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Systematic Analysis of Commuting Behavior in Italy Using K-Means Clustering and Spatial Analysis: Towards Inclusive and Sustainable Urban Transport Solutions

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Abstract: Transport Demand Management (TDM) is crucial in shaping travel behavior and enhancing urban mobility by promoting sustainable transport options. This study represents a comprehensive analysis of employee commuting behavior across seventy-seven cities in Italy, with a focus on Rome as a case study. It investigates some requirements of the workplace travel plan as a TDM strategy for promoting sustainable commuting. An online survey conducted in June 2022 yielded 2314 valid responses, including 1320 from private car drivers. K-means clustering was used to identify distinct behavioral patterns among commuters, revealing four clusters based on demographic factors and transport preferences, such as age, gender, family circumstances, vehicle ownership, willingness to walk, ride bicycles, or e-scooters, and reasons for mode choice. This study analyzed Rome's public transport network, land use, and private car use. Results underscore the need for tailored transport policies that enhance inclusivity and accessibility, especially for employees with family members who cannot commute independently. A spatial analysis of Rome reveals significant infrastructure deficiencies, such as complicated transfers and inaccessible stations, which discourage PT use. Future research should explore the impact of remote work and psychological factors and conduct in-depth subgroup analyses to inform inclusive transport policy development.

Keywords: transport demand management; workplace travel plans; sustainable transport; willingness to use bicycles; e-scooters; walking; K-means clustering

Citation: Babapourdijojin, M.; Corazza, M.V.; Gentile, G. Systematic Analysis of Commuting Behavior in Italy Using K-Means Clustering and Spatial Analysis: Towards Inclusive and Sustainable Urban Transport Solutions. *Future Transp.* **2024**, *4*, 1430–1456. https://doi.org/10.3390/futuretransp4040069

Academic Editor: Lynnette Dray

Received: 18 September 2024
Revised: 3 November 2024
Accepted: 13 November 2024
Published: 19 November 2024

1. Introduction

Transport Demand Management (TDM) is a key component of transport planning that has a significant impact on travel behavior [1]. Meyer defined TDM as providing alternative mobility choices and reducing congestion by shaping travel behavior [2]. It serves as a decision-making tool to support policies to improve urban mobility [3]. Globally, a primary objective of TDM is to shift users toward sustainable modes of transport, a priority increasingly highlighted in policy agendas [1]. TDM encompasses various strategies, including Workplace Travel Plans (WTPs), which encourage employees to adopt sustainable transport options and reduce reliance on single-occupancy vehicles for commuting [3]. The successful implementation of WTPs depends on the collaboration and commitment of multiple stakeholders—employees, employers, broader societal support, and a supportive regulatory framework [4,5]. Recent research suggests that companies can play a critical role in promoting sustainable transport options for employees [6], with organizational support, especially from managers, significantly enhancing employees' willingness to engage in environmental initiatives [7].

Additionally, improving the accessibility and connectivity of public transport (PT) can support WTP objectives considerably, though this aspect has been less frequently researched [8]. Pro-environmental consciousness—linked to environmental concerns related to car ownership or use, as well as a sense of responsibility for environmental care—also influences transport choices. Studies suggest that teachers, for example, exhibit more environmental care than students and administrators [9].

In creating a WTP to promote sustainable commuting among employees, it is essential to understand the reasons behind the choice of certain transport modes, including motivations for using or avoiding PT [10]. Factors that encourage walking as part of a commute [11] and mixed evaluations of cycling, walking, and PT [12] should also be considered. Conversely, some studies focus on the reasons employees prefer private cars or motorcycles [13]. Research has shown that WTP strategies can lead to modest but meaningful increases in active commuting [12]. To effectively promote sustainable commuting, it is important to understand the behaviors, motivations, and barriers faced by users in different urban contexts [14,15]. For example, one study explored employees' willingness to adopt sustainable transport modes and offered recommendations to improve commuting sustainability [16]. Another study highlighted that while employees are willing to use PT if it is available, factors such as childcare needs can pose barriers [17].

2. Literature Review

Research on employee travel behavior highlights that urban design and workplace characteristics significantly influence commuting patterns and mode choices. Factors such as development density, land-use mix, and accessibility to non-work-related activities shape the frequency and types of trips employees undertake [18]. Socio-demographic factors—such as age, gender, income, and vehicle ownership—also play a critical role in shaping travel behavior and mode preferences [19]. For employees with caregiving responsibilities, demands related to assisted transport impact their travel patterns and often necessitate greater schedule flexibility [20].

Most employees prefer commuting by private vehicle due to perceived convenience, time efficiency, and status [21]. However, issues like limited parking, mental stress associated with driving, and environmental concerns can prompt some employees to consider public transport options, especially when these are supported by workplace incentives [21].

In recent years, awareness of environmental impacts has become a key factor, with employees expressing greater openness to sustainable options if companies demonstrate support for green commuting initiatives [22].

A variety of factors influence employees' commuting mode choices, including age, gender, income, car ownership, workplace location, and proximity to home [11,23–25]. Additional factors—such as childcare responsibilities, parking availability, social and built environment characteristics, health considerations, and specific transport mode availability—also play significant roles [26]. For example, employees who have access to dedicated bike lanes or pedestrian-friendly routes are more likely to consider active commuting options, such as cycling or walking [27]. Travel-related variables, particularly travel cost and travel time, are crucial determinants in commuting decisions [28]. Moreover, research indicates that policies improving transport connectivity and reducing costs are instrumental in encouraging public transport use [29].

The characteristics of the surrounding built environment, such as the location of industrial areas and the availability of public transportation, significantly affect sustainable commuting options [30]. Access to shared and active mobility services, like bike-sharing or carpooling options, has also shown the potential to shift employee preferences toward more sustainable commuting modes, particularly in cities with high levels of congestion [31]. Additionally, studies have found that workplace incentives, such as subsidized transport passes, can further motivate employees to choose environmentally friendly options [32].

Added Value of the Current Study

Despite the potential benefits highlighted in previous research, several gaps remain in the effective implementation of Workplace Travel Plans (WTPs). First, more investigation is needed to understand what motivates employees to adopt sustainable commuting behaviors. Second, the rise of shared mobility services (e.g., e-scooters and bicycles) necessitates an examination of employees' willingness to use these options. Third, it is essential to consider various factors to ensure that travel plans are inclusive and address diverse commuting needs. Finally, a comprehensive assessment across multiple cities or regions within a country can provide valuable insights into the varied preferences of the workforce. Additionally, the relationship between the locations of workplaces, residential areas, and the connectivity of transport networks requires further exploration.

Given these gaps, the objectives of this study are multifaceted and include a systematic analysis of the commuting behavior of the Italian workforce. This case study aims to identify commuting patterns and address unsustainable travel choices. While most existing studies focus on a single city, this research uniquely encompasses seventy-seven cities across Italy. This broader scope yields a more generalizable set of findings that can inform national-level policy and practice.

This study investigates different demographic groups to determine their transport needs and preferences. By categorizing employees into various transport preference groups based on survey data, it will explore variations influenced by factors such as age, gender, family circumstances, vehicle ownership, and willingness to walk, use bicycles, or ride e-scooters. A spatial analysis of urban areas, particularly in Rome, will identify critical factors that discourage the use of public transport. This research will assess the impact of current transport policies and infrastructure on accessibility and inclusiveness, especially for individuals with family members who cannot commute independently.

Finally, this study underscores the importance of developing a sustainable, equitable, and efficient urban transport system by addressing the diverse needs of urban commuters through inclusive policies.

In summary, expanding the Transportation Demand Management (TDM) framework through WTPs and understanding varying commuter needs across multiple cities provide valuable insights for designing inclusive transport policies. This review section establishes the context for the objectives and methodology of this study, which are discussed further in the following sections.

This paper begins with an introduction (Section 1) and is followed by a literature review (Section 2) that highlights the need for a more comprehensive analysis of the commuting behavior of the Italian workforce. Next, Section 3 outlines the materials and methods, detailing the dataset, descriptive statistics, clustering method, and an assessment of preferences between private car drivers and public transport users in Rome as part of the case studies. This section also explores the interaction between land use and transport. Section 4 presents the results, while Section 5 offers a discussion of the main findings. Finally, Section 6 concludes this paper by summarizing the key findings and suggesting directions for future research based on these significant results.

3. Materials and Methods

A multistage methodology was employed, starting with an online survey conducted in June 2022, which covered seventy-seven cities in Italy (Figure 1a) and yielded 2314 valid responses, including 1320 valid responses as private car drivers (Figure 1b). Among this dataset, the ten cities with more than thirty responses each accounted for approximately 84% of the total responses, and their population altogether was 8,404,832 (see Table 1 and Figure 2). As Table 1 shows, Milan, Bari, and Rome (Italy) had the highest number of responses, collectively accounting for 62.58% of the entire dataset. Slovin's formula [33] was used to determine whether 1940 responses were statistically appropriate for analyzing a population of 8,404,832 (Equation (1)). In this formula, n is the sample size, N is the population size, and e is the margin of error. For a 95% confidence level (a common choice), the margin of error is 5%. For a population of over eight million, with a 95% confidence level and 5% margin of error, this study needs around 385 responses. Since the current sample has 1940 responses, it exceeds the required sample size for a reliable analysis, even at higher levels of accuracy. Therefore, the sample size of this study was statistically sound to generate significant results.

$$n = \frac{N}{1 + Ne^2}, \tag{1}$$

(a) (b)

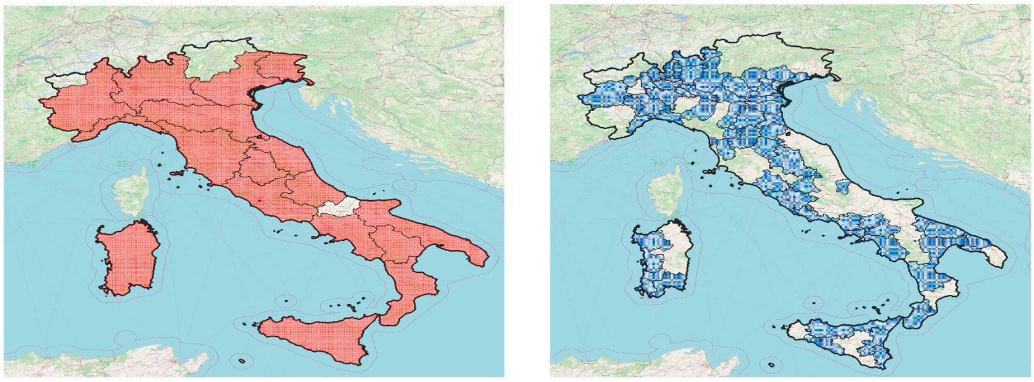


Figure 1. (**a**) Cities covering the entire dataset (2314 valid responses); (**b**) cities covering only private car drivers (1320 valid responses).

Table 1. Population of cities, distribution of city counts, and percentages in the study dataset.

Name of the City	Count (Sample)	Percentage (Sample)	Population [34]
Milan	879	37.99	1,371,850
Bari	307	13.27	316,212
Rome	262	11.32	2,754,719
Monza and Brianza	127	5.49	873,935
Catania	124	5.36	298,209
Napoli	68	2.94	911,697
Torin	56	2.42	846,926
Bologna	47	2.03	390,518
Varese	39	1.69	78,819
Genova	31	1.34	561,947
Total	1940	83.84	8,404,832

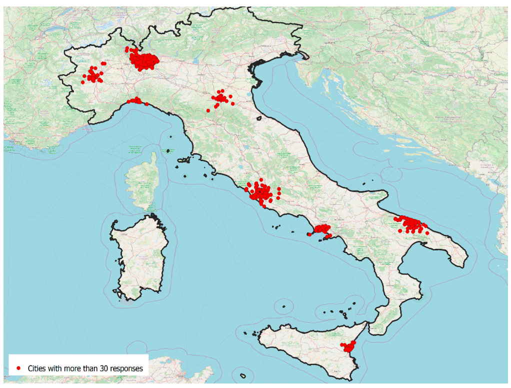


Figure 2. Ten cities with the highest response rate.

Then, data analysis was developed for the whole dataset and Rome as a specific case study. Rome was chosen for a more detailed assessment of the PT network, land use, and transport interactions for several reasons, more specifically: (i) Large population: Rome is the capital city of Italy and one of the largest cities in the country, with a substantial population that relies heavily on private cars and PT; (ii) Diverse transport modes: Rome has a complex and varied PT network that includes buses, trams, metro lines, and suburban trains; (iii) Appropriate response rate: the high response rate from Rome in the survey provides a robust dataset for analysis (262 responses). The availability of a large amount of data specific to Rome allows for a more detailed and accurate assessment of PT and land use interactions, and ultimately, (iv) the authors are from Rome and are familiar with the challenges this city poses.

The clustering method was used to analyze the data. Cluster analysis is a statistical technique used to group similar objects or observations [35,36]. The two primary types of clustering algorithms are hierarchical and K-means [37]. Hierarchical clustering begins with individual clusters, merging them sequentially, while K-means requires specifying the number of clusters in advance [37].

When compared through query redirection, K-means demonstrated better performance and accuracy than hierarchical clustering [38]. However, each method has unique strengths and weaknesses, especially regarding the relevance of segment descriptions and the statistical significance of differences between segments [39]. K-means is particularly noted for its efficiency and scalability with large datasets [40], often outperforming hierarchical clustering in execution time and memory usage [41].

Two-step cluster analysis is another versatile method for segmenting data, particularly effective with large datasets and mixed variable types [42,43]. It can automatically determine the optimal number of clusters and handle both continuous and categorical variables [43].

The current study represents a new application of cluster analysis in the context of employee travel behavior, offering fresh insights into how diverse groups of employees commute and how this information can be used to optimize transportation policies and workplace planning. Since this study covered different cities, the clustering method not only includes people and their travel preferences from a single city but also provides a general overview of employees' systematic commuting patterns, including their limitations and preferences.

Rome's PT system was also evaluated. The metro lines of Rome and the respondents' locations were illustrated on the map. Land use and transport interactions were explained, and analysis was performed regarding private car drivers only.

3.1. Descriptive Statistics—Whole Dataset

In this section, the descriptive statistics are presented, providing an overview of the respondents' demographic profiles, commuting patterns, and preferences, as well as offering a foundational understanding of the data before delving into the cluster analysis. More specifically, these are as follows:

- **Gender and age distribution:** Males predominate and represent about 60% of respondents. The most common age group is 41 to 55 years, with approximately 71% of the participants, with other age groups having smaller proportions.
- **Household composition**: Responses to household composition varied among employees. Some (17%) live in single-person households, while 33% live in households with four or more members. The proportion of respondents whose family members needed transport assistance was evenly split.
- **Employment status**: Most respondents (85%) work full-time, five days a week. Smaller proportions work part-time (9%) or in shifts (6%).
- **Travel choices:** A significant majority (58%) of respondents use a private car daily, while 28% use PT. In addition, 77% of private car drivers reported being satisfied or very satisfied with private car usage.
- **Factors influencing transport choices**: Cost is a significant factor in transport choices, with 24% of respondents citing it as their main reason for choosing a mode of travel.

The desire for independence when traveling is even more influential, cited by 34% of respondents. Parking issues were a concern for only 10% of respondents.

- **Vehicle ownership:** Most respondents own a private car (83%), followed by a motorcycle (15%). Bicycles and e-scooters each account for less than 4% of vehicle ownership.
- **Willingness to walk and use alternative modes of transport**: More employees show interest in a company-purchased bicycle (42%) compared with walking (34%) and e-scooters (27%), though most employees are still not interested in any of these sustainable options.

3.2. K-Means Clustering

The clustering analysis involved segmenting the 2314 participants into k clusters, where k is the predetermined number of clusters. Each data point was assigned to the nearest centroid, and these centroids were then updated based on the average of all data points in that cluster. The process was repeated until the centroids did not change significantly between iterations. Data were input into SPSS v.26 statistical software to perform K-means clustering. The variables used for K-means clustering in this study include the following:

- Demographic factors: gender and age.
- Work situation: full-time, part-time, and shift work.
- Household composition: household size and presence of family members who cannot travel independently.
- Mobility experience: experience in using shared mobility.
- Reasons for mode choice: cost, parking problems, being independent while traveling, and accompanying others.
- Vehicle ownership: private car, motorcycle, bicycle, and e-scooter.
- Willingness to use alternative transport modes: willingness to walk, willingness to use a bicycle purchased by the company, and willingness to ride an e-scooter.
- Mode of transport used to commute: private car, motorcycle, PT, bicycle/e-scooter, walking, and multimodal transport.

Determination of the Number of Clusters

Determining the optimal number of clusters was a crucial step in the K-means clustering procedure, which requires the number of clusters to be known in advance. In the current study, the well-established elbow method [44] was used to determine the appropriate number of clusters. The total within-cluster sum of squares (WSS) was plotted against the number of clusters, revealing a clear "elbow" point. This point indicates that adding more clusters no longer significantly improves the fit of the data.

However, relying solely on one method to determine the number of clusters is insufficient. In addition, the Davies–Bouldin Index was examined. In cluster analysis, Davies–Bouldin is a metric commonly used to measure cluster quality. It assesses how well-separated and compact the clusters are, with lower values indicating better clustering [45].

The elbow point was observed at three clusters, suggesting that additional clusters beyond this number would not notably enhance clustering efficiency (see Figure 3).

From the Davies–Bouldin Index plot, it can be observed that the optimal number of clusters is likely 3, as it has the lowest Davies–Bouldin Index (see Figure 4). Therefore, three clusters were determined to be the optimal choice for this dataset.

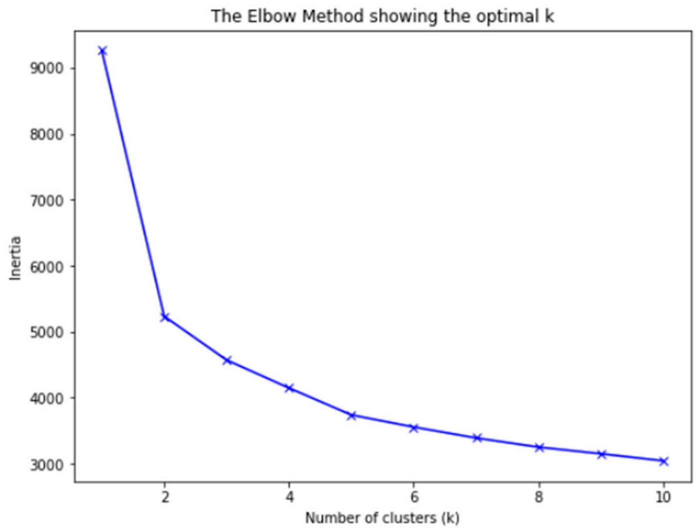


Figure 3. The elbow method.

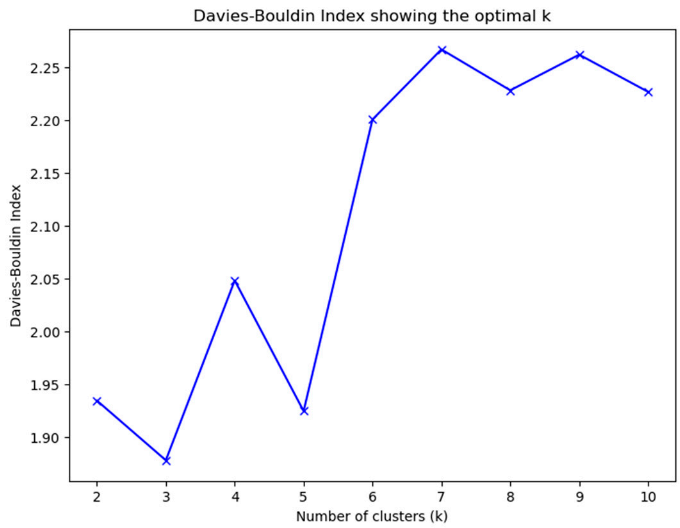


Figure 4. The Davies–Bouldin Index.

3.3. Case Study of Rome

3.3.1. Descriptive Statistics

The survey conducted throughout Italy yielded 262 valid responses from Rome. Analysis of the Rome survey revealed demographic details: 62% of respondents were male, and 38% were female. A considerable proportion, 59%, were between the ages of 41 and 55. In addition, 44% said they had family members who could not travel independently. When asked about their reasons for choosing a private car, 30% cited travel time as a key factor, 44% valued independence while traveling, 33% cited a lack of PT, 32% cited a lack of other alternatives, and 27% preferred driving because it was less stressful. Rome had 167 private car drivers compared with 66 PT users. Among PT users, ten use only buses, twenty-nine use only the metro, nine use both metro and bus services, twelve use both train and metro services, and three use a combination of train, metro, and bus services.

3.3.2. Metro in Rome

The modest satisfaction rate of PT users can be partly explained by contemporary land use and mobility patterns. Until the 1930s, Rome was still a monocentric city, with its form laid more than 2000 years ago and plans to expand towards the Tyrrhenian Sea and create new districts, some of which were to be served by a few metro lines, a novelty at the time, as the only transit supply was surface. This expansion was interrupted by the outbreak of World War II (WWII), halting the plans to serve the city through the planned metro lines (Figure 5). The post-war reconstruction of the city was dictated by housing needs, with transit replicating and expanding the pre-war supply, except for a metro short leg planned in 1941 and opened in 1955. The Master Plan of the 1960s, still focused on housing as a priority, replicated the pre-war approach to transit, and later, ambitious plans to build a network composed of ten metro lines (the so-called 1986 Intermetro Plan) were never executed. The plan's focus on road infrastructure and the increasing motorization rate exacerbated the poor recognizance of metro lines as mass connection opportunities.

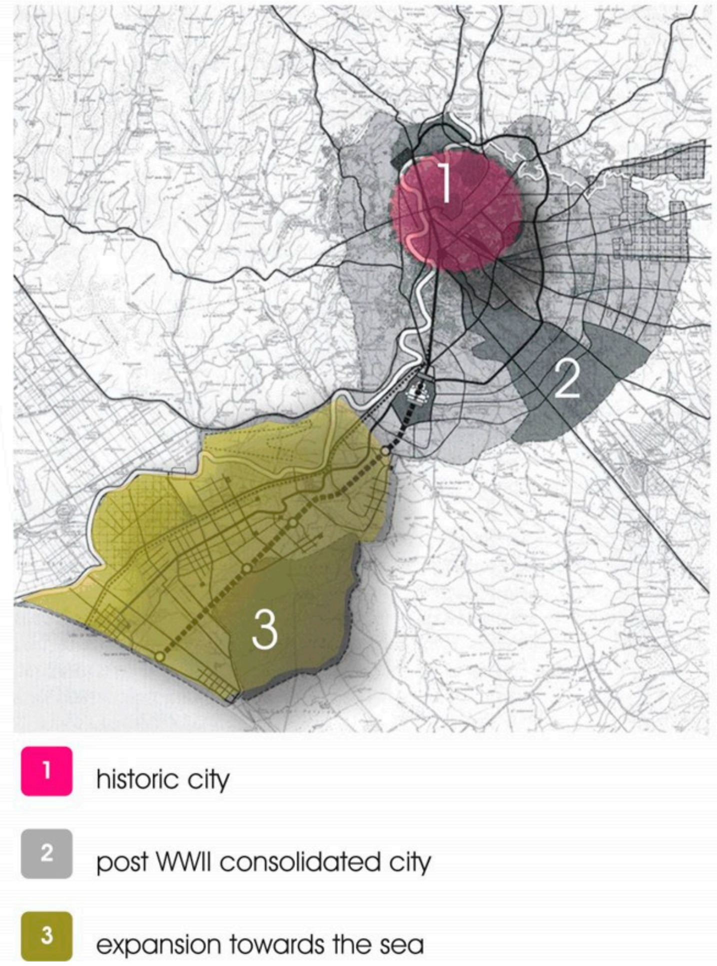


Figure 5. Development of the city, according to [46].

As a result, the city still relies on a bus network, as the backbone of the current metro supply in Rome is represented by a network of 60 km, with three lines [47] complementing a capillary bus network and a series of suburban railway lines (the so-called FM lines) connecting Rome with the neighboring municipalities [48]. The city facts are presented in Table 2.

More specifically, metro line A, marked in orange on the map (Figure 6), was the second line built in the capital, from Ottaviano to Cinecittà. It intersects with line B at the Termini station. The frequency during peak hour is one train every 2 min; at other times, it drops to one train every 10 or 15 min [47].

The Rome metro line B, marked by the color blue (Figure 6), is the expansion of the 1941 original leg and connects the city from the south to the northeast, where it splits into two branches: one to the east and one to the northeast. Its termini are Laurentina (south), Rebibbia (east), and Jonio (northeast). The frequency during peak hour is one train every 3 min; at other times, it drops to one train every 6 min [49].

Table 2. Key mobility figures in Rome.

Urban Features		Year	Source
Population (inh)	2,755,309	2023	[34]
Area (sqkm) Density (inh/sqkm)	1287 2141	2022	[50]
Registered fleet (veh)	1,823,155 pass. cars 389,122 PTWs 7616 buses and coaches	2023	[51]
	194,366 others 2,414,259 total		
Registered electric modes (veh)	13,133		[50]
Car sharing fleet (veh) Motorization rate ([veh/inh] ∗ 1000), Rome Motorization rate ([veh/inh] ∗ 1000), Italy	1408 930 684	2022	[52] [52] [53]
Modal share (%) (2020)	60 pass. cars	2020	[54]
	20 transits		
	18 walking		
	2 bikes		
Travel time (min)	40.6	2024	[55]
Congestion level (%)	38	2021	[56]
Pedestrianized areas (sqm) Bike network (km) Peak daily access to the central LTZs (veh) Transit—bus fleet (veh.) Transit—bus network (km) Average bus route length (km) Average bus travel time (m) Bus commercial speed (km/h)	393,277 230 120,000 2244 4711 12.8 41.5 16.9	2018	[50]
Bus network density (route km/ network km) Electric kick-scooter fleet, estimated (veh)	3.98 14,517	2022	[52]
Park&Ride supply (parking lot) Pay-for-parking, on-street supply (parking lot) Average daily trips (unit) Population daily traveling (%) Average trip per capita (trip/inh) Multimodal trips ([private and public modes] 1000) Average travel time (min)	14,958 74,134 5,900,000 98 2.37 80 <30	2020	[57]
Built-up area per capita (sqm/inh) Land use efficiency (Ratio of land consumption growth rate to population growth rate, 10-year basis)	108 3.6	2015	[58]

Rome's metro line C is characterized by its green color (Figure 6). It runs from Monte Compatri-Pantano in the eastern suburbs of Rome to San Giovanni near the city center, where it joins line A. It is the last metro line built in the city and the first to be fully automated [59] as an upgrade of a former suburban railway line.

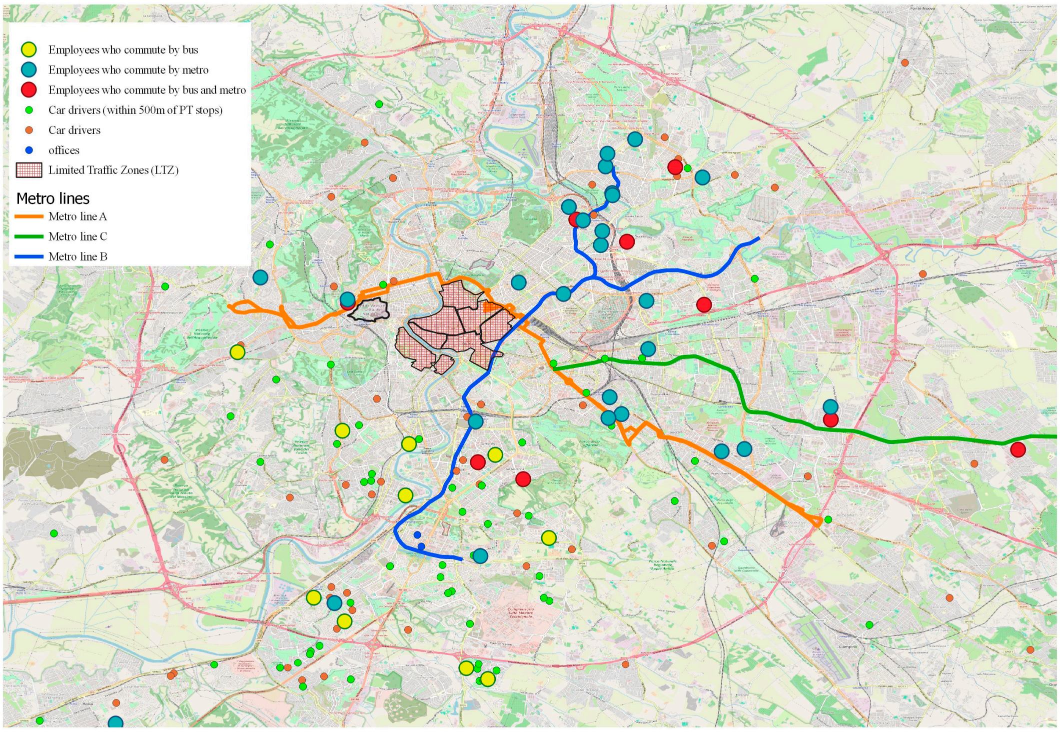


Figure 6. Metro lines and locations of employees in Rome.

Other metro legs are currently under construction to connect the consolidated city with the city center. However, the city relies on a widespread bus network as a backbone to support everyday commutes, with many of the alternatives launched at the beginning of the 20th century (car sharing, carpooling, etc.) [60] remaining niche options.

3.3.3. Land Use and Transport Interactions

Due to poor acknowledgment of transit (and metro lines) as a priority in both pre- and post-WWII Master Plans, the interaction between land use and transit supply in Rome remains a critical and often an under-researched aspect of workplace travel planning. This includes examining how land use policies influence commuting patterns and the feasibility of sustainable transport options. Although in Rome's recent Sustainable Urban Mobility Plan and Master Plan (both fully enforced in the 2000s) complementarity of land use development and transit supply is contemplated, the city still suffers from the delays and inconsistencies of the previous century. As an example, as shown in Figure 6, transport infrastructure and land use are intricately linked: Here, the metro lines (lines A, B, and C) complement the backbone of the city's PT system, connecting different neighborhoods and facilitating accessibility, but the type of PT supply differs. For example, the upper northwestern area of the city is poorly served (Figure 6). This stems from the previous Master Plans, which limited the city expansion in that area due to its hilly morphology; the post-WWII need for housing, however, gave rise to an initially unauthorized building phenomenon, with unplanned infrastructure, later legalized. As a result, although densely populated and mostly monofunctional (residential), this area is served only by the bus network, with the metro A line terminal still marginal. The city center, with its historical layout, in turn, has been preserved since the 1970s, with increasing pedestrianization and traffic restrictions (enforcing a limited traffic zone, further replicated elsewhere outside the city's historical core). Within this push and pull approach [60], the opening of metro line A in the 1980s and its connection with line C recently contributed to the increase in the accessibility of these central areas, characterized by a very mixed land use. It is noted, however, that several stations along line A are poorly accessible to physically challenged passengers (including the very central Spagna, Barberini, Repubblica, Vittorio Emanuele, and San Giovanni) due to the lack of lifts or escalators connecting to the platforms [61]. Notably, San Giovanni is an interchange station between lines A and C of the Rome metro. Consequently, transferring from line C to line A is challenging for many passengers. Eventually, the southern and western areas of the city, being planned along ancient Roman arterials, somehow benefitted from such available surface infrastructure as leading axes in the urban fabric, developing new districts, still served mostly by surface transit.

Land use in general and urban planning patterns still reflecting the above-mentioned approach of the Master Plans were not able to cope with the ever-rising motorization rate, which is now one of the highest in Europe [62]. Traffic congestion and poor parking supply are still critical issues in the city, especially in consolidated and new districts, with long-lamented safety [63] and livability [64] problems.

It is not surprising, then, that the survey results provide the following snapshot of the city (Figure 6):

- **Limited traffic zone:** The red and white grid area indicates the restricted traffic zones in the city's historic center. These zones are designed to minimize private car congestion, improve pedestrian and cyclist safety, and promote a cleaner urban environment.
- **Drivers (brown circles):** Scattered throughout the map, indicating significant private car use throughout the city.
- **Drivers within 500 m of PT stops (green circles):** These represent drivers within 500 m of PT stops, which are widely distributed across the city. Residential areas are well served by PT, especially buses and trams.
- **Employees who commute by bus (yellow circles):** These are scattered throughout the map, indicating that bus use is widespread in various parts of the city.
- **Employees who commute by both bus and metro (red circles):** These are located near metro lines, but are more widely distributed, indicating a mix of bus and metro usage for commuting.
- **Office locations (dark blue circles):** These represent office buildings and are concentrated around metro line B. This spatial arrangement underscores the recent city's strategy to facilitate efficient commuting and reduce private car dependency.

4. Results

In the results section of this study, a detailed analysis of the dataset is presented through the examination of four distinct clusters. Each cluster reveals unique characteristics and behaviors among the respondents, particularly regarding their transport preferences and demographic profiles. The following subsections interpret the composition and key attributes of each cluster, supported by statistical validation using Analysis of Variance (ANOVA). ANOVA compares variance between groups relative to within-group variance, with applications in various experimental sciences [65].

The ANOVA statistical analysis is used to illustrate patterns rather than strictly validate causal relationships [66]. When using clustering, like K-means, the goal is often to maximize the similarity within clusters and minimize the similarity between clusters. The F-value in an ANOVA test helps evaluate how distinct these clusters are [67]. Equation (2) shows the details of F-value as follows:

$$F = \frac{Intergroup\ variance}{Intragroup\ variance} \tag{2}$$

Intergroup Variance (Between-Group Variance): This measures how different the clusters are from one another. It looks at the differences between the centroids (the means) of the clusters. A high intergroup variance indicates that the clusters are well separated and distinct from each other.

Intragroup Variance (Within-Group Variance): This measures how similar the points within each cluster are to each other. It looks at the spread of data points around the centroid of each cluster. A low intragroup variance means that the points are closely grouped around their respective cluster centroids.

Valid Clustering: When F-value is significantly greater than 1, it indicates that the clusters formed are distinct from one another (high intergroup variance) and that the data points within each cluster are like each other (low intragroup variance). This is a sign of a good clustering solution, as it demonstrates both clear separation and cohesion among the clusters.

4.1. Three Clusters

Based on the Davies–Bouldin Index, this study initially proceeded with k-means clustering using 3 clusters. Table 3 presents the results of the ANOVA used to validate the clusters. Some variables yielded non-significant results, such as "Shifts" (p = 0.443), "Ownership of a regular motor vehicle" (p = 0.059), "Ownership of an e-bicycle" (p = 0.878), and "Ownership of an e-scooter". Consequently, a clustering analysis with four clusters was performed to assess if all variables would become significant.

Table 3. Analysis of Variance (ANOVA) outcomes for three-cluster validation.

ANOVA						
	Cluster		Error			
	Mean Square	df	Mean Square	df	F	Sig.
Full-time employee	1.471	2	0.128	2311	11.475	0.000
Part-time employee	1.217	2	0.084	2311	14.54	0.000
Shifts employee	0.045	2	0.056	2311	0.814	0.443
Employee with experience of using a shared mobility	0.114	2	0.023	2311	4.915	0.007
Cost is the reason for chosen mode	11.704	2	0.173	2311	67.528	0.000
Being independent during the trip is the reason for chosen mode	10.172	2	0.216	2311	47.08	0.00
Having parking problems is the reason for the chosen mode	1.772	2	0.087	2311	20.436	0.000
Accompanying others is the reason for the chosen mode	2.777	2	0.071	2311	39.181	0.000
Employees with a private car	7.351	2	0.136	2311	54.181	0.000
Employees with a motorcycle	0.354	2	0.125	2311	2.838	0.059
Employees with an e-bicycle	0.003	2	0.023	2311	0.13	0.878
Employees with an e-scooter	0.099	2	0.034	2311	2.913	0.055
Employees interested in walking	4.68	2	0.222	2311	21.066	0.000
Employees interested in using a bicycle purchased by the company	6.424	2	0.239	2311	26.895	0.000
Employees interested in riding an e-scooter	3.596	2	0.192	2311	18.72	0.000
Employees with private car as their mode choice	38.086	2	0.211	2311	180.713	0.000
Employees with PT as their mode choice mode choice	16.095	2	0.148	2311	109.029	0.000
Employees with bicycle/e-scooter as their mode choice	0.154	2	0.025	2311	6.136	0.002
Employees with walking as their mode choice	0.217	2	0.026	2311	8.513	0.000
Employees with multimodal as their mode choice	0.876	2	0.072	2311	12.202	0.000
Employees with motorcycle as their mode choice	0.873	2	0.074	2311	11.745	0.000
Gender	1.221	2	0.239	2311	5.114	0.006
Age	124.15	2	0.493	2311	251.829	0.000
Having family members who cannot travel independently	95.609	2	0.167	2311	572.245	0.000
Number of family member	1219.756	2	0.309	2311	3948.47	0.000

4.2. Interpretation of Each Cluster

The data show the distribution of cases in four clusters as follows: Cluster 1 contains 513 cases, Cluster 2 contains 373 cases, Cluster 3 contains 810 cases, and Cluster 4 contains 618 cases. With a total of 2314 valid cases and no missing data, the dataset is complete and shows varying numbers of cases across the clusters. Table 4 shows the interpretation of each cluster, and Table 5 presents the results of the ANOVA used to validate the clusters.

Table 4. Final cluster center.

Variables	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Full-time employee	0.86	0.90	0.78	0.90
Part-time employee	0.10	0.05	0.14	0.05
Shifts employee	0.04	0.05	0.08	0.05
Employee with experience of using a shared mobility	0.04	0.03	0.01	0.03
Cost is the reason for chosen mode	0.49	0.43	0.07	0.15
Being independent during the trip is the reason for chosen mode	0.16	0.18	0.45	0.44
Having parking problems is the reason for the chosen mode	0.21	0.19	0.01	0.06
Accompanying others is the reason for the chosen mode	0.03	0.01	0.19	0.02
Employees with a private car	0.66	0.63	0.98	0.89
Employees with a motorcycle	0.27	0.20	0.09	0.09
Employees with a bicycle	0.03	0.04	0.02	0.02
Employees with an e-scooter	0.07	0.03	0.02	0.03
Employees interested in walking	0.58	0.54	0.74	0.68
Employees interested in using a bicycle purchased by the company	0.44	0.55	0.68	0.58
Employees interested in riding an e-scooter	0.65	0.72	0.80	0.73
Employees with private car as their mode choice	0.02	0.12	0.99	0.79
Employees with PT as their mode choice mode choice	0.41	0.51	0.00	0.11
Employees with bicycle/e-scooter as their mode choice	0.07	0.05	0.00	0.01
Employees with walking as their mode choice	0.05	0.05	0.00	0.03
Employees with multimodal as their mode choice	0.21	0.12	0.00	0.04
Employees with motorcycle as their mode choice	0.24	0.14	0.00	0.02
Gender	0.34	0.34	0.46	0.40
Age	1.92	2.27	2.01	1.26
Having family members who cannot travel independently	0.69	0.12	0.75	0.16
Number of family member	2.65	0.59	2.69	0.69

This clustering analysis divides employees into four clusters based on their work status, commuting preferences, mode choices, and personal factors. Here is a breakdown of each cluster's key characteristics:

Cluster 1

Employment Status: Predominantly full-time employees (86%) with low representation of part-time (10%) and shift workers (4%).

Travel Mode Preferences: Moderate interest in cost-effective travel (49%) and private car ownership (66%), with a significant portion using motorcycles (27%).

Independence in Commuting: Lower independence preference (16%) compared with clusters focused on independence.

Mode Choice: Primarily public transport (41%) and private cars (2%), with a moderate interest in multimodal travel (21%) and some walking (58%).

Demographics: Mostly male (34%), with an average age of about 40–45 years (score ~1.92).

Family Needs: A high percentage have family members needing assistance (69%), with an average of ~2.65 dependents.

Cluster 2

Employment Status: High concentration of full-time employees (90%) and low part-time (5%) and shift workers (5%).

Travel Mode Preferences: Moderate cost consideration (43%) and public transport reliance (51%), with some using motorcycles (20%).

Mode Choice: Primarily public transport (51%) with some multimodal users (12%) and moderate interest in walking (54%) and company bicycles (55%).

Demographics: Equal male representation (34%), older (age score ~2.27, suggesting an average age around 45–50).

Family Needs: Few have family travel dependencies (12%), with few dependents (~0.59 per household).

Cluster 3

Employment Status: Mostly full-time (78%) and part-time (14%), with a small presence of shift workers (8%).

Travel Mode Preferences: Emphasis on independence (45%) rather than cost (7%), with a strong preference for private cars (98% ownership).

Mode Choice: The vast majority choose private cars (99%), with minimal interest in public transport (0%), bicycles, or walking.

Demographics: Slightly more male (46%) and middle-aged (age score ~2.01, ~45 years).

Family Needs: Many have dependent family members (75%) and large family sizes (2.69 dependents on average).

Cluster 4

Employment Status: High proportion of full-time (90%) and low part-time (5%) or shift workers (5%).

Travel Mode Preferences: Balance between independence (44%) and cost (15%) considerations, with high private car ownership (89%).

Mode Choice: Primarily use private cars (79%) and some public transport (11%); moderate walking interest (68%).

Demographics: Higher male representation (40%), slightly younger (age score ~1.26, ~35 years).

Family Needs: Few dependents needing assistance (16%), with an average of ~0.69 dependents.

Cluster 1 and Cluster 2 are more public-transport oriented, although Cluster 1 also considers multimodal options and Cluster 2 leans older with fewer family travel needs.

Cluster 3 is distinct for its strong preference for private cars, driven by independence, and includes more dependent family members, suggesting a family-centered travel behavior.

Cluster 4 also prioritizes private cars but balances independence with cost. This cluster skews slightly younger and has fewer dependent family members.

Table 5. Analysis of Variance (ANOVA) outcomes for four-cluster validation.

ANOVA	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
Full-time employee	2.215	3	0.127	2310	17.496	***
Part-time employee	1.254	3	0.083	2310	15.077	***
Shifts employee	0.197	3	0.056	2310	3.553	**
Employee with experience of using a shared mobility	0.132	3	0.023	2310	5.738	**
Cost is the reason for chosen mode	24.239	3	0.152	2310	159.413	***
Being independent during the trip is the reason for chosen mode	14.443	3	0.206	2310	70.041	***
Having parking problems is the reason for the chosen mode	5.475	3	0.081	2310	67.453	***
Accompanying others is the reason for the chosen mode	5.139	3	0.067	2310	77.114	***
Employees with a private car	16.682	3	0.120	2310	138.527	***
Employees with a motorcycle	4.353	3	0.119	2310	36.490	***
Employees with an e-bicycle	0.062	3	0.023	2310	2.677	**
Employees with an e-scooter	0.232	3	0.034	2310	6.846	***
Employees interested in walking	4.563	3	0.220	2310	20.704	***
Employees interested in using a bicycle purchased by the company	5.907	3	0.237	2310	24.942	***
Employees interested in riding an e-scooter	2.435	3	0.192	2310	12.676	***
Employees with private car as their mode choice	135.416	3	0.068	2310	1992.718	***
Employees with PT as their mode choice mode choice	31.731	3	0.120	2310	263.512	***
Employees with bicycle/e-scooter as their mode choice	0.649	3	0.024	2310	26.520	***
Employees with walking as their mode choice	0.299	3	0.025	2310	11.822	***
Employees with multimodal as their mode choice	5.319	3	0.066	2310	80.983	***
Employees with motorcycle as their mode choice	6.906	3	0.066	2310	104.371	***
Gender	2.100	3	0.237	2310	8.858	***
Age	102.827	3	0.467	2310	220.115	***
Having family members who cannot travel independently	65.489	3	0.165	2310	397.197	***
Number of family member	775.532	3	0.358	2310	2166.694	***

*** Significance at 1% level, ** Significance at 5% level.

4.3. Final Cluster Centers Interpretation

Table 6 show the characteristics of the sample and the clusters. The summary of each cluster is as follows:

Cluster 1: This group consists mainly of full-time employees who cite cost and parking problems as the main reasons for their choice of transport mode. They are generally younger compared with other clusters and show a mild representation of females. Members of this cluster have a higher incidence of disabled family members and have expressed an interest in walking and using company-provided bicycles.

Cluster 2: Comprising mainly full-time employees, this cluster prioritizes cost when choosing their mode of transport. They show moderate interest in riding e-scooters, using company-provided bicycles, and walking. The average age of this group is older, and the proportion of women is lower than that in other clusters.

Cluster 3: This cluster includes both full-time and part-time employees who value independence when traveling as a primary reason for their transport choice. They predominantly own a private car and have a strong interest in walking, using company-provided bicycles and e-scooters. This group has a higher proportion of females and a greater incidence of disabled family members.

Cluster 4: Predominantly composed of full-time employees, this group values independence when traveling and mainly owns private cars. On average, they are younger and have a strong interest in walking, using company-provided bicycles, and using e-scooters.

Table 6. Cluster data results.

						Sample	
		Cluster 1	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Count**	**(%)**
	Cluster size (%)	22%	16%	35%	27%	100%	
	Cluster size	513	373	810	618	2314	
Variables							
Gender	Female	18.7%	13.9%	40.6%	26.8%	919	39.7%
	Male	24.4%	17.6%	31.3%	26.7%	1395	60.3%
Age	≤35	11.7%	0.0%	3.3%	85.0%	213	9.2%
	36–40	19.6%	8.1%	30.6%	41.7%	235	10.2%
	41–55	24.1%	16.0%	39.3%	20.7%	1641	70.9%
	56–60	22.5%	35.4%	42.1%	0.0%	178	7.7%
	60≤	14.9%	61.7%	23.4%	0.0%	47	2.0%
Household size	0	0.0%	42.2%	0.0%	57.8%	386	16.7%
	1	0.0%	35.5%	0.0%	64.5%	566	24.5%
	2	39.4%	1.5%	54.0%	5.1%	587	25.4%
	3	35.2%	0.0%	64.8%	0.0%	657	28.4%
	4	43.2%	0.0%	56.8%	0.0%	118	5.1%
Having family members who cannot travel independently	Yes	31.9%	4.1%	55.3%	8.7%	1105	47.8%
	No	13.2%	27.1%	16.5%	43.2%	1209	52.2%
Full-time employee—5 days per week	Yes	22.0%	17.1%	32.1%	28.3%	1961	84.7%
	No	19.8%	10.8%	51.3%	18.1%	353	15.3%
Part-time employee	Yes	22.7%	8.3%	53.7%	15.3%	216	9.3%
	No	22.1%	16.9%	33.1%	27.9%	2098	90.7%
Shift employees	Yes	15.3%	14.6%	47.4%	22.6%	137	5.9%
	No	22.6%	16.2%	34.2%	27.0%	2177	94.1%
Employee with experience using shared mobility	Yes	38.2%	21.8%	10.9%	29.1%	55	2.4%
	No	21.8%	16.0%	35.6%	26.6%	2259	97.6%
Cost is the reason for chosen mode	Yes	15.0%	12.1%	42.8%	30.1%	559	24.2%
	No	44.5%	28.8%	10.6%	16.1%	1755	75.8%
Being independent during the trip is the reason for chosen mode	Yes	10.3%	8.5%	46.3%	34.9%	788	34.1%
	No	28.3%	20.1%	29.2%	22.5%	1526	65.9%
Having parking problems is the reason for the chosen mode	Yes	47.8%	31.4%	4.9%	15.9%	226	9.8%
	No	19.4%	14.5%	38.3%	27.9%	2088	90.2%
Accompanying others is the reason for the chosen mode	Yes	9.2%	1.1%	83.7%	6.0%	184	8.0%
	No	23.3%	17.4%	30.8%	28.5%	2130	92.0%

Table 6. *Cont.*

						Sample	
		Cluster 1	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Count**	**(%)**
Employees with a private car	Yes	17.6%	12.3%	41.4%	28.7%	396	82.9%
	No	44.2%	34.6%	4.0%	17.2%	1918	17.1%
Employees with a motorcycle	Yes	40.2%	22.2%	21.3%	16.3%	338	14.6%
	No	19.1%	15.1%	37.3%	28.5%	1976	84.7%
Employees with an e-bicycle	Yes	30.9%	25.5%	23.6%	20.0%	55	2.4%
	No	22.0%	15.9%	35.3%	26.9%	2259	97.6%
Employees with an e-scooter	Yes	41.5%	14.6%	19.5%	24.4%	82	3.5%
	No	21.5%	16.2%	35.6%	26.8%	2232	96.5%
Employees interested in walking	Yes	27.2%	21.4%	26.8%	24.6%	1516	65.5%
	No	19.5%	13.3%	39.3%	27.8%	798	34.5%
Employees interested in using a bicycle purchased by the company	Yes	29.3%	17.3%	26.9%	26.6%	979	42.3%
	No	16.9%	15.3%	41.1%	26.8%	1335	57.7%
Employees interested in riding an e-scooter	Yes	29.3%	16.9%	26.4%	27.4%	614	26.5%
	No	19.6%	15.8%	38.1%	26.5%	1700	73.5%
Employees with private car as their mode choice	Yes	0.6%	3.4%	59.9%	36.1%	1345	58.1%
	No	52.1%	33.7%	0.5%	13.6%	969	41.9%
Employees with PT as their mode choice mode choice	Yes	44.4%	40.8%	0.0%	14.7%	468	20.2%
	No	16.5%	9.9%	43.9%	29.7%	1846	79.8%
Employees with bicycle/e-scooter as their mode choice	Yes	61.7%	28.3%	0.0%	10.0%	60	2.6%
	No	21.1%	15.8%	35.9%	27.2%	2254	97.4%
Employees with walking as their mode choice	Yes	41.0%	29.5%	3.3%	26.2%	61	2.6%
	No	21.7%	15.8%	35.9%	26.7%	2253	97.5%
Employees with multimodal as their mode choice	Yes	60.4%	25.3%	0.5%	13.7%	182	7.9%
	No	18.9%	15.3%	37.9%	27.8%	2132	92.1%
Employees with motorcycle as their mode choice	Yes	64.0%	27.5%	0.5%	7.9%	189	8.2%
	No	18.4%	15.1%	38.1%	28.4%	2125	91.8%

4.4. Comparison of 3 Clusters vs. 4 Clusters

To compare whether the results with three clusters are better than those with four clusters, the key aspects from both sets of results are broken down:

General Observations. Three clusters: Most factors show strong statistical significance ($p < 0.05$), indicating that the clusters are distinct in terms of these variables. There are a few non-significant results, such as “shifts” ($p = 0.443$), “Ownership of a normal motor” ($p = 0.059$), and “Ownership of an e-bike” ($p = 0.878$). Four clusters: almost all variables show statistical significance with significant p-values, suggesting a strong distinction between the clusters across most factors.

ANOVA and F-values. Higher F-values indicate that the variable has more discriminative power between clusters. For most variables, the F-values in the three-cluster solution are lower than in the four-cluster solution. This suggests that the four-cluster solution provides more differentiation across these variables. For example:

Cost: $F = 67.528$ (three clusters) vs. 159.413 (four clusters)

Mode choice PT: $F = 109.029$ (three clusters) vs. 263.512 (four clusters)

Significance and Interpretation. Both solutions show high significance levels across most variables ($p < 0.05$). In both the three-cluster and four-cluster solutions, important factors like age, family structure, cost, independence, and willingness to adopt alternative modes of transport are statistically significant. However, the four-cluster solution yields higher F-values across the significant variables, indicating that it provides more pronounced distinctions between groups for these variables.

Interpretation of Non-significant Variables. In the three-cluster solution, more variables are non-significant, such as "shifts", "Ownership of an e-bike", and "Ownership of an e-scooter". This might indicate that with three clusters, the model captures fewer distinct patterns for these variables. In contrast, the four-cluster solution has no non-significant variables, which suggests that it captures more variation and differences in the data.

Therefore, based on the ANOVA results, the four-cluster solution appears to provide better differentiation across the key variables, as evidenced by higher F-values and no non-significant factors. While the three-cluster solution is still reasonable, the four-cluster solution is likely better at capturing nuances in the data.

4.5. Gender-Based Analysis

The descriptive statistics reveal distinct differences between female employees and the overall population (both male and female employees) in terms of employment type, mode of transportation, and caregiving responsibilities. Female employees are less likely to work full-time (71.82%) compared with the overall group (84.75%), with a higher percentage in part-time roles (18.72% vs. 9.33%). Additionally, female employees show a lower likelihood of choosing motorcycles (6.09% vs. 14.61%) or e-scooters (1.20% vs. 3.54%) but a higher interest in e-bicycles (9.25% vs. 2.38%). They are also less likely to cite cost as a mode choice reason (19.80% vs. 24.16%) but more likely to have caregiving responsibilities, with 54.52% having family members who cannot travel independently compared with 47.75% across all genders. These differences suggest unique transportation needs for female employees, potentially supporting arguments for gender-sensitive transport policies.

In the cluster analysis of this study, all employees (both male and female) were included to capture overarching patterns in commuting behavior. However, as noted in the descriptive statistics, significant differences exist between female employees and the overall population regarding employment type, transportation mode preferences, and caregiving responsibilities. For example, a lower percentage of female employees work full-time and rely on modes like motorcycles or e-scooters, while a higher percentage are part-time and favor e-bicycles. Additionally, female employees are more likely to have caregiving responsibilities, which could impact their commuting needs and choices.

These distinctions suggest that combining genders might not fully capture gender-specific transportation patterns. As a limitation, this analysis may overlook unique clusters specific to female employees. Future studies could address this by conducting separate cluster analyses for each gender or incorporating gender-specific variables to yield more nuanced insights. This limitation, however, does not detract from the primary findings but highlights the potential benefit of gender-sensitive transport policies.

4.6. Age-Based Analysis

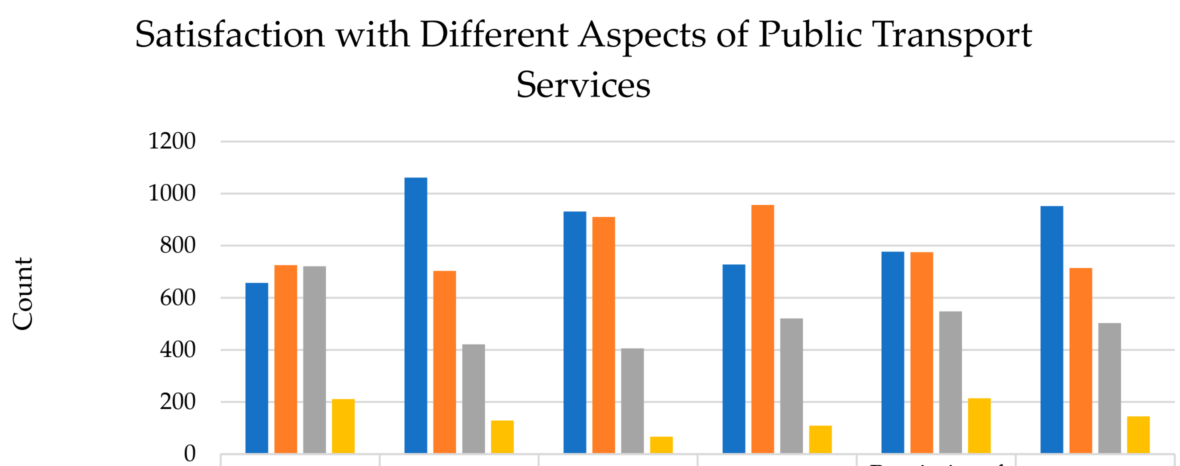
The "Up to 40" age group has a higher percentage of full-time employees (90.18%) compared with all age groups (84.75%) and is more interested in alternative transportation modes: 41.29% are interested in walking (versus 34.49% in all age groups), 56.25% are interested in company-provided bicycles (versus 42.31%), and 40.18% are interested in riding e-scooters (versus 26.53%). They also rely less on private cars as their primary mode (50.67% versus 58.12%) and have a higher percentage choosing multimodal transport (10.27% versus 7.87%). This group also has fewer family members who cannot travel independently (35.94% versus 47.75%) and a higher proportion with only one family member (23.44% versus 16.68%). These statistics highlight the younger group's preference for independent and flexible commuting options, reflecting distinct commuting patterns likely influenced by their lifestyle and family structures.

In the current analysis, notable age-based differences in commuting patterns were identified. The "Up to 40" age group, for instance, includes a higher proportion of full-time employees and shows a stronger preference for alternative transportation options, such as walking, company-provided bicycles, and e-scooters, compared with all age groups. They also exhibit less reliance on private cars and a higher tendency toward multimodal transport options. Additionally, fewer members in this age group have family members who cannot travel independently, which may afford them more flexibility in their commuting choices.

These differences suggest that age may play a significant role in transportation preferences and constraints. While cluster analysis considers all age groups together, future work could explore age-specific clusters to provide a more tailored understanding of these commuting behaviors. This limitation acknowledges that distinct needs and preferences associated with younger age groups, likely shaped by lifestyle and family structures, may not be fully captured when combining all age groups.

4.7. Employee Satisfaction with Public Transport Services

The data reflect user satisfaction across six key aspects of public transport services, categorized into four levels: Very Unsatisfied, Unsatisfied, Satisfied, and Very Satisfied (see Figure 7). The specific attributes assessed were (i) Information Provided; (ii) Travel Time; (iii) Comfort; (iv) Cost; (v) Proximity of PT Stops; and (vi) Punctuality.



	Information	Travel Time	Comfort	Cost	Proximity of PTstops	Punctuality
Very unsatisfied	657	1061	931	728	777	952
Unsatisfied	725	703	910	956	775	714
Satisfied	721	421	406	521	548	503
Very satisfied	211	129	67	109	214	145

Very unsatisfied Unsatisfied Satisfied Very satisfied

Figure 7. Satisfaction with different aspects of public transport services.

Overall Trends:

High levels of dissatisfaction are prevalent across most attributes, with most responses falling under the Very Unsatisfied and Unsatisfied categories. The Very Unsatisfied rating is the most frequent across multiple categories, particularly for Travel Time (1061 responses), Comfort (931), and Punctuality (952).

Positive satisfaction levels are notably low, with few users rating any category as Very Satisfied.

Key Insights:

Travel Time and Punctuality are the most criticized aspects of public transport, with the highest number of Very Unsatisfied responses. Cost is another area of concern, with most users expressing dissatisfaction. Information and Proximity of PT Stops exhibit slightly higher satisfaction levels, suggesting these aspects may hold potential for improvement and are relatively better received by users. Comfort is also a significant pain point, with minimal positive responses indicating widespread dissatisfaction.

4.8. Two-Step Clustering

The same variables used in the k-means clustering analysis were applied in this two-step approach, ensuring consistency in the clustering framework. The results of the two-step clustering analysis reveal a silhouette measure that fell within the "fair" range, indicating moderate cluster quality. This finding suggests that while the clusters formed are somewhat distinct, there may be overlaps or ambiguity among certain groups (see Figure 8).

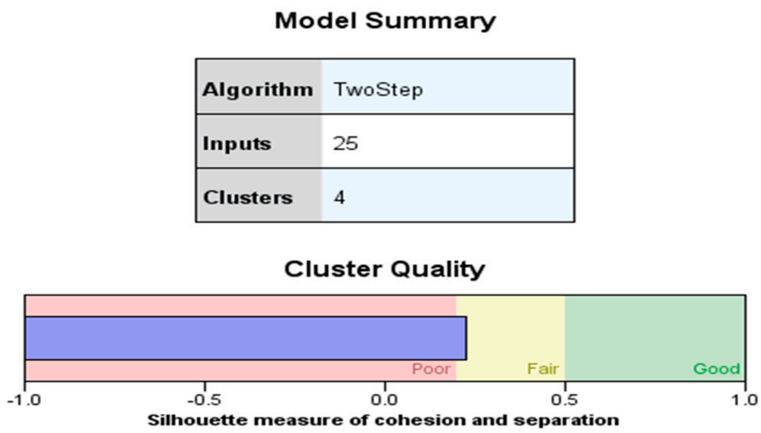


Figure 8. Two-step clustering results.

4.9. Rome's Public Transport

The evaluation of Rome's PT system revealed the following key findings:

Preference to drive a private car: The green dots located near bus and metro stops indicate that even with PT options available, a considerable number of people prefer to drive a private car.

Transfer complexity: The need to transfer between lines, such as from line C to line B via line A, results in significant delays and waiting times. This complexity can act as a disincentive to the use of PT, highlighting the need for more direct connections or improved transfer facilities.

Accessibility: Transferring from line C to line A is a challenge for many passengers, particularly those with reduced mobility.

Reasons for mode choice: For most employees, the main reason for driving a private car is independence during the trip and travel time. Conversely, PT users indicated that parking problems and cost issues are the factors for choosing PT to commute to work.

Living near metro lines: The data suggest that people living near different metro lines have different travel times by private car. Those who live near the starting station of metro line B (Laurentina) have short travel times and are close to transit (mostly bus) stops but still prefer to use a private car. See Table 7, which shows examples of employees who live within five hundred meters of the PT and are remarkably close to the metro but who prefer to travel by private car. This is not surprising given the prominent level of motorization in the area.

Implications for urban planning: The example of employees who live near PT but prefer to drive highlights the need to understand individual preferences. Improving the attractiveness or convenience of PT options could address this.

Table 7. Example of employees who live within five hundred meters of the PT and remarkably close to the metro but who prefer to drive a private car.

Location of the Employee	Age	Travel Time by Private Car (Minutes)
Near the metro C	56–60	45
	41–55	45
Near the metro A	41–55	45
	41–55	40
	56–60	50
	56–60	40
	41–55	65
	60≤	60
	41–55	40
Near the metro B	41–55	15
	41–55	5
	41–55	10

5. Discussion

This study provides an insightful analysis of the systematic commuting behavior of employees in Italy using data from an online survey. The findings highlight the different transport needs and preferences of different demographic groups and the importance of tailored transport policies and services to increase inclusivity and accessibility, as already stressed in the literature [68,69].

Cluster 1 consists of younger full-time employees concerned with parking and cost, who prefer company-provided bicycles and walking, often with family members who cannot commute independently. Cluster 2 includes older full-time employees with cost concerns showing moderate interest in e-scooters and company-provided bicycles. This group has fewer women than others. Cluster 3 primarily consists of private car owners who value independence when traveling, own private cars, and show strong interest in walking and e-scooters. There is a higher representation of females with family members who cannot commute independently. Cluster 4, on the other hand, represents younger individuals who prioritize independence in their commuting choices. This group is gender-balanced and shows a strong preference for active transport options such as cycling and walking.

The demographic analysis of Rome shows that most of the male respondents, primarily between the ages of 41 and 55, have a significant private car dependency due to factors such as travel time and the desire for commuting independence. The results also show that private car users were more satisfied (77%) than PT users (35%). This disparity suggests that existing PT infrastructure may not be meeting the needs or expectations of many commuters, further emphasizing the need for the revision of the current transport policy.

Spatial analysis reveals uneven access to PT across the city, with private car drivers dispersed throughout the city. Interestingly, private car usage near PT stops suggests ongoing issues with transport preferences or accessibility. Furthermore, infrastructure challenges, including transfer complexity and accessibility issues at certain metro stations, discourage the use of PT.

The clustering analysis highlights the need for comprehensive transport policies that address the specific challenges faced by different demographic groups. For instance, the higher incidence of family members with disabilities in clusters 1 and 3 necessitates the provision of transport that is accessible to people with disabilities. To further support these users, it is important to encourage employers to offer flexible working hour options. This would reduce the pressure on commuting during peak times for employees who need to care for disabled family members.

Flexible work arrangements (FWAs) have been shown to benefit both organizations and employees. Successful implementations of FWAs can increase productivity, reduce costs, and improve employee satisfaction [70]. Key factors for successful FWAs include mature dialogue between employers and employees and consideration of both parties' interests [70]. Interventions that positively impact workers' health include enforcing occupational health and safety regulations, providing flexible working arrangements, and implementing certain organizational changes to shift work schedules [71]. Employer-induced initiatives focusing on working time, care arrangements, and supervisor training have been found to decrease work–family conflict, improve physical health and job satisfaction, and reduce absenteeism and turnover intentions [72]. Royal Bank Financial Group's successful implementation of work–family–life initiatives, including dependent care programs and flexible work arrangements, demonstrates the positive outcomes of such interventions [73].

Additionally, providing technological support for telecommuting (teleworking) can minimize the need for daily commutes. The COVID-19 pandemic significantly influenced telecommuting trends and commuting behaviors. Studies show an increase in remote work adoption, leading to reduced reliance on private cars and public transport, which has implications for sustainable transport and urban planning [74,75]. Telecommuting rates vary by job type, income level, and gender, with higher earners and professionals more likely to work remotely [74–76]. Remote work offers substantial benefits, such as reduced commuting time and cost, increased productivity, enhanced work–life balance, flexible working hours, and autonomous task management [77,78]. However, challenges persist, particularly psychological ones, including feelings of isolation due to limited face-to-face interactions and the absence of informal workplace conversations [77]. Telecommuting can also lead to physical inactivity and difficulties in managing family responsibilities, such as childcare and workload, which may blur boundaries between work and personal life. These effects are compounded by family dynamics, particularly in households with children, where access to childcare facilities has become a decisive factor in telecommuting decisions [79]. Furthermore, remote work has created stronger links between travel behavior and organizational practices, with approximately a third of remote working time spent away from home, promoting more flexible work schedules, fewer peak-hour commutes, and potentially more sustainable travel habits [74,75].

Moreover, real-time information on accessible transport options, such as the availability of wheelchair-accessible vehicles and elevators at metro stations, is essential. This would enable families to plan their routes more efficiently, ensuring their specific needs are met. A comprehensive suite of real-time transport services [80] improves accessibility and convenience for public transport users across the city. These services include live tracking for buses and metro lines, allowing commuters to plan routes more effectively, reduce waiting times, and improve travel efficiency. Inclusivity is also a priority, with dedicated resources for people with disabilities providing accessible options and facility information. Together, these resources make public transport more reliable, accessible, and user-friendly, significantly improving the commuting experience in the city (see Figure 9). By integrating these workplace and transport solutions, we can create a more inclusive and supportive environment for all demographic groups.

Investments in infrastructure, creating safe pedestrian routes, and expanding cycle lanes should also be prioritized. Such improvements would not only promote active transport options but also enhance the overall convenience and safety of commuting, as emphasized by many researchers and policymakers. Ultimately, creating a more interconnected and accessible transport network will support the shift towards sustainable commuting practices and reduce dependency on private cars.

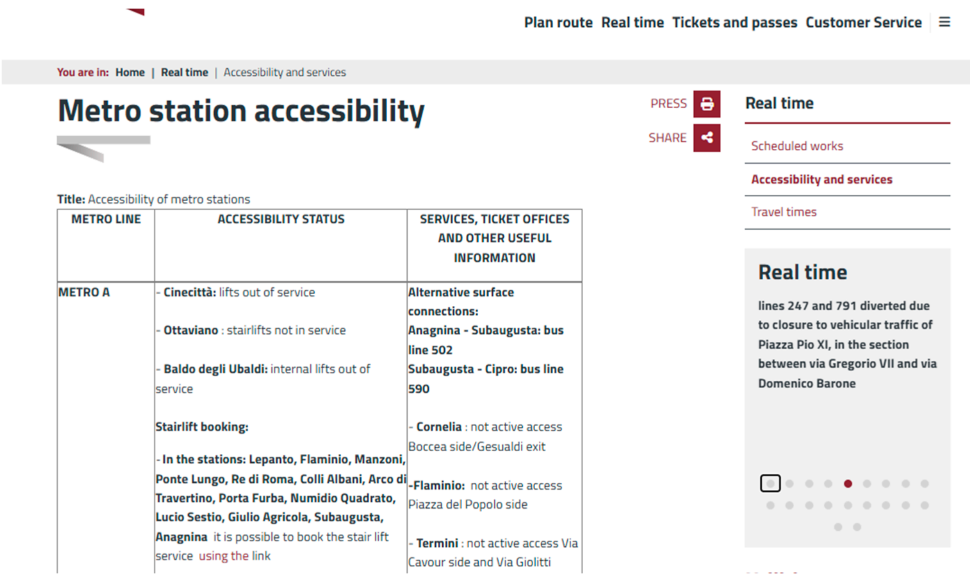


Figure 9. Metro station accessibility.

6. Conclusions

This study provides a comprehensive analysis of commuting behaviors in Italy with a focus on Rome, highlighting the need for comprehensive transport policies that address the diverse needs of urban commuters. The findings of this research are critical for developing effective WTPs and improving PT infrastructure, both of which are essential for reducing private car dependency and promoting sustainable commuting practices.

Despite its valuable insights, this study faces three caveats:

Demographic imbalance: The sample is predominantly male (60%) and skewed toward an older age group, with 71% of respondents aged between 41 and 55. This demographic imbalance may limit the generalizability of the results to the broader population.

Self-reported data: This study relies on self-reported data, especially regarding respondents' willingness to switch transport modes. This reliance may introduce bias, as participants could overestimate or underestimate their willingness to change behaviors, potentially affecting the accuracy of the findings. While self-reported survey data provide valuable insights into commuter preferences and behavior, they also introduce potential biases. Respondents may overestimate or underestimate their commuting patterns or preferences, which could affect the accuracy of the results. For example, individuals may overestimate their willingness to switch to sustainable modes or underestimate their reliance on private cars. Incorporating objective data sources, such as travel logs, GPS tracking [81,82], or transport network usage data, could help validate these self-reported responses and provide a more accurate picture of commuting behavior. Future research could benefit from triangulating self-reported data with these objective measures to reduce bias and improve the reliability of results. Explicitly acknowledging this limitation helps to interpret the findings with caution and highlights the importance of methodological rigor in urban mobility research.

Socio-economic and workplace factors: This study does not account for socio-economic factors, such as income levels and house prices, which may affect individuals' access to different transport modes and their willingness to use sustainable options. Higher-income groups may have more flexibility to choose between private and public transport modes. Additionally, workplace flexibility, such as remote or hybrid work arrangements, has become increasingly influential in commuting patterns. Individuals with greater flexibility may reduce their commuting frequency, possibly increasing sustainable mode usage over fewer trips. Future research could incorporate these socio-economic and workplace factors to gain a more comprehensive understanding of commuting behavior and support the development of nuanced transport policies.

Based on the discussion section, several suggestions for future research can be proposed to enhance the understanding and implications of urban commuting behavior:

In-depth analysis of demographic subgroups: While the current study identifies clusters based on general demographic characteristics, future research could delve deeper into the specific needs of subgroups within these clusters (e.g., gender analysis or focus on different income levels). Understanding the nuanced needs of these subgroups could help tailor more effective and inclusive transport policies.

Impact of remote working on commuting patterns: With the rise of remote and hybrid working arrangements, future studies could explore how these trends affect commuting behavior and transport preferences. This could include analyzing how reduced commuting frequency affects the use of different transport modes and whether it leads to a shift towards more sustainable practices.

Exploring psychological factors: Future studies could integrate psychological theories to explore the underlying motivations and attitudes that influence commuting choices. For instance, the Theory of Planned Behavior [83] helps explain how attitudes, subjective norms, and perceived control influence commuting decisions. This method could provide deeper insights into behavior change strategies.

Accessibility for all: Real-time information on metro stations' facilities for physically challenged users who need to use lifts or escalators. This stresses the need to integrate all urban form elements to enhance the adoption of sustainable transportation modes for both work and non-work travel [84].

In conclusion, addressing these gaps and expanding the scope of future research will further enhance our understanding of urban commuting behavior and support the development of more effective and inclusive transport policies.

Author Contributions: Conceptualization, M.B. and M.V.C.; methodology, M.B.; software, M.B.; validation, M.B.; formal analysis, M.B.; investigation, G.G.; resources, G.G.; data curation, G.G.; writing—original draft preparation, M.B.; writing—review and editing, M.B. and M.V.C.; visualization, M.B.; supervision, G.G. and M.V.C.; project administration, G.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available upon request from the corresponding author due to privacy and confidentiality concerns. The dataset contains sensitive information, such as the geographical locations of employees and companies, which could potentially identify individuals or reveal confidential business information.

Conflicts of Interest: The authors declare no conflicts of interest.

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