Hovering not only highlights the station under the mouse, by increasing its size, but also shows its ID and name. Moreover, for the selected time frame, the usage flow of the selected station is emphasized. Therefore, we can see, directly over the map, to which docking stations customers are departing as well as from which stations they are arriving. Clicking on any station will highlight it (coloring it in red). It will also generate or update the analysis, details, and flow views. In addition, an in-situ filter box will appear to allow users to select the type of flow they are interested to see (arrivals or departures). When the *Users location* checkbox is selected, the map will also display the locations of the customers by adding a layer (see Fig. 5). This view solves requirement **R3**.

Filtering parameters. The control panel on the left lets the user change several parameters: year, month, day, and hour interval. The map also has different layers that can be activated through the panel:

- Station's Use: to color the docking stations according to their usage ratio (see Fig. 5). It also displays a legend that helps users to easily identify which stations are more concurred.
- Users' locations: shows the distribution of customers in the city (see Fig. 5).
- Trips information: displays the customers' information (distribution by age, gender, traveled distance, among others)(see Fig. 6).
- Descriptions: important to generate reports, as it shows verbose descriptions of every plot in the dashboard (see Fig. 7).

All interactions in the control panel are propagated immediately to the other views. This includes the central text box (*Details*

View), which facilitates, not only understanding the current status of the exploratory analysis, but also providing the needed information for exporting the whole set of views (with the *Export Button*), or a subset, as already mentioned. This fulfills our self-imposed requirement of facilitating the report generation.

Details view. The box below the map (see Fig. 3) is also linked to the other views. Thus, its contents, based on the Control Panel parameters, or the docking station selected in the map, is dynamically changed upon user input.

Flow view. This view is also dynamic. Besides loading upon docking station selection on the map, we also provide hovering to get the details of the flow, i.e., how many bikes arrived or departed from each station in the flow. Finally, users may drag the nodes to different positions if necessary. This information can be displayed for different moments using the *Control Panel* and the *Filtering parameters* fulfilling requirement **R1**.

Analysis view. The bottom view shows the usage details of the selected docking station. It displays information on different time ranges (seasons, weeks) and in comparison with previous year data, solving requirement **R2**. The four charts in this view update dynamically with the selected parameters, and each of them provides the exact details of the data upon mouse hovering. When no station is selected, the charts show an overview of all stations' average use for the selected period.

Extended analysis view. The extended mode provides information about customers and the trips they made. Trip information includes details such as distance traveled or more popular stations. Customers' information includes age ranges and gender, fulfilling requirement **R4**. To choose a design that was easy to compare and familiar to the users, we used age pyramid charts and paired bar charts. The exact numbers of both genders appear on hover, to further make sure that the details are properly read. As with previous views, they also change dynamically when filtering or selecting different options in the *Control Panel*.

5. Application scenarios

Several relevant use cases can be explored using our tool. We select three of them to explain the advantages of our web application, and show how the exploratory analysis can also help us find new insights on the data beyond the initial requirements.

5.1. Use case 1: Comparing seasons

Our visual tool allows users to easily identify usage patterns between different time slots. Using the analysis view, it is possible to analyze the use of bicycles for a particular docking station, identify if the usage has increased or decreased between different periods or if the trend is similar. For instance, if users suspect that one station will temporally need more bikes or docking points during a certain season due to its high demand, they can use the last year's seasons flow to check their hypothesis. In fact, by exploring the behavior of the most used stations, it is possible to identify that their use increase during the spring and autumn seasons (See Fig. 8 -right). This could be explained by the favorable weather conditions.

5.2. Use case 2: frequently used stations

In this case, users want to know where a new docking station should be added or if any of the existing ones should increase their capacity. To check this, they can go to the *Control Panel* and select the *Stations Use* and *Users location* check-boxes. The *Stations Use* check-box will color the stations on the map according to their use, so the stations with more demand will be highlighted and easily identified. The *Users location* check-box will show on the map where the addresses registered by the customers (usually home or job addresses) are. We can see (Fig. 5) that stations with more frequency of pickups or drop-offs are located in the city center, as well as most of the registered customers addresses. Our users could consider increasing the capacity of the most used stations or adding new ones in certain key zones of the city. For instance, close to the train station.

5.3. Use case 3: Gender differences

It is well known that BSS systems exhibit gender gaps in their usage [33,35]. And these differences can be attributed to different factors, such as the perceived safety, the presence of bike lanes [35], or the availability of more docking stations [33]. Thus, the investigation of gender and age usage is important to our collaborators. BSS managers can use this information to create specific campaigns to motivate the bike's use between those groups that have minimal levels of usage. To accomplish this, they can select the *Trips information* checkbox in the Control Panel to show customers' information. They can analyze how many current customers are registered in the system by age and gender, as well as their average traveled distance. Fig. 6 shows that men usually travel longer distances with the bike than women, except in the age group 70+. They can also investigate why some stations are more frequently used by men than women. Or during which time intervals the usage of women and men are similar (6-right). Usage gaps in stations may be related to traffic safety issues. The most commonly used stations chart shown in Fig. 6, can be a starting point for investigation. We can see that stations where bigger usage gaps appear between genders, are placed in the center of the city. This is what also happens in other places such as New York [35]. Even when we cannot make comparisons between them due to the considerable differences in size of both cities and BSS systems, this could be a starting point for further analysis.

5.4. Other findings

By using the tool for exploratory analysis, other interesting insights can be gained from the data. For example, users can use the tool to confirm the hypothesis that BSS usage increased after the Covid-19 restrictions were lifted. This is shown in Fig. 8, where we can see that use patterns are similar between 2021 and 2020. However, 2021 usage is remarkably high. Considering that during 2021 hard restrictions were lifted and citizens are looking for alternative means of transportation to avoid crowds, this usage behavior was expected.

In addition to this, exploring data by seasons also helped us to discover there is a curious usage pattern in summer. During weekdays at evening, the number of used bikes is higher than usual. On the other hand, during weekends in the same hour interval, usage patterns follow the usual trend. This tendency is only visible at evenings, but it does not happen in the summer mornings/afternoons. Users can explore this pattern by selecting a summer month and analyzing the season chart over different days. This behavior is illustrated, for a couple of different days (Thursday and Sunday), in Fig. 9. We can clearly see that the summer trend (orange) indicates a larger usage around afternoons on Thursday. This trend is very similar for all weekdays, while weekends' behavior is more in line with the rest of the seasons.

It is also possible to get insights from the communication between stations. For example, users may wonder what the different usage trends along the week are, and they will discover that on weekends there is less traffic than on weekdays. This

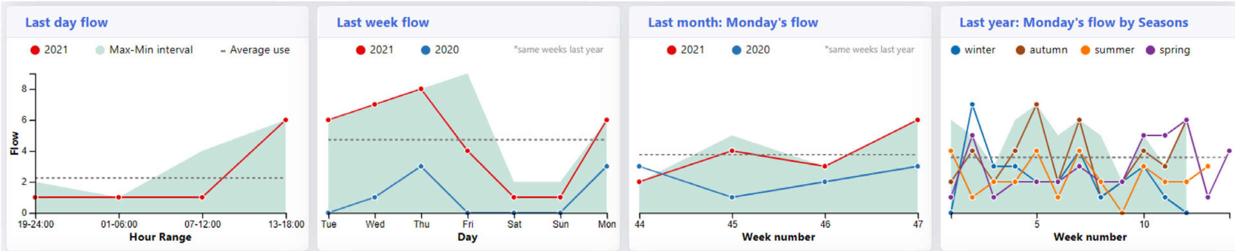

Fig. 8. Analysis View: these charts show the information in different time frames. From left to right: *(i)* last 24 h by time range. *(ii)* last 7 days in the selected hour interval, in comparison to the same week in the previous year *(iii)* last month flow, for the selected hour interval, in comparison to the same weeks in the previous year *(iv)* last year flow by weather seasons.

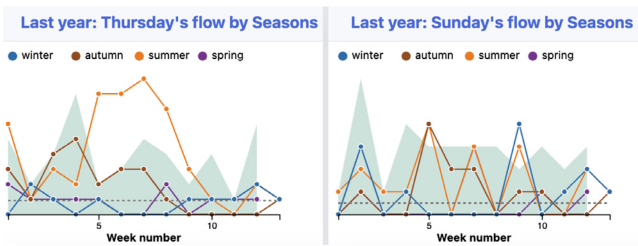

Fig. 9. In summer (orange), there is a higher usage of bicycles during the afternoon, but mainly in weekdays (left). On weekends (right), the behavior tends to be more similar throughout the year.

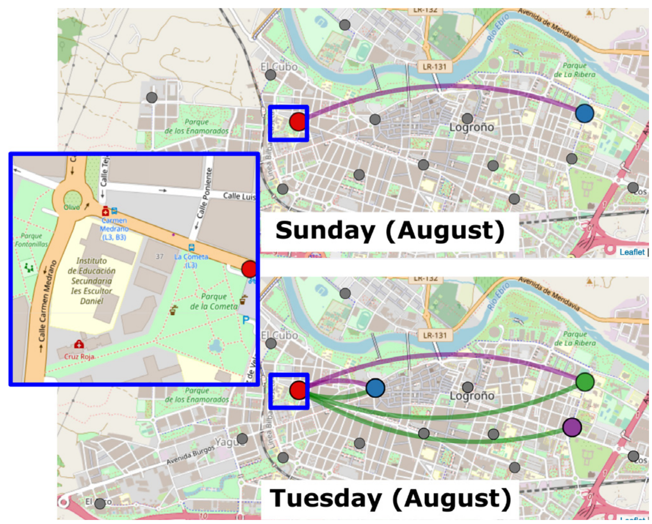

Fig. 10. The top view displays an example of usage in the afternoon (range 12pm-18am) in a Sunday, while the bottom image shows it on a Tuesday. Note how in the weekend, bicycles are used less. This pattern repeats the whole year. Zooming in on the map (inset on the left) can help us understand if there are any facilities that may influence this behavior.

might seem surprising because one would assume that customers would have more spare time on the weekends and thus have more opportunities for using the system for leisure. To analyze this pattern, users can simply select the station of interest and explore different dates. This usage pattern is visible in Fig. 10 for a Tuesday (bottom) and Sunday (top). Both weekend and weekday, belong to the month of August, but this pattern repeats throughout the year. This may make us infer that bikes are mostly used for displacements to work or errands during the week, and they are less needed during the weekends. And we can also zoom in the map to see whether any environmental element may be influential. For example, we see in yellow a high school and many parks in green. These could also be the focus of leisure activities during the summer weekdays that might be fostering the bicycle usage. This pattern is also spotted using the *Day View*. For example, in Fig. 8, we can see that, for the selected station, the lines drastically drop on Saturday and Sunday for both years.

Other discoveries can be used for further exploration. The case already mentioned in Fig. 6 is pretty interesting. Exploring the *Users by age* chart, we can see only small differences in the number of customers by gender and age. If we turn to the *Traveled distance* chart, there is a general pattern: men do travel larger distances than women. However, for the 50–59 age group, this difference becomes huge. Other two noticeable outcomes are also present, in both extreme ranges, women travel larger distances than men. We do not have yet any explanation of why this happens, but it might be worth for further investigation.

Users can also compare the overall usage of all stations during a certain period by employing the usage layer. For instance, on Sundays people hardly use the system, as shown in the center image of Fig. 11. In this case, the images correspond to three consecutive days (Saturday, Sunday, and Monday) of September 2021 during the same time interval. Some interesting patterns arise. For example, the purple circles indicate a zone where citizens can go shopping or to the cinema in a big mall. On the contrary, the brown circle (Los Lirios) marks a region where the largest facilities are educational (there is a school, a high school, as well as a sports center). Therefore, the usage is low in this hour interval. The blue circle corresponds to a docking station with many bars and small shops. By changing the date and the hour interval, users can get an idea of the overall usage of the stations any day.

Other insights can also be gained using the zooming feature. For example, users might hypothesize that stations that are (or are not) close to public transportation systems, may exhibit unusually high (or low) flows. The Leaflet maps will reveal land usage, facilities, parking lots, as well as public transportation points. This way, policymakers can make informed decisions on how to complement other public transportation systems.

Finally, as we found during the final evaluation with the City Hall officials, by displaying the locations of the customers' declared addresses, policymakers can get a better sense of where the customers live, and analyze if there are areas which are not properly covered. This can drive the decision of deploying new docking stations.

6. Evaluation

After the system was finished, we presented an interactive demo to two domain experts from Logroño City Hall, and we interviewed them. As it was mentioned in Section 3, users were not involved in the design decisions of the visual system. Throughout our initial interviews, we gathered their requirements, and then we decided to create a visual interface to facilitate the understanding of the data and the fulfillment of the requirements.

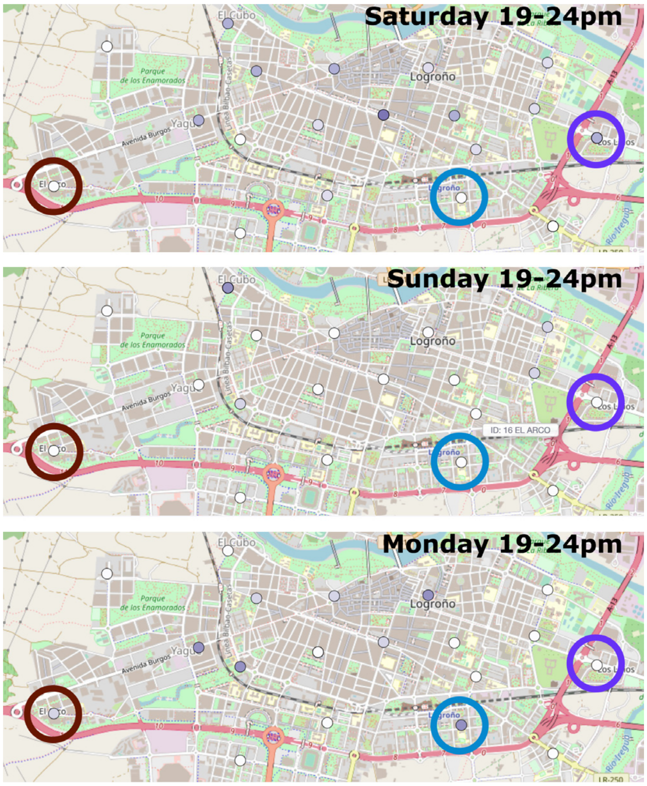

Fig. 11. These three views show the average usage for three different days: Saturday (top), Sunday (center), and Monday (bottom) at evening (range 19.00–00.59). The brown circle indicates a docking station in a neighborhood (El Arco) that is surrounded by education and sports centers. The blue circle corresponds to a docking station in a zone surrounded by bars, restaurants, and small shops. The rightmost station, named Los Lirios and marked with purple, has a set of big malls as well as cinemas. And thus its high usage on Saturday evening.

Table 1
Users' evaluation of the usefulness of different factors.

Question	Grades
Station usage along the day	7, 7
Flowcharts between stations	7, 7
Station usage by hours intervals	6, 7
Station usage along the month	6, 5
Station usage along the year	7, 6
Hour intervals to understand bike's use	7, 6
Usage average	7, 7
Max and Min usage	4, 6
Information by gender	6, 7

Later, we showed them a first version of our visual tool and collected feedback to improve it. All design decisions were made by the authors based on these interviews. The priority during the design phase was to create a tool easy to learn and operate, with a user-friendly interface which allows the effortless analysis of information.

During the last meeting, we performed an informal evaluation. It was composed of two parts: *(i)* An open dialogue where we showed the tool, presented a demo of how to use it and some of the use cases we found. Any doubt about the tool was also covered. *(ii)* A questionnaire where we focused on their opinion about the importance of potential features of the system. The questionnaire consisted of a series of questions evaluated using a 1–7 Likert scale, where 1 means strongly disagree and 7 means strongly agree.

Table 1 contains the results of the questionnaire. The interviewed users agreed on the strong usefulness of being able to see usage patterns along different time frames, such as hour intervals, days, months, or weather seasons across the year. The views with this information help them to understand customers' behavior and the relationship between the station's usage flows. Regarding the average, maximum, and minimum usage, they think these can help them to understand the behavior of the selected station in comparison to the others. However, they believe this information could be indirectly understood from other charts in the tool. For example, using the interactive map, it can be checked the usage of all stations activating the *Station's Use* button in the *Control Panel*. About the customers' information by age group and gender, they found that it could help them to create campaigns and policies to motivate certain groups to increase their interest in this public BSS. Besides, they found that the information about customers' registered location displayed on the map is very useful to make decisions such as creating, increasing the size, or changing the placement of docking stations. In general, both users were enthusiastic about the application, and they believe the tool can be helpful for transportation and mobility planning. They have also provided significant feedback for future improvements.

7. Discussion

In this paper, a system intended to analyze Logroño's bicycle sharing system has been presented. The data available is specific for this system, thus, some visual aspects, such as the map, cannot be reused directly for other cities. However, we believe that most of the components of the current application are applicable to any BSS with a similar or larger number of docking stations (e.g., up to 70 or 80). For instance, in Spain with around 40 BSSs, it would be possible to adapt our tool to 35 of them. Only larger systems (Madrid, Barcelona...) would require some modifications, such as more space dedicated to the map and probably to the Sankey diagrams. But, the data analysis procedures, as well as the individual charts, could remain the same.

Complementing our visual tool with usage data of other transportation systems was another interesting option we considered. Unfortunately, neither official information about Logroño's public transportation nor private scooter companies were available. Despite our efforts, our requests to gather the data were unsuccessful. Bus stops are placed in the map but other information such as buses timetables, closed or new stops, is unavailable.

An in-situ demo and an evaluation where users interact with the tool would be highly valuable to improve the user-friendliness of our system. Unfortunately, we were unable to do this because during the development, COVID-19 measures did not allow us to do in-person meetings and most of the interviews were remote. Thus, users did not interact with the tool because it would require a local installation. Additionally, an evaluation of our visual system with a larger audience would be desirable to collect more feedback and eventually improve the tool. The sample size was limited to the people having domain-specific knowledge and time availability in the municipality. At the time of this investigation, this was limited to 2 users who represents the majority of the team of stakeholders devoted to this area in Logroño City Hall. Afterwards, we also performed another interview with an expert of Girona whose duties include surveying their BSS (Girocleta) that has a similar size. His comments were also very positive highlighting the importance of a system like ours to help him to answer queries from City Hall officials, and users observations and complaints.

We dismissed certain information during data cleaning, notably three new docking stations were added to the system in the last quarter of 2021. For the analysis of extended periods, beyond 2022, it will be interesting to add them back. Similarly, customers' data with missing information were removed. These represented less than 5% of missing data, which is an acceptable quantity according to the literature.

Additionally, 16.6% of customers were removed for the analysis as they live outside the region. We cannot confirm whether some of these customers are actually living inside the region, but have registered a different address in the Bicilog website. The focus of our investigation is to study long-term customers behavior and get insights to improve the system. Nevertheless, a more in-depth analysis of short-term customers could be beneficial to understand how they are using the system. Information about their profile (gender, age), how many days they use the system, during which seasons, how many times a day, how long are their trips and which stations are the most popular among them would help system monitors to improve the BSS towards tourists.

8. Conclusions and future work

We designed and implemented a full web-based visualization system to help domain-expert users (called users) to analyze and explore data from public BSS. Our application uses data from Logroño's BiciLog system. Compared with the available alternatives, our tool provides numerous features that help users drill down the data. For instance, they can check the station's flows in different moments of time and analyze the system usage by gender or age group. They can also check how the docking stations share bicycles between them, which ones receive more bikes during certain periods or seasons, or at what moment of the day some stations are empty while others are full.

Our system was designed as an analysis tool for planning the mid and long-term mobility development in a city. To this end, we added the *reporting mode*, which has been designed to generate BSS usage reports that can be shared with other stakeholders. But, after seeing the final version of our tool, users expressed their interest in creating an extension with the ability to gather and report data in real-time.

The tool was designed based on the knowledge acquired through several meetings with domain experts from Logroño City Hall to better understand the requirements of a relatively small system. A final interview was performed to evaluate the tool. Users gave positive feedback about it and think it could help with mobility policy planning. However, it is important to consider the lockdown period during COVID-19 pandemic has modified people's behavior for several months and some interpretations during this period can be misleading.

There are more development lines we are bearing in mind. Even when the available data to evaluate prediction is limited in time due to the effect of the 2020 lockdown, we have started to test some forecast models such as ARIMA or Random Forest to predict the usage behavior. Besides, we plan to perform a more in-depth study to evaluate other algorithms' performance. Another possibility is to analyze the relationships between this BSS and other transportation means, such as buses or private scooter companies. In the same line, the relationship between BiciLog and the number of shops (coffee, supermarkets, etc.), offices or education centers would open other possibilities to perform more advanced analysis. A study of long-term patterns would be also another possibility once enough data is collected. For example, how customers employed the system over a few months period or how new added stations are being used. Moreover, real-time reports would be possible with permanent access to the original sources and setting up a server to handle the data. A wider evaluation considering more users with different backgrounds would be needed to improve the tool and evaluate how easily it could be adapted to different BSS. Finally, thanks to its design, it is easy to adapt the current tool to any other public BSS, compare the results, assess the main similarities and differences between cities and create more features if needed. In this line, we showed the final application to the managers of the Girocleta service in Girona, and they are currently discussing internally whether to commission us a version for them.

CRediT authorship contribution statement

Alexandra Cortez-Ordoñez: Methodology, Data curation, Software, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **José Antonio Sanchez-Espigares:** Writing – review & editing, Formal analysis. **Pere-Pau Vázquez:** Conceptualization, Methodology, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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