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Expansion of Lisbon's Docked Bike-Sharing System

Spatial and Temporal Analysis of Bike-Sharing Use in Lisbon for System Expansion

Eva Frade Garcia

Project Work

presented as partial requirement for obtaining the Master's Degree in Statistics and Information Management

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Analysis and Expansion of a Docked Bike-Sharing System

Lisbon Case Study

by

Eva Frade Garcia

Project Work presented as partial requirement for obtaining the Master's degree in Statistics and Information Management, with a specialization in Risk Analysis and Management

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Eva Garcia
Almada, July 15th, 2024

ABSTRACT

The implementation and utilization of bike-sharing systems represents a sustainable alternative for city residents and visitors in the urban environment. This study uses the case of Lisbon's Docked Bike-Sharing System, GIRA, to analyse and construct a possible expansion of the system. Data was collected on daily usage patterns, trip characteristics, bike detections, GIRA dock occupancy, existing public transportation, bicycle lanes, and points of interest in the city. Geographic Information Systems were then used for spatial analysis of bike-sharing station locations. Their integration with the factors previously mentioned incorporated in a weighed Multi-Criteria Decision-Making approach, allowed the development of a suitability map for new station locations. The research then employed a Business Intelligence approach, building a dimensional model with the data gathered, and carrying out a quantitative analysis relying on data visualization in a final dashboard. The results of this research include an in-depth understanding of bike sharing in Lisbon, including usage patterns, and integration with existing transportation networks and points of interest. Through the results of the spatial analysis, 18 new stations were proposed around Lisbon for system improvement.

KEYWORDS

Business Intelligence; Geographic Information Systems; Spatial Analysis; Bike-Sharing Systems; Sustainable Mobility

SUSTAINABLE DEVELOPMENT GOALS (SDG)

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LIST OF ABBREVIATIONS AND ACRONYMS

AHP	Analytic Hierarchy Process
BSS	Bike-Sharing System
BI	Business Intelligence
BK	Business Key
CSV	Comma-Separated Values
CRISP-DM	Cross Industry Standard Process for Data Mining
DAX	Data Analysis Expressions
DBSS	Docked Bike-Sharing System
ETL	Extract, Transform and Load
GIS	Geographic Information System
GeoJSON	Geographic JavaScript Object Notation
GPS	Global Positioning System
JSON	JavaScript Object Notation
MCLP	Maximum Covering Location Problem
MCDM	Multi-Criteria Decision-Making
OLAP	Online Analytical Processing
POI	Points of Interest
SAW	Simple Additive Weighting
SK	Surrogate Key
SDG	Sustainable Development Goals
TMS	Target Market Share
TOPSIS	Technique for Order Preference by Similarity to the Ideal Solution
VIKOR	VIse Kriterijumska Optimizacija I Kompromisno Resenje

1. INTRODUCTION

1.1. MOTIVATION

In the dynamic landscape of urban transportation, the implementation and utilization of Bike-Sharing Systems (BSS) represents a sustainable alternative for city residents and visitors. The global surge in popularity of BSS shows the growing recognition of their role as a sustainable and efficient mode of urban mobility (Maleki et al., 2023; Zhou et al., 2023). These systems empower users with seamless access to bicycles for short-term rentals, fostering quick and eco-friendly journeys throughout the city. However, their effective management needs a deep understanding and the ability to handle numerous challenges. These challenges encompass predicting the demand and availability of bikes, optimizing the infrastructure supporting BSS, and scrutinizing the patterns of bike activity (Liang et al., 2023). This context requires an in-depth exploration of these critical topics, with the goal of enhanced efficiency and sustainability in the cities.

The motivation behind this study is aligned with the global initiative of the United Nations' Sustainable Development Goals (SDG) (United Nations, 2024). Specifically, this study supports: SDG 3 - Good Health and Well-being - promoted by encouraging cycling, as well as improving urban air quality and health; SDG 9 - Industry, Innovation, and Infrastructure - advanced through innovative ways to optimize urban infrastructure (Sustainable Development, 2024); SDG 11 - Sustainable Cities and Communities - directly supported by promoting sustainable urban mobility, integrating bike-sharing with public transportation, and ensuring accessibility; SDG 13 - Climate Action - is addressed by providing an eco-friendly alternative to traditional transportation, contributing to the reduction of air pollution and greenhouse gas emissions.

This study uses the real-world case of Lisbon's Docked Bike-Sharing System (DBSS), GIRA. The service has gained traction as a vital component of the city's urban mobility strategy. To reinforce the sustainability goals of the city, it is essential to review data regarding pollution levels in Lisbon. According to recent studies, air pollution in the city has reached alarming levels, with particulate matter and nitrogen dioxide exceeding recommended limits (ZERO, 2023). The effective utilization of BSS can play a pivotal role in reducing pollution, offering an environmentally friendly mode of transportation. Analysing the usage patterns of GIRA and its integration with existing infrastructure provide valuable insights for improving its efficiency and ensuring its contribution to the broader sustainability goals.

1.2. OBJECTIVES AND METHODOLOGY

Despite the growing popularity of docked bike sharing services, there exists a research gap in the specific context of Lisbon concerning the analysis of GIRA’s usage, the integration of bike sharing within the city's transportation system in the most recent years and a focus on optimizing station locations and the bicycle network (Albuquerque et al., 2021). This absence of analysis inhibits a precise understanding, particularly regarding usage patterns and integration dynamics, crucial for targeted improvements to the system, to ensure the long-term effectiveness of the bike-sharing service.

The primary objective of this research is to identify new locations for bike-sharing stations to enhance service coverage. In addition to this, a secondary objective is to descriptively analyse the various usage patterns and integration dynamics using a business intelligence approach. This approach aims to facilitate better decision-making by providing the understanding of the factors influencing bike-sharing in Lisbon. Considering this, the research aims to answer the following questions:

1. How can the urban dynamics of the city of Lisbon, including usage patterns, integration with existing transportation networks, points of interest and cycling lanes, guide the identification of new station locations for better service coverage?
2. How does bicycle usage vary across different days of the week and times of the day?
3. What is the impact of the time of the year on bike sharing usage?
4. How is the bike sharing system integrated into existing transportation networks in the city?
5. What are the key points where users can transition between bike sharing to points of interest around the city?
6. Does the proximity of bike sharing stations to popular destinations and transportation hubs influence usage patterns?

Data was collected from *EMEL Open Data*, focusing on metrics related to daily usage patterns, trip characteristics and bike detections. Data was also obtained from the *Lisboa Aberta* portal regarding GIRA dock occupancy, existing public transportation, bicycle lanes and points of interest (POI) in the city. Geographic Information Systems (GIS) were then used for spatial analysis of bike-sharing station locations and their integration with the factors previously mentioned with a weighed Multi-Criteria Decision-Making approach. This analysis includes buffering and proximity analysis, aimed at identifying potential areas for optimizing station placements. A Business Intelligence approach was then carried out to build a dimension model and enable quantitative analysis, with the support of data visualization. Findings are presented through an interactive dashboard, enabling stakeholders to make informed decisions for service optimization.

The results of this research include an in-depth understanding of the DBSS in Lisbon, including usage patterns, and integration with existing transportation networks, and POIs. The findings facilitate evidence-based decision-making for stakeholders, leading to the optimization of station locations and improved user experience. Through the results of the suitability scores, 18 new stations were proposed, facilitating evidence-based decision-making for stakeholders and leading to the optimization of station locations.

The sections of this work are organized as follows: The Related Work delves into the diverse methodologies previously applied to address the main challenges within BSS systems locations and existing studies on Lisbon's BSS; The Data and Methodology section offers an analysis of GIRA's data and introduces all the steps taken to derive meaningful insights for the service; Moving on to Results and Discussion, the outcomes of the analysis and achievements for GIRA are presented and analysed, giving a thorough understanding of the research; In the Conclusions section, the research is reviewed and concluded; The final section, Limitations and Future Works, highlights the study's limitations, and proposes possible routes for future studies.

2. RELATED WORK

This section delves into **Bike-Sharing Systems (BSS)**, that have become increasingly popular in cities worldwide as a sustainable and efficient mode of transportation. These systems offer users convenient access to bicycles for short-term rentals, enabling them to make quick and eco-friendly trips around the city. However, managing BSS effectively requires understanding and addressing various challenges, including predicting bike demand and availability, optimizing BSS infrastructure, and analysing bike activity patterns.

2.1. Network Design and Planning

In the domain of network design, several works have delved into diverse methodologies aimed at elevating operational efficiency, spatial effectiveness, and overall accessibility of BSS within urban environments. These studies recognize the pivotal role of efficient infrastructure in the success of BSS. Researchers have explored innovative approaches to address spatial challenges, considering factors such as population density, traffic patterns, and urban topography. Additionally, attention has been directed towards enhancing accessibility, with a focus on strategically locating stations to meet the demands of all users.

In order to identify new bike station locations, Banerjee et al. (2020) used data from Baltimore City and developed a location allocation model using bike-share Global Positioning System (GPS) data, emphasizing frequently used routes. Their methodology, rooted in a modified Huff's gravity model, factored in considerations such as proximity to transportation hubs less than 1000 m away, entertainment destinations less than 300 m away and removal of the 300 m around already existing stations. Successfully identifying three potential locations for new bike stations, their model serves as a valuable tool for strategic expansion planning within a BSS.

Bahadori et al. (2021) explored the field of station location problems, criteria, and methodologies for bicycle-sharing systems. The authors identified two primary station location problems as initial network design and operational improvement. Drawing from their analysis, they proposed four key criteria for selecting suitable station locations: bike network, operator considerations, user needs, and city infrastructure. The techniques for location modelling to solve these problems were also grouped into three categories: Mathematical Algorithms, Multi-Criteria Decision Making (MCDM), and Geographic Information Systems (GIS). From their research findings, they advocate a combined approach involving GIS and MCDM, concluding that these methods reveal more precise results in the context of station location determination.

In the context of expanding BSS with a focus on equity and accessibility, Beairsto et al. (2021) conducted a study based on 'Nextbike,' a BSS in Glasgow, Scotland. Their approach integrated demand modelling with accessibility analysis to pinpoint optimal locations for new bike-sharing stations. Through an analysis of spatio-temporal usage trends, an assessment of spatial equity of access, and the application of a Maximum Covering Location Problem (MCLP), they aimed at maximizing the population served while considering both demand and accessibility, revealing ten new locations for station locations. They used distance to transit stations (within 400 m), the ratio of cycling lanes to streets (within 500 m) and other sociodemocratic variables for analysis, using the 500 m buffer distance to already served areas. With their conclusions, they highlight the importance of a holistic approach in BSS expansion strategies, ensuring considerations of both demand patterns and equitable access.

Eren and Katanalp (2021) presented a fuzzy-based approach with the Analytic Hierarchy Process (AHP), *VIse Kriterijumska Optimizacija I Kompromisno Resenje* (VIKOR), and new Psychometric-VIKOR methods in order to determine suitable BSS station locations in Izmir, Turkey, and evaluate the changes in the weights of the effectiveness of the spatial criteria. They excluded the locations 250 m from the existing stations, and the criteria used were the distance to transportation networks, population density, commercial, entertainment and recreational areas, and topography. In this study, the numbers of alternative BSS station locations dterminded were 42 for transportation-related land uses and 28 for recreational land uses. In future BSS site selection studies, it is suggested that the fuzzy AHP method be utilized while weighting the criteria.

Mangold et al. (2022) proposed a methodological framework to support geo-fence planning for dockless bike-sharing services and to apply the framework in the case study of Zurich, Switzerland. The criteria used included population density, proximity to large public transit, to small public transit, to cycling paths, to sports facilities and to higher education organizations, as well as density of commercial and entertainment facilities within a 2 km buffer. Then, the importance of each criterion is weighted by the AHP method. Candidate locations of geo-fences were ranked using the VIKOR method and a spacing of 200 to 500 m between bike-sharing facilities The results demonstrate that the framework is effective in determining the sites for geo-fences by quantifying the bike-sharing demand coverage of the final geo-fence locations and comparing them with the existing bike-sharing stations.

Mix et al. (2022) proposed an integrated approach to model the demand for bike-sharing trips and determine the optimal location of stations, using built environment and accessibility-based variables and data from the BSS of Santiago de Chile. Key variables included accessibility to dwellings, offices, commerce sites, and the subway (with a 500 m buffer as area of reference), along with street factors. First, trip generation models were estimated through multiple regressions for various types of trips and different periods of the week. Secondly, maximum demand coverage models were developed to allocate the BSS stations based on the trip generation models and various proposed scenarios. Results indicated a strong relationship between the built environment and the use of public bicycles, highlighting the significant impact of residential and office land uses, as well as the presence of extensive bicycle lanes near the stations.

Ebrahimi et al. (2022) utilized two location-allocation models, Target Market Share (TMS) and Maximize Coverage and Minimize Facility, to evaluate the coverage of bike-share and transit networks in Washington D.C. The methodology applied in this study considers a 300-meter distance between bike-share stations and attraction sites and a 1000-meter convenient walking distance from bike stations. Optimal bike station locations were identified using the TMS model based on proximity to bus stops, metro stations, and residential neighbourhoods. The findings indicated that the bike-share system in Washington D.C. is more accessible for transit users as an access/egress mode, whereas docking stations in areas farther from downtown D.C. were more distantly spaced and provided less coverage, particularly in residential-only zones

Desjardins et al. (2022) conducted a study on the accessibility of the BSS in Ontario, Canada, using a balanced floating catchment area approach. A sensitivity analysis was performed to assess accessibility at different walking times from population cells to docking stations: three minutes (minimum), five minutes (average), ten minutes (maximum), and fifteen minutes (extreme). Their findings revealed that equity stations enhanced accessibility for the serviced population across all thresholds, though the increase was relatively modest, particularly for populations in the bottom 20% of median total household income.

Garipagaoglu et al. (2023) identified priority districts for the supply of Electric Bike Sharing Systems in the Istanbul Metropolitan area, considering it a public investment. They applied AHP as a Multi-Criteria Decision-Making method. Among the criteria, bikeability and public transit were given higher weights compared to others. Specifically, the railway system criterion had the highest global weight, followed by the existing separated bicycle lane criterion. This prioritization guided the ranking of districts for the provision of shared e-bike services.

De Moura et al. (2024) utilized data from Salvador, Brazil, to achieve two primary objectives: outlining the potential user profiles at stations or along urban rail lines and identifying areas suitable for implementing a BSS. They applied criteria grouped into categories such as demand profile, public security, land use, terrain slope, and road suitability for cycling. The spatial distribution of factors related to demand profiles and the urban environment guided the development of intervention strategies for areas classified as having low and very low suitability. Consequently, recommendations for infrastructure and mobility management were made for environmental factors like slope, land use, and road network in stations with low suitability. These medium-term policy interventions aim to enhance the potential for implementing and operating an integrated BSS with urban rail transit.

Addressing the challenge of determining optimal locations for new DBSS, Chen et al. (2024) proposed a three-stage framework. Unlike previous studies primarily focusing on demand, their approach considered both travel demand and accessibility factors. The framework involved creating a demand-based suitability map, generating a DBS accessibility map, and applying a location allocation model to identify suitable and accessible locations for new stations. The authors used variables related to the built environment, external connectivity and intermodal connection, and defined as inaccessible the DBSS stations or demand points where the shortest network distance exceeds the threshold network distance (1000 m). Applied to data from Nanjing, China, their framework demonstrated effectiveness in expanding DBSS service coverage and enhancing accessibility, presenting a better method for strategic placement of new bike-sharing stations.

2.2. LISBON'S BIKE-SHARING SYSTEM

Lisbon, the capital of Portugal, has also embraced docked bike-sharing as a sustainable and convenient mode of urban transportation, exemplified by its established system known as GIRA. Some studies have been undertaken to assess the system's effectiveness and explore approaches for optimization, reflecting the importance of enhancing this sustainable mobility practice.

Abad and Van Der Meer (2018) conducted a study aimed at quantifying the connectivity of Lisbon's bicycle network using open data. In their evaluation, they introduced an exploratory score that weighs the accessibility of essential destinations, including schools, universities, supermarkets, and hospitals, from various parts of the city within an acceptable biking distance. The results underscored the need for improvements in connectivity, revealing an overall score of 8.6 out of 100 points.

To further explore Lisbon's bike-sharing system, Albuquerque et al. (2021) delved into a study using the CRISP-DM data mining methodology to unravel spatiotemporal patterns related to station and trip activity. The investigation encompassed factors such as trip rates, weather influences, and the impact of the COVID-19 pandemic on bike-sharing usage. The findings highlighted the predominant occurrence of bike trips on weekdays under favourable weather conditions, showcasing a notable growth in trip count during the study period, with the exception of a temporary decline attributed to the COVID-19 pandemic.

Bahadori et al. (2022) also contributed to the optimization discourse by employing GIS combined with MCDM to strategically locate new bike-sharing stations in Lisbon. They used four categories for the criteria: bike network, operator, user, and city infrastructure. Their methodology incorporated AHP to rank and weight criteria, derived from questionnaires made to staff members. Population density, slope, unbaled station and high transaction station were the criteria with higher weights given. Ultimately, their study identified and ranked 45 potential station locations using the Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS), offering valuable insights for the city to expand and refine its bike-sharing infrastructure.

3. DATA AND METHODOLOGY

The methodology used in this study follows the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework, a widely known methodology in data science and analytics (Figure 3.1). CRISP-DM provides a structured path, designed to address data-driven challenges with precision (Shearer, 2000). This proven framework ensures a methodical progression from the foundational stage of business understanding to the conclusive phase of deployment. Its systematic approach provides a solid foundation, allowing for an efficient and purpose-driven exploration of the GIRA service.

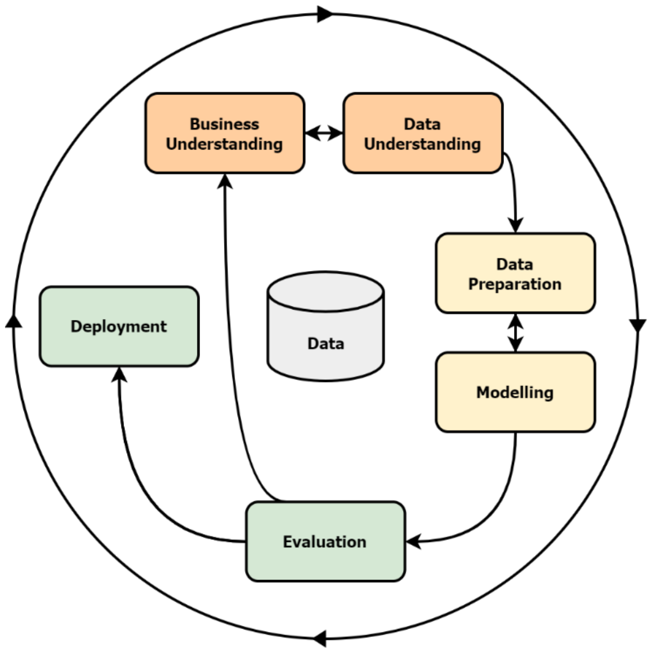

Figure 3.1 - CRISP-DM method framework. Adapted from Shearer (2000).

The next subsections will study the specific phases of the methodology, illustrating how each step contributes to the overall understanding and optimization of the GIRA service. Subsection 3.1 will cover the phase of Business Understanding, followed by Subsection 3.2 which will cover the phase of data understanding. Subsection 3.3 will encompass both data preparation and modelling and Section 4 will explain the evaluation and deployment stages of the process.

3.1. Business Understanding

The process starts with understanding the business questions and requirements The primary objective of this research is to identify new locations for bike-sharing stations to enhance service coverage. In addition to this, a secondary objective is exploring the dynamics of bicycle usage patterns on a temporal basis, the integration of the DBSS within the city's transportation systems and points of interest. Considering this, the research aims to answer the following questions:

1. How can the urban dynamics of the city of Lisbon, including usage patterns, integration with existing transportation networks, points of interest and cycling lanes, guide the identification of new station locations for better service coverage?
2. How does bicycle usage vary across different days of the week and times of the day?
3. What is the impact of the time of the year on bike sharing usage?
4. How is the bike sharing system integrated into existing transportation networks in the city?
5. What are the key points where users can transition between bike sharing to points of interest around the city?
6. Does the proximity of bike sharing stations to popular destinations and transportation hubs influence usage patterns?

By aligning the methodology with these specific business requirements, a solid foundation is built for the subsequent steps, ensuring the analyses are not just data-driven but connected to the needs of the BSS. These questions examine various aspects of GIRA, aiming to uncover insights that can inform decisions for system optimization and expansion.

3.1.1. STUDY AREA

The study area for this work encompasses all 24 parishes, within Portugal's capital and largest city, **Lisbon** (Figure 3.2). Home to more than half a million people, Lisbon holds a significant position in the national demographic landscape, constituting approximately 5% of Portugal's total population and encompassing over 100 km² (INE, 2021). The city has demonstrated a commitment to meet ambitious environmental targets, with a strategic goal of achieving a 45%-55% reduction in emissions by the year 2030 and 65%-75% by 2040 (Lisboa 2030, 2024; Republic Diary, 2020). Furthermore, Lisbon, like many other cities worldwide, has plans to be a global example by aiming for carbon neutrality by 2050 (Portuguese Republic, 2019). This commitment to sustainability was solidified by Lisbon's recognition as the European Green Capital in 2020 by the European Commission (2024).

Figure 3.2 - Map of the city of Lisbon, Portugal.

Despite being known by its distinct topography, characterized by a hilly terrain, Lisbon is composed of 73% plain streets, allowing an extensive cycling infrastructure. The city features around 118 km of dedicated bike lanes, a number aspired to increase to 200 km (CML, 2020). Notably, since 2017, the city has undergone significant infrastructure developments aimed at improving its cycling network, with a focus on enhancing its public Docked Bike-Sharing System, known as GIRA, which was launched in the same year (GIRA, 2024). Managed by Lisbon's mobility authority, EMEL, GIRA has contributed significantly to the surge in cycling activity throughout the city, counting on 130 stations, over 1600 bicycles, and more than 2500 docks (André, 2022).

3.2. DATA UNDERSTANDING

This study relies on data sourced from two primary repositories, the EMEL Open Data[1] and *Lisboa Aberta*[2] portals. The primary focus centres around Lisbon's bike-sharing system, using several datasets related to the service and its characteristics. Additional datasets related to transport stations, bike lanes, and points of interest (POI) across the city are also used to improve the overall analysis of the BSS and its surroundings.

Within the EMEL portal datasets, detailed information is captured through two distinct JavaScript Object Notation (JSON) files, each contributing with insights about the usage of Lisbon's BSS throughout the years 2022 and 2023. The files provide a daily overview of the trip statistics (Table 3.1) and usage data (Table 3.2).

[1] https://opendata.emel.pt/

[2] https://lisboaaberta.cm-lisboa.pt/

Table 3.1 - Description of the trip statistics data file.

Field Name	Data Type	Description
tripStartDate	Date	Start date of the bicycle trips
avgTripSeconds	Numeric	Average duration of bicycle trips in seconds during each day
avgTripSecondsRush	Numeric	Average duration of bicycle trips in seconds during rush hours

Table 3.2 - Description of the usage data file.

Field Name	Data Type	Description
tripStartDate	Date	Start date of the bicycle trips
totalSecondsPerDay	Integer	Number of seconds of bicycle trips on each day
userQtyUnique	Integer	Number of unique users that did bicycle trips on each day
avgTripByUserSeconds	Numeric	Average duration of bicycle trips per user on the specified day

Moreover, another JSON file was extracted, providing details about each GIRA station and its attributes and functionalities (Table 3.3). The details provided offer insights into the spatial distribution and operational aspects of GIRA stations.

Table 3.3 - Description of the GIRA stations data file.

Field Name	Data Type	Description
id_expl	Integer	Unique identifier for the station
estacaolocalizacao	String	Name or location description of the station
latitude	Numeric	Latitude coordinate of the station's location
longitude	Numeric	Longitude coordinate of the station's location
dispbicicleta	Integer	Number of available bicycles at the station
aberturadt	Datetime	Date and time when the station was opened
criacaodtt	Datetime	Date and time when the station was created
atualizacaodtt	Datetime	Date and time of the last update for the station

Additionally, the study involved the extraction of a JSON file detailing the locations of detectors for GIRA bicycles (Table 3.4). These detectors are strategically positioned throughout Lisbon (Figure 3.3), serving to track the movement and utilization of bikes within the city.

Table 3.4 - Description of detectors data file.

Field Name	Data Type	Description
locationId	Integer	Unique identifier for the detector location
tenantIdentifier	String	Identifier for the GIRA service
name	String	Name or description of the detector location
freguesia	String	Parish of the detector location
latitude	Numeric	Latitude of the detector location
longitude	Numeric	Longitude of the detector location

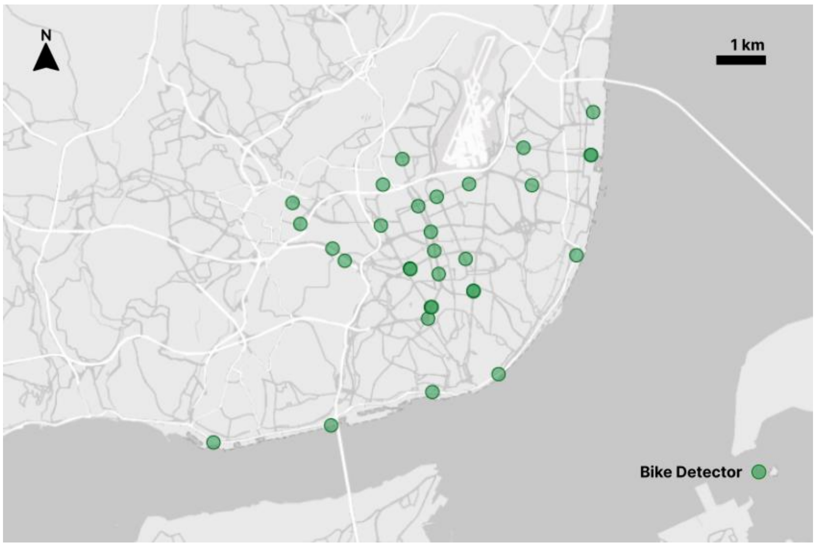

Figure 3.3 - Location of the GIRA Bike Detectors within the city of Lisbon.

The study also used data on bike detections recorded throughout the entirety of 2023 by the detectors described previously (Table 3.5). These detections offer a view of bike usage across different locations and timeframes within Lisbon.

Table 3.5 - Description of detections data files.

Field Name	**Data Type**	**Description**
detectionId	Integer	Unique identifier for each bike detection
tenantIdentifier	String	Identifier for the GIRA service
locationId	Integer	Identifier for the detector
detected	Datetime	Timestamp of the bike detection
direction	Integer	Direction of the detected bike
count	Integer	Number of bikes detected at the specified time

Furthermore, a diverse set of datasets was obtained from the *Lisboa Aberta* portal to explore and analyse the GIRA service, transportation, and points of interest in the city of Lisbon. Firstly, a Geographic JSON (GeoJSON) file describing Lisbon's parishes was retrieved (Figure 4.2). Additionally, Comma-Separated Values (CSV) files with historical data regarding dock occupancy throughout 2021 and the first trimester of 2023 were extracted, describing the availability of bicycles at each station at different dates and times (Table 3.6).

Table 3.6 - Description of the dock occupancy data files.

Field Name	**Data Type**	**Description**
desigcomercial	String	Code and commercial designation associated with each station
numbicicletas	Integer	Number of bicycles available at the corresponding station
numdocas	Integer	Number of docking spaces available at each station
position	JSON	Geographical coordinates (latitude and longitude) of the station
entity_ts	Datetime	Time and date of the snapshot
estado	String	Operational state of the station

An overview of the yearly distribution of the data extracted from the previously described files is given in Table 3.7, including the dock occupancy, bike detections, trip statistics and usage files. This table offers a concise look at how these records vary from year to year, contributing to the understanding of the data that will be analysed.

Table 3.7 - Number of records retrieved per file by year.

Year	Dock Occupancy	Bike Detections	Trip Statistics	Usage
2021	1,232,857	-	-	-
2022	1,852,775	-	365	365
2023	677,782	7,473,171	365	365

Datasets focused on transportation were then extracted, including text files with geographic information on train, metro, and boat stations (Figure 3.4). A GeoJSON file was also retrieved regarding the bike lane network, giving information about the organization of the cycling infrastructure. Moreover, the research incorporates several more GeoJSON datasets, each delineating specific points of interest around the city of Lisbon: casinos, cinemas, libraries, fairs, gardens, markets, monuments, museums, parks, radical sports facilities, schools, shopping centres, theatres, and viewpoints (Figure 3.5). These diverse datasets collectively provide a rich foundation for spatial analyses, enabling a detailed study of the urban dynamics in Lisbon.

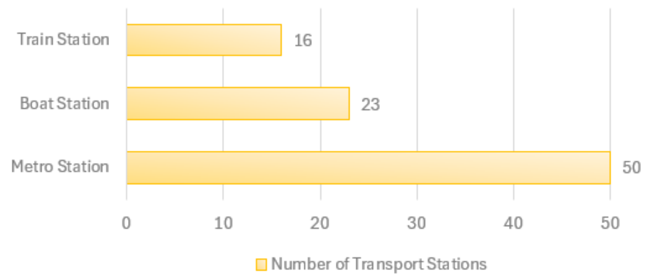

Figure 3.4 - Number of transport stations retrieved.

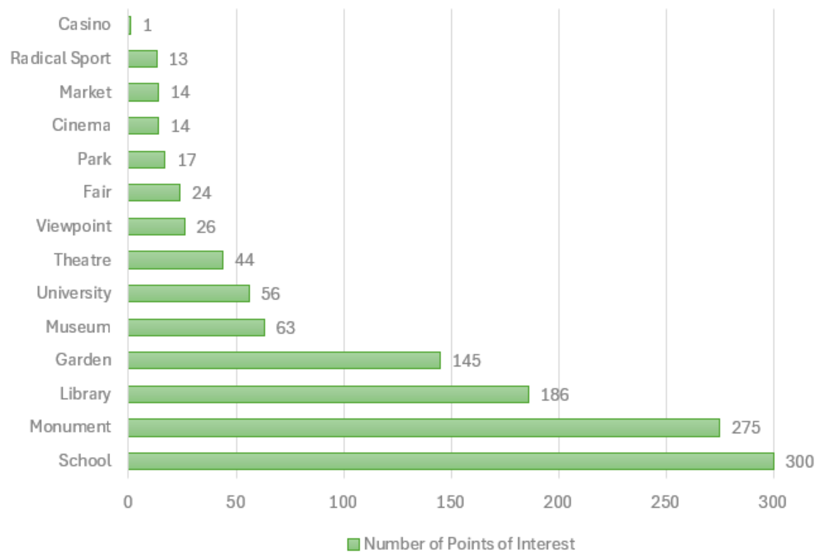

Figure 3.5 - Number of points of interest retrieved.

3.3. Modelling

In the pursuit of optimizing sustainable urban mobility with the GIRA service, this study's methodology will integrate geospatial analysis, dimensional modelling, and dashboard development (Figure 3.6). The process begins by extracting essential data from reliable sources, ensuring a solid foundation for analysis, as described in the previous section. The next is the Criteria Weight Distribution. This step is fundamental in the decision-making process as it involves assigning weights to the various criteria that influence the selection of optimal locations for new BSS stations. Using the Simple Additive Weighting (SAW) method, each criterion is evaluated based on its perceived importance in achieving this goal.

Following this, an Extract, Transform and Load (ETL) process is used. For geospatial data, a database is created using QGIS[3] after transforming the data. This tool enables the visualization and analysis of geospatial data, offering a deeper understanding of station locations and urban dynamics in the city of Lisbon, enabling spatial analysis for suggesting potential areas for new stations using a weighted Multi-Criteria Decision Making (MCDM) approach, which was selected based on its prevalent use in the Related Work section. This method is advantageous due to its ability to incorporate multiple factors and assign different weights, leading to more informed and balanced decision-making, with the goal to develop a suitability map that reflects the scores assigned to each location, indicating their suitability for new GIRA Stations. A dimensional model is then crafted in Power BI's[4] Power Query, an important step for efficiently querying and organizing structured data. Following this, the data is loaded and a dashboard will be created to visualize and make accessible the results of the modelling process.

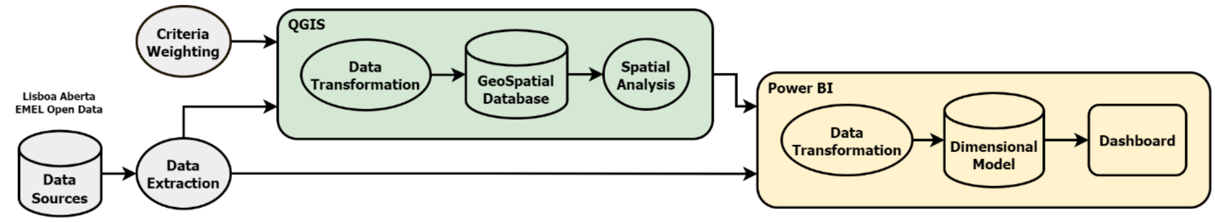

Figure 3.6 - Framework of the study.

3.3.1. Criteria Weight Distribution

The Simple Additive Weighting (SAW) method was employed to assign weights to the criteria influencing the selection of optimal locations for new BSS stations within the city of Lisbon. This method involves assigning weights to each criterion based on its perceived importance in

[3] https://www.qgis.org/

[4] https://powerbi.microsoft.com/

the decision-making process. The formula used to give a normalized weight to the alternatives of the criteria (Karabulut et al., 2021), is expressed in Equation 3.1.

n_{ij} – Normalized value of the i^{th} alternative and the j^{th}criterion.
w_j – Weight assigned to the j^{th} criterion.

$$A_i = \sum_{j=1}^{n} n_{ij} w_j \tag{3.1}$$

For the criteria outlined in Table 3.8, weights were calculated considering the existing related works and the weight's given to similar criteria, combined with the goals of the current study. The highest weight is attributed to the distance to existing GIRA Stations (Banerjee et al., 2020; Eren and Katanalp, 2021), which aligns with the goal of optimizing the distribution of BSS stations throughout Lisbon by preventing overcrowding or redundancy in areas where bike stations are already established, ensuring a more complete coverage of the city Following is proximity to Bike Lanes, which highlights the significance of ensuring that new BSS stations are strategically located in areas characterized by well-developed bike infrastructure. Such an emphasis highlights the importance of accessibility and safety to encourage increased bike usage (Garipagaoglu et al., 2023). The third criterion was decided on proximity to Transport Stations, signifying the importance of integrating BSS stations with existing public transport hubs, thereby enhancing the overall multi-modal connectivity within the city (Mangold et al., 2022). The next criterion, proximity to Top 20 GIRA Stations, draws attention to high-traffic areas based on availability change (calculated through the dimensional model described in the next subsection). By prioritizing proximity to these top stations, the analysis aims to strategically place new BSS stations in locations where they are likely to attract a substantial number of users and contribute to overall system efficiency (Bahadori et al., 2022). Lastly, the criterion of proximity to POI carries the lowest weight. While still considered in the analysis, this criterion takes a more supplementary role, recognizing the contextual importance of placing BSS stations near cultural, commercial, or other points of interest without compromising the primary focus on other critical criteria (Beairsto et al. 2021).

Table 3.8 - Weight by criteria for suitability score.

Criteria		Weight
C1	Distance to existing GIRA Stations	0.30
C2	Proximity to Bike Lanes	0.25
C3	Proximity to Transport Stations	0.20
C4	Proximity to Top 20 GIRA Stations	0.15
C5	Proximity to Points of Interest in Lisbon	0.10

To proceed with SAW methodology, it's needed to select appropriate alternatives for each criterion (Table 3.9). Making use of the existing related work, distinct distances were selected for each criterion. For the distance to existing GIRA Stations and to the top 20 GIRA Stations criteria, biking-appropriate distances were considered, resulting in alternatives of greater than 1 km, to 1 km, and less than 500 m for GIRA Stations, and less than 1 km, 1 km to 2 km, and greater than 2 km for the top 20 GIRA Stations. These distances were chosen to ensure that users can access stations conveniently while cycling. Likewise, the alternatives for proximity to Bike Lanes, to Transport Stations, and to Points of Interest were determined based on appropriate walking distances. This led to alternatives of less than 200 m, 200 m to 500 m, and greater than 500 m (Eren & Uz, 2020). These distances were chosen to reflect pedestrian-friendly distances, enabling users to comfortably walk to and from BSS stations while accessing key attractions, transport hubs, and cycling infrastructure.

Table 3.9 - Alternatives for each criterion by distance in kilometres.

Criteria		**A1**	**A2**	**A3**
C1	Distance to existing GIRA Stations	> 1	0.5 - 1	< 0.5
C2	Proximity to Bike Lanes	< 0.2	0.2 - 0.5	> 0.5
C3	Proximity to Transport Stations	< 0.2	0.2 - 0.5	> 0.5
C4	Proximity to Top 20 GIRA Stations	< 1	1 - 2	> 2
C5	Proximity to Points of Interest in Lisbon	< 0.2	0.2 - 0.5	> 0.5

Expanding on the identified alternatives, points were assigned for each, which will contribute for the suitability scores of each location. The points given were 10 for A1, 5 to A3 and 1 to A3, and afterwards underwent normalization to ensure consistency and comparability across different criteria and alternatives. This normalization process involved scaling down the values to a common range, between 0 and 1, by dividing each value by a constant factor per criteria. By doing so, the values were adjusted to align with the requirements of the formula used in the SAW method, facilitating the calculation of suitability scores. The resulting normalized weights in Table 3.10 represent the relative importance of each criterion for every alternative in the calculation of the suitability score for every location.

Table 3.10 - Relative weight of each criterion and alternative.

	C1	**C2**	**C3**	**C4**	**C5**	**Weight**
A1	0.18750	0.156250	0.1250	0.093750	0.06250	**0.6250**
A2	0.09375	0.078125	0.0625	0.046875	0.03125	**0.3125**
A3	0.01875	0.015625	0.0125	0.009375	0.00625	**0.0625**
Weight	**0.3**	**0.25**	**0.2**	**0.15**	**0.1**	**1**

3.3.2. SPATIAL ANALYSIS

The collected geographic datasets were integrated into a geospatial database in the QGIS software. The goal was to create a database that enables an analysis of the urban dynamics in Lisbon for new stations within the GIRA service. The integration involved gathering the datasets encompassing information on existing bike stations, transport stations, bike lanes, and points of interest across the city, and preparing them in GeoJSON or CSV formats for an easy integration into QGIS.

Upon importing the datasets into the software, distinct layers were created for each dataset. Visualizations are then generated, providing an initial spatial overview of the urban dynamics and mobility in Lisbon (Figure 3.7). This aids in identifying potential spatial correlations and patterns and making sure the spatial data is ready for further analysis.

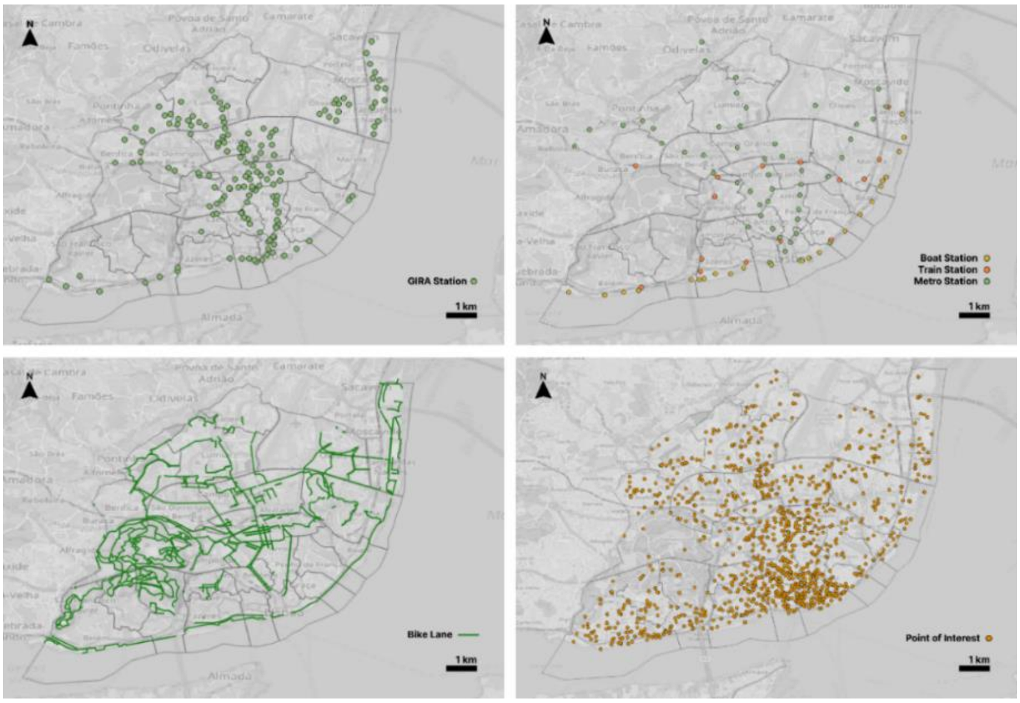

Figure 3.7 - Map of GIRA stations, transport stations, points of interest and bike lanes.

An additional layer was generated by filtering the GIRA stations layer. This new layer highlights the top twenty stations with the most significant availability changes, as discerned through the dimensional model described in the next subsection.

The spatial analysis was carried out by a weighted Multi-Criteria Decision Making (MCDM) framework. The subsequential steps employed five primary vector point and line layers, serving as the criteria that will be integrated into the MCDM analysis. These layers include “gira_stations”, “bike_lanes”, “transports”, “top_stations”, and “points_of_interest”.

To be able to begin the analysis, the first step was to do a conversion of each vector layer into raster format. The Vector Conversion tool was employed for rasterization, using a batch process to rasterize all layers simultaneously. The next step involved generating proximity raster layers, reflecting the distance to the five layers being used. For this the Proximity (Raster Distance) tool was used as a batch process and created the new five layers. Following, new layers were produced with the Raster Calculator tool and represent a reclassification of the previous proximity raster layers, wherein the scores calculated in Subsection 3.3.1. were allocated based on the defined distances (Figure 3.8).

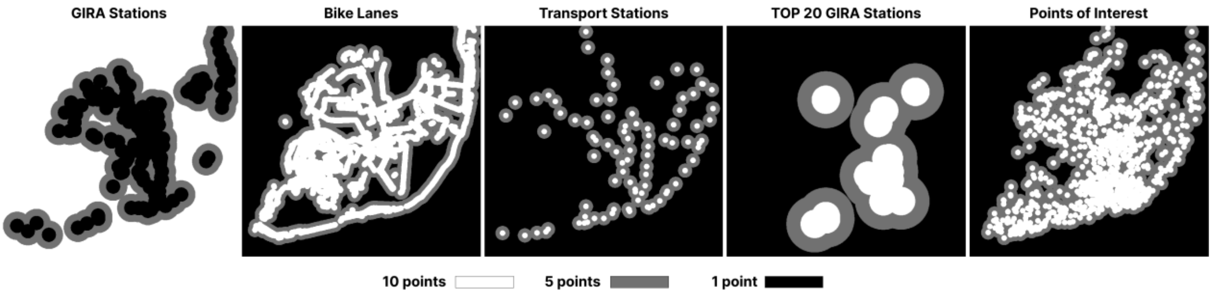

Figure 3.8 - Calculated raster layers per criteria.

The final step aimed to integrate the suitability scores for all five layers combined. The Raster Calculator tool was employed again to combine these factors, where the weights assigned to each criterion were used for calculation. A Clip Raster by Mask Layer tool was finally used to remove the areas outside the city boundary, resulting in the layer that will be used to identify suitable areas for new stations.

3.3.3. Dimensional Modelling

For optimizing the GIRA service, a dimensional model is essential for gaining deeper insights, allowing the analysis of data from multiple perspectives. The construction of a multidimensional model involved a data transformation process to ensure the seamless integration of the various datasets described in the previous sections into a Star Schema. This model design revolves around a central fact table that encapsulates primary data, surrounded by dimension tables, each representing specific attributes related to the data. This design is particularly advantageous for scenarios requiring swift and straightforward data retrieval, such as reporting and analytics (Kimball & Ross, 2013). The steps taken to develop the dimensional model followed the four-step technique suggested by Kimball and Ross (2013):

1. Select the business process.
2. Declare the grain.
3. Identify the dimensions.
4. Identify the facts.

Following this technique, the initial phase of the approach focused on the task of selecting the business process for the analysis of Lisbon's BSS, which will follow the questions in the Business Understanding section. Firstly, the business process includes the analysis of system's possible expansion, for better city coverage. Additionally, one of the goals is to analyse and understand the daily usage patterns and influencing factors that characterize the service. It is also important to address fundamental questions related to the variation in bike usage across different days of the week, times of the day and times of the year. Furthermore, the investigation extends to exploring the impact of station proximity to popular destinations and transportation hubs on overall usage patterns.

The next phase in the dimensional design process involves declaring the grain, specifying the level of detail at which measurements are stored within the dimensional model.

In this study, it has been established that every individual entry within the dock availability dataset corresponds to the bike availability at each timestamp, with associations to specific stations. Similarly, within the detection's datasets, each entry denotes a recorded bike detection at a specific timestamp linked to a particular detector. Regarding the trip statistics and usage files, the declared grain dictates that each row is in regard to daily statistics, facilitating the examination of the usage patterns on a daily basis. Concerning the points of interest and transport stations files, the grain is determined by the calculation of distances between stations and points of interest. Each entry represents a spatial relationship between every POI and station. Lastly, the suitability scores are presented wherein each line concerns a specific location within Lisbon.

The subsequent stage involves the delineation of dimensions crucial to shaping the model. Each dimension enables the exploration of specific data aspects, contributing to a more complete understanding of the data. The dimensional model incorporates the six dimensions summarized in Table 3.11, along with their respective attributes and hierarchies.

Table 3.11 - Dimension tables description.

Dimension	**Description**
DIM_DATE	Represents individual dates, facilitating time-based analysis.
DIM_TIME	Captures temporal information, providing hour, minute, and second details.
DIM_DETECTOR	Represents bike detectors, aiding in understanding the detections of bicycles.
DIM_STATION	Encompasses details about GIRA bike stations.
DIM_POINT_OF_INTEREST	Encompasses various points of interest and transport stations.
DIM_GEOGRAPHY	Encompasses information regarding Lisbon’s parishes.

The Date dimension focuses on date-related information within the dataset, serving as a basis for temporal analysis. Crafted in Power Query's advanced editor, it spans from 2021 to 2023 and includes the attributes Year, Month, Day, Day Name, Day of Week, Day of Year, Month Name, Quarter, Week of Year, Short Month, and Short Month Year. A surrogate key (SK) column was created (SK_DATE) to provide a numerical representation for unique identification in the “YYYYMMDD” integer format, which will facilitate the connection with fact tables. The hierarchical structure is defined as: Year > Quarter > Month > Day.

Designed to capture time-related information, the Time dimension spans the entire 24-hour day. Also constructed in Power Query's advanced editor, it includes the attributes Hour, Minute, and Second. The SK_TIME primary key provides a numerical representation in the integer format “HHMMSS” for unique identification in each row. The hierarchical structure is defined as: Hour > Minute > Second.

The integration of information regarding Lisbon's parishes was done to implement the Geography dimension. It was created through the GeoJSON file retrieved and encompasses the information of each parish's name, area, and perimeter.

Dedicated to information about bike detectors in Lisbon, the Detector dimension is transformed using data from the Detectors JSON file. The business key (BK), BK_DETECTOR, is derived from the original Name column and SK_DETECTOR is derived as an index for unique identification. Other attributes of this dimension are Latitude and Longitude.

The Station dimension contains essential details about bike stations in Lisbon, transformed using data from the Stations JSON file. The attributes of this table include the Description, Latitude, Longitude, Available Bikes, Creation Date, and Last Update. The SK_STATION is an index that serves as a unique identifier, while BK_STATION is the business key derived from the original file. An intersection with data regarding Lisbon's parishes was done using QGIS to add the attribute "Parish" to this data, representing the parish in which the station is located, that would later be integrated into the fact tables within the Geography Dimension.

Integrating the points of interest and transport stations data, the Point of Interest dimension combines attributes such as Type, Longitude, Latitude, and Name. Seeing as each type of POI came from a different file, the type of each point was derived from the name of the respective file. The development process also involved adding an index column, SK_POINT, for unique identification. Similarly to the stations dimension, the attribute "Parish" was also calculated using QGIS to then be integrated into the fact tables with relationship to the Geography dimension. Providing a structured representation for analytical depth, the hierarchy is declared as: Type > Name.

The final phase is focused on defining the fact tables that will constitute the core of the model. Fact tables play a pivotal role in encapsulating transactional data and quantifiable metrics, forming the basis for analytical insights. The model counts on five fact tables that are summarized in Table 3.12.

Table 3.12 - Fact tables description.

Fact Table	**Description**
FCT_USAGE	Captures daily bike-sharing statistics, revealing user behaviour and system usage patterns.
FCT_AVAILABILITY	Compiles data on dock availability throughout the day for analysing how each station is used over different time periods.
FCT_DETECTIONS	Records bike detection events from detectors, providing insights into bicycle use patterns over time.
FCT_DISTANCES	Calculates spatial relationships and distances, aiding in understanding bike station and point of interest distribution.
FCT_SUITABILITY	Compiles the information from the Spatial Analysis conducted, representing the suitability score for new stations in every location in Lisbon.

In the construction of the Usage fact table, data preparation took place within Power Query, integrating information from both the usage and statistics data files covering the time span from 2022 to 2023. The SK_DATE column, encompassing daily information, served as the sole foreign key for this fact table, formatted from the TripStartDate original column. No additional SK components were required due to the granularity of the dataset, which focuses on daily statistics. The central measures of this fact table include Daily Users, Average Trip Time (Seconds), Average Trip Time Seconds (Rush), Time per day (Seconds) and Time per User (Seconds). Two calculated columns were introduced to express the average trip time in minutes and the Time per day in hours, transforming the temporal aspect from seconds. Its relationship to the Date dimension through the SK facilitates the extraction of meaningful insights from the used datasets.

The Availability fact table incorporates information from dock occupancy data files across the period of 2021 to 2023. Subsequently, the desigcomercial column, which contains station codes and descriptions, underwent a separation process based on delimiter to retrieve the foreign key SK_STATION, which also makes the connection to the respective Parish within DIM_GEOGRAPHY. Simultaneously, the entity_ts column was dissected into date and time components that were formatted according to the respective dimension tables, to create the foreign keys SK_DATE and SK_TIME. The resulting fact table features SK_STATION, SK_GEOGRAPHY, SK_DATE and SK_TIME as the composite primary key, that guarantee a relationship with the Time, Date, Station, and Geography dimensions. Two calculated metrics, Availability Ratio (Jara-Díaz et al., 2022) and Availability Change are computed using Data Analysis Expressions (DAX) and the Equation 3.2.

$$Availability\ Ratio\ (AR) = \frac{Bikes}{Total\ Docks}$$

$$Availability\ Change\ = AR_{TS} - AR_{Previous\ TS} \tag{3.2}$$

In the creation of the Detections fact table, the focus is on capturing information surrounding bike detections, closely tied to the Detectors dimension. The locationId column was incorporated to establish a link between the fact table, the detectors dimension, and the geography dimension. Additionally, two foreign keys are included in this fact table: SK_DATE and SK_TIME. These keys were derived from the detectionDate to ensure an easy relationship to Time and Date dimensions. The measures within this fact table are "Bike Detections" and "Direction," offering insights into the specifics of each detection.

In the construction of the Distances fact table, a distinctive approach was employed. The goal was to compute the distances between bike stations and points of interest. The creation of the Distances fact table involved a cross join[5] between the surrogate keys

[5] A cross join, also known as Cartesian join, is an operation where every row from one table is combined with every row from another table, creating a new one with all possible combinations of rows from both tables.

SK_POINT and SK_STATION from the respective dimensions. This method combined each point of interest to every GIRA station. The Haversine formula (Sinnott, 1984) was then integrated into the fact table through DAX to calculate the Distance (d) column in kilometres using the Earth's Radius (R), and Latitude (lat) and Longitude (lon) of each point, as represented in Equation 3.3.

$$R = 6.371\ km$$
$$\Delta lat = lat_2 - lat_1$$
$$\Delta lon = lon_2 - lon_1$$

$$a = sin^2\left(\frac{\Delta lat}{2}\right) + cos(lat_1) \cdot \cos(lat_2) \cdot sin^2\left(\frac{\Delta lon}{2}\right)$$

$$c = 2 \cdot atan2\,(\sqrt{a}, \sqrt{1-a}) = 2 \cdot atan\left(\frac{\sqrt{a}}{\sqrt{1-a}}\right)$$

$$d = R \cdot c \tag{3.3}$$

A calculated column for distance in meters was also derived from this column. Additionally, through each POI's parish, an additional connection to the Geography dimension was created to allow an analysis on parish level.

To incorporate the product of the spatial analysis in the final dashboard along with the model, the last raster layer was transformed into a polygon vector layer using the Raster Conversion tool, intersected with the parishes layer, and was uploaded into GitHub as a GeoJSON file[6]. This file was also used to create a new table (FCT_SUITABILITY) in the Power BI model, incorporating the ID of each polygon (SK_LOCATION), their suitability score and their Parish trough the geography dimension (SK_GEOGRAPHY). This allows the use of the Icon Map[7] tool within Power BI, which represents the locations within Lisbon and their suitability score for new bike stations, providing a clear and interactive view of the system's possible expansion.

Figure 3.9 illustrates the culmination of the created data model, showcasing the interconnected dimensions and fact tables. The dimensions, representing dates, time, bike detectors, GIRA bike stations, points of interest, and geography, provide crucial context for analysing temporal, spatial, and usage patterns. Complementing these, the fact tables, capturing dock availability, bike detections, usage statistics, distances, and suitability scores, form a strong foundation for insightful analyses. The relationships between dimensions and fact tables facilitate a seamless exploration of the whole dataset.

[6] https://raw.githubusercontent.com/evagarcia07/New_Stations/main/NewStationsFinal.geojson

[7] https://www.icon-map.com/

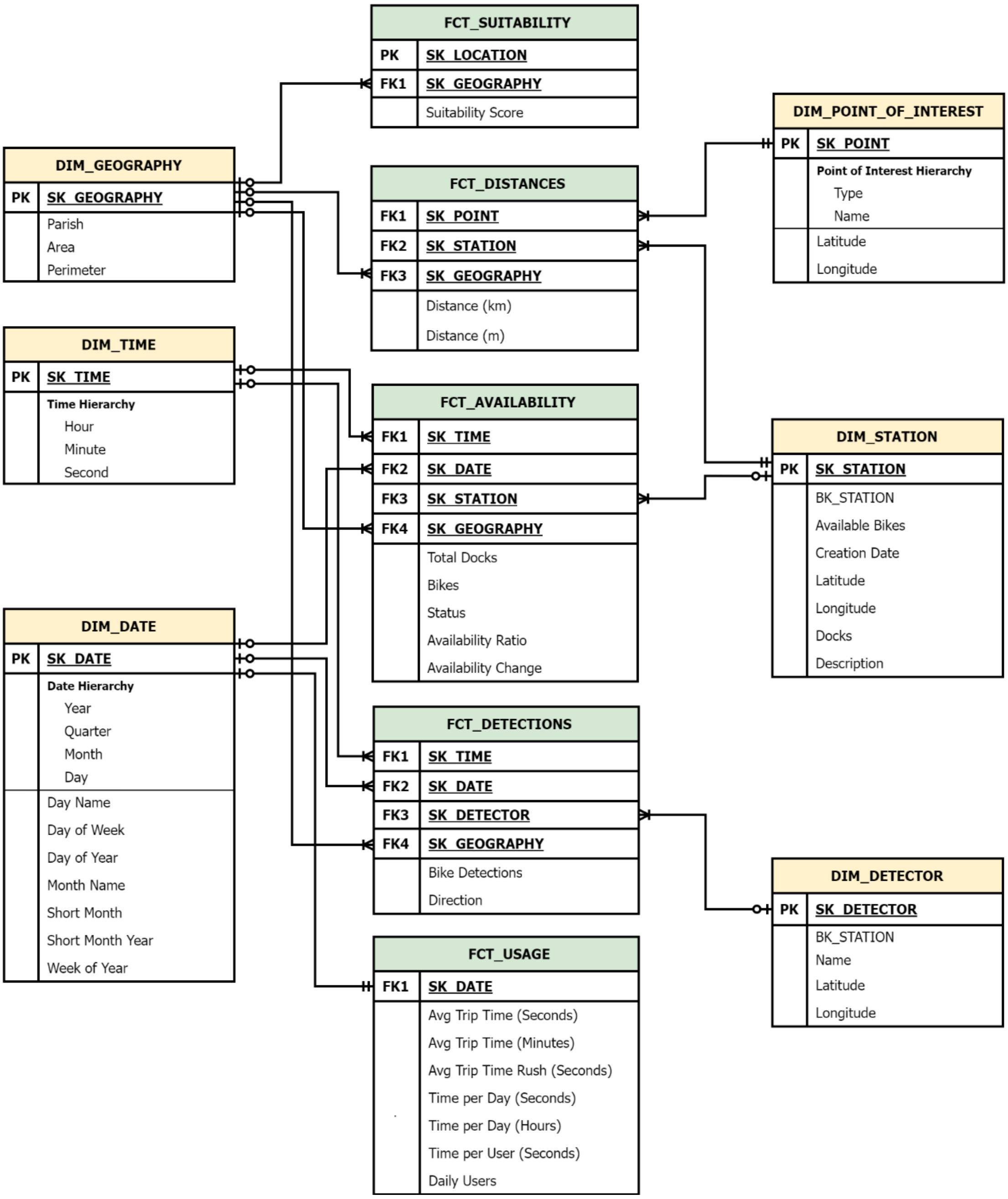

Figure 3.9 - Multidimensional model diagram.

4. RESULTS AND DISCUSSION

This section is divided into a temporal analysis and a geographic analysis, making use of the dashboard created. This phase of the research explains the aspects of bike usage patterns, the impact of temporal patterns on usage, the integration of the DBSS within the city's transportation networks and points of interest, and the results of potential optimizations of the service for city coverage.

4.1. SYSTEM EXPANSION

To address the first and primary research question, " How can the urban dynamics of the city of Lisbon, including usage patterns, integration with existing transportation networks, points of interest and cycling lanes, guide the identification of new station locations for better service coverage?", this research analysed distinct factors aiming to identify strategic locations for new bike-sharing stations that optimize coverage and accessibility for the city's residents and visitors. The results of the Multi-Criteria Decision Making (MCDM) method, conducted using QGIS, are depicted in Figure 4.1. This map illustrates the Suitability Score assigned to various locations within the city of Lisbon, ranging from 14 to 93. The Suitability Score serves as an indicator of the level of need for a new GIRA Station in each location, with higher scores indicating a greater need.

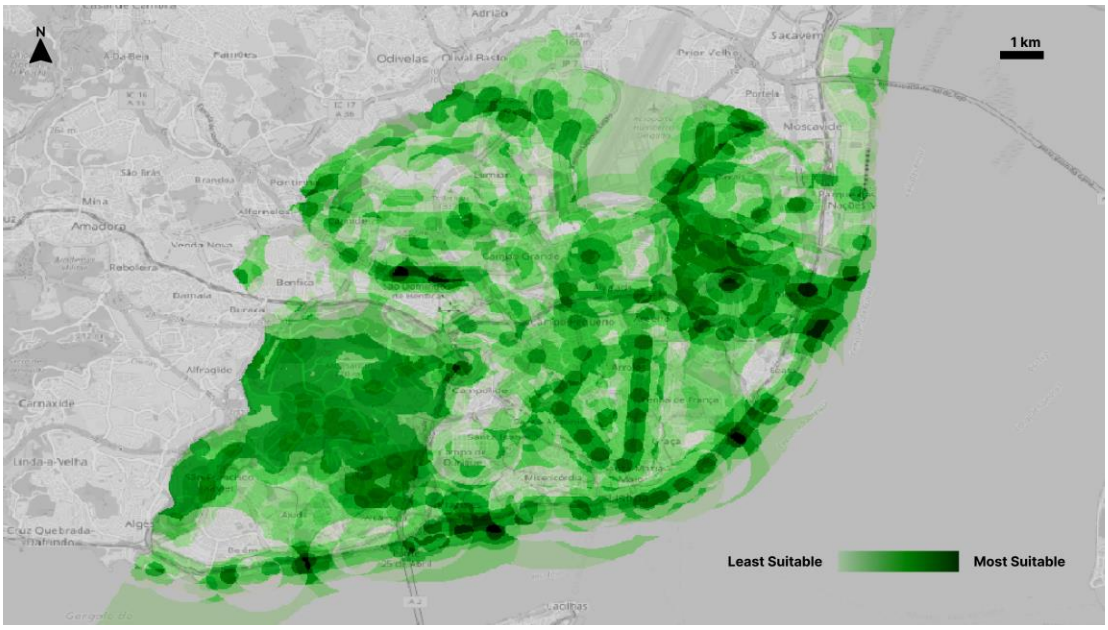

Figure 4.1 - Map of Lisbon with Suitability scores.

In order to assess the influence of criteria weights on the Multi-Criteria Decision Making (MCDM) results, a comparison was done between two distinct analyses: one incorporating weights assigned to each criterion, and another where all criteria had an equal weight. Upon visual inspection of the maps generated from these analyses (Figure 4.2), a notable difference emerged in areas where existing GIRA stations are located. In the analysis with weighted criteria, the suitability scores in these areas were appropriately suppressed, reflecting the diminished need for additional stations in zones already well-served by the bike-sharing service. However, in the analysis without weights, the absence of prioritization based on distance to existing stations led to inflated suitability scores in these same areas.

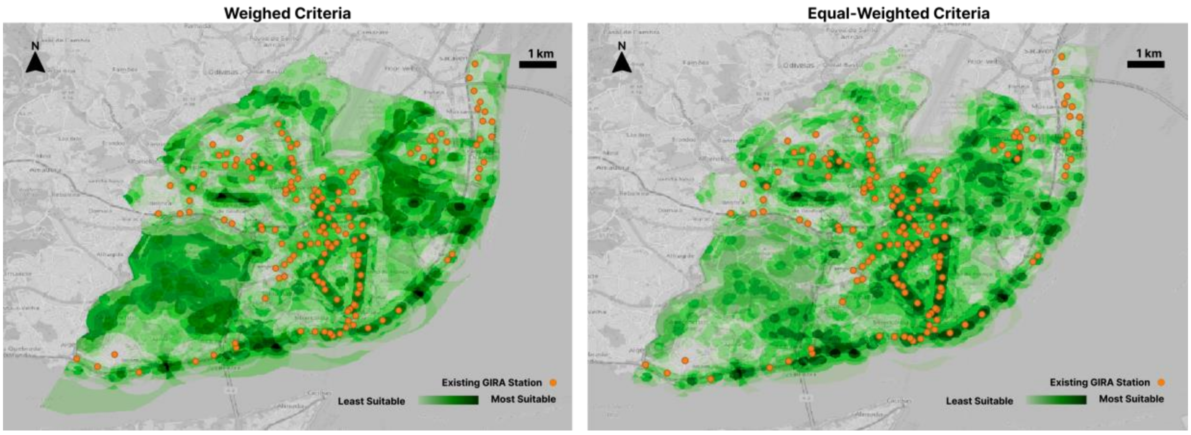

Figure 4.2 - Weighed criteria vs. equal-weighted criteria maps.

This discrepancy emphasizes the importance of appropriately weighting criteria, particularly when considering factors such as proximity to existing infrastructure. The contrast between the two analyses highlights the important role that the criteria weighting played in the MCDM methodology. The factors and their weights pinpointed as the most influential in this work are derived with the recommendations derived from numerous studies in the field, contrasting with the existing GIRA study of Bahadori et al. (2022), which prioritized population density and slope and minimized the effects of proximity to current stations in their approach.

The parishes containing locations with a Suitability Score higher than 85 include Belém, Alcântara, Estrela, Campolide, São Domingos de Benfica, Santa Clara, Olivais, Marvila, Areeiro, Beato, Penha de França and São Vicente. The elevated Suitability Scores in these areas emphasize a greater need for additional GIRA stations in them. By analysing these results, 18 locations were pointed out as potential new stations in the areas with higher suitability scores, as can be visualized in Figure 4.3 and GitHub[8]. This includes five new stations in Marvila, three in Olivais, two in Estrela and São Domingos de Benfica and one in Areeiro, São Vicente, Santa Clara, Campolide, Alcântara and Belém.

[8] https://github.com/evagarcia07/New_Stations/blob/main/ProposedNewStations.geojson

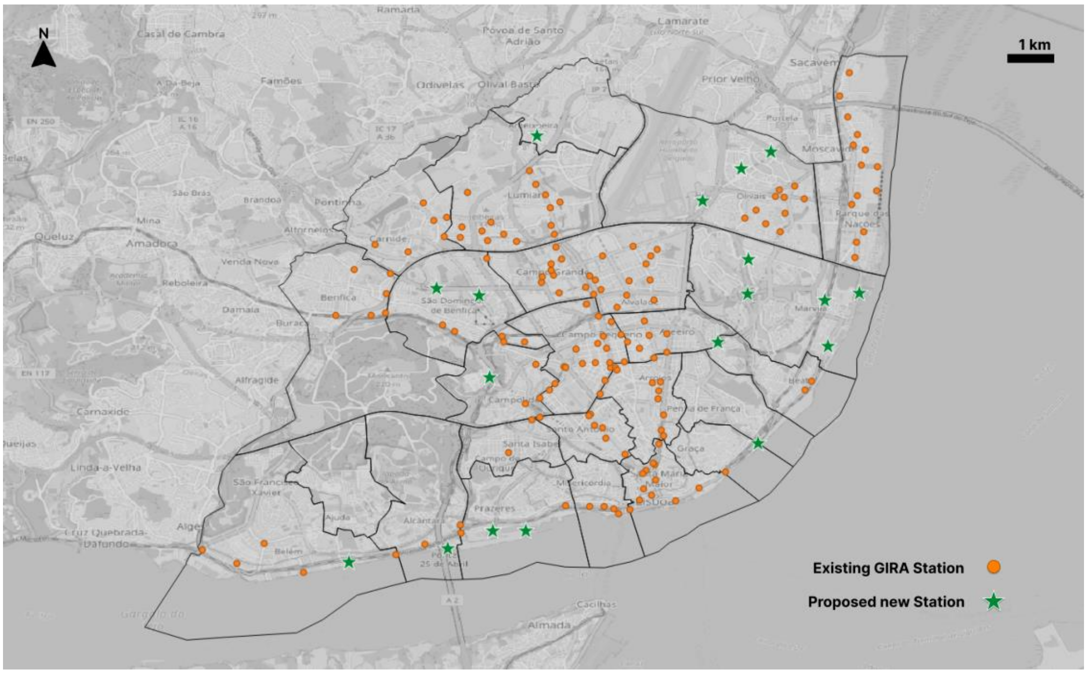

Figure 4.3 - Proposed new stations.

4.2. Temporal Analysis

The dashboard was made available online[9], and comprises six distinct pages. The first page serves as the home tab (Figure 4.4), which enables navigation to the other pages, each representing a different approach to the available data, as detailed in the next subsections.

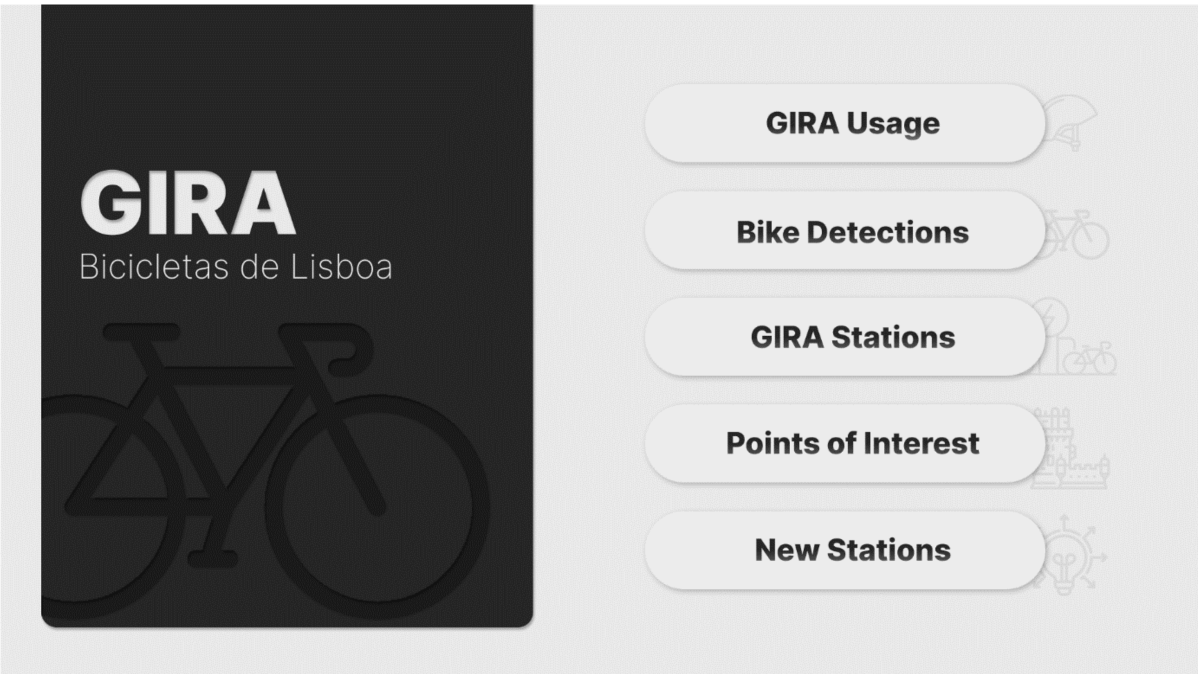

Figure 4.4 - GIRA Dashboard's Home page.

[9] https://tinyurl.com/GIRABicicletas

The temporal analysis in the dashboard created is divided into two distinct pages. The dashboard's “GIRA Usage” page (Figure 4.5) offers a detailed view of usage patterns within the BSS, focusing on key metrics such as the number of users and hours logged per month and average trip times. This page also allows filtering the analysis date.

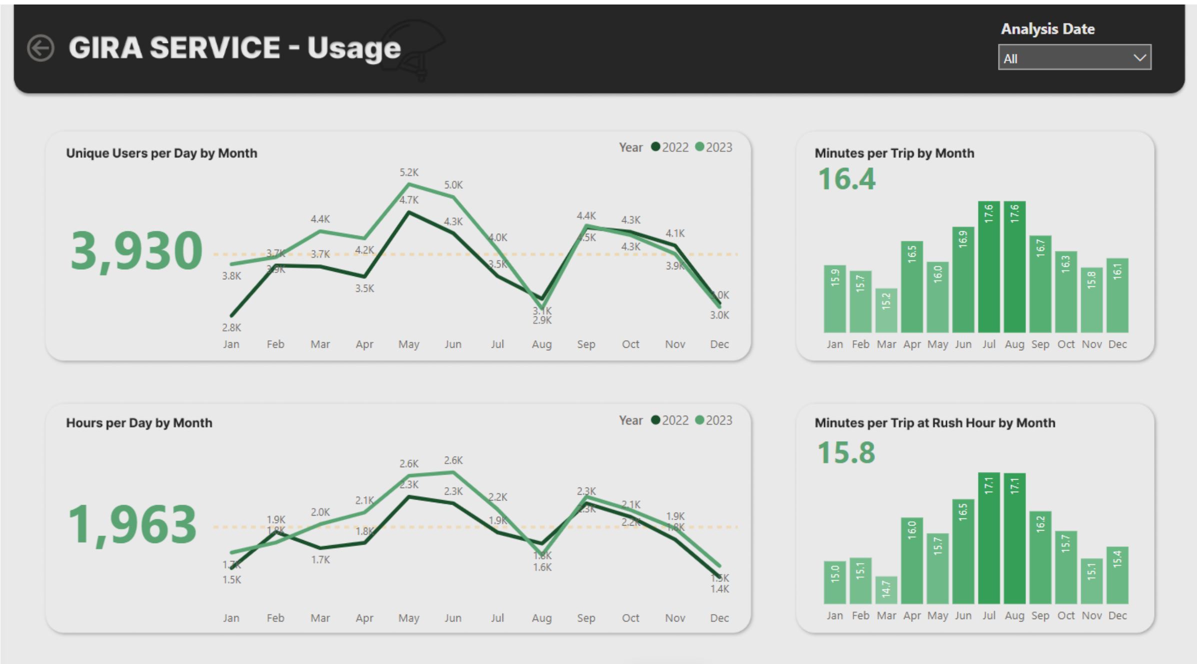

Figure 4.5 - GIRA System’s Usage Dashboard page.

The next page of the dashboard developed is “Bike Detections” (Figure 4.6), which offers an analysis of bike detection data from the 31 detectors placed across Lisbon, that can be filtered by each of Lisbon’s parishes, Hour, and Day of the Week. Users can visualize the spatial distribution of these detectors, identifying areas with higher or lower levels of bike traffic. Dynamic visuals then provide insights into usage patterns across months, weekdays, and hourly intervals, enabling an understanding of temporal trends in bike activity.

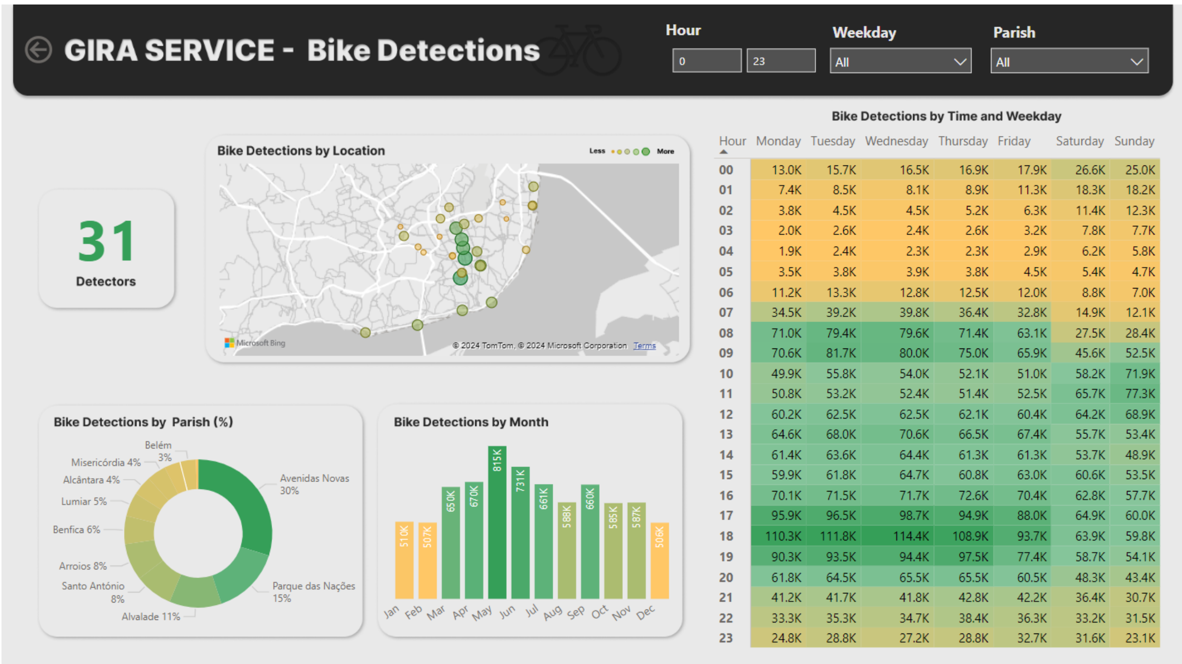

Figure 4.6 - Bike Detections Dashboard page.

4.2.1. Daily Bicycle Usage Patterns

In response to the second research question, "How does bicycle usage vary across different days of the week and times of the day?", this chapter will analyse temporal usage patterns of the GIRA bike-sharing service, which offers valuable insights into the temporal dynamics of urban mobility in Lisbon. By examining the patterns of bike detections, it can be analysed how residents use this sustainable mode of transportation in their daily lives.

A significant concentration of bike detections is observed during weekdays, notably during the morning rush from 8 to 9 AM and in the evening from 5 to 7 PM, as can be seen in Figure 4.7. The substantial increase in bike activity during these hours highlights the system's convenience and efficiency in facilitating travel to and from workplaces (Li et al., 2021), which is aligned with Albuquerque et al. (2021) study, which noticed bike demand start and end stations are in Lisbon office areas. Furthermore, this temporal focus not only illustrates the integration of the BSS into the daily life in Lisbon, but also highlights its significance as a convenient and efficient means of transportation for residents.

Bike Detections by Hour and Weekday

Hour	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
00	13.0K	15.7K	16.5K	16.9K	17.9K	26.6K	25.0K
01	7.4K	8.5K	8.1K	8.9K	11.3K	18.3K	18.2K
02	3.8K	4.5K	4.5K	5.2K	6.3K	11.4K	12.3K
03	2.0K	2.6K	2.4K	2.6K	3.2K	7.8K	7.7K
04	1.9K	2.4K	2.3K	2.3K	2.9K	6.2K	5.8K
05	3.5K	3.8K	3.9K	3.8K	4.5K	5.4K	4.7K
06	11.2K	13.3K	12.8K	12.5K	12.0K	8.8K	7.0K
07	34.5K	39.2K	39.8K	36.4K	32.8K	14.9K	12.1K
08	71.0K	79.4K	79.6K	71.4K	63.1K	27.5K	28.4K
09	70.6K	81.7K	80.0K	75.0K	65.9K	45.6K	52.5K
10	49.9K	55.8K	54.0K	52.1K	51.0K	58.2K	71.9K
11	50.8K	53.2K	52.4K	51.4K	52.5K	65.7K	77.3K
12	60.2K	62.5K	62.5K	62.1K	60.4K	64.2K	68.9K
13	64.6K	68.0K	70.6K	66.5K	67.4K	55.7K	53.4K
14	61.4K	63.6K	64.4K	61.3K	61.3K	53.7K	48.9K
15	59.9K	61.8K	64.7K	60.8K	63.0K	60.6K	53.5K
16	70.1K	71.5K	71.7K	72.6K	70.4K	62.8K	57.7K
17	95.9K	96.5K	98.7K	94.9K	88.0K	64.9K	60.0K
18	110.3K	111.8K	114.4K	108.9K	93.7K	63.9K	59.8K
19	90.3K	93.5K	94.4K	97.5K	77.4K	58.7K	54.1K
20	61.8K	64.5K	65.5K	65.5K	60.5K	48.3K	43.4K
21	41.2K	41.7K	41.8K	42.8K	42.2K	36.4K	30.7K
22	33.3K	35.3K	34.7K	38.4K	36.3K	33.2K	31.5K
23	24.8K	28.8K	27.2K	28.8K	32.7K	31.6K	23.1K

Figure 4.7 - Heatmap of Bike Detections by Hour and Weekday.

Regardless of the time of year, a consistent trend emerges within the data: the time spent on bike trips during rush hours (15.8 minutes) is consistently lower than the overall average trip duration (16.4 minutes). Despite the higher activity during peak commuting hours, users appear to choose shorter trips during this time, indicative of their tendency to use the system as a convenient mode of transportation for shorter distances.

4.2.2. Seasonal Bicycle Usage Trends

This subsection aims to answer the third research question, "What is the impact of the time of the year on bike sharing usage?", where the seasonal variations in bike-sharing activity are investigated. By examining the bike-sharing usage in relation to the time of the year, it can be seen in Figure 4.8 that the months of May and June emerge as peak periods, exhibiting higher usage counts and daily time use. Conversely, December and January, along with July and August, witness a noticeable dip in both usage count and daily time spent, indicative of reduced bike-sharing activity during vacation periods. This temporal trend suggests that vacation seasons relate with a decline in the number of users engaging with the system, while higher temperatures in work months, can lead to higher usage (Schimohr & Scheiner, 2021).

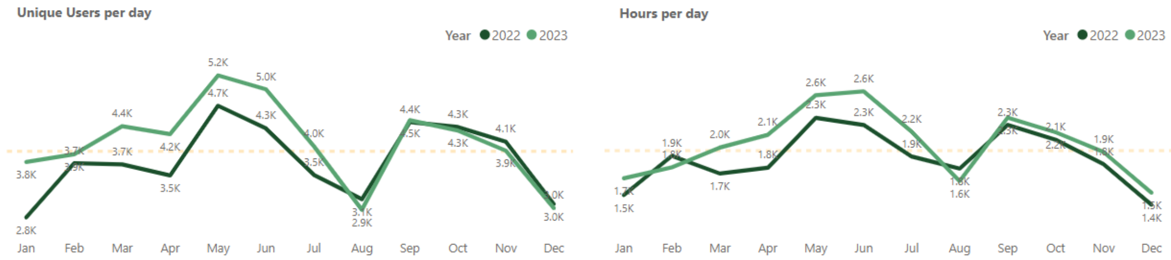

Figure 4.8 - Unique Users and Hours logged per month.

An interesting revelation surfaces during July and August in the Usage data. While these months experience a decrease in the overall usage count, there is an increase in the average time per trip (Figure 4.9). This shift in behaviour implies that, despite a reduction in the sheer number of users, those who engage with the system during the typical summer vacation months tend to embark on longer trips. The BSS's ability to serve both daily commuters and users enjoying longer trips during vacations showcases its flexibility and makes it a versatile and inclusive part of how people get around the city. This fact can be explained by analysing the weather on these months, since according to the findings of Albuquerque et al. (2021), the users of GIRA’s system reach a higher speed when there is no precipitation. Another factor influencing is that, according to Xing et al. (2020), users tend to embark on longer journeys for leisure destinations, when comparing to going to work.

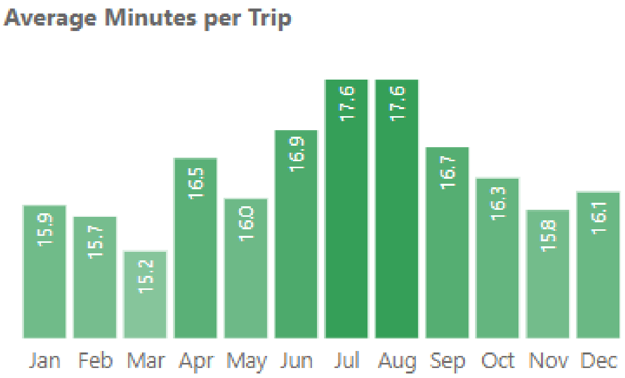

Figure 4.9 - Average Minutes per Trip by Month.

4.3. Geographic Analysis

The geographic analysis section of the dashboard offers a detailed analysis of the spatial dimensions surrounding bike usage within Lisbon. This section will introduce three distinct pages, each providing unique perspectives on the spatial distribution of the system. An additional geographic analysis can also be conducted through the previously described Bike Detections page (Figure 4.6), showing information about the detections in each parish trough every hour and day of the week.

The “GIRA Stations” page (Figure 4.10) focuses on GIRA stations and their attributes, presenting an overview of the spatial distribution of stations across Lisbon. Users can explore the key attributes of station availability, and dock availability changes ratios. An analysis can also be done on the parish level, showing how the stations are distributed across them and what parishes have stations with higher availability change. This page can also be filtered by the analysis date and parish.

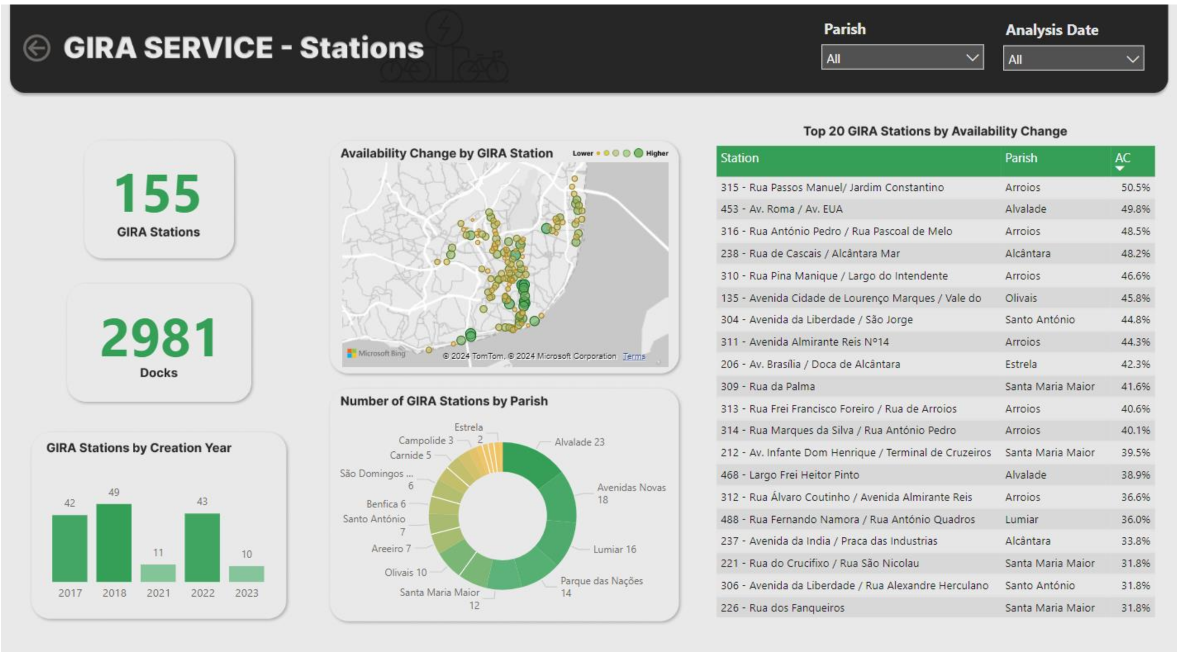

Figure 4.10 - GIRA Stations Dashboard page.

Moving forward, the “Points of Interest” page (Figure 4.11) showcases the relationship between GIRA stations and points of interest within the city. Users can review the distances between stations and various POI, being able to filter the analysis by their type (e.g. school, stations, markets, etc.) and their Parish. Maps within this page offer an analysis of the proximity between GIRA stations and POI, revealing how the two elements are integrated.

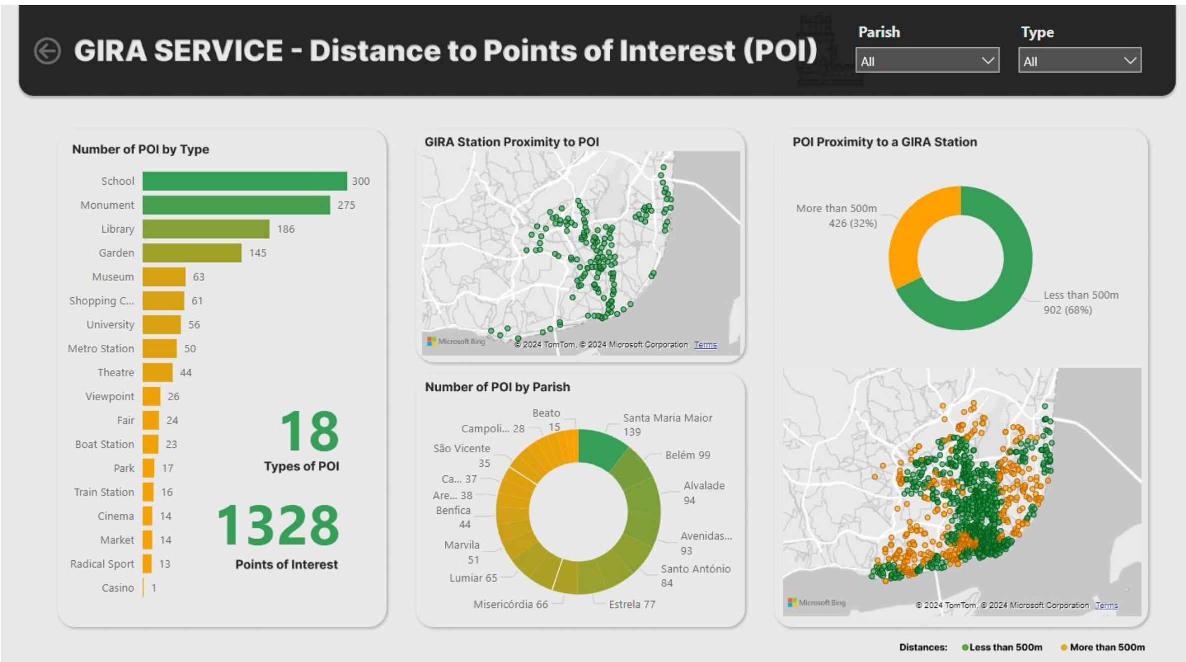

Figure 4.11 - Points of Interest Dashboard page.

Finally, the “New Stations” page (Figure 4.12) presents the results of spatial analysis conducted, with a map of the already existing stations for comparison. This page allows filtering for suitability score ranges and Parishes, allowing an interactive view of the result of the spatial analysis carried out. This feature is particularly useful for stakeholders and planners to make informed decisions about the placement of new GIRA stations.

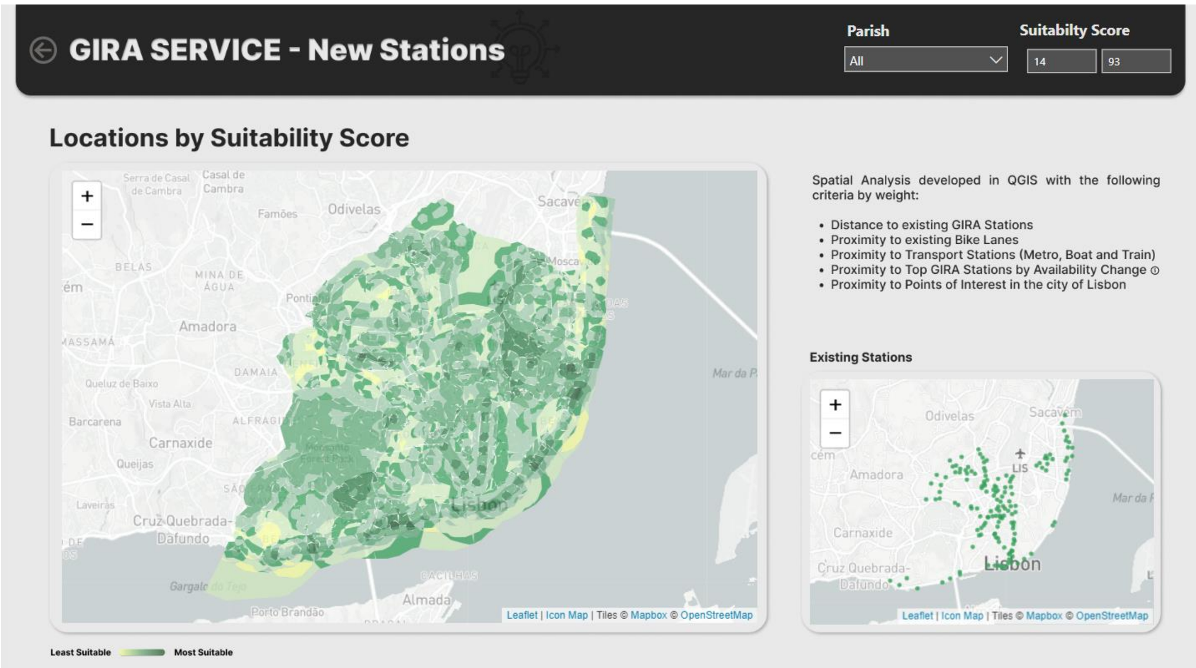

Figure 4.12 - New Stations Dashboard page.

4.3.1. Integration with the Transportation Network

To address the fourth research question, "How is the bike-sharing system integrated into existing transportation networks in the city?", this subsection examines the integration of the bike-sharing system into existing transportation networks in Lisbon, which is a critical aspect that promotes its usability and accessibility for city residents and visitors, since bike-sharing can enhance urban transport resilience and the proximity to transportation networks increases the usage of the systems (Fan & Zheng, 2020; Cheng et al., 2021). The expected time people are typically willing to walk to use a BSS is 5 to 7 minutes (Engel, 2019), which on average speed would be approximately 500 meters (Alves et al., 2021). Figure 4.13 provides a visual representation of this integration. Among the transportation hubs analysed, it's notable that the majority are within the 500-meter radius of a GIRA station, with 57 out of 89 (64%) falling within this range.

Figure 4.13 - Transportation Hubs Proximity to GIRA Stations.

Delving into specific types of transportation stations, we observe that:

- Boat terminals: 14 out of 23 (60.87%) are within 500 meters of a GIRA station.
- Metro stations: 33 out of 50 (66%) are within the 500-meter range.
- Train stations: 10 out of 16 (62.5%) fall within 500 meters of a GIRA station.

These findings highlight a proper integration of the system with existing transportation infrastructure, enhancing the accessibility and usability of all modes of transportation. However, these results also highlight that almost 36% of the transportations hubs still fall outside this 500-meter range. This showcases that there is still room for improvement by expanding the system. By locating GIRA stations near transportation hubs, the city promotes sustainable and efficient urban mobility solutions, encouraging residents and visitors to embrace multimodal transportation options for their daily commutes and activities (Fan & Zheng, 2020; Yu et al., 2021).

4.3.2. Integration with Points of Interest

In response to the fifth research question, "What are the key points where users can transition between bike sharing to points of interest around the city?", this subsection will identify and analyse strategic transition points within the city. Analysing the data on proximity between GIRA bike stations and points of interest reveals several potential transition points across Lisbon. This analysis was conducted by examining the proximity of points of interest to GIRA stations within the same 500-meter radius as the previous section (Figure 4.14) and ensuring a detailed analysis for each type of point of interest.

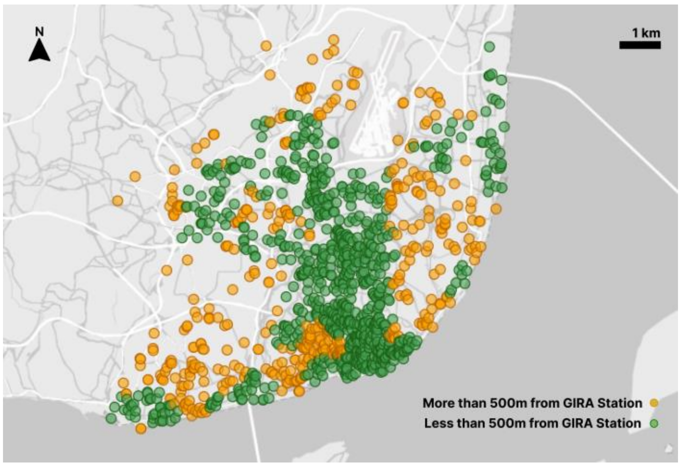

Figure 4.14 - Points of Interest by minimum distance to a GIRA Station.

With 218 monuments within a 500-meter radius of GIRA stations, users can easily explore Lisbon's rich cultural and historical heritage. Additionally, the presence of 120 libraries and 185 schools near GIRA stations supports this sustainable mode of transportation for educational and recreational needs. The city also offers different cultural experiences, with 14 cinemas, 31 theatres, and 47 museums within easy reach of GIRA stations. This enhances accessibility to cultural venues and promotes eco-friendly exploration of the city's arts scene. Lisbon's green spaces further enrich the urban landscape, with 87 gardens and 3 parks nearby, providing outdoor experiences. This proximity to several leisure points of interest promotes even further environmental sustainability through cycling, since leisure activities generally have a longer average trip distance and duration than going to work or home (Xing et al., 2020).

Despite the proper integration of GIRA bike sharing into Lisbon's cultural, educational, and recreational landscape, it's noteworthy that approximately 32% of points of interest lie outside the 500-meter radius of GIRA stations. This, along with the analysis on transportation hubs, highlights an opportunity for system improvement to further enhance accessibility to these areas and expand the reach of sustainable transportation options. By addressing the locations that fall beyond the current coverage range, GIRA can better serve the diverse needs of residents and visitors, ensuring that even more key transition points across the city are easily accessible via bike sharing, which several studies have shown to increase bike usage (Eren & Uz, 2020; Chen et al., 2021).

4.3.3. Influence on Usage Patterns

To address the sixth and last research question, "Does the proximity of bike-sharing stations to popular destinations and transportation hubs influence usage patterns?", this subsection will investigate the relationship between station locations and their surrounding environments. A correlation analysis was conducted between the number of nearby points of interest and the availability change in each station (Figure 4.15), which revealed a correlation coefficient of approximately 0.175. Since the coefficient is close to zero, it suggests that there is essentially no meaningful correlation between the calculated Availability Change metric and the distance to the Points of Interest that were extracted. This means using both variables as criterion for the suitability analysis won't affect the magnitude of their relative contribution (Shrestha, 2021).

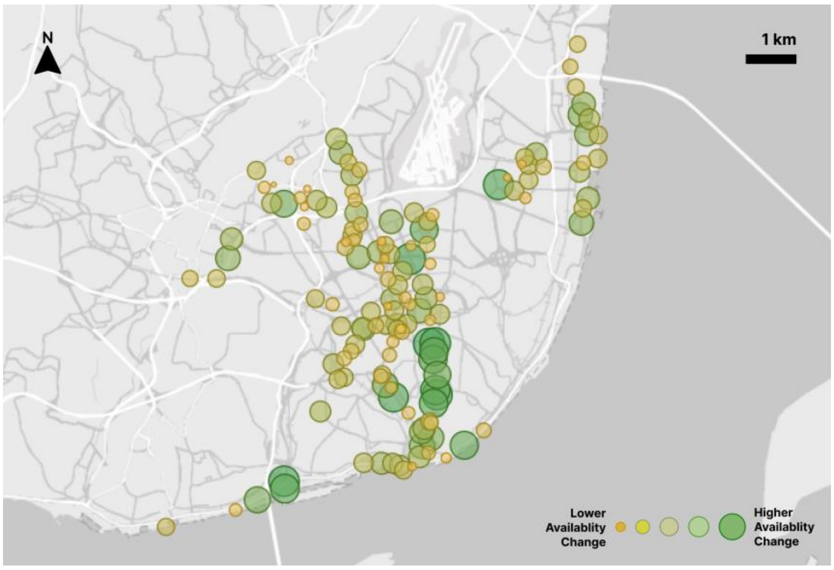

Figure 4.15 - GIRA Stations by Availability Change.

Although there is no significant correlation between the number of nearby points of interest and availability change in each station, it is worth noting that certain parishes stand out in terms of both the density of attractions and bike-sharing activity. For instance, the parishes with a higher number of points of interest include Santa Maria Maior, Belém, Alvalade, Avenidas Novas, Santo António, and Arroios. Interestingly, most of these same parishes also exhibit more bike detections, with notable areas being Avenidas Novas, Parque das Nações, Alvalade, Santo António, Arroios, and Benfica. Furthermore, when considering availability change, parishes such as Arroios, Alvalade, Alcântara, Olivais, Santo António, Estrela, and Santa Maria Maior show higher rates of fluctuation. This observation suggests that while there may not be a direct correlation between proximity to points of interest and availability change, the parishes of Santa Maria Maior, Arroios, Alvalade and Santo António seem to be hubs of both cultural activity and bike-sharing usage. On the same regard, the previous study by Albuquerque et al. (2021) showed the main areas where users unlock GIRA bikes belong to the parishes of Parque das Nações, Alvalade, Avenidas Novas and Santa Maria Maior.

5. CONCLUSIONS

This study provides an analysis of the temporal and geographic dynamics of the GIRA bike-sharing system in Lisbon, exploring usage patterns, integration with transportation networks and points of interest, and opportunities for optimization. The work involved criteria weighting using the SAW methodology and relying on existing studies' recommendations. With these weights, a MCDM combined with GIS approach was carried out in QGIS, highlighting each location in Lisbon and its suitability score for new bike stations, according to the criteria previously weighted. All this information, along with data from daily trip statistics, bike detections, bike availability and points of interest and transport stations were all integrated into Power BI, to carry out a BI approach and build a dimensional model, which allows the analysis of the data and the whole work carried out through an interactive dashboard.

The identification of areas with the highest suitability scores for new GIRA stations highlighted priority areas for expansion. These areas mainly include the parishes of Belém, Estrela, São Vicente, Penha de França, Marvila, São Domingos de Benfica, Campolide, and Olivais. Through the results of the suitability scores, 18 new stations were proposed around these areas.

In terms of temporal analysis, the research revealed clear patterns in daily and seasonal bicycle usage. Weekday bike detections, particularly during rush hours, suggest the system's seamless integration into commuters' daily routines, serving as a convenient mode of transportation for short-distance trips. Seasonal variations in bike-sharing activity, with peak periods in May and June and dips in December and January, highlight the influence of vacation periods and weather on user behaviour. Despite reduced overall usage during vacation months, the system accommodates longer trips, showcasing its versatility for both commuting and leisurely rides.

Geographic analysis reveals the proper placement of GIRA stations near transportation hubs and points of interest, enhancing multimodal connectivity and promoting sustainable urban mobility options. Furthermore, the integration with points of interest enriches the system's attractiveness and accessibility, although areas beyond the current coverage range present opportunities for expansion to serve a wider range of user needs. Moreover, while no significant correlation exists between proximity to points of interest and availability change, the parishes of Santa Maria Maior, Arroios, Alvalade and Santo António emerge as hubs of both cultural activity and bike-sharing usage.

The assessment of the GIRA bike-sharing system provides valuable insights for optimizing its performance and promoting sustainable and inclusive urban mobility in Lisbon. By handling these findings, stakeholders can develop targeted strategies to enhance system accessibility, coverage, and efficiency, ultimately improving the quality of life for residents and visitors of the city.

6. LIMITATIONS AND FUTURE WORKS

While this study has provided valuable insights into the temporal and geographic dynamics of the GIRA bike-sharing system in Lisbon, there are several limitations that should be acknowledged, along with suggestions for future research to address these limitations and further enhance the understanding of the system.

The analysis conducted in this study could be enhanced by incorporating trip origin and destination data. By analysing trip trajectories, researchers can gain a better understanding of user travel patterns and preferences, identifying popular routes, and areas for infrastructure improvement. Additionally, assessing street suitability for bike stations and bike lanes could improve the accuracy of suitability score analysis. Factors such as road width, traffic volume, and terrain elevation could influence the accessibility and safety of cycling infrastructure, guiding the strategic placement of new stations and bike lanes to maximize user convenience and safety. Additionally, the integration of data on bus stops and places of work in Lisbon could also provide valuable insights to identify areas with high demand for bike-sharing services.

The weighting methodology used in the MCDM analysis could be strengthened by incorporating stakeholder feedback, expert opinions, and empirical evidence. A more robust weighting approach would ensure that suitability score calculations accurately reflect stakeholders' preferences and goals, guiding them in making informed decisions about system expansion and optimization.

One path towards a future work is the integration of a business intelligence methodology of real-time data streams. This can provide more dynamic and up-to-date insights into system performance and user behaviour, enabling stakeholders to respond more effectively to changing conditions and user needs. Combining this approach with cloud services and more data sources, would enable the GIRA service to improve its decision making on various areas (e.g. financial and inventory models). Additionally, a simulation model that varies distinct POIs and other factors could be developed to assess how these variations influence the results of the suitability analysis.

Addressing these limitations and pursuing future research directions could contribute to the continued improvement and optimization of the GIRA bike-sharing system, ultimately promoting sustainable urban mobility and enhancing the quality of life for residents of Lisbon.

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