Highlights

Network structure and urban mobility sustainability: a topological analysis of cities from the urban mobility readiness index

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- Dense, interconnected networks improve urban mobility and sustainability outcomes.
- Economic resources and network structure are key predictors of mobility readiness.
- Compact, well-connected urban networks enhance resilience and efficiency.

Network structure and urban mobility sustainability: a topological analysis of cities from the urban mobility readiness index

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Abstract

In the context of rapid urbanization, efficient and sustainable urban mobility is critical. This study explores the impact of urban network structure and socio-demographic factors on Urban Mobility Readiness (UMRi) across 62 cities worldwide. Using complex network analysis, Principal Component Analysis, and multiple linear regression models, we identify significant relationships between network metrics—such as average node degree, clustering coefficient, and graph diameter—and urban mobility performance. Cities with denser, more interconnected networks tend to achieve higher UMRi scores, indicating better preparedness for modern mobility challenges.

Our findings also highlight the importance of economic resources, with GDP per capita emerging as a significant predictor of UMRi. Cities with well-funded and well-designed transportation networks demonstrate stronger performance in terms of mobility readiness and sustainability. Conversely, cities with more dispersed networks face greater challenges in optimizing their transportation systems. These insights underscore the importance of compact, resilient networks that promote accessibility and efficiency.

This study emphasizes the critical role of network structure in shaping urban mobility outcomes and offers strategic guidance for enhancing transportation systems in rapidly growing urban areas. Future research should focus on integrating emerging technologies, such as autonomous vehicles and smart city solutions, to further optimize urban mobility. This approach offers a novel perspective on how the structure of urban networks influences the sustainability and efficiency of public transport in diverse urban contexts.

Keywords: Urban mobility, Complex network analysis, Sustainable transportation, Sustainable urban development, Urban planning, Topological Data Analysis.

1. Introduction

Global urbanization, driven by increasing migration to metropolitan areas, presents critical challenges for urban mobility. As cities expand, the demand for efficient and sustainable transportation systems grows, which are vital not only for convenience and the local economy but also for addressing global issues such as pollution and climate change.

Densely populated cities face the challenge of maintaining traffic flow while minimizing environmental impact. Balancing these aspects is crucial to ensure an adequate quality of life and long-term sustainability (Folt'ynová et al., 2020; Gallo and Marinelli, 2020; Jacyna and Kotylak, 2020; Porru et al., 2020). According to UN estimates, by 2050, nearly 70% of the world's population will live in urban areas (see `https://www.undp.org/policy-centre/singapore/smart-cities-and-urbanisation`), making efficient urban mobility management a priority.

Sustainable mobility involves more than simply providing access to public and private transport; it requires a holistic approach considering accessibility, safety, comfort, and energy efficiency (Ceder, 2021; Friman et al., 2020;

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Tsavachidis and Le Petit, 2022). Transportation policies must integrate with urban planning to foster community development that reduces the need for long commutes and promotes greener transportation modes. Effective policy development requires a detailed analysis of mobility trends and their impact on urban development, leveraging advanced technologies and big data (Chang et al., 2020) to ensure that urban mobility solutions are sustainable and adaptable to the growing population's needs (Kandt and Batty, 2021; Jiang et al., 2022; Ristvej et al., 2020).

A sustainable city (Toli and Murtagh, 2020; Girardet, 2021) integrates environmental, social, and economic aspects into its urban development. In the context of mobility, this involves creating transportation systems that minimize environmental impact while maximizing accessibility and efficiency for citizens. Such systems are crucial for reducing dependence on private vehicles, thereby alleviating congestion (Karimi et al., 2021) and lowering greenhouse gas emissions (Patil, 2021; Hoornweg et al., 2020).

Sustainable urban planning also involves developing compact cities that optimize urban space, bringing people closer to basic services and reducing commuting distances. This not only improves transport efficiency but also contributes to greater social cohesion and a more integrated urban environment (Abduljabbar et al., 2021; Bibri et al., 2020). Cities that successfully implement these principles move toward environmental sustainability and offer a higher quality of life, with cleaner, safer, and more livable urban spaces (Mouratidis, 2021; Mouratidis and Yiannakou, 2022).

Efficient public transportation also supports urban economic growth by improving access to employment and educational opportunities, thus contributing to socioeconomic development (Zhang and Cheng, 2023; Pokharel et al., 2023). The accessibility and affordability of public transport are key to inclusive mobility, aligning with the United Nations' Sustainable Development Goals. Finally, a commitment to innovation and technological adaptation can transform public transport systems, making them more sustainable and attractive (Alessandrini et al., 2023).

Urban mobility faces critical challenges that demand attention and innovative solutions. One of the most prominent problems is vehicular congestion, which reduces transportation efficiency, increases pollution levels, and affects the quality of life in cities (Wang et al., 2023; Haseli et al., 2024). Additionally, many cities struggle with outdated transport infrastructure that fails to meet current demand, and upgrading it requires substantial investment, often hampered by financial and logistical constraints. Another significant challenge is resistance to change (Wen, 2023), which can arise from both the public and government entities when changes in transportation policies are proposed, especially when such changes involve significant alterations to daily routines or existing infrastructure. Integrating sustainable transportation solutions, such as electric vehicles and public bicycle systems, remains challenging (Putro et al., 2023), as they require not only adequate infrastructure but also a cultural and social shift toward embracing new forms of mobility.

Furthermore, the lack of coordination between urban planning and transportation systems is evident in many cities, where urban projects are developed without effectively integrating with existing transport systems. This leads to mobility solutions that neither meet current user needs nor support sustainable city growth. Overcoming these challenges requires a collaborative approach involving multiple sectors and levels of government to ensure that transportation policies and practices align with urban development and environmental sustainability goals.

To address these urban mobility and sustainability challenges, analyzing the topological structure of transportation networks is essential. The efficiency and connectivity of these networks play a crucial role in urban mobility. Analyzing the topology of urban transport networks using computational tools such as OpenStreetMap and advanced complex network analysis packages reveals their direct impact on cities' efficiency and sustainability (Cheng et al., 2023; Zhang et al., 2022b; Shang et al., 2020). A well-connected network not only reduces travel times but also improves overall accessibility, which is fundamental for efficient urban mobility. Topological characteristics such as connection density and node centrality are crucial as they influence traffic distribution and access to transportation services (Zhang et al., 2011; Lin and Ban, 2013; Wang et al., 2017; Xie and Levinson, 2007; Wu et al., 2021).

Complex network topology tools have found applications across various disciplines, offering innovative methods to characterize and model complex systems. For instance, in biology, these tools study protein interaction networks (Khattak et al., 2021; Yadav and Singh, 2022), helping to identify critical components in cellular processes. In sociology, complex network analysis examines relationship patterns and social dynamics within large groups, revealing how social influences propagate (Valeri and Baggio, 2021).

In epidemiology (Park et al., 2021; Lee et al., 2021), network modeling has been crucial for understanding and predicting the spread of infectious diseases through populations, facilitating the development of more effective intervention strategies. In economics, it is applied to analyze financial transaction networks, identifying points of risk and stability within financial markets (Bier et al., 2020; Bardoscia et al., 2021). These examples highlight the versatility and potential of complex network analysis to provide deep and valuable insights in various fields of knowledge.

Zhang et al. (2021) presents an innovative methodology for analyzing urban transit systems to promote sustainability. The authors introduce an integrated graph embedding approach that combines graph theory with advanced embedding techniques to model complex transit networks. By representing urban transit systems as graphs, they capture the relationships between various transit nodes—such as bus stops and train stations—and the routes connecting them. The graph embedding method (Perozzi et al., 2014; Cai et al., 2018) transforms these high-dimensional network graphs into lower-dimensional spaces while preserving their structural properties. This enables the identification of underlying mobility patterns and community structures within the transit network. The main findings demonstrate that this approach effectively uncovers hidden transit mobility structures, providing valuable insights for urban planners and policymakers. The significance of their work lies in its ability to analyze and interpret large-scale transit networks efficiently, facilitating the development of targeted strategies to improve mobility, reduce congestion, and enhance the overall sustainability of cities worldwide.

Recent advancements in graph-based methodologies have significantly contributed to the understanding and enhancement of sustainable urban mobility. Ahmed et al. (2022) presented a knowledge graph-based approach for trajectory outlier detection in sustainable smart cities, emphasizing micro-level mobility patterns to identify anomalous trajectories that could affect transportation efficiency and safety. Their method leverages knowledge graphs to model and analyze individual movement patterns within urban environments, facilitating real-time monitoring and management of transportation systems. This micro-level analysis complements macro-level studies—such as ours—that focus on the impact of overall network structures and socio-demographic factors on Urban Mobility Readiness (UMRi) across multiple cities. By integrating insights from a granular perspective, we can develop a more comprehensive understanding of urban mobility dynamics. This integrated approach underscores the critical role of graph-based techniques in shaping effective strategies for optimizing transportation systems, ultimately advancing the sustainability and efficiency of urban mobility in rapidly growing cities (Li et al., 2023; Liu and Yuan, 2024).

Extracting and analyzing data from OpenStreetMap enables detailed modeling of any city's transportation network. This type of analysis is invaluable for urban planners and policymakers, providing a solid foundation for making informed decisions on optimizing transportation resources and infrastructure.

Evaluating urban sustainability through topological analysis offers an additional dimension in urban planning. It considers not only the functionality of networks but also how these networks can be designed or modified to support long-term sustainability goals.

Aims and Scope

This study aims to demonstrate how topological indicators of urban transport networks in cities listed in the Urban Mobility City Rankings correlate with key sustainability indices: UMR Index, Sustainable Mobility, and Public Transit. By using OSMnx to analyze the topology of these networks, the study seeks to identify patterns that can serve as predictors of urban mobility efficiency and sustainability. This approach not only highlights the relationship between the physical structure of transport networks and sustainability indicators but also proposes a methodological framework to evaluate and compare the effectiveness of public transport and sustainable mobility policies across different cities. By correlating these topological measures with the aforementioned indices, the study provides an innovative and quantitative perspective that can influence future urban planning and policy decisions towards more sustainable and efficient cities.

Our particular contribution to the field is the integration of complex network analysis with urban sustainability metrics to elucidate the relationships between the topological structures of urban transport networks and their mobility performance. By employing OSMnx to extract and analyze transport network data from 62 cities worldwide, we have identified specific topological indicators—such as average node degree, clustering coefficient, and graph diameter—that significantly correlate with the UMR Index and other key sustainability indices. This study not only demonstrates the predictive power of these network metrics but also introduces a novel methodological framework for assessing and comparing the effectiveness of public transport and sustainable mobility policies across different urban contexts. Our approach provides a quantitative tool for urban planners and policymakers to evaluate existing transportation networks and to inform future strategies aimed at enhancing connectivity, efficiency, and sustainability in rapidly urbanizing cities.

2. Data and Methods

2.1. Data Used

This study uses data from the 2023 Urban Mobility City Rankings, provided by the Oliver Wyman Forum, which ranks cities globally based on their readiness for future urban mobility (see: `https://www.oliverwymanforum.com/mobility/urban-mobility-readiness-index/ranking.html`). The ranking is based on a detailed analysis of various urban mobility indicators, focusing on cities' preparedness for sustainable and efficient transportation systems.

The UMRi offers an in-depth analysis of 65 global cities, selected for their geographic diversity and unique mobility challenges. These cities span six regions—North America, Latin America, Europe, the Middle East, Asia Pacific, and Africa—and include a range of urban environments, from sprawling megacities like Tokyo and Delhi to more compact cities such as Oslo and Washington D.C.

The Oliver Wyman Forum compiles the UMRi using publicly available data, expert assessments, and statistical indicators. The data sources include international organizations, government agencies, and reputable academic and industry research. The index evaluates cities based on five key dimensions: infrastructure, social impact, market attractiveness, system efficiency, and innovation. Each dimension comprises multiple key performance indicators (KPIs), collectively identifying which cities are ready to excel in meeting future mobility challenges.

The data collection process focuses on metrics that are critical to building future-ready urban mobility ecosystems, such as the strength of multimodal networks, public transit utilization, electric vehicle adoption, cycling infrastructure, and walkability. The UMRi does not incorporate any personal or smartphone-derived data, nor does it involve public complaints or individual user information. All data is aggregated at the city level, ensuring that individual privacy and information security are maintained.

The methodology emphasizes characteristics that businesses, consumers, and policymakers consider indispensable now and in the future. The index assesses how cities are integrating mobility systems, making them accessible and sustainable, encouraging innovation, fostering collaboration, and building resilience against challenges. By focusing on these attributes, the UMRi provides actionable insights that cities can use to improve their mobility performance.

Weights for the KPIs were determined through discussions with urban planners, traffic managers, transportation finance specialists, and mobility technology executives. Convex optimization techniques were used to validate the weight structure, ensuring that the index reliably benchmarks cities against each other. This rigorous methodology reinforces the integrity of the UMRi and its suitability for academic research.

Our study leverages the UMRi data to analyze the impact of urban network structures and socio-demographic factors on urban mobility readiness. By using this comprehensive and responsibly sourced dataset, we ensure that our research maintains high ethical standards without compromising information security or individual privacy.

The dataset includes three key indicators: the UMR Index (UMRi), which measures a city's overall preparedness for future urban mobility; the Sustainable Mobility Index (SMi), which assesses the sustainability of a city's transportation practices; and the Public Transit Index (PTi), which evaluates the quality and effectiveness of the public transportation system.

The 2023 dataset comprises 65 cities across multiple continents, distributed as follows: 12 in North America, 9 in South America, 18 in Europe, 14 in Asia, and 12 in Africa and Oceania. This broad geographic distribution allows for an analysis that encompasses diverse cultural and economic contexts of urban mobility (See Fig. 1).

The top five cities in the 2023 ranking—Helsinki, Amsterdam, Stockholm, San Francisco, and Munich—demonstrate strong performance in sustainable mobility and transportation efficiency. These cities feature well-developed public transport systems, effective sustainable mobility policies, and robust infrastructure supporting various modes of transit, including walking and cycling. Additionally, they show a commitment to technological innovation and urban environmental improvements.

Conversely, the bottom five cities in the ranking—Quito, Lima, Manama, Nairobi, and Lagos—face significant challenges, such as underdeveloped transport infrastructure, limited investment capacity in sustainable mobility, and congestion issues. These cities are often in phases of rapid development, complicating the short-term implementation of effective transport solutions.

The 2023 dataset reveals significant variability among cities in terms of urban mobility readiness. UMRi values range from 23.7 to 70.9, with a mean of 53.28 and a standard deviation of 13.33, indicating diverse levels of preparedness globally. SMi values range from 22.5 to 76.8, with a mean of 46.69 and a standard deviation of 12.84,

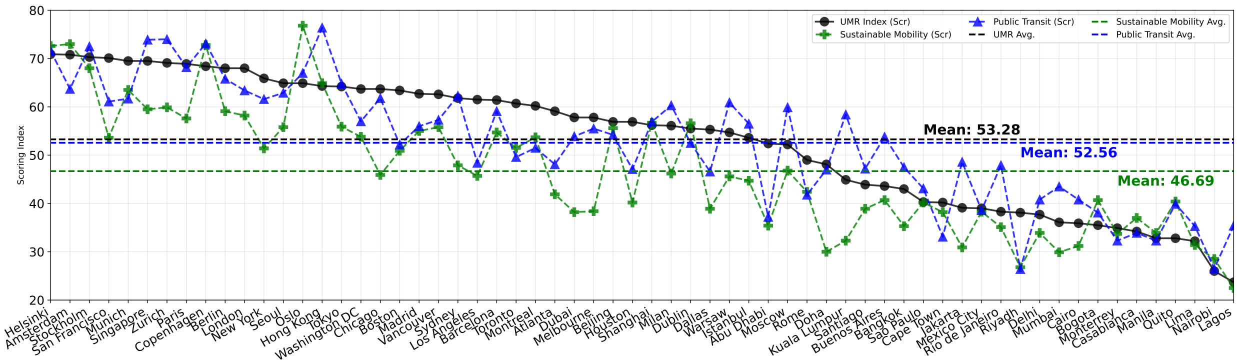

Figure 1: Comparison of cities based on the 2023 UMRi, SMi, and PTi. The figure highlights the relative performance of cities in terms of their preparedness for future urban mobility, the sustainability of their transportation systems, and the effectiveness of their public transit infrastructure. Top-performing cities, such as Helsinki and Amsterdam, demonstrate strong results across all indicators, while lower-ranked cities, such as Quito and Lima, face challenges in these areas.

reflecting varied adoption of sustainable transport policies and technologies. Finally, PTi values range from 26.4 to 76.4, with a mean of 52.56 and a standard deviation of 12.56, suggesting differing levels of public transport efficiency and accessibility among cities.

The statistics highlight the diversity in urban mobility approaches and outcomes, forming the foundation for investigating how specific aspects of transport networks influence these indices (Sierra Porta and Herrera Acevedo, 2024). This analysis will explore the relationship between the physical structure of urban transport networks and their performance in the Urban Mobility City Rankings.

2.2. Methods and analysis strategies

2.2.1. Topological complex network analysis

Complex networks (Boccaletti et al., 2006; Kaminski et al., 2021; Estrada, 2012; Kim and Wilhelm, 2008) are mathematical structures formally represented as graphs $G = (V, E)$, where V is a set of vertices (or nodes) and E is a set of edges (or links) connecting pairs of nodes. In the context of urban mobility, each node $v_i \in V$ can represent intersections, transit stations, or significant traffic areas within the city. The edges $(v_i, v_j) \in E$ represent the pathways between these nodes, such as roads or transit routes, and can be either directed or undirected, depending on the directionality of movement.

Edges can be weighted based on variables such as distance, travel time, or capacity, represented by a weight function $w : E \mapsto \mathcal{R}^+$ that assigns a positive real number to each edge. This weighting allows for more nuanced analysis of the network's flow and efficiency. The network's structure can be represented by an adjacency matrix A, where each element a_{ij} indicates the presence and weight of a direct link between nodes i and j. Node degree, a fundamental concept in network analysis, refers to the number of edges connected to a node. In directed networks, nodes have both in-degree and out-degree, representing incoming and outgoing connections, respectively.

Network analysis provides a powerful framework for studying urban mobility by quantifying characteristics such as connectivity, flow dynamics, and structural properties that are crucial for effective urban planning and management (Scardoni and Laudanna, 2012; Bröhl and Lehnertz, 2019). Algebraic topology (Giblin, 2013; Franz, 2020) and topological geometry (Polterovich et al., 2020) extend network analysis by focusing on spatial properties and structures that remain invariant under certain transformations. Applied to urban networks (Tokuda et al., 2022; Badhrudeen et al., 2022), these techniques can reveal hidden features such as persistent cycles or disconnected regions that may indicate vulnerabilities or inefficiencies. For instance, persistent homology allows for the identification of holes or gaps in the network, which can correspond to areas lacking connectivity or facing potential bottlenecks.

Topological invariants such as cycles or paths are useful for understanding the robustness of the network under disruption. This approach enables a deeper understanding of how the structure of the transportation network influences its functionality and resilience, which is essential for planning sustainable urban mobility systems.

Our study begins with the extraction and generation of a specific dataset based on the geographic locations of cities listed in the Urban Mobility City Rankings. Using this geographic information, we employed the Python library OSMnx (Boeing, 2017b,a) to construct complex networks of vehicular mobility connections for each city. OSMnx retrieves and models street networks and other urban infrastructure directly from OpenStreetMap, converting geographic locations into graphs where nodes represent intersections or street terminations, and edges represent street segments. Edges are weighted based on physical distance, which provides a more accurate representation of urban mobility dynamics.

Once the networks were constructed, OSMnx enabled us to extract both basic and advanced network statistics, such as dispersion measures, distances, and node distributions. Additionally, we computed several graph metrics, including centrality measures like betweenness centrality and closeness centrality, as well as other metrics that reveal the connectivity and accessibility within the network. These metrics allow us to capture both local and global properties of the network, such as the distribution of connections, the centrality of key nodes, and the overall structure of the network.

The core of our analysis involves correlating these graph metrics with the indices provided by the Urban Mobility City Rankings—specifically, the UMRi, SMi, and PTi scores. Our goal is to uncover patterns that suggest how certain topological characteristics of a city's transportation network influence its overall mobility efficiency and sustainability. For each city, we calculated a series of network metrics using OSMnx, including node and edge metrics such as circuity, clean intersection count and density, edge density, average and total edge length, intersection count and density, average node degree, and node count. Additionally, we computed node density, self-loop proportion, street density, average and total street length, street segment count, and average streets per node. Furthermore, several graph metrics were calculated, including normalized average betweenness centrality, closeness centrality, and degree centrality, as well as graph entropy, diameter, density, clustering coefficient, average path length, constraints, assortativity degree, mean degree, reciprocity, and diversity.

These metrics collectively provide a comprehensive characterization of the urban transportation networks analyzed in this study. By comparing these metrics with the mobility and sustainability indices provided in the Urban Mobility City Rankings, we aim to identify significant relationships between the physical structure of urban transportation networks and their performance in terms of mobility efficiency and sustainability.

Additionally, we integrated original dataset metrics, including demographic and economic variables such as region, city address, population (millions), surface area (km^2), population density (people/km^2), and GDP per capita ($). These variables provide important context for understanding the broader factors that may influence urban mobility beyond the network structure itself.

From this comprehensive methodological approach we aims detailed assessment of urban transport infrastructure and its impact on city mobility and sustainability ratings. The combination of network analysis with topological and statistical methods provides a robust framework for addressing modern urban mobility challenges.

2.2.2. Principal Component Analysis

We conducted a detailed Principal Component Analysis (PCA) to study the classification of cities in terms of their UMRi, SMi, PTi, and topological network variables. PCA is a multivariate statistical technique that transforms a set of correlated variables into a set of uncorrelated variables called principal components, capturing the maximum variance in the data (Jolliffe and Cadima, 2016).

In our analysis, we first selected a set of numerical variables that included topological network metrics derived from our graph analysis—such as average node degree, clustering coefficient, graph diameter, average edge length, and streets per node—as well as socio-demographic factors like GDP per capita and population density. These variables are relevant to urban mobility and provide a comprehensive view of the factors influencing the indices.

Prior to performing PCA, we standardized the selected variables using z-score normalization to ensure that each variable contributed equally to the analysis regardless of their original scales. Standardization involved subtracting the mean and dividing by the standard deviation for each variable, resulting in variables with a mean of zero and a standard deviation of one (Bro and Smilde, 2014): $Z_i = (X_i - \mu_i)/\sigma_i$, where Z_i is the standardized value, X_i is the original value, μ_i is the mean, and σ_i is the standard deviation of the each variable.

With the standardized data, we computed the covariance matrix to understand how the variables varied together. We then performed eigenvalue decomposition on the covariance matrix to extract the eigenvalues and eigenvectors.

The eigenvalues represent the amount of variance explained by each principal component, while the eigenvectors define the direction of the principal components in the multidimensional space.

We ranked the principal components based on their corresponding eigenvalues in descending order. The first principal component (PC1) accounted for the largest variance in the data, followed by the second principal component (PC2), and so on. We retained the first three principal components because they collectively accounted for approximately 61% of the total variance, which is a substantial proportion for meaningful analysis (Abdi and Williams, 2010).

To interpret the principal components, we calculated the scores and loadings. The scores were obtained by projecting the standardized data onto the principal components, providing the coordinates of each city in the new principal component space. The loadings were calculated to determine the contribution of each original variable to the principal components. The loadings are the coefficients of the eigenvectors and indicate the weight of each variable in the principal components.

We visualized the results using explained variance plots and scatter plots. The explained variance plot showed how much variance each principal component captured, confirming that the first three components accounted for a significant portion of the variance. The scatter plots of the principal component scores allowed us to visualize the clustering patterns among the cities. In these plots, cities were color-coded based on their UMRi scores, enabling us to observe how cities with similar mobility readiness levels grouped together in the principal component space.

We also created biplots by superimposing the loadings onto the score plots. The biplots illustrate the relationships between the original variables and the principal components, with the loadings vectors indicating the direction and magnitude of each variable's contribution. This visualization helped us interpret how the variables influenced the positioning of the cities in the principal component space.

The PCA was implemented using the Python programming language due to its robust libraries for data analysis. We used Pandas and NumPy for data manipulation and numerical computations. The Scikit-Learn library was utilized for performing PCA, specifically the PCA function, which provides efficient tools for this type of analysis (Pedregosa, 2011).

By conducting PCA, we effectively reduced the complexity of our dataset while retaining the most significant information. The principal components allowed us to identify the key variables that influence urban mobility readiness and to observe clustering patterns among cities. The analysis revealed that cities with higher UMRi scores tended to cluster together and were associated with variables such as average node degree, clustering coefficient, and GDP per capita. Conversely, cities with lower UMRi scores were associated with variables like graph diameter and average edge length, indicating less efficient network structures.

This detailed PCA provided valuable insights into how topological network characteristics and socio-demographic factors collectively impact urban mobility performance. It highlighted the importance of network connectivity, economic resources, and efficient urban design in enhancing mobility readiness. The findings support the argument that strategic planning and investment in network infrastructure are crucial for developing sustainable and efficient urban transportation systems.

3. Results and Discussion

3.1. Correlation Analysis

3.1.1. Correlations among Key Indices

The first step in our analysis was to explore the relationships between various network metrics derived from the urban networks and the key dependent variables: UMRi, SMi, and PTi. We employed Kendall's correlation coefficient to capture both linear and non-linear relationships, which is particularly useful given the complex nature of urban systems, where interactions are not always strictly linear. Figure 2 visually represents the non-linear correlations between the pairs of variables considered in this study, including both socio-economic-demographic metrics and the network metrics derived from the graph analysis of each city's transportation network.

To facilitate the understanding of the figures and tables presented, we inform that the names of the axes and variables correspond to abbreviations that are defined in detail in the abbreviations section at the end of the article. These abbreviations include both context variables provided by the Oliver Wyman index and topological measures derived from the complex networks constructed for each city.

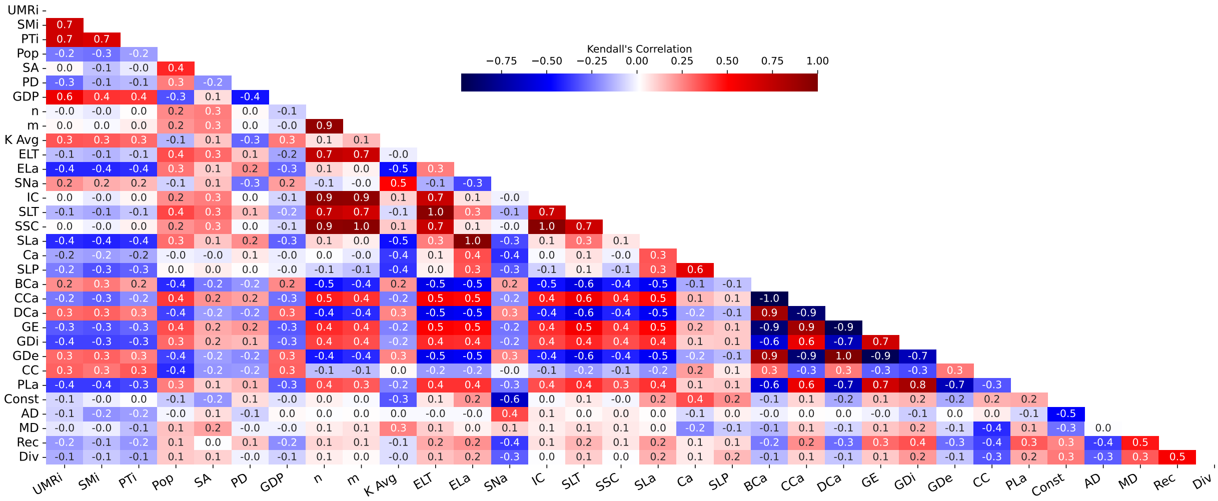

Figure 2: Correlation heatmap of key urban mobility metrics and network metrics derived from the graph analysis of city transportation networks. The heatmap shows significant correlations between the UMRi, SMi, PTi metrics, and several graph metrics such as node degree, centrality measures, and street density. This highlights the interplay between network topology and urban mobility performance.

The results indicate strong and significant positive correlations among the three primary dependent variables. Specifically, UMRi is highly correlated with SMi ($\tau = 0.696$, $p < 0.001$) and PTi ($\tau = 0.693$, $p < 0.001$), suggesting that cities with higher readiness for urban mobility tend to have more effective public transportation systems and better-implemented sustainable mobility policies. Similarly, SMi and PTi are strongly correlated ($\tau = 0.650$, $p < 0.001$), reinforcing the notion that high-quality public transportation infrastructure is inherently linked to urban sustainability.

These findings align with previous research indicating that investments in public transit systems not only improve mobility but also contribute to environmental sustainability by reducing reliance on private vehicles and lowering greenhouse gas emissions (Wimbadi et al., 2021). The strong interrelationships among these indices underscore the integrated nature of urban mobility systems, where advancements in one area can have positive spillover effects on others (Punzo et al., 2022; Mavlutova et al., 2023; Ceder, 2021).

3.1.2. Correlations between UMRi and Socioeconomic and Demographic Variables

The UMRi exhibits several significant correlations with key socioeconomic variables, which help to elucidate the relationship between urban mobility readiness and broader demographic and economic factors. One of the most notable findings is the strong positive correlation of 0.58 with GDP per capita. This suggests that cities with higher mobility readiness often coincide with those having higher income levels. Wealthier cities have greater financial resources to invest in advanced mobility infrastructure, strategic urban planning, and sustainability initiatives. This supports the idea that economic prosperity enables cities to prioritize and implement effective mobility solutions, making income a relevant predictor of mobility readiness.

The finding that the Urban Mobility Readiness Index (UMRi) exhibits a strong positive correlation of 0.58 with GDP per capita underscores the critical relationship between urban mobility readiness and economic development. This correlation suggests that cities with higher economic output are better positioned to invest in and develop effective urban mobility systems. Economic prosperity often translates into increased public and private investment in infrastructure, including transportation networks, which enhances mobility options for residents.

Furthermore, the correlation between UMRi and GDP per capita reflects broader demographic and economic factors that influence urban mobility. Ruktanonchai et al. (2021) emphasize that socioeconomic factors, including income levels, significantly impact mobility patterns, suggesting that wealthier populations tend to have greater access to diverse transportation options. Additionally, Lenormand et al. (2020) discuss how transportation mobility is a major player in urban economies, indicating that effective mobility systems are not only a product of economic growth but also a catalyst for further economic activity. Therefore, understanding the interplay between urban mobility readiness and economic indicators like GDP per capita is crucial for policymakers aiming to enhance urban mobility and promote sustainable economic development.

An interesting inverse correlation is observed between UMRi and population density, with a moderate negative relationship of -0.24. This indicates that cities with higher population density tend to be less prepared for urban mobility. Densely populated cities face challenges such as traffic congestion, infrastructure limitations, and spatial constraints, which complicate efforts to enhance mobility. These findings align with existing research suggesting that high population density can strain urban infrastructure, making it more difficult to implement efficient mobility solutions (Jiménez-Espada et al., 2022; Porru et al., 2020).

The correlation between UMRi and the surface area of cities is very weak, at 0.02, indicating that geographic size does not play a significant role in determining urban mobility readiness. This reinforces the notion that urban mobility is more dependent on strategic planning and resource allocation than on the sheer physical extent of the city. Cities like Helsinki and Amsterdam demonstrate that compact urban areas can achieve high mobility readiness through thoughtful design and investment, regardless of their geographic size.

3.1.3. Correlations between UMRi and Urban Network Structure Metrics

The analysis of correlations between UMRi and various urban network structure metrics reveals important patterns, highlighting the critical role of connectivity, network design, and structural efficiency in shaping urban mobility readiness.

The finding that the UMRi exhibits a positive correlation of 0.34 with average node degree indicates that cities with higher mobility readiness tend to have more interconnected transportation networks. This interconnectedness is crucial for enhancing network resilience and operational efficiency. A higher average node degree implies that there are more connections per node within the network, which facilitates greater redundancy and alternative routing options. Such characteristics are essential for effectively distributing traffic and mitigating congestion, particularly during peak travel times or in the event of disruptions. The ability of a transportation network to provide multiple routes and options can significantly improve the overall mobility experience for residents, allowing for more flexible travel choices and reducing reliance on any single route or mode of transport.

Conversely, the moderate negative correlations of -0.40 between UMRi and both average edge length and average street length suggest that cities with longer streets tend to be less prepared for urban mobility. Longer streets may indicate a less dense network, which can limit transportation options and increase travel times. This finding aligns with the notion that compact, well-connected street networks are vital for efficient urban mobility. As highlighted by Cordero and Rodriguez (2022), the resilience and sustainability of urban networks are influenced by their structural characteristics, including connectivity and centrality measures. Furthermore, Wang (2015) emphasizes that urban road networks function similarly to cardiovascular systems, where efficient branching structures are necessary for effective traffic distribution. Therefore, these findings underscore the importance of designing urban environments with shorter distances between nodes and higher connectivity to promote accessibility and reduce congestion, ultimately enhancing urban mobility readiness.

The finding that graph entropy exhibits a moderate negative correlation of -0.30 with the UMRi suggests that cities with higher mobility readiness tend to possess more ordered and predictable transportation networks. Lower entropy indicates a more structured network with a less random distribution of connections, which can enhance routing efficiency and promote smoother traffic flow. This observation aligns with the principles of network theory, where structured networks are often associated with reduced complexity and increased navigability. Well-planned urban networks facilitate efficient movement and minimize travel uncertainties, which are crucial for both daily commuters and urban planners. The implications of this finding underscore the importance of intentional urban design in fostering mobility readiness, as organized networks can significantly improve navigation and reduce the cognitive load on users, thereby enhancing the overall travel experience (Purvis et al., 2019; Mantzaris et al., 2024).

Moreover, the positive correlation of 0.31 between degree centrality and UMRi indicates that cities with higher mobility readiness often feature transportation networks where key nodes serve as central hubs with a greater number of direct connections. These central nodes play a vital role in enhancing network efficiency by facilitating quick transfers and minimizing the need for long detours. This finding is consistent with the work of Zhao et al. (2017), who emphasize the significance of centrality in urban networks for optimizing mobility and accessibility. From an urban planning perspective, these insights suggest that targeted investments in these key nodes could yield substantial benefits for the entire mobility system. Enhancing the connectivity and functionality of central nodes not only improves the overall performance of the transportation network but also supports broader goals of sustainable urban development by promoting efficient public transit options and reducing reliance on private vehicles.

Similarly, betweenness centrality shows a positive correlation of 0.24 with UMRi, implying that cities with higher mobility readiness often have networks where a few critical nodes facilitate traffic flow. These nodes act as bridges between different parts of the network, optimizing connectivity and reducing travel distances. This highlights the importance of strategic hubs in ensuring a well-functioning transportation system. In contrast, closeness centrality presents a negative correlation of -0.24, suggesting that cities with higher mobility readiness are less dependent on minimizing direct distances between nodes. This could imply that in well-prepared cities, the emphasis is on creating robust, resilient pathways rather than solely focusing on proximity. Such an approach ensures that cities can maintain mobility even when certain routes are disrupted, supporting a more sustainable and adaptable urban transport system.

The analysis reveals a moderate negative correlation of -0.35 between the Urban Mobility Readiness Index (UMRi) and graph diameter, suggesting that cities with smaller graph diameters—indicative of shorter average distances between nodes—tend to be better prepared for urban mobility. A smaller graph diameter reflects a more compact and efficiently designed transportation network, where travel between any two points can be achieved with fewer steps. This compactness enhances accessibility and reduces travel times, which are critical factors in achieving effective urban mobility outcomes.

The implications of this finding are significant, as they highlight the importance of urban design in facilitating efficient mobility. A compact network structure not only improves the overall connectivity of the transportation system but also fosters a more user-friendly environment for residents. As noted by Cai et al. (2024), urban areas with well-connected and compact networks can better accommodate various modes of transport, including public transit, cycling, and walking, thereby promoting sustainable mobility practices. Furthermore, the relationship between graph diameter and urban mobility readiness aligns with the principles of network theory, which posits that shorter distances within a network can lead to enhanced efficiency and reduced congestion (Chen et al., 2021). Therefore, urban planners and policymakers should prioritize the development of compact, well-connected transportation networks to improve mobility readiness and overall urban sustainability.

Average path length shows a negative correlation of -0.36 with UMRi, further supporting the idea that cities with shorter average path lengths are better equipped for urban mobility. Shorter paths allow users to reach their destinations more quickly, enhancing mobility efficiency and reducing congestion. These findings align with research emphasizing the benefits of compact urban design in promoting sustainable mobility (Bibri et al., 2020; Maltese et al., 2021).

The analysis indicates a positive correlation of 0.32 between the clustering coefficient and the Urban Mobility Readiness Index (UMRi), suggesting that cities with higher levels of local clustering—where nodes form tightly-knit groups—tend to be better prepared for urban mobility. A high clustering coefficient reflects a network structure that promotes local connectivity, enabling residents to efficiently complete short trips within their neighborhoods. This localized connectivity is essential for enhancing accessibility, as it allows individuals to reach essential services and amenities without relying on long-distance travel. Consequently, this reduction in reliance on longer routes alleviates congestion on major thoroughfares and fosters more sustainable travel behaviors, such as walking and cycling, which are vital for promoting urban sustainability.

The implications of this finding are significant, as they underscore the importance of fostering localized networks in urban planning. As highlighted by Kovačić et al. (2022), neighborhoods characterized by high clustering can enhance social interactions and community engagement, further supporting sustainable mobility practices. Additionally, the relationship between clustering and urban mobility readiness aligns with the principles of network theory, which posits that localized connectivity can lead to more resilient transportation systems (Xu et al., 2020). By prioritizing the development of neighborhoods with high clustering coefficients, urban planners can create environments that not only improve mobility readiness but also contribute to the overall quality of life for residents.

These findings offer valuable insights for urban planners and policymakers. First, the strong correlations between network centrality, density, and mobility indices suggest that designing well-connected and compact transportation networks should be a priority for cities aiming to improve mobility readiness. Investing in key nodes and ensuring local connectivity can enhance overall network efficiency and sustainability. Second, the significant role of economic factors, such as GDP per capita, highlights the need for equitable investment in transportation infrastructure, especially in economically disadvantaged cities, to reduce mobility inequalities.

Finally, the observed non-linear relationships in this study suggest that urban mobility systems require more nuanced planning approaches that account for the complexity of network behavior. Incorporating advanced modeling techniques, such as machine learning and network simulations, can provide deeper insights into the dynamics of urban mobility, leading to more resilient and sustainable transport systems.

3.2. Principal Component Analysis (PCA)

To reduce the dimensionality of the dataset and better understand how graph-derived variables influence the key dependent variables, we conducted a PCA (Yu et al., 2020; Zhang et al., 2022c). This analysis allowed us to identify the linear combinations of variables that capture the most variability in the dataset, revealing underlying patterns and relationships.

The PCA results (see Fig. 3) revealed that the first three principal components explained a significant portion of the total variance, with the first component accounting for 31.14%, the second for 17.53%, and the third for 12.33%. Collectively, these three components explain over approximately 61% of the total variance in the dataset. This indicates that a substantial amount of the variability in the data can be attributed to just a few dimensions, making PCA a useful tool for reducing complexity while preserving the most important information.

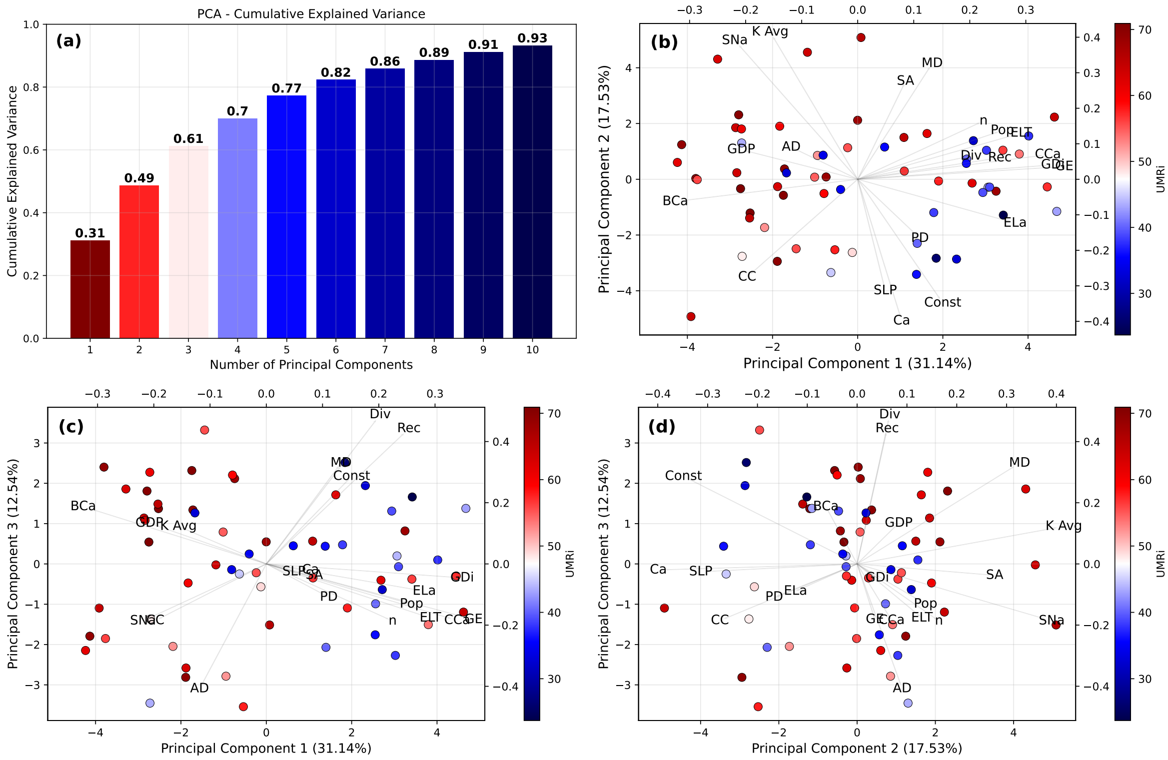

Figure 3: (a) Cumulative explained variance by principal components from the PCA analysis, showing that the first three components account for approximately 61% of the total variance. (b) Scatter plot of the first two principal components (PC1 vs PC2), showing the clustering of cities based on their UMRi scores. (c) Scatter plot of PC1 vs PC3, and (d) scatter plot of PC2 vs PC3, providing additional perspectives on the clustering patterns and the relationships between the variables. Cities with higher urban mobility readiness tend to group together, suggesting shared characteristics in their transportation networks, such as higher connection density and efficiency.

When visualizing the PCA results in various 2D scatter plots, we observed clear clustering of cities based on their urban mobility. Cities with higher UMRi indices consistently grouped together across the principal component spaces, suggesting that these cities share common characteristics in their transportation networks. These characteristics likely include higher connection density, greater route efficiency, and better distribution of transportation flows, all of which contribute to enhanced mobility readiness and sustainability.

According to the Fig. 3(b) scatter plot (PC1 vs PC2), cities with higher UMRi scores generally have lower values on PC1. These cities are associated with variables such as average node degree (K Avg), average streets per node, clustering coefficient, betweenness centrality, assortativity degree, and GDP per capita. This suggests that cities with higher urban mobility readiness tend to have more interconnected networks with a higher degree of clustering and centrality, as well as greater economic resources, which collectively contribute to their enhanced mobility performance.

For instance, in the previous figure, cities with high UMRi values and correlations with GDP, AD, and BCa measures, which show negative scores on the first principal component, are primarily European and North American cities. Cities with high sustainable mobility indices typically prioritize integrated, efficient, and accessible transportation networks that promote non-motorized modes (such as cycling and walking) and high-quality public transit services. These features shape traffic networks so that certain nodes or transfer points (like train stations, bus hubs, and transport interchanges) become crucial in connecting different parts of the city, thereby increasing betweenness centrality.

Moreover, assortativity degree reflects the tendency of nodes in a network to connect with others of similar degree. In the context of an urban traffic network, a high assortativity degree indicates that high-degree nodes (highly connected areas like central stations) tend to connect with each other. This property supports efficient and resilient traffic distribution.

Finally, there is a strong correlation between high GDP and the capacity to invest in advanced infrastructure, which is a key factor in sustaining efficient and sustainable mobility. Cities with higher GDP can allocate more resources to infrastructure improvements for public transportation (e.g., trains, electric buses, bike-sharing systems). These funds allow for urban space reconfiguration to prioritize sustainable modes and create networks with reduced car dependency. Economic resources also facilitate the implementation of smart traffic management systems and mobility applications, further optimizing traffic networks.

In other words, cities like Singapore, Abu Dhabi, Doha, and Buenos Aires have achieved high sustainable mobility indices despite not being located in Europe or North America. Their cases illustrate how deliberate planning, substantial investments, and innovative policies can foster sustainable urban mobility, even outside the Western context. Singapore (Shamsuzzoha et al., 2021), Abu Dhabi (Farid et al., 2021), Doha (Mareeva et al., 2022; Furlan et al., 2021; Al-Malki et al., 2024), and Buenos Aires (Grassi and Díaz, 2024; Vecchio et al., 2021) exemplify how strategic investment, forward-thinking policies, technology adoption, and strong government leadership can foster high sustainable mobility indices outside the Western context. These cities have prioritized dense, well-integrated transit networks (e.g., metros, BRTs), regulated private car use through policies like congestion pricing, and used smart technology for real-time transit management. Environmental and economic pressures, particularly in the Middle East, have also driven these cities to reduce car dependency and adopt sustainable practices. Together, these initiatives illustrate that with cohesive urban planning, substantial infrastructure investment, and public education, cities worldwide can achieve efficient, sustainable mobility.

In contrast, cities with lower UMRi scores tend to have higher values on PC1 and are more closely related to variables such as closeness centrality, graph diameter, average edge length, total edge length, reciprocity, and diversity. These cities are characterized by networks with longer paths, larger diameters, and lower degrees of interconnectedness, which can result in less efficient transportation systems. Additionally, the relationships between these variables highlight the challenges these cities face in achieving optimal network configurations for efficient urban mobility.

Cities such as Santiago, São Paulo, Mexico City, Rio de Janeiro, Quito, Lima, Cape Town, Riyadh, Cairo, Nairobi, and Lagos face notable challenges in achieving sustainable mobility, largely due to rapid urbanization, sprawling development, and limited infrastructure investment in Latin American and Middle East and Africa. These cities typically exhibit high graph density and graph diameter within their transit networks, reflecting extensive, complex layouts that often lack cohesive connectivity. The fragmented nature of their public transportation networks results in a heavy reliance on informal transit modes, such as minibuses and shared taxis, which add to network density but reduce system efficiency and reliability (Vecchio et al., 2020, 2021; Shamsuzzoha et al., 2021; Kaiser and Barstow, 2022; Guzman et al., 2020). Additionally, high street length averages, combined with underdeveloped traffic management systems, exacerbate congestion issues, creating bottlenecks and extended travel times. Together, these characteristics make it challenging for residents to access reliable, integrated transit options, hindering mobility sustainability.

Socioeconomic factors, including income inequality and dependence on low-cost informal transit, further shape mobility outcomes in these cities. Geographic constraints in areas like Rio de Janeiro and Quito, along with environmental issues such as air pollution from vehicular emissions, compound these challenges, limiting options for cohesive transit expansion. Addressing these issues requires focused efforts to improve transit infrastructure funding, integrate formal and informal transit networks, and enhance regulatory frameworks to ensure efficiency and safety. A strategic shift toward multimodal, accessible transportation could help reduce reliance on private vehicles, lower congestion, and foster more sustainable urban mobility systems.

In other words, in cities like Santiago, São Paulo, Mexico City, Rio de Janeiro, Quito, Lima, Cape Town, Riyadh, Cairo, Nairobi, and Lagos, cultural barriers significantly influence the adoption of sustainable traffic technologies. Long-standing habits and a preference for private vehicles, often linked to social status or the perception of greater reliability and safety compared to public transit, create resistance to shifting toward shared or eco-friendly modes. Additionally, in some of these regions, the informal transit sector (e.g., minibuses, motorcycle taxis) is deeply embedded in daily life and employment structures, making regulatory efforts challenging and hindering the uptake of new, sustainable technologies. Public mistrust in the consistency and quality of formal transit options also plays a role, deterring people from fully embracing innovations like electric buses, ride-sharing apps, or even urban cycling initiatives. Overcoming these barriers will require not only technological investments but also strong public awareness campaigns, community engagement, and government support to foster a positive cultural shift toward sustainable and efficient mobility solutions.

Additionally, in most cities of Middle East, Africa and Latin America, cultural barriers significantly influence the adoption of sustainable traffic technologies. Long-standing habits and a preference for private vehicles, often linked to social status or the perception of greater reliability and safety compared to public transit, create resistance to shifting toward shared or eco-friendly modes. This resistance is compounded by the deeply embedded nature of the informal transit sector in many of these regions, where minibuses and motorcycle taxis play a crucial role in daily life and employment structures. As noted by Chaudhry et al. (2023), the informal sector often provides essential mobility services that are not only convenient but also culturally ingrained, making regulatory efforts to promote formal transit options challenging. The prevalence of informal transit systems can hinder the uptake of new, sustainable technologies, as these systems may not align with the goals of formal public transportation initiatives.

Furthermore, public mistrust in the consistency and quality of formal transit options exacerbates the situation, deterring residents from fully embracing innovations such as electric buses, ride-sharing apps, or urban cycling initiatives. This mistrust is often rooted in historical experiences with unreliable public transport systems, as well as perceptions of safety and accessibility. As highlighted by Cresswell (2011), the complexities of mobility in urban contexts are influenced by social and cultural factors, which can shape individual attitudes toward different modes of transport. Overcoming these barriers will require not only technological investments but also strong public awareness campaigns, community engagement, and government support to foster a positive cultural shift toward sustainable and efficient mobility solutions. Initiatives that emphasize the benefits of sustainable transport, coupled with efforts to improve the reliability and safety of public transit, can help to build trust and encourage a transition away from private vehicle dependence.

These findings reinforce the idea that the topological structure of transportation networks plays a critical role in determining urban mobility and sustainability performance. Cities with more efficient and compact networks, characterized by higher node interconnectivity, clustering, and centrality, tend to perform better in terms of mobility readiness and sustainability outcomes, while cities with less efficient and more dispersed networks struggle with lower performance in these areas. The Fig. 3(c) biplot (PC1 vs PC3) further reinforces the behavior observed in the PC1 vs PC2 analysis, indicating consistent patterns across different principal component spaces.

3.3. Regression Models

In addition to the descriptive analysis, we developed multiple linear regression models to quantify the relationships between the key dependent variable, Urban Mobility Readiness Index (UMRi), and various graph-derived metrics and socio-demographic factors. The Ordinary Least Squares (OLS) regression model yielded an R^2 value of 0.815, indicating that approximately 81.5% of the variability in the UMRi can be explained by the selected independent variables. The adjusted R^2 value, which accounts for the number of predictors in the model, was 0.755, suggesting that the model fits the data well, with significant explanatory power.

Table 1 and Fig. 4 summarizes the results of the OLS regression model, showing the relationships between urban mobility readiness and various graph-derived metrics and socio-demographic factors.

Among the significant predictors, GDP per capita ($p < 0.001$) showed a positive coefficient, reinforcing the idea that cities with higher economic resources are better positioned to invest in advanced mobility infrastructure and

Table 1: OLS regression results showing the relationships between urban mobility readiness (UMRi) and various graph-derived metrics and socio-demographic factors. The model demonstrates strong predictive power with an R^2 value of 0.815 and an adjusted R^2 of 0.755. The F-statistic is 13.51 with a p-value of 3.91e-12, indicating the overall significance of the model. Significant variables include GDP per capita, streets per node, graph diameter, clustering coefficient, and assortativity degree.

Variable	Coefficient	Std. Error	t-Statistic	p-Value
Constant	-53.4467	45.916	-1.164	0.250
Population	-0.1657	0.196	-0.843	0.404
Surface Area	0.0007	0.001	0.972	0.336
Population Density	0.0004	0.000	1.501	0.140
GDP per Capita	0.0002	0.000	4.703	0.000**
Avg. Edge Length	-0.0071	0.099	-0.072	0.943
Streets per Node	29.0956	8.206	3.546	0.001**
Avg. Street Length	-0.0731	0.099	-0.741	0.462
Self-Loop Proportion	-1006.7279	839.290	-1.199	0.236
Betweenness Centrality	-367.3166	531.923	-0.691	0.493
Closeness Centrality	0.0051	0.003	1.717	0.093*
Graph Entropy	1.3536	3.163	0.428	0.671
Graph Diameter	-0.0504	0.020	-2.568	0.014**
Clustering Coefficient	190.4389	48.556	3.922	0.000**
Assortativity Degree	-45.1994	10.473	-4.316	0.000**
Mean Degree	2.7369	2.260	1.211	0.232

sustainability initiatives, which contribute to higher UMRi scores. This finding aligns with previous research that highlights the role of wealth in enabling the development of efficient and resilient transportation systems.

Streets per node average also emerged as a significant predictor ($p = 0.001$), with a positive coefficient. This suggests that cities with more interconnected street networks, where each node connects to multiple streets, tend to perform better in terms of urban mobility readiness. Dense and well-connected networks provide more routing options, reducing congestion and enhancing overall network efficiency. These findings are consistent with the idea that network density and interconnectivity are key factors in promoting efficient urban mobility (Alessandretti et al., 2023; Yang et al., 2022).

Conversely, graph diameter had a significant negative coefficient ($p = 0.014$), indicating that cities with larger network diameters, which reflect longer paths between nodes, tend to have lower UMRi scores. This supports the notion that compact and efficiently connected networks are crucial for urban mobility performance, as shorter paths reduce travel times and improve accessibility. Similar results have been observed in studies that emphasize the benefits of compact urban design for improving transportation efficiency (Gallo and Marinelli, 2020).

The clustering coefficient also had a significant positive impact on UMRi ($p < 0.001$), indicating that cities with higher levels of local clustering, where nodes are tightly interconnected within neighborhoods, tend to have higher mobility readiness. This reflects the importance of local connectivity in urban networks, which promotes accessibility and supports efficient short-distance travel.

On the other hand, assortativity degree had a significant negative coefficient ($p < 0.001$), suggesting that cities where nodes with similar degrees tend to connect with each other are less prepared for urban mobility. This could imply that assortative mixing may lead to segregated clusters within the network, which can hinder the overall flow and efficiency of the transportation system. This finding aligns with previous research indicating that overly homogenous network structures can create bottlenecks and reduce system-wide performance (Zhang et al., 2022a).

While several other variables were included in the model, such as population density and closeness centrality, they did not show significant predictive power in this context. However, their inclusion still helped control for their effects, allowing us to isolate the impact of the more influential predictors.

These results suggest that cities with denser, more interconnected transportation networks and efficient local clustering tend to perform better in terms of mobility readiness and sustainability. Conversely, cities with more dispersed and segregated networks may face greater challenges in optimizing their urban mobility systems. These findings provide important insights for urban planners, highlighting the critical role of network structure in shaping the effec-

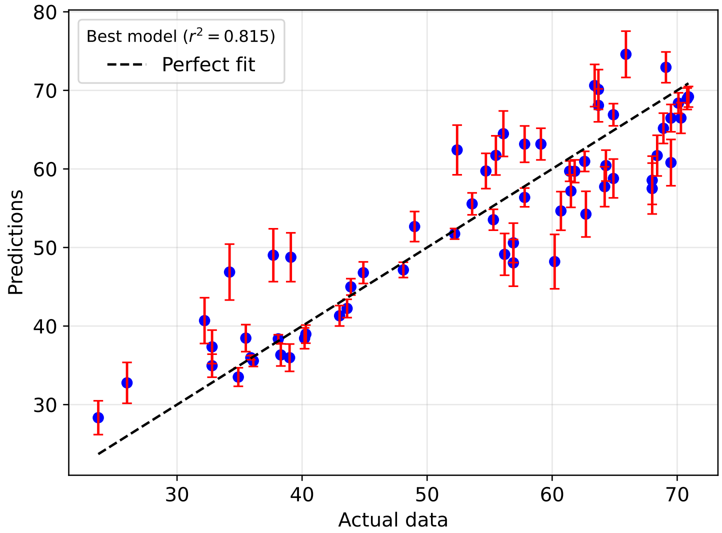

Figure 4: Scatter plot comparing the actual data with the predictions from the best regression model. The model achieved an R^2 value of 0.815, indicating strong predictive accuracy for urban mobility readiness based on the graph-derived metrics and socio-demographic factors. The solid line represents the perfect fit scenario.

tiveness of transportation infrastructure.

This study encompasses a diverse range of cities with varying socio-economic backgrounds, from affluent metropolises to rapidly developing urban centers. To account for these differences, we included socio-demographic variables such as GDP per capita, population density, and surface area in our regression models, enabling us to control for economic and demographic disparities effectively. This approach ensures that our analysis captures the unique challenges and opportunities faced by cities at different stages of economic development. By doing so, we aim to provide insights that are relevant and applicable across a broad spectrum of urban environments.

The conclusions drawn from our analysis are intended to be robust across these diverse contexts, although the strength and nature of the relationships may vary. For instance, while more interconnected and dense urban networks are generally associated with higher mobility readiness, the impact of these network characteristics can differ based on a city's economic capacity and developmental stage. Wealthier cities may have more resources to invest in advanced mobility infrastructure, thereby enhancing the positive effects of network connectivity. In contrast, developing cities might face constraints that moderate these relationships, such as limited financial resources or infrastructural challenges. Future research should further explore these contextual factors to deepen our understanding of how socio-economic disparities influence urban mobility dynamics and to refine strategies for enhancing mobility readiness in varied socio-economic settings.

4. Conclusions

This study provides important insights into the relationship between urban network structures, socio-demographic factors, and urban mobility readiness (UMRi). By employing a combination of complex network analysis, Principal Component Analysis (PCA), and multiple linear regression models, we demonstrated that cities with denser and more interconnected transportation networks generally achieve higher UMRi scores. Key metrics, including average node degree, clustering coefficient, and graph diameter, were identified as crucial factors contributing to enhanced mobility performance and sustainability. Cities characterized by more compact networks, where nodes are closely connected, tend to exhibit greater resilience and efficiency in their transportation systems, leading to better preparedness for urban mobility challenges.

The regression models underscored the significant role of both network structure and economic resources. Variables such as GDP per capita and streets per node were strong predictors of higher UMRi scores, highlighting that cities with greater financial resources and well-designed networks are better equipped to implement sustainable and efficient transportation solutions. Conversely, cities with more dispersed and less connected networks, indicated by metrics like graph diameter and average edge length, tend to face greater challenges in achieving higher mobility readiness.

This study offers a novel and comprehensive analysis of how urban transport network topology influences mobility readiness and sustainability across a diverse set of global cities. By integrating complex network metrics with socio-demographic factors, we have demonstrated that specific topological characteristics are significant predictors of urban mobility performance. Our methodological framework provides a new quantitative approach for evaluating and comparing the effectiveness of public transport systems and sustainable mobility policies in different urban contexts. This research not only contributes to the existing body of knowledge by highlighting the critical roles of network design and economic resources but also offers practical insights for urban planners and policymakers. By elucidating the direct correlations between transport network structures and key sustainability indicators, we underscore the importance of developing dense, interconnected, and well-funded transportation networks to enhance urban mobility readiness. This work thus adds valuable knowledge that can inform future urban planning and policy decisions aimed at fostering more sustainable and efficient cities.

Our findings indicate that more interconnected urban networks not only enhance mobility readiness but also significantly contribute to environmental sustainability. Efficient network structures facilitate the use of public transportation and non-motorized transport modes such as cycling and walking, thereby reducing reliance on private vehicles and lowering greenhouse gas emissions. This alignment between network topology and sustainable mobility practices underscores the critical role of thoughtful urban design in mitigating environmental impacts and promoting a greener urban future.

Furthermore, the topological characteristics of urban transportation networks have profound implications for long-term urban planning and resilience. Well-connected and compact networks support adaptable and scalable mobility solutions, enabling cities to better respond to future challenges such as population growth, technological advancements, and climate change. By prioritizing network interconnectivity and sustainability, urban planners can design transportation systems that are not only efficient and resilient but also aligned with the overarching goals of sustainable urban development.

These findings offer critical guidance for urban planners and policymakers seeking to enhance urban mobility and sustainability. Prioritizing the development of well-connected and dense networks, fostering local clustering, and reducing overall network dispersion can significantly improve urban mobility performance. Additionally, the results emphasize the importance of integrating economic considerations into urban planning strategies, ensuring that investments in transportation infrastructure are both equitable and strategically targeted.

Future research should explore the evolving relationship between network topology and emerging technologies, such as autonomous vehicles and smart city infrastructure. As urban environments become more complex, understanding how new technologies interact with existing transportation networks will be vital in shaping the future of urban mobility. Moreover, examining the non-linear dynamics and feedback loops within these systems can provide deeper insights into the long-term sustainability and efficiency of urban transportation networks. By addressing these challenges, cities can better navigate the complexities of modern urbanization and move towards more resilient and sustainable mobility solutions.

Despite the significant findings of this study, we recognize certain limitations that should be considered. First, our analysis is based on aggregate data from 62 cities, which, while providing a global perspective, may not capture local or regional particularities affecting urban mobility. In addition, the network metrics and indices used, while robust, depend on the quality and availability of data provided by sources such as the Oliver Wyman Forum and OpenStreetMap. Any inaccuracies or biases in these data could influence our results.

In other words, for future research, it would be valuable to expand the scope of the study by including more cities and considering additional variables that may affect urban mobility, such as specific government policies, more detailed environmental impacts, and user behaviors. Also, exploring more advanced analysis methods, such as machine learning models or dynamic simulations, could provide a deeper understanding of the complex interactions between urban network structure and mobility. This would contribute to developing more effective strategies to improve sustainable mobility in cities.

Abbreviations

UMRi: Urban Mobility Readiness Index
SMi: Sustainable Mobility Index
PTi: Public Transit Index
Pop: Population (millions)
SA: Surface Area (km^2)
PD: Population Density (people/km^2)
GDP: GDP per capita ($)
K Avg: Graph's average node degree (in-degree and out-degree)
ELT: Graph's total edge length
ELa: Graph's average edge length (=ELT/m)
m: Count of edges in graph
n: count of nodes in graph
SNa: Graph's average count of streets per node
IC: Count the intersections in a graph
SLT: Graph's total street segment length
SSC: Count the street segments in a graph
SLa: Graph's street segment average (=SLT/SSC)
Ca: Average street circuity using edges
SLP: Percent of edges that are self-loops in a graph
BCa: Average Betweenness Centrality (Normalized)
CCa: Average Closeness Centrality (Normalized)6
DCa: Average Degree Centrality (Normalized)
GE: Graph Entropy
GDi: Graph Diameter
GDe: Graph Density
CC: Clustering Coefficient
PLa: Average Path Length
Const: Constraints
AD: Assortativity Degree
MD: Mean Degree, average number of edges per node in the graph
Rec: Reciprocity, measure of the likelihood of vertices in a directed network to be mutually linked
Div: Measure of diversity for all vertices
PCA: Principal Component Analysis

CRediT authorship contribution statement

DDHA: Formal analysis, Software, Methodology, Writing – review, Resources, Data Curation, Visualization. **DSP:** Writing – original draft, Formal analysis, Conceptualization, Writing - Original Draft, Writing – review - editing, Software, Methodology, Formal analysis, Investigation, Resources, Data Curation, Visualization, Supervision.

Declaration of competing interest

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

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Data availability

Data is open and reported in this paper.

Supplementary data

Supplementary material related to this article can be found online at (Sierra Porta and Herrera Acevedo, 2024):

Sierra Porta, David; Herrera Acevedo, Daniel (2024), "Topological data analysis and Network analysis approach for sustainable mobility in cities", Mendeley Data, V1, doi: `https://doi.org/10.17632/gmyt9wrgst`.

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