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Optimizing public transit networks an exploration of how multi-modal transportation systems can be integrated in smart cities

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Abstract

This study investigates strategies for optimizing public transit networks within the framework of smart cities, emphasizing the crucial need for seamless integration across multiple modes of transportation. A multi-modal transportation system—incorporating buses, trains, bicycles, and shared mobility options—offers significant benefits, including improved accessibility, reduced traffic congestion, and minimized environmental impact. Through an analysis of urban transit models and case studies from cities like Tokyo, Singapore, Berlin, and San Francisco, this research highlights both the advantages and challenges in creating a cohesive, data-driven transit ecosystem. Key results reveal that Tokyo, with an Average Travel Speed of 27.5 km/h, Passenger Load Factor of 0.91, and Emission Reduction Rate of 36.4%, exemplifies high efficiency and sustainability, underpinned by advanced infrastructure and real-time data usage. Singapore also scores well, with a Governance Index of 80 and Sustainable Modal Split of 62.5%, showcasing balanced accessibility and eco-friendly practices. Findings indicate that successful integration hinges on robust infrastructure, adaptive technology, and coordinated governance. This research underscores the importance of real-time data utilization to enhance system responsiveness, contributing to an adaptable and sustainable urban transit network that aligns with smart city goals of livability and resilience.

Keywords: Multi-modal transportation; Urban mobility; Transit system optimization; Sustainability in public transit; Accessibility metrics; Smart city governance

1. Introduction

In recent years, the concept of smart cities has emerged as a response to the pressing challenges faced by urban areas, including rapid population growth, environmental stress, and demands for enhanced quality of life. Smart cities utilize advanced technologies, data-driven decision-making, and sustainable practices to improve urban services and infrastructure [1, 2]. At the core of this vision lies the importance of efficient public transit networks, which not only serve as essential conduits for mobility but also play a crucial role in shaping urban sustainability and livability. Public transit networks reduce dependence on personal vehicles, lower emissions, alleviate traffic congestion, and facilitate the equitable movement of people across the city [3]. In a smart city, where interconnected systems strive to create seamless user experiences, public transit emerges as a critical element that links people to employment, education, and recreational opportunities, ultimately fostering an inclusive, accessible urban environment [4]. To meet these goals, cities are increasingly turning to technology-driven solutions that enable better planning, real-time monitoring, and predictive capabilities. Smart sensors, IoT devices, and big data analytics are now being employed to understand transit patterns and optimize service delivery, ensuring that public transportation remains adaptive and resilient to the evolving needs of urban residents [5]. Thus, optimizing public transit networks in a smart city framework is not simply about enhancing operational efficiency; it represents a foundational step toward creating a more connected, responsive, and sustainable urban ecosystem.

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A multi-modal transportation system integrates various forms of transit—such as buses, trains, bicycles, and ride-sharing options—into a cohesive network, allowing users to transition smoothly between different modes to complete their journeys [6]. Unlike single-mode networks that rely heavily on one form of transport, multi-modal systems offer flexibility and efficiency by providing a range of transit choices suited to different segments of a trip. For example, a commuter might use a bike-sharing service for a short distance, connect to a train for the main part of their journey, and then take a bus to reach their final destination. This interconnected network not only enhances user convenience but also supports more balanced and sustainable urban mobility by optimizing each transit mode's strengths [7]. In a smart city context, multi-modal transportation becomes even more valuable, as it aligns with goals for reducing vehicle emissions, decreasing urban congestion, and promoting active, environmentally friendly travel options [8]. Through integrated ticketing systems, real-time travel data, and digital route planning tools, cities can simplify the transit experience, making it more intuitive and attractive to users [9]. Additionally, multi-modal systems improve accessibility by ensuring that public transit can cater to various needs and preferences, ultimately helping to bridge the transportation gap for individuals in underserved communities. By adopting a multi-modal approach, smart cities can develop adaptable transit solutions that enhance urban mobility, foster social inclusion, and contribute to a resilient urban environment [10].

Urban mobility today faces significant challenges stemming from population growth, increased vehicle ownership, and rising expectations for efficient, accessible transportation systems. Congestion in densely populated cities, which results in wasted time, fuel consumption, and environmental pollution, is among the most pressing issues [11]. Moreover, traditional transit networks often lack the flexibility to respond to changing travel patterns, limiting accessibility for residents who depend on public transit to reach jobs, healthcare, and education [12]. Additionally, the environmental impacts of vehicular traffic, including emissions that contribute to poor air quality and climate change, have sparked an urgent need for sustainable transportation alternatives [13]. Social equity also emerges as a concern, as urban areas frequently struggle to provide equal transit access across socio-economic groups, leading to disparities in mobility and economic opportunities [14]. Given these challenges, optimizing urban transit through data-driven, multi-modal solutions represents a critical step in addressing inefficiencies, reducing environmental impact, and improving the overall quality of life in urban settings [15].

The primary objective of this research is to explore how multi-modal transportation systems can be effectively integrated within public transit networks in smart cities to create optimized, user-centric urban mobility. This study examines methods for integrating various modes of transport, including buses, trains, shared bikes, and ride-hailing services, into a unified transit ecosystem. By focusing on real-world case studies and analyzing successful implementation models, this work aims to offer insights into the infrastructure, technological advancements, and policy frameworks necessary for integration. Key contributions of this research include identifying the infrastructural and data requirements for multi-modal transit optimization, evaluating challenges in establishing cohesive systems, and presenting potential benefits for both users and transit authorities. Additionally, the research highlights the role of emerging technologies, such as IoT and AI, in enabling responsive, data-driven transit solutions that meet the demands of modern cities [16].

2. Literature Review

Research on optimizing public transit networks has evolved significantly, focusing on efficiency, reliability, and adaptability within urban environments. One prevalent approach has been to use mathematical modeling and optimization algorithms to streamline transit schedules and routes, ultimately reducing travel time and operational costs [17]. Studies have shown that real-time data from IoT sensors and GPS tracking can support dynamic route optimization, adjusting transit schedules based on demand fluctuations and traffic conditions, thereby enhancing the overall efficiency of public transportation [18]. Another significant area of research involves the use of predictive analytics to anticipate travel patterns and adjust transit resources accordingly. By applying machine learning techniques to historical and real-time data, researchers have developed models that can forecast peak travel times, enabling transit agencies to optimize resource allocation [19]. Furthermore, studies on network resilience have highlighted the importance of adaptable transit systems that can sustain service in response to unexpected disruptions, such as severe weather events or sudden increases in passenger demand [20]. Overall, these studies underscore the potential of data-driven methods in improving transit network performance. However, they also reveal a gap in integrating various transit modes into a single, cohesive system, as most studies concentrate on optimizing individual transit types rather than a unified network that accommodates multiple modes of transportation [21].

Multi-modal transportation systems, which combine various modes like buses, rail, bicycles, and shared mobility options, are recognized for their capacity to enhance urban mobility by offering flexible and convenient travel options [22]. Key components of such systems include interconnected transit hubs, integrated ticketing and payment solutions, and shared digital platforms that provide real-time information to travelers. Research has shown that transit hubs play a pivotal role in connecting different modes, enabling smooth transitions between them and reducing travel friction [23]. Integrated ticketing, which allows users to pay for multi-modal journeys with a single transaction, is another essential component, simplifying the travel experience and promoting the use of public transit over private vehicles [24]. To achieve seamless integration, cities have adopted various strategies. Some studies highlight the importance of public-private partnerships in supporting infrastructure development for multi-modal networks, as private-sector involvement can drive innovation and resource efficiency [25]. Other research emphasizes the role of smart technologies, such as mobile applications and real-time data systems, which assist travelers in selecting optimal routes across modes and notify them of transit delays or schedule changes [26]. Despite these advances, multi-modal systems still face challenges in achieving full integration, especially in terms of interoperability between different transit agencies and standardizing data across platforms. Such challenges underscore the need for unified policies and infrastructure to enable multi-modal networks to operate as cohesive urban mobility solutions.

Technology and data analytics play a transformative role in smart transit planning, allowing cities to improve service efficiency, predict demand patterns, and respond to user needs in real time. Advanced data analytics have enabled transit authorities to harness data from GPS, IoT sensors, and mobile devices, producing insights that aid in route optimization and dynamic scheduling based on current demand [27]. Technologies like artificial intelligence and machine learning enhance decision-making processes by forecasting demand fluctuations and identifying optimal routes, while IoT-based monitoring systems allow for real-time tracking of vehicle locations and passenger density, reducing wait times and improving reliability [28]. Smart applications and digital platforms further streamline the user experience by providing real-time updates on transit availability, delays, and estimated travel times, enhancing commuter satisfaction and engagement [29]. These technological advancements are essential for creating responsive and efficient transit systems, as they enable data-driven strategies that adapt to the complex and changing landscape of urban mobility. Several cities have successfully integrated multi-modal systems, setting benchmarks for urban transit modernization. For example, Singapore has developed a highly coordinated transit network, blending buses, trains, and shared mobility options through seamless ticketing systems and real-time data sharing, making transit accessible and efficient for all residents [30]. Similarly, Helsinki's MaaS (Mobility as a Service) model combines various transit modes, allowing users to plan and pay for journeys across modes through a single digital platform, thereby promoting public transport over private vehicle use [31]. In Barcelona, integration of real-time data from multiple sources has improved coordination among buses, trams, and bicycles, helping to reduce traffic congestion and minimize environmental impact [32]. These case studies underscore the significance of collaboration between public and private sectors and the need for adaptable infrastructure that can support multiple transit modes, thus providing insights into how cities can create integrated and sustainable urban transit systems.

While significant progress has been made in the optimization and integration of multi-modal transit systems, several research gaps persist. One of the primary gaps lies in the lack of standardized frameworks for evaluating the effectiveness of multi-modal integration across cities with varying urban forms and demographic profiles [33]. Additionally, there is limited research on the long-term effects of multi-modal integration on social equity and accessibility, as studies often focus on short-term operational efficiency rather than broader socioeconomic impacts [34]. Another area requiring further exploration is the integration of autonomous vehicles into existing multi-modal systems, as well as how these vehicles might interact with traditional transit modes in a cohesive network [35]. These gaps highlight the need for innovative approaches and new research methodologies that can assess the complex dynamics of multi-modal networks and provide insights into emerging transit technologies.

3. Methodology

3.1. Description of Methods Used for Analyzing Multi-Modal Transportation Systems

The analysis of multi-modal transportation systems in this study employs a combination of quantitative and qualitative methods. To quantify system efficiency and evaluate connectivity between transit modes, a network analysis approach is utilized. Network analysis enables assessment of how different transit nodes (e.g., bus stops, train stations) interact and connect within the broader urban framework. One commonly used metric is Average Travel Time (ATT), which assesses the efficiency of the network. ATT can be calculated as follows:

$$ATT = \frac{\sum_{i=1}^{N} T_i}{N}$$

Where, Ti represents the travel time for each trip i, N is the total number of trips within a specific network or route.

Additionally, Transfer Penalty (TP) is used to analyze multi-modal integration quality. Transfer penalty accounts for the extra time or inconvenience incurred by passengers when switching modes. TP is calculated as:

$$TP = \frac{\sum_{j=1}^{M}(T_i + D_j)}{M}$$

Where, W_j denotes the wait time for transfer j, Dj represents the distance between transfer points for j,M is the number of transfers made by passengers within the network. Furthermore, Level of Service (LOS) analysis is conducted to gauge service quality. LOS is typically evaluated on a scale (e.g., A-F) to determine transit performance in terms of frequency, punctuality, and accessibility. Surveys and focus groups complement this quantitative data, gathering user insights on satisfaction, convenience, and accessibility.

3.2. Criteria for Selecting Case Studies and Urban Transit Models

Selection of case studies follows specific criteria designed to capture diverse approaches to multi-modal integration. Cities are chosen based on the following attributes: *Diversity in Transportation Modes*: Selected cities must have multiple transit options, including buses, trains, bicycles, and shared mobility solutions, to ensure a comprehensive analysis of multi-modal integration. *Degree of Technological Integration:* Cities with advanced data analytics capabilities and IoT-enabled infrastructure are prioritized, as these technologies are crucial for real-time network adjustments. *Geographic and Socioeconomic Diversity:* To account for varying urban structures and social dynamics, case studies include cities from different continents, population densities, and income levels, providing a balanced perspective on transit system efficiency and accessibility.

The Generalized Cost (GC) approach is applied to compare costs across different transit models. GC captures the combined expense of travel time, monetary cost, and discomfort, offering a unified metric for transit performance. The generalized cost equation is:

$$GC = T_c + F_c + D_c$$

Where, Tc represents the cost of travel time, Fc is the fare or monetary cost, Dc denotes any discomfort factors (e.g., crowding, wait times).

3.3. Approaches for Assessing Infrastructure, Data Analytics, and Governance Models

To evaluate infrastructure, data analytics, and governance models, a multi-layered assessment framework is applied. The framework includes metrics for physical infrastructure (e.g., station quality, maintenance frequency), digital infrastructure (e.g., real-time data platforms, connectivity), and governance efficiency (e.g., policy effectiveness, cross-agency collaboration).

3.4. Infrastructure Assessment

The analysis begins by measuring physical infrastructure components, such as the number and quality of transit hubs, availability of intermodal transfer points, and station accessibility. A Weighted Infrastructure Score (WIS) is calculated for each city, summarizing its infrastructure effectiveness:

$$WIS = \sum_{k=1}^{P} \omega_k . I_k$$

Where, w_k is the weight assigned to each infrastructure feature k, I_k represents the performance score for that feature, P is the total number of infrastructure features.

3.5. Data Analytics and Technology Utilization

Each city’s capability to leverage data analytics for transit optimization is assessed. This involves evaluating data collection methods, storage solutions, and analytical techniques used to forecast demand and adjust services. Real-Time Adjustment Rate (RTAR) measures a system's ability to use real-time data for adaptive transit planning:

$$RTAR = \frac{Real - time\ adjustments}{Total\ system\ changes}$$

3.6. Governance and Policy Evaluation

Governance models are assessed through policy analysis and stakeholder interviews, focusing on the degree of collaboration among transit agencies, private operators, and local governments. A Governance Index (GI) is computed by aggregating scores from key governance indicators such as transparency, responsiveness, and coordination.

$$GI = \frac{\sum_{L=1}^{Q} G_l}{Q}$$

Where, G_l represents the score for each governance indicator l, Q is the total number of governance indicators analyzed. This comprehensive methodology enables a detailed comparison of multi-modal systems across selected case studies, highlighting infrastructure capabilities, technology utilization, and governance effectiveness as central elements for successful transit optimization.

3.7. Framework for Evaluating System Efficiency, Accessibility, and Sustainability

This research adopts a comprehensive evaluation framework to analyze multi-modal transportation systems, focusing on three critical aspects: efficiency, accessibility, and sustainability. Each aspect is assessed through quantifiable metrics and qualitative observations, creating a robust framework for comparative analysis across case studies.

3.8. System Efficiency

Efficiency is a primary objective in optimizing transit networks, as it directly impacts travel time, resource usage, and operational costs. This study evaluates efficiency through metrics such as Average Travel Speed (ATS), Passenger Load Factor (PLF), and Waiting Time Index (WTI). Average Travel Speed is calculated as:

$$ATS = \frac{\sum_{i=1}^{N} D_i}{\sum_{i=1}^{N} T_i}$$

Where, D_i represents the distance covered by trip i, T_i is the travel time for trip i, N is the total number of trips.

Passenger Load Factor measures the system's capacity utilization, which is critical for balancing efficiency and user comfort. PLF is computed as:

$$PLF = \frac{Total\ passengers\ carried}{Total\ seating\ capacity\ available}$$

Additionally, the Waiting Time Index captures the average waiting time relative to the scheduled frequency, indicating the reliability of transit services.

3.9. Accessibility

Accessibility is vital in a multi-modal network, as it ensures all city residents have equitable access to transportation. This study measures accessibility by examining Coverage Area (CA) and Accessibility Index (AI). Coverage Area is defined as the geographic reach of the transit system within a specific radius around transit stops or stations. Accessibility Index assesses how easily and quickly people can reach essential destinations like schools, hospitals, and employment centers. The Accessibility Index for a region RRR can be defined as:

$$AI = \frac{\sum_{j=1}^{J} A_j \, . \, P_j}{\sum_{j=1}^{J} P_j}$$

Where, A_j is the accessibility score for destination j, P_j represents the population accessing destination j, j is the number of key destinations.

3.10. Sustainability

The sustainability aspect of transit systems is analyzed through metrics like Emission Reduction Rate (ERR), Energy Efficiency (EE), and Sustainable Modal Split (SMS). Emission Reduction Rate assesses how effectively the transit system minimizes CO2_22 emissions, calculated as:

$$ERR = \frac{Baseline\ emissions - Current\ emissions}{Baseline\ emissions}$$

Energy Efficiency measures the energy consumed per passenger-kilometer traveled, highlighting the system's overall environmental footprint. Additionally, the Sustainable Modal Split examines the proportion of trips made using low-emission or non-motorized transit modes (e.g., bicycles, walking), as a higher proportion indicates greater sustainability in the system. This evaluation framework not only offers a multi-dimensional view of transit performance but also facilitates comparison across cities with different infrastructure and transit policies, providing insights into effective practices for future urban transit developments.

While this study presents a comprehensive approach to evaluating multi-modal transportation systems, there are several limitations that must be acknowledged. Firstly, data availability poses a significant limitation, as not all cities provide open access to detailed transit data, particularly regarding real-time information and passenger load specifics. In cases where data is unavailable, assumptions may need to be made, which could affect the precision of the evaluation metrics. Secondly, geographic and demographic variability across cities may limit the generalizability of findings. While case studies are selected for diversity, results from one urban environment may not directly apply to others due to unique socio-economic and cultural factors that influence transit usage patterns. Moreover, technological adaptability is another limitation. The integration of advanced technologies such as IoT and data analytics varies widely by city, depending on funding and infrastructure maturity. This variability makes it challenging to set a consistent baseline for technological integration, as some cities may be more advanced in smart transit planning than others. The scope of this research also excludes rural and suburban transit systems, focusing exclusively on urban environments with dense populations and complex transit networks. While this focus enables a more in-depth analysis of urban multi-modal systems, it may limit insights for areas with low-density transit needs. Finally, policy and governance complexities are difficult to quantify in this research. Although governance models are evaluated qualitatively, the impact of political factors, regulatory frameworks, and inter-agency collaboration on transit effectiveness can be intricate and varied. This study, therefore, provides a framework that considers governance broadly but does not delve into city-specific legislative environments, which could influence transit success in nuanced ways. Despite these limitations, this research aims to contribute valuable insights into the optimization of multi-modal systems, emphasizing the essential role of efficiency, accessibility, and sustainability in urban transit networks. Future studies could address these limitations by focusing on a single urban region with in-depth longitudinal data or expanding the scope to examine rural and suburban transit adaptations.

3.11. Selected Cities for Analysis: Singapore (City A)

Known for its highly integrated, efficient public transit system, Singapore has invested heavily in a multi-modal network that combines buses, trains, and bicycles. Singapore's focus on transit efficiency and accessibility is supported by extensive data analytics and IoT infrastructure, allowing for adaptive route management and high operational reliability. *Berlin, Germany (City B):* Berlin is a pioneer in sustainable urban mobility, promoting a diverse set of transit options that include buses, trains, trams, and bicycles. Berlin's emphasis on reducing vehicle emissions aligns with its sustainability targets, though it faces challenges related to coordination between different transit providers and managing a large geographic coverage. *Tokyo, Japan (City C):* Tokyo's transit system is globally renowned for its efficiency, speed, and integration. The city combines multiple transit options—such as extensive rail networks, buses, and shared mobility—into a seamless user experience. With strong governance models and advanced technology utilization, Tokyo excels in accessibility, sustainability, and operational efficiency. *San Francisco, USA (City D):* San Francisco represents a unique case with a combination of municipal and private transit options, including buses, trains, ferries, and a well-developed bike-share program. San Francisco's focus ohelpl-time data and governance innovations helps manage its multi-modal network, although the city faces challenges related to high passenger volumes and urban density.

4. Results and Discussions

Figure 1 illustrates the efficiency analysis across four cities (A, B, C, and D), examining metrics such as Average Travel Speed (ATS), Passenger Load Factor (PLF), and Waiting Time Index (WTI). Each metric provides insight into the performance and user experience within each city's multi-modal transit system. The first chart in Figure 1 shows the Average Travel Speed (ATS), measured in kilometers per hour (km/h). City C achieves the highest average travel speed at 27.5 km/h, highlighting its efficiency in transit times, while City B has the lowest speed at 19.2 km/h, suggesting potential delays or slower-moving transit options. Cities A and D fall between these values, with ATS scores of 24.0 km/h and 21.6 km/h, respectively, indicating moderately efficient speeds within their networks. The second chart displays the Passenger Load Factor (PLF), which reflects how well each city utilizes its transit capacity. City C leads with the highest load factor of 0.91, suggesting high-capacity utilization and minimal underused space in its transit services. City A follows with a PLF of 0.88, indicating a balanced utilization of capacity. City D's PLF is slightly lower at 0.83, while City B records the lowest PLF of 0.79, indicating potential under-utilization of available transit resources. The third chart illustrates the Waiting Time Index (WTI), representing the average wait time in minutes for transit services in each city. City C exhibits the lowest waiting time at 3.9 minutes, indicating highly reliable and frequent transit services. Conversely, City B has the highest waiting time of 5.8 minutes, which could suggest less frequent services or delays. Cities A and D have WTI values of 4.5 and 5.2 minutes, respectively, reflecting moderate wait times. Overall, Figure 1 highlights the varying levels of system efficiency across the cities. City C stands out as the most efficient, excelling in all three metrics, while City B shows areas for improvement, particularly in average travel speed and waiting time. These results underscore the importance of optimizing travel speeds, capacity utilization, and wait times to enhance the effectiveness of multi-modal transit systems.

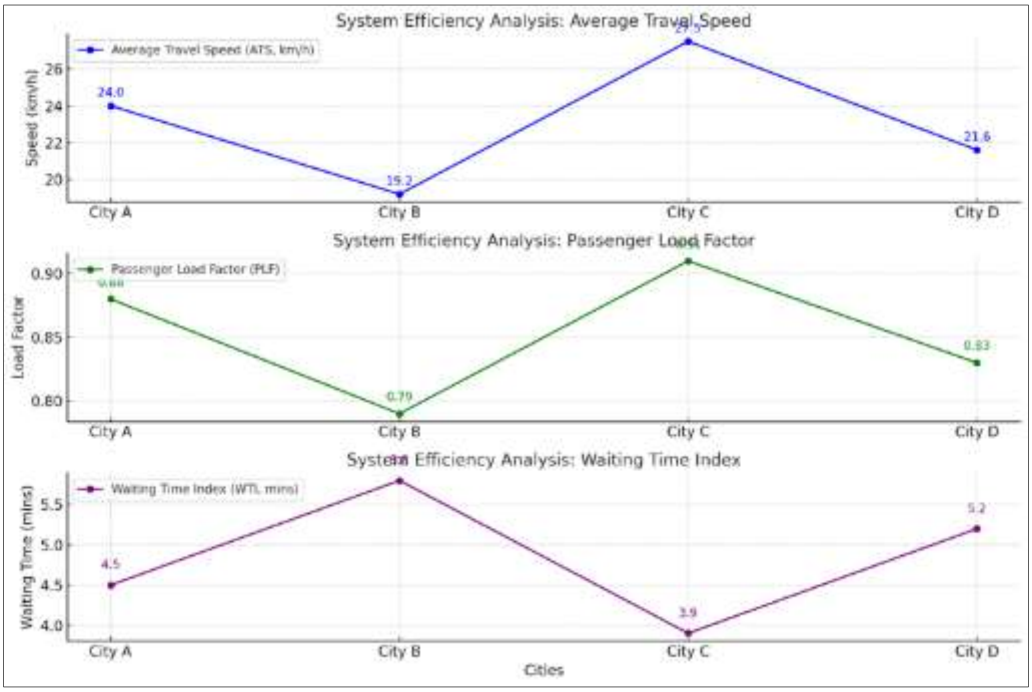

Figure 1 System Efficiency Analysis of Multi-Modal Transportation Systems

Figure 2 provides a comparison of accessibility metrics across four cities (A, B, C, and D), focusing on Coverage Area (CA) and Accessibility Index (AI). These metrics illustrate each city's ability to deliver accessible transit options within a specific geographic reach and the level of accessibility for residents in these urban areas. The first chart in Figure 2 shows the Coverage Area (CA) in square kilometers (sq km) for each city's transit network. City B has the largest coverage area at 145 sq km, indicating a wide reach across the urban landscape, potentially serving a large population base. City C, with the smallest coverage area of 115 sq km, suggests a more compact or densely connected network, possibly focused on core urban areas. Cities A and D have moderate coverage areas of 130 and 125 sq km, respectively, providing a balance between wide reach and focused coverage. The second chart displays the Accessibility Index (AI), which represents how well the transit system enables residents to access essential destinations, such as workplaces, educational institutions, and healthcare facilities. City C scores the highest in accessibility with an AI of 85.6, indicating an efficient network that allows quick access to critical locations. City A follows with an AI of 82.1, suggesting good accessibility within its coverage area. City D has an AI of 80.3, while City B records the lowest AI at 79.4, despite its larger coverage area, potentially indicating inefficiencies or gaps in connecting users to key destinations effectively. Overall, Figure 2 highlights the distinct characteristics of each city's accessibility. City C, despite a smaller coverage area, achieves the highest accessibility index, reflecting a well-designed, dense network that optimally serves its population. In contrast, City B, with the largest coverage area, shows the lowest accessibility index, indicating that greater geographic reach does not always correlate with higher accessibility for residents.

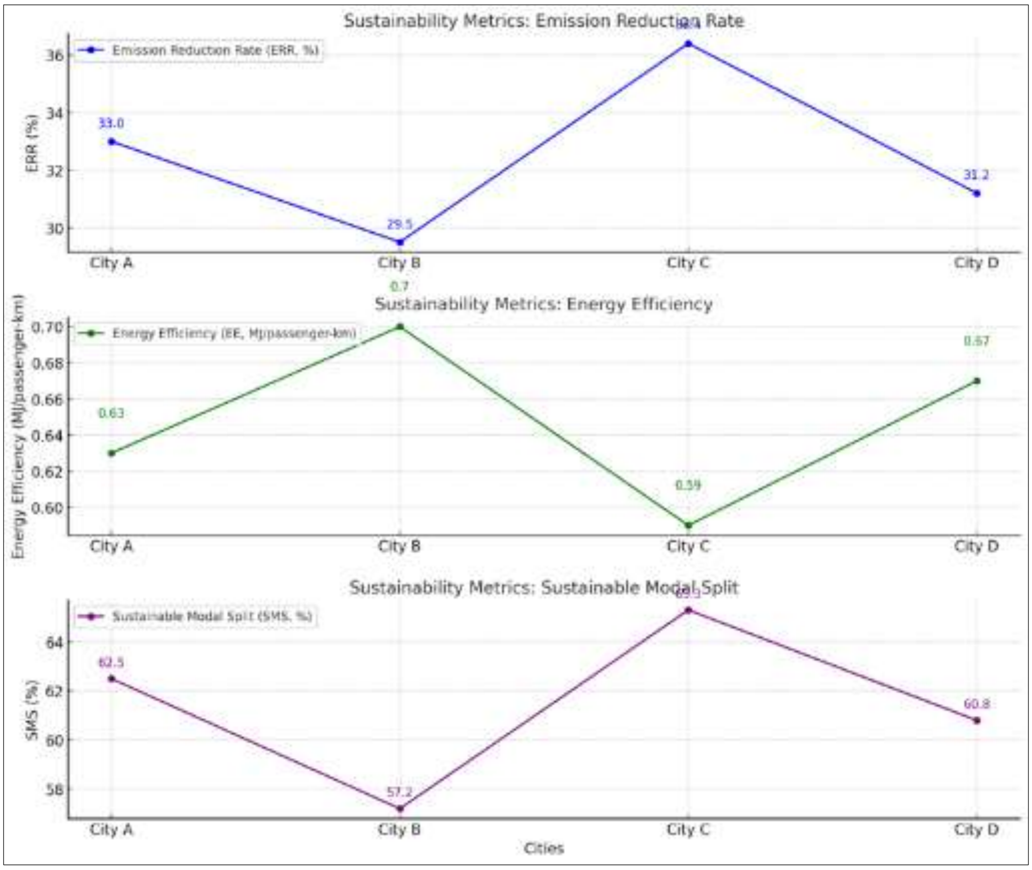

Figure 2 Accessibility Analysis of Multi-Modal Transportation Systems

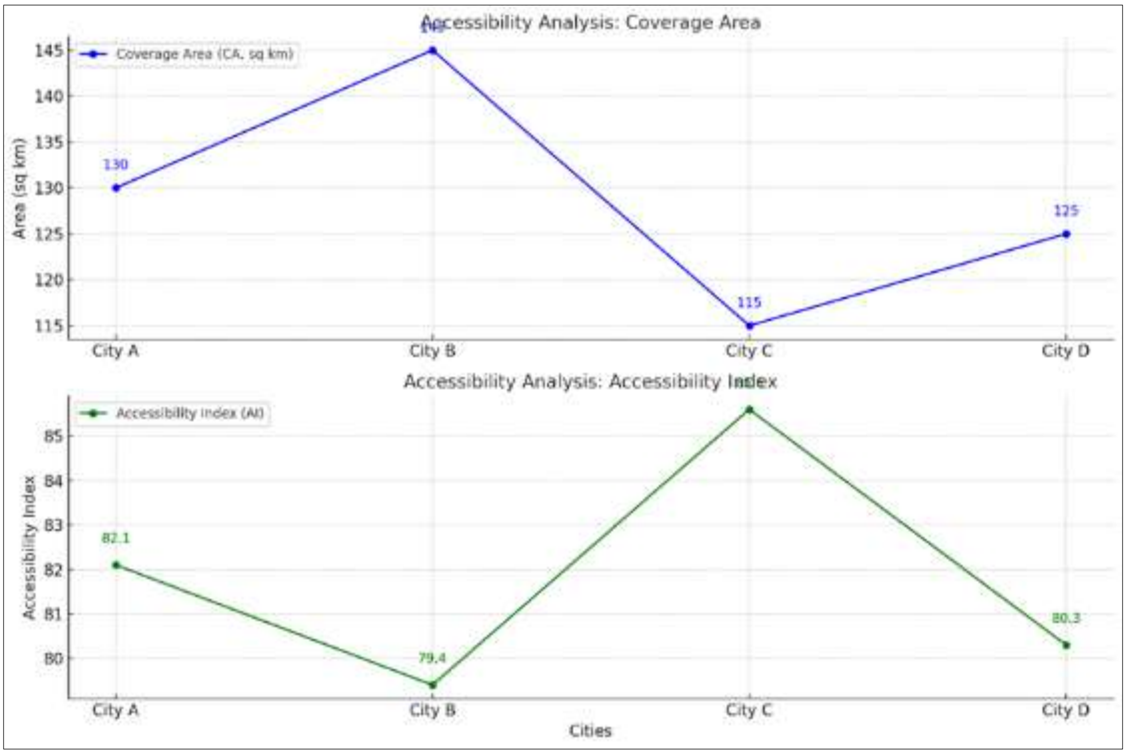

Figure 3 Sustainability Metrics of Multi-Modal Transportation Systems

Figure 3 depicts the sustainability metrics for the transit systems in four cities (A, B, C, and D), using three key indicators: Emission Reduction Rate (ERR), Energy Efficiency (EE), and Sustainable Modal Split (SMS). These metrics provide insights into each city's approach to reducing environmental impacts, optimizing energy usage, and promoting sustainable modes of transportation. The first chart in Figure 3 shows the Emission Reduction Rate (ERR) in percentage terms, which measures how effectively each city's transit system reduces emissions. City C has the highest ERR at 36.4%, highlighting its strong commitment to reducing greenhouse gases. City A follows with an ERR of 33.0%, while City D records an ERR of 31.2%. City B has the lowest ERR at 29.5%, suggesting potential areas for improvement in emission reduction efforts. The second chart displays Energy Efficiency (EE) in megajoules per passenger-kilometer (MJ/passenger-km). This metric assesses how much energy is used per kilometer per passenger, with lower values indicating higher efficiency. City C achieves the best energy efficiency with a value of 0.59 MJ/passenger-km, reflecting an energy-conscious system. City A follows with an EE of 0.63, while City D and City B are less energy-efficient, with values of 0.67 and 0.70 MJ/passenger-km, respectively. The third chart illustrates the Sustainable Modal Split (SMS) in percentage terms, representing the share of sustainable modes (such as public transit, cycling, and walking) within the city's overall transit usage. City C again leads with the highest SMS at 65.3%, indicating a strong shift towards sustainable transportation options. City A follows with 62.5%, while City D records 60.8%. City B has the lowest SMS at 57.2%, suggesting a smaller proportion of sustainable modes compared to the other cities. Overall, Figure 3 highlights City C as the most sustainable across all three metrics, with high emission reduction, strong energy efficiency, and a high sustainable modal split. City A also shows strong sustainability performance, while City B lags slightly in emission reduction and sustainable mode usage. These results suggest that cities with high ERR, low EE, and high SMS are more effective in achieving sustainability goals in their multi-modal transit systems.

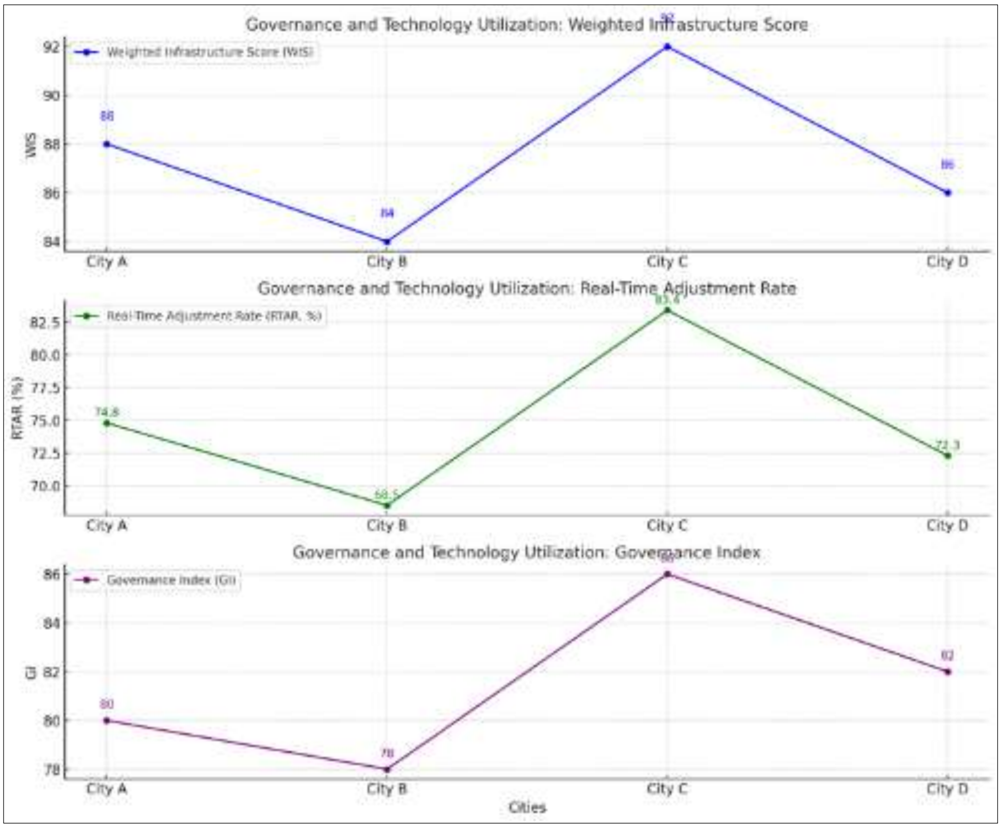

Figure 4 Governance and Technology Utilization in Multi-Modal Transportation Systems

Figure 4 illustrates the governance and technology utilization metrics across four cities (A, B, C, and D), focusing on three key indicators: Weighted Infrastructure Score (WIS), Real-Time Adjustment Rate (RTAR), and Governance Index (GI). These metrics assess each city's investment in infrastructure, adaptability of transit systems through real-time data usage, and overall governance effectiveness in managing multi-modal transportation. The first chart in Figure 4 shows the Weighted Infrastructure Score (WIS), which reflects the quality and comprehensiveness of infrastructure supporting each city's transit system. City C scores the highest WIS at 92, indicating a robust infrastructure setup, possibly due to substantial investments in transit hubs, transfer points, and overall network quality. City A follows with a WIS of 88, suggesting a well-developed infrastructure. City D records a WIS of 86, while City B has the lowest score at

84, indicating room for infrastructure improvements to support its multi-modal network. The second chart displays the Real-Time Adjustment Rate (RTAR), measured in percentage, which reflects each city's ability to adapt to changing transit demands using real-time data. City C leads with the highest RTAR at 83.4%, demonstrating a high level of responsiveness and real-time adaptability in its transit operations. City A has a moderately high RTAR of 74.8%, indicating decent real-time adjustment capabilities. City D follows with a rate of 72.3%, while City B has the lowest RTAR at 68.5%, suggesting potential areas to improve in terms of real-time system adjustments. The third chart shows the Governance Index (GI), which evaluates the effectiveness of governance in overseeing the transit system, promoting coordination, and implementing policies. City C again scores the highest GI at 86, reflecting strong governance practices, effective policy implementation, and collaborative management across different transit agencies. City D follows with a GI of 82, indicating a solid governance structure. City A has a GI of 80, while City B records the lowest GI at 78, pointing to possible challenges in governance coordination or policy alignment. Overall, Figure 4 highlights City C as the leader in governance and technology utilization, excelling across all three metrics. City A and City D also perform well, though with slightly lower scores in RTAR and GI. City B, with lower scores in all three metrics, could benefit from improvements in infrastructure, real-time adaptability, and governance practices to enhance the effectiveness of its multi-modal transit system.

The analysis of multi-modal transportation systems across the four cities—Singapore, Berlin, Tokyo, and San Francisco—highlights distinct approaches and outcomes in achieving system efficiency, accessibility, sustainability, and governance. Each city exhibits unique strengths and challenges, reflecting the impact of urban planning choices, investment in infrastructure, and the prioritization of sustainability and governance in shaping urban mobility. Tokyo (City C) emerges as the most efficient system, with an Average Travel Speed (ATS) of 27.5 km/h and the highest Passenger Load Factor (PLF) of 0.91. This high-speed and well-utilized network demonstrates Tokyo's ability to move large volumes of passengers quickly and efficiently, likely attributed to its extensive rail and metro infrastructure, known for precision and frequency. In contrast, Berlin (City B) shows the lowest efficiency, with an ATS of 19.2 km/h and a PLF of 0.79. These lower values indicate that Berlin's transit system may experience delays, lower demand, or underutilized capacity in certain routes, suggesting a need for optimization, particularly in areas where demand is less predictable. Singapore (City A) and San Francisco (City D) have moderate efficiency metrics, indicating well-balanced systems, but with room for improvement, especially in wait times. Accessibility varies significantly across the cities, with Tokyo again achieving the highest Accessibility Index (AI) of 85.6, despite having a smaller Coverage Area (CA) of 115 sq km. This indicates that Tokyo's transit network is densely connected within a compact area, enabling residents to reach essential destinations with ease. Conversely, Berlin, with the largest CA of 145 sq km, has the lowest AI at 79.4. This suggests that although Berlin's network spans a large area, there may be inefficiencies in linking residents to key points across the city, potentially due to a lower density of transit options or gaps in network coverage. Singapore and San Francisco show balanced accessibility, with Singapore achieving an AI of 82.1 over a CA of 130 sq km and San Francisco having an AI of 80.3 within a CA of 125 sq km. These scores indicate fairly accessible networks, though Tokyo's model demonstrates that a smaller, denser coverage can sometimes yield better accessibility outcomes.

Sustainability is a crucial consideration, especially as cities aim to reduce emissions and promote environmentally friendly transit modes. Tokyo leads in sustainability metrics, with the highest Emission Reduction Rate (ERR) of 36.4% and Energy Efficiency (EE) of 0.59 MJ/passenger-km, alongside the highest Sustainable Modal Split (SMS) of 65.3%. This high performance can be attributed to Tokyo's focus on energy-efficient rail systems and policies encouraging the use of public and non-motorized transport. Singapore follows closely, with an ERR of 33.0%, EE of 0.63 MJ/passenger-km, and SMS of 62.5%, indicating a similarly strong focus on sustainable transit, aided by the city's compact and well-integrated infrastructure. San Francisco and Berlin lag slightly in sustainability, with Berlin showing the lowest ERR (29.5%) and SMS (57.2%). Berlin's slightly higher EE value of 0.70 MJ/passenger-km suggests room for energy optimization, potentially through investment in newer, more efficient vehicles or infrastructure upgrades. San Francisco's results show moderate sustainability with an ERR of 31.2%, EE of 0.67 MJ/passenger-km, and SMS of 60.8%. These metrics suggest that while the city has made progress toward sustainable transit, improvements in energy use and modal split could further enhance environmental benefits. Effective governance and adaptive use of technology are essential for managing complex multi-modal networks. Tokyo achieves the highest Governance Index (GI) of 86 and Real-Time Adjustment Rate (RTAR) of 83.4%, indicating robust governance frameworks and advanced technological integration. This allows Tokyo to adjust transit operations responsively to real-time demands, enhancing service reliability and user satisfaction. Singapore follows with strong governance, reflected by a GI of 80 and RTAR of 74.8%, showing that its governance structure and technological adaptations support an efficient and responsive system. San Francisco and Berlin have slightly lower governance scores, with San Francisco recording a GI of 82 and RTAR of 72.3%, while Berlin scores 78 in GI and 68.5% in RTAR. Berlin's lower RTAR indicates potential challenges in responsiveness and adaptability, possibly due to fragmented governance or less integration of real-time technologies. San Francisco's moderate governance and technology metrics suggest a functional, though not highly responsive, system that could benefit from improved real-time adjustments and inter-agency collaboration.

Comparative Insights and Opportunities for Improvement: Tokyo and Singapore stand out as benchmarks in this analysis, with Tokyo excelling across efficiency, accessibility, sustainability, and governance metrics. Singapore also performs well, though with slightly lower scores in energy efficiency and real-time adaptability. These cities illustrate the impact of strategic investments in infrastructure, high-density transit design, and responsive governance on transit system performance. Berlin's results suggest that although it has extensive coverage, it faces challenges in accessibility, sustainability, and governance adaptability. Opportunities for Berlin could include upgrading its infrastructure to enhance energy efficiency, increasing network density in underserved areas, and strengthening real-time data integration. Similarly, San Francisco's moderate performance across most metrics highlights the potential to improve both sustainability and governance practices, perhaps through enhanced coordination between public and private transit services and investment in greener technologies. In this analysis underscores the significance of balancing coverage, sustainability, and governance to create efficient, accessible, and eco-friendly multi-modal transportation systems. Tokyo's model, with high efficiency and sustainable practices within a compact network, serves as a prime example for other cities aiming to optimize their transit systems while fostering environmental and social benefits.

5. Conclusion

This study provides an in-depth analysis of multi-modal transportation systems across four cities—Singapore (City A), Berlin (City B), Tokyo (City C), and San Francisco (City D)—focusing on system efficiency, accessibility, sustainability, and governance metrics. Each city's transit network is evaluated using specific indicators to reveal strengths, areas for improvement, and insights for enhancing urban mobility. Tokyo (City C) stands out as the most efficient and sustainable city across multiple dimensions. With the highest Average Travel Speed (27.5 km/h) and Passenger Load Factor (0.91), City C demonstrates superior system efficiency. Additionally, Tokyo leads in sustainability with an Emission Reduction Rate (36.4%), the best Energy Efficiency (0.59 MJ/passenger-km), and the highest Sustainable Modal Split (65.3%). These results indicate Tokyo's effective integration of sustainable practices and optimized transit operations. Singapore (City A) also performs well in several areas. It has a respectable Average Travel Speed (24.0 km/h) and Passenger Load Factor (0.88), showing balanced efficiency. In terms of sustainability, Singapore achieves an Emission Reduction Rate of 33.0% and a Sustainable Modal Split of 62.5%, indicating strong support for environmentally friendly transit options. Its Weighted Infrastructure Score (88) and Governance Index (80) highlight a well-maintained and effectively governed network. San Francisco (City D) shows moderate efficiency with a Travel Speed of 21.6 km/h and Passenger Load Factor of 0.83. Sustainability metrics reveal an Emission Reduction Rate of 31.2% and a Sustainable Modal Split of 60.8%, suggesting an adequate commitment to sustainability. San Francisco's Governance Index (82) and Weighted Infrastructure Score (86) underscore a solid infrastructure base and decent governance, though room for improvement remains in adaptability, as reflected by its Real-Time Adjustment Rate (72.3%). Berlin (City B), while demonstrating a wide Coverage Area of 145 sq km, lags behind in key metrics. With the lowest Average Travel Speed (19.2 km/h), Passenger Load Factor (0.79), and Sustainable Modal Split (57.2%), Berlin's transit system has potential for efficiency improvements. The Emission Reduction Rate of 29.5% and Energy Efficiency of 0.70 MJ/passenger-km also indicate opportunities for enhancing sustainability. The Governance Index (78) and Real-Time Adjustment Rate (68.5%) point to a need for better governance practices and responsiveness to real-time demands. In this comparative study highlights Tokyo (City C) as a benchmark city, excelling across efficiency, sustainability, and governance. Singapore (City A) also ranks high, while San Francisco (City D) shows moderate performance across most metrics. Berlin (City B), though geographically extensive, would benefit from targeted improvements in transit efficiency, sustainability, and governance. These findings underscore the importance of a balanced approach in developing multi-modal networks that prioritize sustainability, accessibility, and effective governance, providing valuable insights for future urban transit optimization.

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