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A Novel Approach for Road Traffic Analysis in Iran Using Social Network Analysis

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Abstract
Urban transportation networks are critical to the economic and social vitality of metropolitan regions, yet rapid urbanization and population growth have exacerbated traffic congestion, particularly in rapidly expanding cities such as Tehran, Iran. This study employs Social Network Analysis (SNA) to examine the structural characteristics and efficiency of road traffic network in Tehran province, focusing on the impact of seasonal traffic fluctuations during high travel periods. Leveraging directional traffic data from 141.ir, the research constructs and analyzes four network graphs to evaluate key metrics such as betweenness centrality, degree distribution, and clustering coefficients. Findings reveal that Tehran exhibits highly centralized network structure, with Tehran and the Tehran Freeway, functioning as critical hubs. However, this centralization poses significant risks, including network fragility and vulnerability to disruptions. Seasonal variations highlight shifts in traffic distribution, with peripheral nodes gaining importance during peak travel periods. The study underscores the need for diversifying transportation routes, strengthening intermediary nodes, and developing surrounding infrastructure to enhance network resilience and reduce dependency on central hubs. By integrating SNA with empirical traffic data, this research provides actionable insights for urban planners and policymakers, offering evidence-based strategies to optimize road network efficiency, mitigate congestion, and improve long-term transportation sustainability. Despite limitations related to data accessibility and external factors, this study demonstrates the utility of SNA as a robust analytical framework for understanding and addressing complex urban transportation challenges.
Keywords: Social Network Analysis; Road Transportation; SNA

1. Introduction

Urban transportation networks serve as the backbone of economic and social interactions in metropolitan regions [30]. Efficient and sustainable road transportation is critical for managing population growth, reducing congestion, and enhancing mobility [31]. In rapidly growing urban centers such as Tehran, the capital of Iran, road traffic congestion has become a pressing issue, necessitating the adoption of modern analytical techniques for network optimization. Social Network Analysis (SNA) has emerged as a powerful tool for understanding complex transportation systems by identifying key intersections, evaluating traffic flow, and optimizing road network efficiency [1].

Tehran, as the most populous city in Iran and one of the largest metropolitan areas in the world, faces numerous challenges in urban transportation. Rapid population growth, increasing road density, and unbalanced urban expansion have led to severe congestion, extended travel times, and declining quality of life for residents. According to official statistics, Tehran has a population exceeding 8 million within its urban limits and more than 15 million in its greater metropolitan area, making it one of the most traffic-congested cities globally (Statistical Center of Iran, 2021). This high population density and road network saturation necessitate innovative and efficient approaches to transportation planning and management.

One of the primary challenges in urban transportation planning in Tehran is the increasing complexity of road networks and the growing demand for higher efficiency. Traditional transportation analysis methods, while precise and based on sophisticated models, often require extensive time, financial resources, and computational efforts [1]. Moreover, conventional models tend to focus on static traffic conditions, lacking the dynamic and relational perspectives needed to capture the evolving nature of urban road networks [32].

To address these limitations, Social Network Analysis (SNA) has gained traction as an effective framework for examining road transportation systems. By leveraging graph theory, SNA models road intersections as nodes and traffic flow as directional edges, allowing for a comprehensive evaluation of network efficiency, centrality, and resilience [33].

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Several studies have demonstrated the effectiveness of SNA in identifying traffic bottlenecks, optimizing signalized intersections, and improving traffic distribution in urban environments [34]. In the context of Iran, a comprehensive SNA-based study of road networks in Tehran can provide crucial insights into urban mobility patterns and inform data-driven policy decisions aimed at alleviating congestion and enhancing accessibility.

Despite the growing importance of traffic network analysis in Iran, studies employing Social Network Analysis (SNA) methodologies in the country's road transportation sector remain limited. Prior research indicates that urban road networks with highly central intersections are more prone to congestion, necessitating decentralized flow strategies to improve overall traffic efficiency [35]. This study utilizes cleaned directional traffic data from 141.ir to explore a key research question: How does the centrality of major intersections in Tehran's road network influence traffic congestion and overall network performance? By leveraging SNA-based methodologies, this research seeks to bridge a crucial gap in Iranian transportation studies through an analysis of real-world directional traffic data and the application of advanced computational techniques.

Analyzing urban traffic dynamics requires both a spatial perspective on road connectivity and a temporal evaluation of variations in traffic flow. Seasonal shifts in traffic patterns significantly impact congestion levels, transportation efficiency, and road safety regulations. In Iran, travel intensity fluctuates throughout the year, with notable differences between low and high travel seasons. Esfand (February–March) represents one of the busiest traffic periods, as millions of Iranians undertake trips in preparation for Nowruz, traveling to visit relatives, pilgrimage sites, or tourist destinations (Iran Traffic Police, 2020).

This study focuses on assessing the structural characteristics of Tehran's road traffic network during Esfand, a peak travel period. By constructing and analyzing network graphs representing the city's road traffic conditions, the research aims to address the following key questions:

1. How do seasonal surges in urban traffic affect the overall connectivity and efficiency of Tehran's road network?
2. Do highly central nodes (such as major intersections or highways) experience significant shifts in congestion levels during peak traffic periods?
3. How does the spatial distribution of traffic loads change in high-traffic months, and what implications does this have for traffic control and urban mobility strategies?
4. Can network resilience and congestion mitigation efforts be enhanced by identifying structural vulnerabilities in the road system during peak travel times?
5. What insights can be drawn from comparative SNA metrics—such as betweenness centrality, degree distribution, and clustering coefficients—to support future infrastructure planning and traffic management policies?

By leveraging **directional traffic data from *141.ir***, this study will quantify how seasonal variations impact road network structure and efficiency. The results will provide **empirical insights** for policymakers and transportation engineers, offering evidence-based recommendations for optimizing road network performance during high-traffic seasons while maintaining efficiency in lower-traffic months.

2. Literature Review

The research conducted by El-adaway et al. [1] utilizes Social Network Analysis (SNA) to identify critical intersections in the transportation networks of Louisiana. This study has successfully identified critical points with reduced costs and time by employing various centrality measures in SNA. The findings of this research align with reports from the Louisiana Department of Transportation and highlight the effectiveness of SNA in transportation planning and the rapid identification of critical points. This tool can serve as a complement in the analysis of transportation networks.

The article published by Kuşkapan et al. [2] examines the road network of Erzurum Province in Turkey using SNA. In this study, intersections are considered as nodes and the connecting roads as edges. The edges are weighted based on traffic volume data, resulting in an undirected network where each edge represents the total bidirectional traffic. Common centrality measures in SNA are used for network and node analysis. This research demonstrates that various centrality concepts can assist in determining the most critical points, and the findings are compared with actual data to ascertain the accuracy of the centrality measurements.

In another study conducted by El-adaway et al. [3], transportation network analysis was performed in two case studies in Mississippi using SNA. This research indicates that by initially identifying critical intersections through SNA, the resources required for transportation planning can be reduced, allowing for a more comprehensive approach to network assessment.

The research published by Chang Liu et al. [36] employs SNA to enhance the logistics management of equipment in construction projects. This study introduces an innovative metric called the Direct Delivery Index (DDI), which evaluates equipment logistics performance based on historical equipment transfer data across distance and number of transfers. This method identifies critical points for optimization by analyzing the movement data of equipment within a network, facilitating the identification of management groups and improving decision-making. The results obtained from applying this index demonstrate that this approach can significantly enhance equipment logistics efficiency and reduce associated costs.

The article published by Qingyu Qi and Oh Kyoung Kwon [4] explores the characteristics of high-speed rail (HSR) and air transport networks in China based on a weighted complex network. This paper employs weighted centrality measures such as centrality, triangle betweenness centrality, and weighted harmonic centrality. In this network, nodes represent cities, and edges represent passenger traffic. As a result of this analysis, important nodes and sections of the network are identified, and some suggestions for future network development are provided.

The research conducted by Emre Kuşkapan et al. [5] examines the characteristics of the highway network in Istanbul using SNA in two case studies before and after the construction of the third Bosphorus Bridge. This paper utilizes traffic data from the road network affected by this project, comparing the state of the roads and the network as a whole before and after the project implementation. The construction project led to changes in the ranking of certain nodes and edges and increased the resilience of the network.

The study conducted by Yiping Wang et al. [6] investigates the relationship between an environmental metric across different cities and years in China's transportation industry using various methods alongside SNA. It maps and analyzes the correlation network of this metric. In this paper, various centrality measures are calculated, and an analysis of the distribution of important nodes in the geography of China and potential reasons for it is conducted, ultimately providing suggestions for future developments.

The article published by Nikhilesh Prabhakar et al. [7] examines the global air transport network and airports worldwide using SNA. In this research, centrality measures, average shortest paths, and Python are used for visualization.

The article published by Muhammad Nor Hafiz Bin Yaacob et al. [8] explores the rail passenger network of a region in Malaysia using SNA. The primary tool in this paper is clicks and the examination of their changes over time to understand travel patterns in urban and rural areas. In this paper, network clicks are plotted at different times. Micro, meso, and macro analyses are conducted on the network, and ultimately, the resilience of the network is examined.

The article published by Xia et al. [9] investigates the movement network of tourists between attractions using SNA in Beijing. In this study, tourist attractions are considered as nodes, and edges are established between them if tourists visit the attractions consecutively. The research tools for this study include centrality measures, network density, and the JNBC method. In the results section of this paper, some behaviors and patterns of tourists are analyzed, and recommendations for improvement are provided.

The article published by Jun-Yeop Lee and Shuyun Wang [24] examines the inter-provincial rail network in China using SNA. The results indicate that logistical convergence between the eastern and western provinces of China has increased; however, some provinces, such as Sichuan and Henan, have become bottleneck points. This study highlights the importance of network analysis in identifying logistical centers and improving regional coordination.

The article published by AD Koon et al. [25] investigates multi-sector coalitions for road safety in Brazil using SNA. The results indicate that local and international networks play a significant role in facilitating information flow, but they face challenges such as data scarcity. This study emphasizes the importance of multi-sector collaborations to improve road safety.

The research conducted by Z Shan et al. [26] combines the N-K model and SNA to examine safety risks in bridge construction. The results show that human and managerial factors have the most significant impact on the occurrence of incidents, and interactions between these factors can increase risk. This study underscores the importance of comprehensive risk analysis in construction projects.

The article published by L Jing et al. [27] analyzes the bibliometric research on traffic injuries using co-occurrence analysis of keywords and SNA. The results indicate that topics such as speed, alcohol consumption, and safety management are among the prominent subjects in this field. This study highlights the importance of comprehensive analysis of past research to identify future trends.

The research conducted by Y Wang et al. [28] investigates the risks in the supply chain of fresh products by combining the N-K model and SNA. The results indicate that warehousing and distribution planning are among the key risks, and increasing the number of synergistic factors can raise the likelihood of incidents. This study highlights the importance of risk management in the supply chain of fresh products.

The article published by K Oh et al. [29] analyzes the demand for postal services using SNA. This paper examines patterns of demand for postal services following the COVID-19 pandemic. The results indicate that identifying communities of shared goods with similar demand patterns can facilitate more effective distribution of goods. This study demonstrates the importance of network analysis in optimizing logistics and reducing costs.

Figure1, provided by using citationtree.org, illustrates the citation network of the article by El Adaway et al. [1]. As mentioned earlier, this paper focuses on the analysis of road transportation networks using SNA. The observation of the citation network, differentiated by time on the vertical axis, effectively demonstrates the interdisciplinary nature of this topic and the integration of transportation concepts with social network analysis

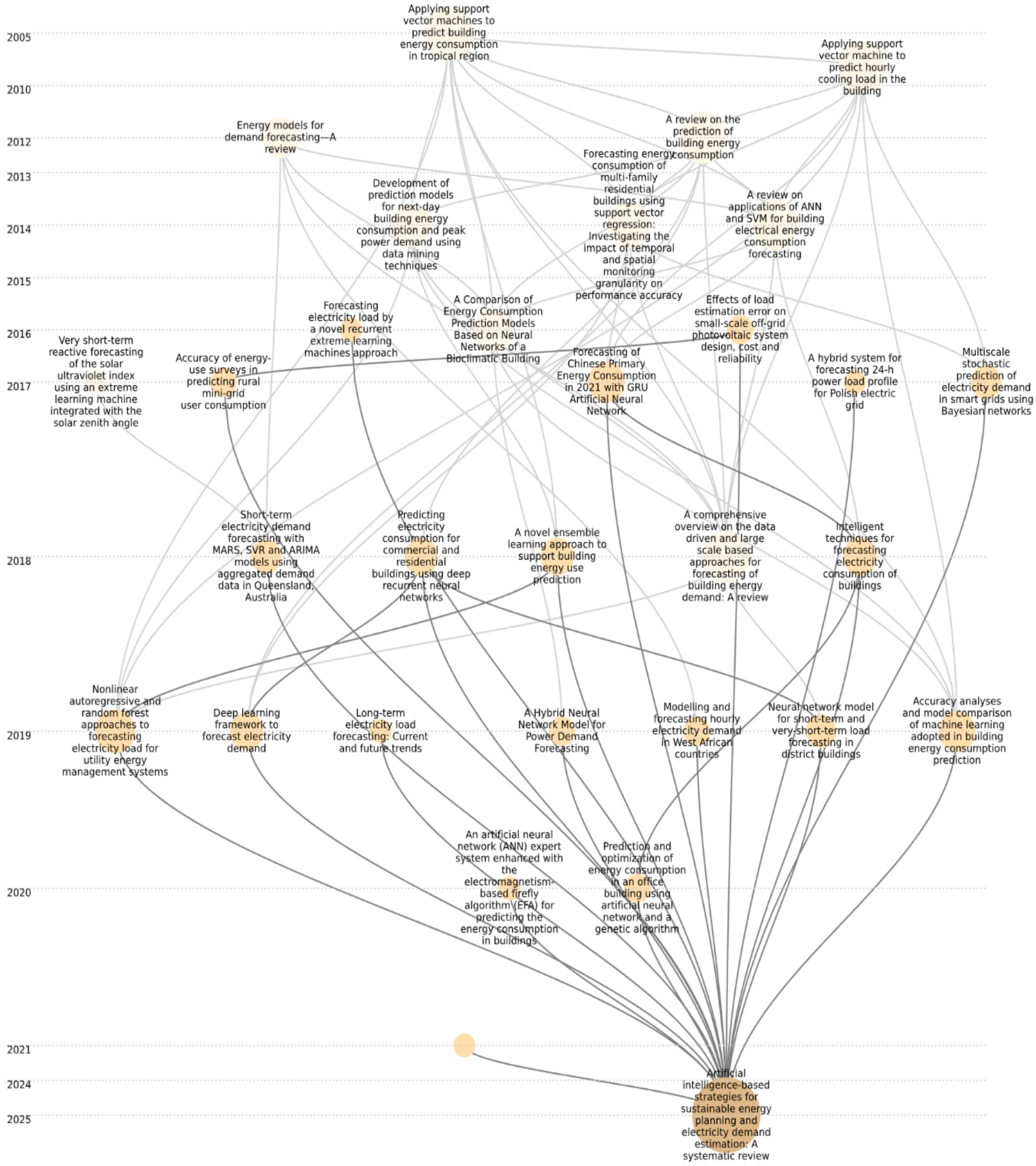

Figure 1: Citation Tree for El-Adaway's 2016 paper, indicating the inter-relation of Transport Management and Social Science fields.

Table 1. Literature Review Summary

Researchers and Year	Problem	Data	Analysis Tools	Results

Seongman Jang, Youngsoo An, [22]	Examines the relationship between centrality indices of urban railway stations and the number of passengers and average travel distance.	- Metro traffic data: Monthly passenger traffic reports from 2011 provided by KORAIL. - Urban railway network information: Collected from KOTI. - Land use characteristics: Calculated using building registration data in Seoul.	ArcGIS for network analysis, centrality measures (betweenness, reach, closeness), and multivariate regression models.	1. Increased explanatory power of models. 2. Identification of effective centrality indices. 3. Application in urban transportation planning.
Nir Sharav, Shlomo Bekhor, Yoram Shiftan, 25 January 2018	Evaluates the performance of Tel Aviv's public transport network and assesses whether proposed metro and tramway plans meet Israel's strategic goals for public transport.	Data on Tel Aviv's transport network, including the number of lines, stations, intersections, route lengths, and speeds of metro and tram lines. Collected from strategic transport plans and reports.	Graph theory and network analysis tools, including coverage, connectivity, complexity, degree of connection, and directness of routes.	Metro-focused plans (e.g., 5M) score higher in connectivity and route directness, while tram-focused plans score lower.
Jun-Yeop Lee, Shuyun Wang, 31 August 2012	Analyzes China's interprovincial railway logistics network using SNA to evaluate regional economic correlations.	Data from China's transportation statistical yearbook, including input-output volumes for each province in a 30x30 matrix.	Degree centrality, betweenness centrality, and community modularity.	Increased logistics convergence between eastern and western provinces, indicating stronger national economic ties. Central provinces like Sichuan and Henan face high logistics pressure.
Adam D. Koon et al., 11 Feb 2022	Strengthens multisectoral collaboration for road safety by identifying and analyzing organizational interactions.	Data collected through interviews and network questionnaires with 57 members of road safety coalitions in São Paulo and Fortaleza (August–October 2019).	Kumu for network visualization, STATA for statistical analysis, NVivo for qualitative data, and SNA.	Fortaleza's network is centralized and dense, led by an international NGO. São Paulo's network is more dispersed, with more local organizations. Both networks face challenges in data collection and analysis.
Z Shan, L Qiu, H Chen, J Zhou, 28 August 2023	Addresses safety risks in bridge construction, emphasizing the complexity of risk factors. Combines K-N model with SNA.	Data from 126 documented bridge construction incidents in China (2006–2023). Includes human, equipment, managerial, and environmental risk factors.	SNA and N-K model.	Increased risk with multiple interacting factors. Human errors, managerial issues, and equipment failures are key risk factors.
L Jing, W Shan, Y Zhang, 03 Feb 2021	Reviews trends in traffic injury research, identifying gaps and using bibliometric analysis, SNA, and clustering.	Data from Science of Web database (1928–2018), including 4,184 articles. Keywords reduced to 60 for analysis.	BibExcel for keyword extraction, co-occurrence analysis, SNA, and clustering.	Key topics: Causes of accidents (e.g., speed, alcohol), analysis methods (e.g., regression), health impacts, and safety management.
Y Wang, X Wang, X Geng, L Lv, R Sun, 2022	Examines risk management in fresh product supply chains, combining K-N model and SNA.	Data from scientific sources and field studies, identifying 27 direct and indirect risk factors.	K-N model for risk synergy analysis, UCINET for SNA.	Key risks: Storage and planning for fresh products. Increased risk with more interacting factors.
K Oh, S Kim, HBS Choi, H Lee, 2022	Analyzes postal service demand, which surged post-COVID-19.	Data from Company A's postal demand in Seoul (April 2021), including product categories and delivery regions.	SNA, Louvain and Girvan-Newman algorithms for community detection, centrality measures.	Identified communities with similar demand patterns and high-demand regions for specific products.
Islam H. El-adaway et al. (2018)	Identifies key traffic intersections using SNA in three case studies in Louisiana.	Traffic volume data (undirected) from three case studies in Louisiana.	SNA centrality measures, betweenness, UCINET, NetDraw.	Demonstrates SNA's potential in transportation planning (TP) and its advantage over traditional methods.
Emre KUŞKAPAN et al. (2021)	Identifies key traffic intersections using SNA in Erzurum, Turkey.	Traffic volume data (undirected).	SNA centrality measures, Bonacich Power, UCINET, NetDraw.	SNA is widely applicable in TP, with Bonacich Power being the most suitable measure.
Islam H. El-adaway et al. (2016)	Identifies key traffic intersections using SNA in two case studies in Mississippi.	Traffic volume data (undirected).	SNA centrality measures, Bonacich Power, 2-step reach, eigenvector, and betweenness.	SNA uniquely examines traffic networks locally and globally, with high potential in TP.
Chang Li et al. (2019)	Evaluates equipment logistics performance using SNA and DDI index.	Data collected by a third party from a Canadian construction contractor.	SNA centrality measures, clustering, DDI.	SNA is effective in preliminary TP network analysis, offering a comprehensive view.
Qingyu Qi et al. (2021)	Examines China's HSR and air transport networks, assessing stability and spatial distribution.	Data from China's HSR ticket reservation site and published air transport data.	SNA centrality measures, mean association, triangle betweenness centrality, weighted harmonic centrality, robustness analysis, ArcGIS 10.2.	Insights into HSR and air transport networks, recommendations for future development, and network stability evaluation.

Emre Kuşkapan et al. (2022)	Analyzes Istanbul's highway network using SNA, comparing before and after the Third Bosphorus Bridge.	Traffic data from Istanbul's Transport and Highway Management Center.	SNA centrality measures, SVM, Bonacich Power.	The central intersection shifted from L to K after the bridge. Bonacich Power is the best measure.
Yiping Wang et al. (2022)	Assesses GTFP index in China's transport industry over time, identifying key regions and nodes.	Data from China's statistical yearbooks and energy statistics.	SNA, environmental metrics, DEA-Malmquist model, QAP analysis.	Key regions identified based on centrality. Growth in most indices over time, with a skew toward eastern and coastal regions.
Nikhilesh Prabhakar et al. (2021)	Examines the global airport and flight network, identifying key nodes.	Data from openflights.org.	SNA centrality measures, average shortest path, Python for visualization.	Identified the most important airports globally based on various centrality measures.
Muhammad Nor Hafiz Bin Yaacob et al. (2020)	Analyzes the rail network in Klang Valley, understanding passenger travel patterns.	Data from Touch n Go Valley LRT, MRT, and Monorail journeys (10 columns, 5,686 rows).	SNA centrality measures, clique and triangle analysis, connectedness, and robustness analysis.	Clique and hub analysis using SNA provides deeper insights into the rail network.
Xia, M. et al. (2020)	Applies SNA to evaluate connection strength among tourist attractions in Beijing.	Massive car-hailing data on tourist travel patterns and spatial movement.	Network density, centralization, degree centrality, betweenness centrality, JNBC method.	Tourists focus on core attractions like the Forbidden City, with weaker connections to peripheral attractions.
Rezakhani & Kermani (2025)	Implements SNA on Iran's interprovincial road traffic network, focusing on Tehran during holidays.	Road traffic data from Iran's Road Maintenance and Transportation Organization (141.ir).	SNA centrality measures, betweenness, UCINET, NetDraw, Gephi, Python.	Identified key intersections and routes in both provinces during specific holiday period. Recommendations for future traffic planning.

3. Research Methodology

Social Network Analysis (SNA) serves as a powerful and innovative tool for understanding the structure and dynamics of networks, particularly in the context of road transportation. This method enables researchers to examine the relationships and interactions among various nodes within a network, providing insights into key elements such as traffic flow, connectivity, and centrality. In this research, we will analyze a social network in Iran's road traffic system, focusing on the province of Tehran, using directional traffic data collected and compiled from the "141.ir" website using Python. The primary objective of this study is to identify critical traffic nodes, evaluate their centrality, and assess the overall structure of the road traffic network in these regions. By applying SNA to Iran's road traffic network, this research aims to provide actionable insights for improving transportation planning and infrastructure development.

Figure2 illustrates the step-by-step methodology employed in this study to analyze Iran's road traffic network using Social Network Analysis (SNA). The process begins with data collection, where directional traffic data for the province of Tehran were obtained from the "141.ir" website for the month of Esfand. The data preprocessing phase involves using a Python script to extract and aggregate traffic data from multiple Excel files, ensuring the data is formatted correctly for network analysis. In the network formation step, the processed data is structured into a format suitable for visualization tools like Gephi, UCINET, or NetworkX, with columns representing origin, destination, and traffic weight. Finally, network calculations and analysis are conducted using key SNA measures such as Node Degree, Betweenness, Eigenvector Centrality, and Bonacich Power to evaluate the centrality and connectivity of nodes within the road traffic network. This structured approach ensures a comprehensive analysis of the network's structure and performance.

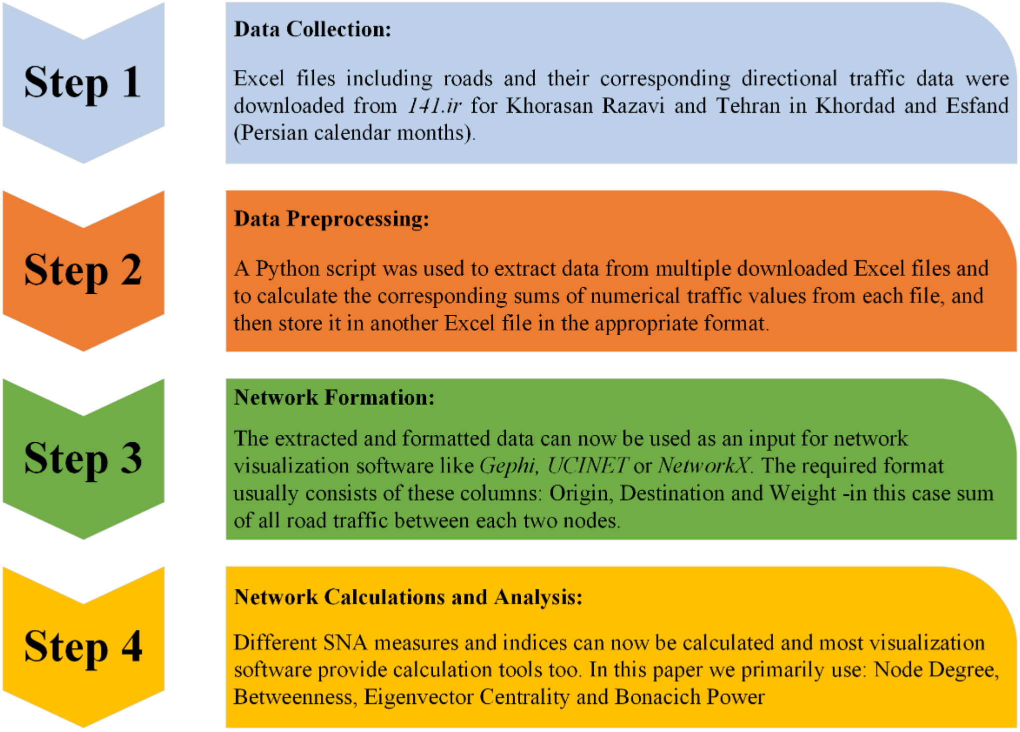

Figure 2: The overall procedure and methods used in this research.

تعداد وسیله نقلیه کلاس 5	تعداد وسیله نقلیه کلاس 4	تعداد وسیله نقلیه کلاس 3	تعداد وسیله نقلیه کلاس 2	تعداد وسیله نقلیه کلاس 1	تعداد کل وسیله نقلیه	مدت زمان کارکرد (دقیقه)	زمان پایان	زمان شروع	نام محور	کد محور
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604	451	670	1113	44769	47607	1330	1403/01/06 00:00:00	1403/01/05 00:00:00	آزادراه تهران - ساوه (تهران-رباط کریم	113258
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576	201	803	1029	38342	40951	1295	1403/01/10 23:05:00	1403/01/10 00:00:00	آزادراه تهران - ساوه (تهران-رباط کریم	113258
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230	122	413	770	34590	36125	1440	1403/01/14 00:00:00	1403/01/13 00:00:00	آزادراه تهران - ساوه (تهران-رباط کریم	113258
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667	272	817	1108	46637	49501	1440	1403/01/25 00:00:00	1403/01/24 00:00:00	آزادراه تهران - ساوه (تهران-رباط کریم	113258
1210	405	1517	1502	48696	53330	1350	1403/01/26 00:00:00	1403/01/25 00:00:00	آزادراه تهران - ساوه (تهران-رباط کریم	113258
2782	670	2414	2793	52290	60949	1435	1403/01/27 00:00:00	1403/01/26 00:00:00	آزادراه تهران - ساوه (تهران-رباط کریم	113258
2242	604	2191	2525	49337	56899	1375	1403/01/28 00:00:00	1403/01/27 00:00:00	آزادراه تهران - ساوه (تهران-رباط کریم	113258
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2327	648	2298	2787	59906	67966	1435	1403/01/31 00:00:00	1403/01/30 00:00:00	آزادراه تهران - ساوه (تهران-رباط کریم	113258
484	185	841	886	47441	49837	1435	1403/02/01 00:00:00	1403/01/31 00:00:00	آزادراه تهران - ساوه (تهران-رباط کریم	113258

Figure 3: An example Excel file obtained from 141.ir

3.1. Data Collection and Preprocessing

As shown in Figure2, after obtaining the relevant Excel files from the Iranian Road Management Center's website, the desired data is extracted using a Python script. Figure3 provides an example of the Excel files. It is important to note that all files available on the website follow the same structure.

The column names are: *Code of the Axis, Name of the Axis, Start Time, End Time, Duration of Operation (minutes), Total Number of Vehicles, Number of Class 1 Vehicles, Number of Class 2 Vehicles, Number of Class 3 Vehicles, Number of Class 4 Vehicles, Number of Class 5 Vehicles, Average Speed, Number of Speeding Violations, Number of Unauthorized Distance Violations, Number of Unauthorized Overtaking Violations, Estimated Number*.

The Python script extracts two nodes from the assigned name of the road by the website. For instance, if the name is "Tehran Freeway-Saveh", *Tehran Freeway* and *Saveh* will be stored as two nodes. The weight of the edge connecting these two nodes is calculated by the summation of all the daily traffic data in their relevant Excel file. Note that not every node is necessarily a city; in this case Tehran Freeway is not the city itself but only an intersection at the beginning of the Freeway which itself is represented as an Edge and the numerical value of the traffic data indicates its weight.

3.2. Traffic Counting Guide

Traffic count data has been collected visually since 1995 (1374 in the Iranian calendar). From 2002 (1381), traffic statistics have been collected mechanically using an underground inductive loop system on the roads. Since 2010 (1389), traffic count information has been collected and reported online, and to this day, at the end of each month, offline data for each traffic count axis has been made available on the website in daily and hourly formats.

Each traffic count axis is identified by a six-digit code, representing one direction of travel, such as the Tehran-Qom Freeway (Nalbandan).

In the data, Class 1 refers to passenger cars and pickups, Class 2 includes light trucks and minibuses, Class 3 encompasses standard trucks under 10 meters and three-axle vehicles, Class 4 is for buses, and Class 5 includes trailers and vehicles with more than three axles. This research specifically focuses on data related to Class 1.

According to the contract, traffic count data should have an accuracy of 95%. However, considering potential issues, an average accuracy of around 90% of the total expected data is estimated. Generally, the Road Maintenance Organization publishes the collected data on this page directly and without editing.

3.3. SNA Centrality Measures

Social Network Analysis provides a powerful framework for evaluating the structure and efficiency of transportation networks, where different locations (nodes) are connected by roads, railways, or transit routes (edges). One of the most critical aspects of SNA is the concept of centrality measures, which quantify the importance and influence of specific nodes within the network (Freeman, 1978).

In the transportation domain, centrality measures help identify critical intersections, highways, or railway stations that play a pivotal role in network performance (Rodrigue, 2020). For instance, nodes with high centrality values often act as transportation hubs, and their failure or congestion could significantly disrupt mobility (Wasserman & Faust, 1994). Understanding these metrics allows planners to prioritize infrastructure investments, improve traffic flow, and enhance resilience against disruptions (Borgatti & Everett, 2006).

In the following sections, we will introduce some of the most widely used centrality measures and explore their practical applications in transportation network analysis.

- **Degree Centrality**

Degree centrality is the simplest centrality measure, which quantifies the number of links connected to a node. In transportation networks, this measure indicates the number of streets connected to an intersection. Intersections that are connected to more streets have higher degree centrality. This measure is useful for identifying intersections that play a significant role in connecting different parts of the network (Freeman, 1979).

The formula for calculating degree centrality is as follows:

$$\boldsymbol{K_i = \sum_{j=1}^{n} A_{ij}}$$

In this formula:

- Ki is the degree centrality of node i.
- Aij equals 1 if there is a link between node i and node j; otherwise, it equals 0 (Wasserman & Faust, 1994).

- **Betweenness Centrality**

Betweenness centrality indicates the number of times a node appears on the shortest path between two other nodes. In transportation networks, this measure helps us identify intersections that play a critical role in connecting different parts of the network. If these intersections experience disruptions, the entire network may face significant issues (Freeman, 1979).

The formula for calculating betweenness centrality is as follows:

$$CB(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

In this formula:

- CB(v) is the betweenness centrality of node v.
- σst is the total number of shortest paths from node s to node t.
- σst(v) is the number of those paths that pass through node v (Brandes, 2001).

❖ **Eigenvector Centrality**

Eigenvector centrality measures the importance of a node based on the importance of the nodes to which it is connected. In other words, if a node is connected to more important nodes, it will have a higher eigenvector centrality. This measure is useful for identifying intersections located in significant and high-traffic areas of a city (Bonacich, 1987).

The formula for calculating eigenvector centrality is as follows:

$$x_v = \frac{1}{\lambda}\sum_{i \in M(v)} x_i = \frac{1}{\lambda}\sum_{i \in G} a_{vi} x_i$$

In this formula:

- x_v is the Eigenvector centrality of node v
- λ is a constant, typically the largest eigenvalue of the adjacency matrix.
- a_{vi} equals 1 if there is a link between node v and node i; otherwise, it equals 0 (Bonacich, 1987).

❖ **Bonacich Power Centrality**

Bonacich power centrality is a weighted measure that assesses the centrality of a node based on the centrality of its connected nodes and the strength of the connections among them. This measure is particularly useful for analyzing networks where the strength of connections between nodes varies (Bonacich, 1987).

The formula for calculating Bonacich power centrality is as follows:

$$C(\alpha, \beta) = \alpha(I - \beta R)^{-1} R$$

In this formula:

- α is a scaling vector.
- β is a parameter that determines the influence of the connected nodes.
- R is the adjacency matrix of the network.
- I is the identity matrix.

3.4. Software for Analysis

Gephi is a user-friendly software designed for visualizing and analyzing complex networks. Specifically tailored for social network analysis, it provides powerful tools for graph representation, community detection, and structural feature analysis such as centrality and density. Gephi employs advanced algorithms like Force Atlas for graph layout and allows for data filtering and dynamic modifications. This software is particularly beneficial for researchers and social network analysts who require visual representation and qualitative analysis of networks.

Python is a versatile and powerful programming language widely used in social network analysis. With numerous libraries such as NetworkX, Pandas, and Matplotlib, users can easily process, analyze, and visualize social network data. Python offers high flexibility in working with both structured and unstructured data, enabling the execution of complex algorithms such as community detection, path analysis, and centrality calculations. Due to its simplicity and large developer community, it has become one of the most popular tools for social network analysis (Hagberg, Swart, & Sculley, 2008).

UCINET is a specialized and widely used software for social network analysis that allows researchers to comprehensively analyze and interpret network data. This software provides tools for calculating centrality measures (such as degree, betweenness, and eigenvector centrality) and advanced analyses like clustering and network mapping, making it a powerful tool in network studies (Borgatti, Everett, & Freeman, 2002). In this research, UCINET was utilized to calculate Bonacich power centrality for each node. Additionally, UCINET supports various data formats and integrates with other software such as NetDraw, making it an ideal tool for visualizing and interpreting network analysis results.

Excel is a powerful and ubiquitous tool for data management and analysis, which is also applicable in social network analysis. Users can organize, filter, and analyze social network data using Excel. It offers tools like Pivot Tables and charts for data visualization and enables simple calculations such as degree centrality or identification of outliers. Although Excel may have limitations for more advanced social network analyses, it serves as a useful primary tool for data collection and preprocessing. This software is particularly suitable for users who are not familiar with programming.

3.5. Network Formation

The formation of transportation network in Tehran involves the intricate interplay of various routes, intersections, and transit points that connect different regions and facilitate movement within these urban areas. In the following network, nodes represent major intersections, while edges signify the roads that link these nodes. The visualization of the network is crucial for understanding the flow of traffic, identifying critical intersections, and analyzing the accessibility of different regions.

By employing advanced visualization techniques, researchers can uncover patterns of connectivity and detect communities within the transportation network. For instance, centrality measures can highlight intersections that play a pivotal role in connecting high-traffic areas, revealing potential vulnerabilities in the network. Understanding these dynamics is essential for urban planning and infrastructure development, as it allows for the optimization of transit routes and the enhancement of overall network efficiency. Ultimately, the analysis of transportation network provides valuable insights into the movement behaviors of residents and the effectiveness of the urban transit systems.

Like mentioned earlier, not every node is necessarily a city but only an intersection at the beginning or end of a road; which are shown as edges and the directional traffic data are considered as its weight.

In the following network, edge widths, colors and directions are based on the traffic data obtained earlier. Red and yellow/orange colors represent more traffic on that edge. Node names are also proportional to the maximum degree of each node (i.e. if in-degree of a node is 2 and out-degree is 5, its maximum degree is 5).

Figure 4 represents the transportation network of Tehran province in Esfand, showing Tehran as the central hub with extensive connections to nearby cities such as Qom, Damavand, and Karaj. Notably, key highways like the Tehran-Qom Freeway and the Tehran-Karaj axis are marked with thicker and colored edges, reflecting their critical role in regional connectivity. The diagram underscores the importance of these routes for managing traffic flow and addressing potential bottlenecks during this period.

Here in Table 2, we have node rankings of the Tehran-Esfand Network. Further analysis of the results will take place in discussion section.

Table 2: Tehran's nodes ranked based on Esfand traffic data

	MAX. DEGREE		*BETWEENNES*		*EIGENVECTOR CENTRALITY*		*BONACICH POWER*	
RANK	**node**	**value**	**node**	**value**	**node**	**value**	**node**	**value**
1	Tehran	10	Tehran	63	Tehran	1	Tehran (Toll)	4183298
2	Tehran Freeway	9	Damavand	39	Tehran Freeway	0.947	Tehran	4145741
3	Damavand	7	Tehran Freeway	36	Damavand	0.427	Tehran (Old Toll)	4110800
4	Firuzkuh	7	Rudhen	21	Firuzkuh	0.381	Pakdasht	3764127
5	Shahriar	5	Firuzkuh	21	Pakdasht	0.364	Karaj (Old Toll)	3669200

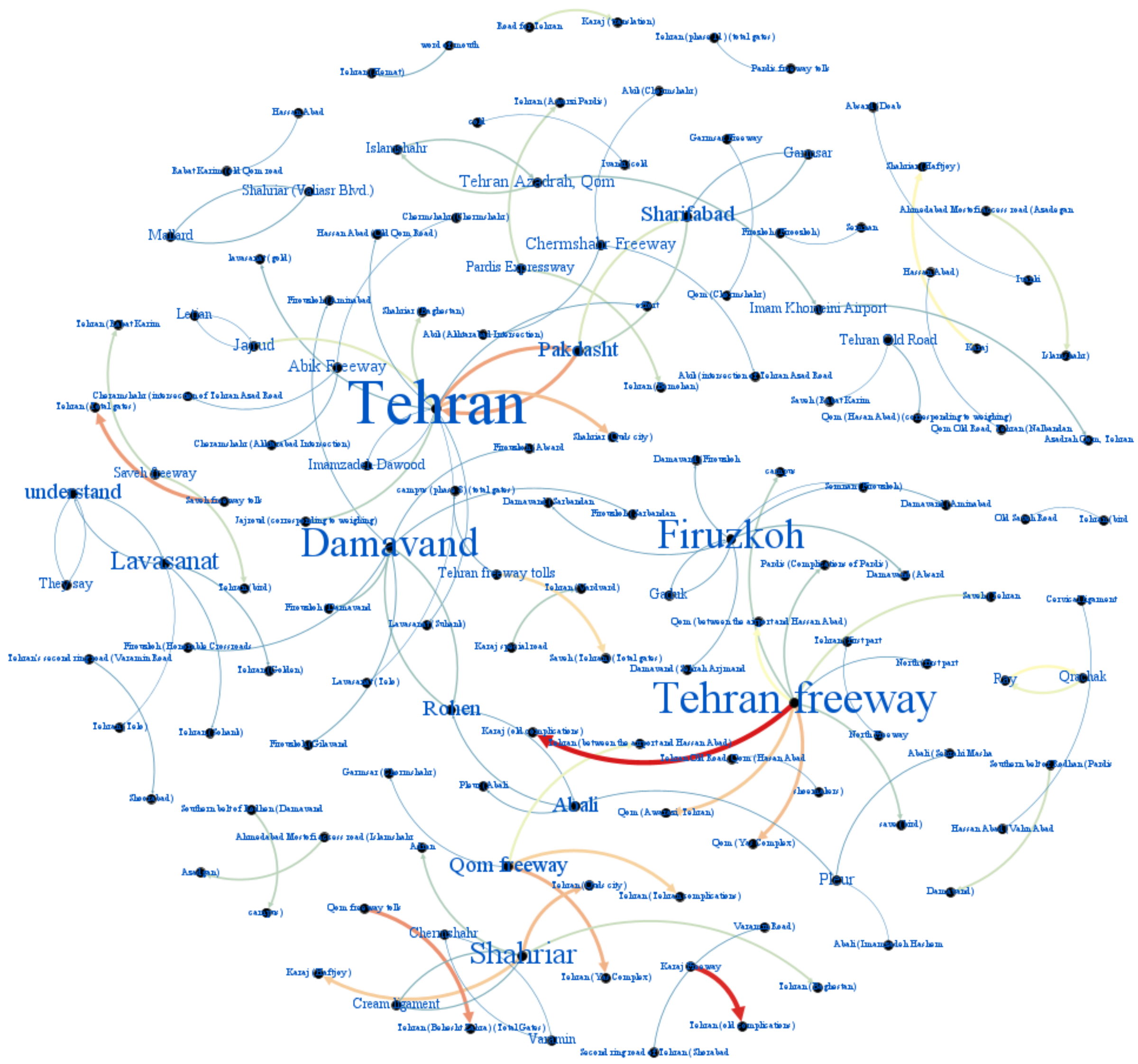

Figure 4: Road Traffic of Tehran Province in Esfand

4. Discussion

The analysis of road traffic data in Tehran Province using network metrics indicates that Tehran and the Tehran Freeway act as the main hubs of the network. These points not only have the highest traffic volumes but also play a critical structural role in connecting other points within the network. However, several non-obvious and thought-provoking insights emerge from this analysis:

Tehran ranks first or second in all metrics (degree, betweenness, eigenvector centrality, and Bonacich power). This indicates that the road traffic network in Tehran Province is highly centralized, with Tehran functioning as a monopole node. This concentration may lead to excessive pressure on Tehran's infrastructure, and any disruption at this point could trigger a crisis throughout the entire network.

This pattern may reflect a regional imbalance in the development of transportation infrastructure. In other words, while points such as Firuzkuh, Shahriar, and Damavand are important, they have not been sufficiently developed to reduce Tehran's role as the primary traffic center.

The Tehran Freeway, with a very high betweenness value (45), indicates that this route serves as a crucial artery for traffic between other points. This freeway manages not only intra-city traffic in Tehran but also inter-provincial and even international traffic. This highlights the strategic importance of this freeway, as any disruption could have widespread impacts on the entire network.

However, this heavy reliance on a specific route (the Tehran Freeway) may indicate a weakness in the diversity of alternative routes. Developing alternative routes, such as enhancing parallel roads or creating new freeways, could alleviate pressure on this vital artery.

Firuzkuh and Shahriar, with relatively high betweenness values (21 and 10), act as intermediary nodes. While these points may not be as busy as Tehran in terms of direct traffic, their geographical locations play a key role in connecting various regions. This suggests that improving infrastructure at these points could enhance the overall efficiency of the network, even if these points do not individually handle high traffic volumes.

The Bonacich power of Tehran (Tehran Freeway) and Tehran (Old Toll Road) indicates that these points are not only influential themselves but are also connected to other very important nodes. This shows that the indirect influence of these points on the network is substantial. In other words, disruptions at these nodes could have cascading effects on other points in the network. This pattern may suggest that the road traffic network in Tehran Province is structurally fragile, as disruptions at a few key points could impact the entire network.

Given the severe concentration of power in Tehran, it can be concluded that surrounding areas like Pakdasht and Karaj (Old Toll Road) have greater potential for development. While these areas currently play a lesser role in the network, improvements in infrastructure and the creation of new routes could allow them to serve as secondary hubs and reduce pressure on Tehran.

The analysis of the road traffic network in Tehran Province indicates that this network is structurally highly centralized and dependent on a few key points. While this concentration may enhance network efficiency in the short term, it could lead to network fragility and increased vulnerability to disruptions in the long term. To mitigate this risk, it is recommended to:

- ✓ Diversify main routes by developing freeways and alternative roads.
- ✓ Strengthen intermediary points like Firuzkuh and Shahriar to enhance network flexibility.
- ✓ Develop surrounding areas like Pakdasht and Karaj as secondary hubs to reduce dependence on Tehran.

5. Conclusion

This study utilized social network analysis to examine the structure and characteristics of road traffic network in a major Iranian metropolis, Tehran Province, during Esfand. The results indicate that the network is highly centralized, with the city of Tehran as the main hub. While this concentration may enhance network efficiency in the short term, it could lead to network fragility and increased vulnerability to disruptions in the long term. For instance, any disruption in the infrastructure of the city could have widespread effects on the entire network.

The Tehran Freeway was identified as a vital artery that plays a key role in connecting various points in the network. However, the heavy reliance on this route indicates a weakness in the diversity of alternative routes

Theoretically, these findings align with studies such as Devlin (2018), which emphasize the importance of diversifying main routes and strengthening intermediary points to enhance the flexibility of transportation networks. Furthermore, this analysis demonstrates that the indirect influence of certain nodes, such as Firuzkuh in Tehran, can be much greater than their direct impact, highlighting the need for special attention to these points in future planning efforts.

Ultimately, this study illustrates that social network analysis is a powerful tool for understanding the structure and characteristics of road traffic networks. This method can assist transportation planners in identifying critical points in the network and implementing necessary actions to improve traffic conditions and reduce congestion at these points. However, to create sustainable and resilient transportation networks, there is a need to develop surrounding infrastructures, establish alternative routes, and reduce dependence on central nodes.

6. Challenges and Limitations

Several challenges and limitations were encountered in conducting this analysis that should be considered in future studies. First, limited access to accurate and up-to-date road traffic data was a primary challenge. The data used in this analysis may not cover all aspects of road traffic, which could impact the accuracy of the results. Additionally, the fragmented nature of data access required programming for collection, which may have introduced errors.

Second, the failure to account for external factors such as weather conditions, traffic incidents, and seasonal changes in the analysis was another limitation of this study. These factors can significantly influence traffic patterns and, consequently, affect the results of the analysis.

Third, the focus on a large city and the lack of examination of other cities and regions may limit the generalizability of the findings to other road traffic networks in Iran. To achieve a more comprehensive understanding of road transportation networks, there is a need to examine other cities and regions as well.

Finally, the limitation of using network metrics alone, without considering other social, economic, and cultural factors, may result in an analysis that does not capture all the complex dimensions of road traffic networks. To achieve more accurate and practical results, it is recommended that future studies employ mixed methods that consider both network metrics and external factors.

Despite these challenges and limitations, this study demonstrates that social network analysis can serve as a powerful tool in road transportation planning. With improved data and analytical methods, a better understanding of the structure and characteristics of road traffic networks can be achieved, leading to more effective solutions for their improvement.

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