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Rethinking Urban Mobility from Sustainable Cities to Intelligent Transportation Systems Using TOPSIS methods

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ABSTRACT

This article examines the concept of "smart" in relation to urban mobility and sustainability, and identifies inconsistencies in the current literature. The study explores how smart technologies can solve transportation problems, focusing on integrating artificial intelligence and machine learning to improve autonomy in transportation services. The study also emphasizes the importance of environmental protection in urban mobility strategies by focusing on low-emission transport and the move towards Mobility-as-a-Service (MaaS). This paper highlights the need for comprehensive transportation models and addresses the challenges cities face in implementing them.

This study addresses an important gap in the developing field of the smart urban movement, where the meaning and implementation of "smart" is still unclear, despite significant investments in technology and infrastructure. By examining the link between “smart” urban mobility and sustainability, the research points to inconsistencies in the existing literature and emphasizes the need for a more defined framework for smart mobility initiatives. The findings are significant in that they emphasize the role of integrated technological solutions—such as artificial intelligence and machine learning—in enhancing transport autonomy, improving urban freight logistics, and advancing sustainable, low-emission mobility practices.

Bus Rapid Transit (BRT), Light Rail Transit (LRT), Electric Scooters (E-Scooters), Shared Ride-Hailing Services, Bicycle Sharing Systems. Evaluation Preference: Cost Efficiency (CE), Environmental Impact Reduction (EIR), Implementation Cost (IC), Congestion Contribution (CC).

The results indicate that Bicycle Sharing Systems achieved the highest rank, while Bus Rapid Transit (BRT) had the lowest rank being attained.

The value of the dataset for Optimising urban mobility through smart transportation systems, according to the weighted product method, Bicycle Sharing Systems achieves the highest ranking.

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Introduction

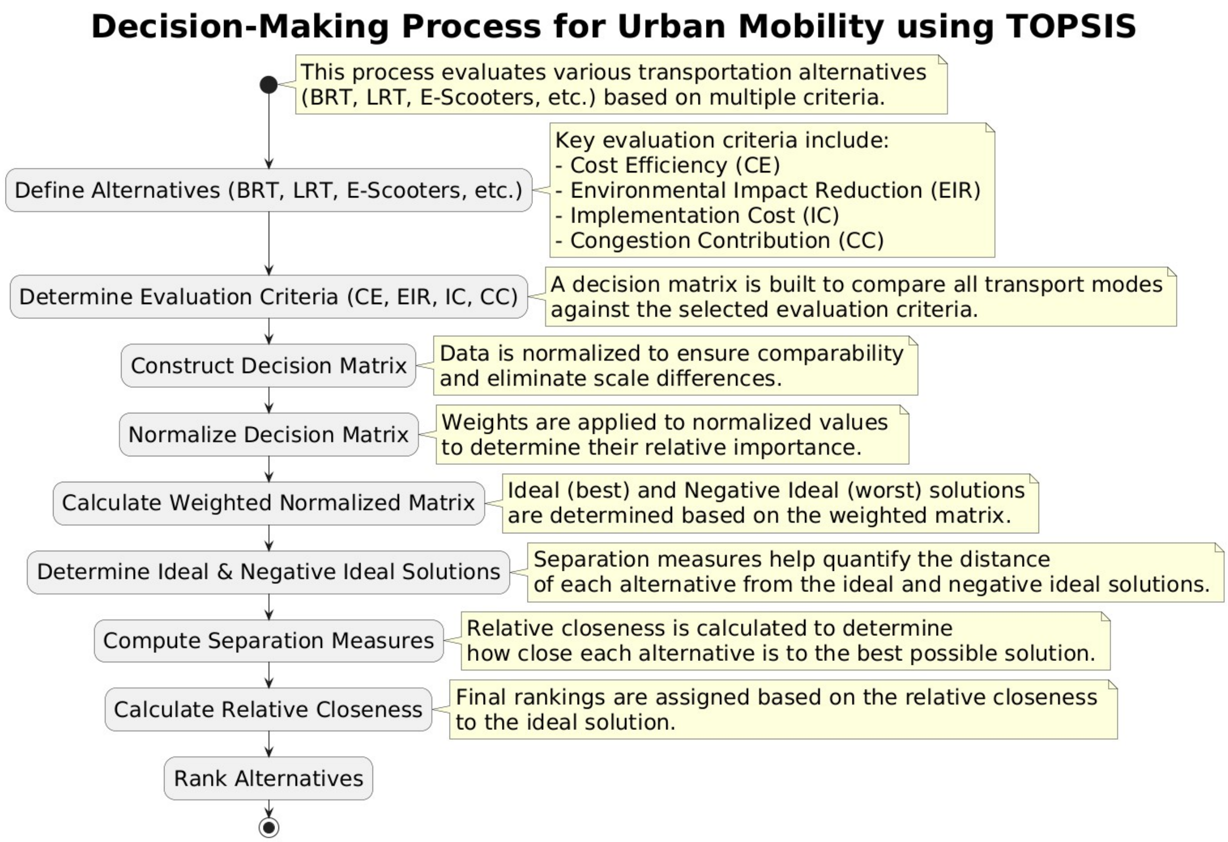
Previously, transport experts and urban planners mainly focused on sustainable urban transport and creating sustainable cities. However, with the rise of the digital age, the focus has shifted or expanded to include smart cities and smart urban mobility. It's intriguing to consider what might come after "Smart" in the future. Although "smart" is currently a popular term, it seems to be a controversial concept without a clear definition. This ambiguity is concerning given the considerable importance and resources devoted to smart technologies for shaping the urban future.[1] The author seeks to explore the concept of "smart" as it relates to intelligent urban mobility and sustainability. Through their analysis, they have identified inconsistencies and gaps in the existing literature on the smart urban movement and provided a comprehensive examination of its definition. [2] The two framework project agreements helped the city tackle its transportation and mobility challenges by adopting comprehensive strategies that take into account the relationship between various land uses, transportation supply and demand, and alternative modes of travel.

This analysis was made possible by the skillful negotiation of several local bodies. [4] The Fig Model is an essential tool for mobility planning, providing sophisticated and reliable analysis to aid decision-making. Its adaptability enables it to support municipal activities, from transport system planning to local traffic management. However, many cities do not have a transit model, possibly due to the expected costs associated with its development and maintenance. [5] Smart Mobility is a comprehensive approach aimed at fostering sustainable development by improving transport services and tackling technical, social, economic and environmental challenges. Environmental protection is an important element in many global and European policies. Low-emission mobility is critical to moving towards a low-carbon, circular economy, as it is essential to address both individual transport needs and the movement of goods. [6] As a result, intelligent transportation systems have evolved from combining multiple physical elements such as connected vehicles, transportation infrastructure, and individuals to encompass a variety of societal factors, including economic development, urban planning, and emergency management.[7] There is a need to promote autonomy in transport services.

Combining artificial intelligence and machine learning with crowd data can significantly improve services such as real-time traffic monitoring, traffic forecasting, travel time predictions and travel activity monitoring. Collectively, these improvements will lead to greater levels of autonomy within the transport system..[8] Sustainable development addresses current needs while ensuring that future generations can meet their own needs. These needs typically include objectives related to economic development, social and human progress, and environmental and environmental health. In natural resource policy, sustainability involves managing resource use in a way that avoids degradation and allows time to develop complementary or alternative solutions. [11] Mobility-as-a-Service (MaaS) is a promising concept that, while generating considerable interest, is still in the early stages of wider adoption. In its ideal future state, Mamas is expected to provide digital solutions for personalized multimodal transportation that will transform private vehicle ownership. This will be accomplished through a smart online platform that seamlessly integrates travel planning, booking, intelligent ticketing and real-time information services. [12] Regulating the entry time of vehicles helps reduce the speed at which queues form in collision zones, thereby reducing congestion recovery time and increasing efficiency in these areas. We now face the challenge of determining the optimal control inputs (acceleration or deceleration) for connected and automated vehicles (CAV) in each control zone while adhering to strict safety constraints to prevent collisions.[13] Achieving full automation in the transportation system requires more than automating vehicles. It is necessary to automate the complete transport network, which includes elements such as road and field support teams, traffic police, road inspections and rescue services. [15] Recent advances in information technology and telematics have opened new avenues for urban freight operators to reduce their costs. Consequently, the third objective of the paper is to develop a state-of-the-art tour planning system that provides real-time information on the booking status of networks and delivery bays. [16] Developing a comprehensive matrix of intelligence indicators involves combining technologies with advanced application capabilities.

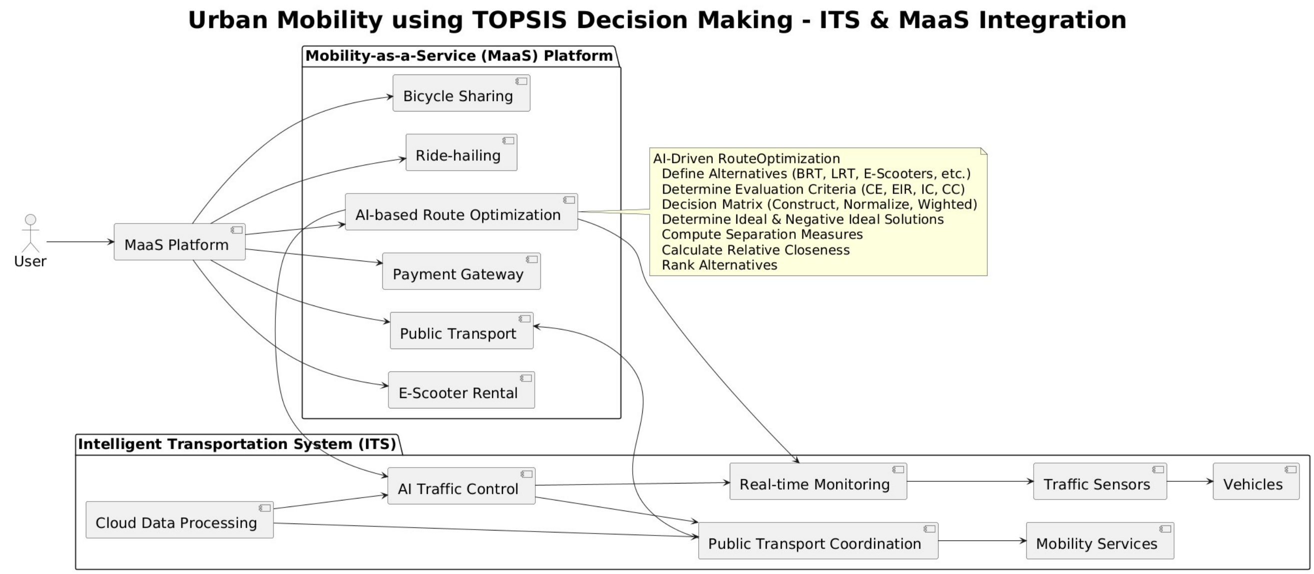
For this research, data is collected from three primary sources: technologies from city officials' websites and publications, technologies from service providers' websites, and emerging technologies from commercialized or in-development city master plans and service providers. Projects and research institute publications. [17] System dynamics modeling facilitates the development of frameworks that help explore the various factors that influence demand and help understand how to change user perceptions and behaviours. Models can be developed with stakeholder input and used in simulations or interactive games for policy learning. However, the existing literature assumes that user behaviours and needs are static, failing to place them at the canter of mobility-related decision-making.[19] Future urban traffic management systems will need to create, store, supervise, test, optimize and efficiently deploy various mobile agents. Additionally, they will need a decision-support system to communicate with traffic managers.

An advanced and user-friendly decision-support system is a major trend in the development of urban traffic management systems. Consequently, future systems should incorporate these features. [21] Gestational freight distribution involves multiple freight operators. For example, in the parcel and express transport sector, large transport companies often cooperate with very small companies, which may only have a few employees or drivers. In major cities such as Lyon or Paris, thousands of small companies often subcontract to large companies to manage materials and complete final deliveries for them. This segment of the commodity market faces extremely low profit margins and challenging working conditions. As a result, smaller operators may be reluctant to invest in new technology, instead relying on their existing resources to handle delivery challenges. [22]



MATERIALS AND METHODS

In n-dimensional spaces with weights (for n > 3), computing Euclidean distances for rank indices can be misleading due to the spatial distribution of the data set, leading to unjustified results. This study It provides an in-depth analysis to clearly emphasize this issue, which aims to enhance the TOPSIS methodology and the broader MCDM literature. The article concludes with a summary of the findings. TOPSIS is a widely used evaluation method for solving multiple criteria decision making (MCDM) problems. Its applications include comparing company performance, evaluating financial ratios in specific sectors, and evaluating financial investments in advanced manufacturing systems. However, the method has its limitations. Many improvements to the original TOPSIS approach have focused on optimizing the weighting process to increase the sensitivity of the R value. Composite index scores exhibit stronger associations with deaths per million populations than single-layer TOPSIS methods. This underscores the effectiveness and value of the hierarchical fuzzy TOPSIS method in combining indicators within hierarchical systems to form a composite index. It also illustrates the applicability of the method in performance evaluation and decision making in various domains. This paper uses Analytic Hierarchy Process (AHP) to evaluate the relative importance of different criteria and TOPSIS method to evaluate different power plant technologies using natural gas or hydrogen as fuel based on economic, environmental and technical factors. [4] The basic principle of the TOPSIS method is that the selected alternative should be "closer" to the positive ideal solution and "far" from the negative ideal solution. Further research and validation of new approaches and solutions to address RRP in the traditional TOPSIS method is necessary. This can be done by applying the method to various decision problems and performing comparative statistical analyses. Ferreira notes that the method demonstrates how well the new approach aligns with the basic principles of the traditional TOPSIS method. We examine the fundamentals, including the fuzzy extension of TOPSIS, and the difficulties in effectively implementing fuzzy TOPSIS. However, since weighted aggregation is often inappropriate for aggregating local metrics in many real-world situations, we recommend exploring alternative aggregation methods. [7] Wang and Lou identified the rank inversion problem in the TOPSIS method, but did not present a solution. These rank reversals violate the invariance principle of utility theory, which raises concerns about the reliability of the TOPSIS method. [8] A frequent limitation of existing methods for extending TOPSIS to interval values is that they provide interval-valued optimal solutions based on different assumptions. This conflicts with the basic tenets of classical TOPSIS methodology and often stems from heuristic assumptions that lack sufficient justification..[9] In the proposed fuzzy TOPSIS method, the objective criteria are adjusted using the Hsu and Chen approach, which aligns the values of these criteria with the linguistic evaluations of the subjective criteria. [10] TOPSIS system is also linked to DAD. Consequently, both the EM and TOPSIS methods have only a small correlation with DAD. [11] We evaluated six normalization techniques using a small illustrative example and conducted a detailed evaluation to identify the most suitable technique for the TOPSIS method. This example illustrates the evaluation procedure outlined in this study. [12] Various stochastic problems at different scales were developed and tested to compare fuzzy TOPSIS rankings with interval values obtained from different distance metrics.



[13] These methods convert qualitative data into quantitative measurements by considering all relevant parameters. In this study, TOPSIS method was used to identify the best blasting technique for Tamara limestone mine in Iran. [14] Ultimately, it selects the information system that aligns with the optimal preference of the decision maker. [15]

ANALYSIS AND DISSECTION

TABLE 1. Optimising urban mobility through smart transportation systems

DATA SET				
	Cost Efficiency (CE)	Environmental Impact Reduction (EIR)	Implementation Cost (IC)	Congestion Contribution (CC)
Bus Rapid Transit (BRT)	0.78	0.65	0.68	0.75
Light Rail Transit (LRT)	0.72	0.8	0.9	0.4

Electric Scooters (E-Scooters)	0.9	0.6	0.2	0.85
Shared Ride-Hailing Services	0.85	0.5	0.3	0.8
Bicycle Sharing Systems	0.95	0.75	0.15	0.6

Bus Rapid Transit (BRT) scores well on cost efficiency (0.78) and congestion reduction (0.75), making it a relatively effective solution, though its environmental impact reduction (0.65) and implementation cost (0.68) suggest moderate environmental benefits and costs. Light Rail Transit (LRT) stands out for its high environmental impact reduction (0.8) but has a significantly high implementation cost (0.9). It also has a relatively low congestion contribution (0.4), making it environmentally friendly but costly to implement. Electric Scooters (E-Scooters) excel in cost efficiency (0.9) and have a low implementation cost (0.2), making them economically attractive. However, they contribute heavily to congestion (0.85) and provide only moderate environmental benefits (0.6). Shared Ride-Hailing Services offer a balance of cost efficiency (0.85) and moderate environmental impact reduction (0.5), but have a higher congestion contribution (0.8), making them less ideal for reducing traffic

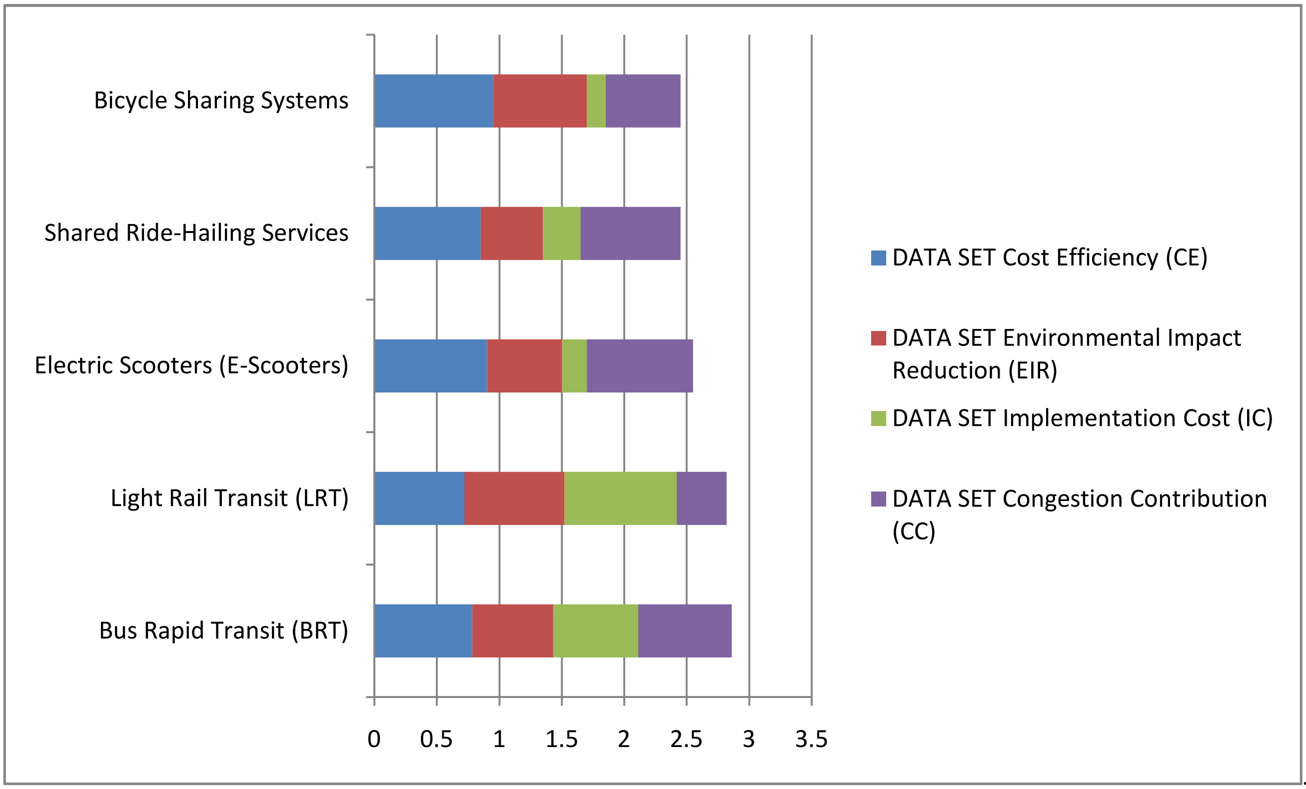


FIGURE 1. Optimizing urban mobility through smart transportation systems

Each mode of transportation is represented by a horizontal bar, with distinct color-coded segments corresponding to the four evaluation metrics. For instance, Cost Efficiency (CE) is indicated in blue, Environmental Impact Reduction (EIR) in red, Implementation Cost (IC) in green, and Congestion Contribution (CC) in purple. The length of each colored segment within a bar represents the score of that mode of transport in that particular dataset.From the graph, it can be inferred that Bicycle Sharing Systems score notably higher in Cost Efficiency, while Light Rail Transit (LRT) and Bus Rapid Transit (BRT) exhibit relatively larger contributions in Congestion Contribution (CC) and Implementation Cost (IC).

TABLE 2. Normalized Data

Normalized Data			
0.4133	0.4348	0.5697	0.4796
0.3815	0.5351	0.7540	0.2558
0.4769	0.4013	0.1675	0.5436
0.4504	0.3345	0.2513	0.5116
0.5034	0.5017	0.1257	0.3837

The first mode (0.4133 CE, 0.4348 EIR, 0.5697 IC, 0.4796 CC) demonstrates moderate performance across all categories. It balances environmental benefits and costs but doesn't particularly excel in any one area. The second mode (0.3815 CE, 0.5351 EIR, 0.7540 IC, 0.2558 CC) is highly focused on environmental impact reduction (0.5351), though it comes with the highest implementation cost (0.7540). It also contributes least to congestion (0.2558), making it an environmentally strong but expensive option. The third mode (0.4769 CE, 0.4013 EIR, 0.1675 IC, 0.5436 CC) excels in cost efficiency and low implementation cost (0.1675), making it economically viable. However, it has a higher congestion contribution (0.5436), indicating traffic issues despite being low-cost. The fourth mode (0.4504 CE, 0.3345 EIR, 0.2513 IC, 0.5116 CC) offers a fair balance between cost and congestion but shows lower environmental impact reduction (0.3345).

TABLE 3. Weight

Weight			
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25

By assigning equal significance to all categories, the analysis emphasizes a balanced approach to transportation solutions, where no single factor dominates the decision-making process. Cost efficiency, environmental impact, cost of implementation, and the contribution to congestion are all seen as equally critical in determining the effectiveness of each mode. This approach suggests a holistic view of transportation systems, encouraging solutions that not only offer cost-effective and environmentally-friendly options but also minimize congestion while maintaining reasonable implementation costs.

TABLE 4. Weighted normalized decision matrix

Weighted normalized decision matrix			
0.1033	0.1087	0.1424	0.1199
0.0954	0.1338	0.1885	0.0640

0.1192	0.1003	0.0419	0.1359
0.1126	0.0836	0.0628	0.1279
0.1258	0.1254	0.0314	0.0959

The first mode (0.1033 CE, 0.1087 EIR, 0.1424 IC, 0.1199 CC) exhibits balanced performance, with a slightly higher emphasis on cost efficiency and congestion reduction. However, it does not particularly excel in any one area, suggesting a moderate, well-rounded option. The second mode (0.0954 CE, 0.1338 EIR, 0.1885 IC, 0.0640 CC) shines in environmental impact reduction and implementation cost, but struggles with a low score in congestion contribution (0.0640). This implies an environmentally friendly solution, but one that comes with high costs and limited impact on congestion. The third mode (0.1192 CE, 0.1003 EIR, 0.0419 IC, 0.1359 CC) excels in cost efficiency and has the lowest implementation cost. However, it faces challenges in environmental impact and contributes significantly to congestion, indicating that while it's affordable, it's not ideal for sustainability or traffic relief.

TABLE 5. Positive Matrix

Positive Matrix			
0.1258	0.1338	0.0314	0.0640
0.1258	0.1338	0.0314	0.0640
0.1258	0.1338	0.0314	0.0640
0.1258	0.1338	0.0314	0.0640
0.1258	0.1338	0.0314	0.0640

This matrix signifies the ideal or target performance levels for each criterion. The highest value is for Environmental Impact Reduction (0.1338), emphasizing the importance of sustainability in transportation decisions. Cost Efficiency is also prioritized (0.1258), indicating the need for economic viability. The lowest values are assigned to Implementation Cost (0.0314) and Congestion Contribution (0.0640), highlighting the goal of minimizing costs and reducing traffic congestion. The uniformity across all modes suggests that, regardless of the mode being analyzed, these are the benchmark values that transportation solutions should aim for.

TABLE 6. Negative matrix

Negative matrix			
0.0954	0.0836	0.1885	0.1359
0.0954	0.0836	0.1885	0.1359
0.0954	0.0836	0.1885	0.1359
0.0954	0.0836	0.1885	0.1359
0.0954	0.0836	0.1885	0.1359

These values highlight the areas where performance would be considered poor or suboptimal. The highest value is for Implementation Cost (0.1885), indicating that high implementation costs are undesirable. Similarly, the high score for Congestion Contribution (0.1359) reflects the negative impact of increased congestion, which should be minimized in transportation systems. Cost Efficiency (0.0954) and Environmental Impact Reduction (0.0836) scores are relatively low in this matrix, suggesting that inadequate cost efficiency and poor environmental performance are the least favorable outcomes. The uniformity across all modes implies that these represent the worst possible scenarios, regardless of the transportation solution being evaluated. This negative matrix serves as a reference point to identify which modes are performing poorly in relation to the desired standards.

TABLE 7. Si Negative

Si Negative	
Bus Rapid Transit (BRT)	0.0554
Light Rail Transit (LRT)	0.0877
Electric Scooters (E-Scooters)	0.1495
Shared Ride-Hailing Services	0.1271
Bicycle Sharing Systems	0.1701

Bus Rapid Transit (BRT) has the lowest Si Negative value of 0.0554, suggesting it is the closest to avoiding the worst-case scenario. This indicates that BRT performs well across the evaluated criteria and maintains a strong balance between cost efficiency, environmental impact, implementation cost, and congestion contribution. Light Rail Transit (LRT) follows with a Si Negative value of 0.0877, showing that while it is farther from the negative benchmark than BRT, it still performs well, particularly in areas like environmental impact reduction, though it may face challenges in other areas like congestion contribution. Electric Scooters (E-Scooters), with a value of 0.1495, and Shared Ride-Hailing Services at 0.1271, perform moderately. These modes may struggle with specific criteria like congestion or environmental impact but are still better than the worst possible performance.

TABLE 8. Ci

Ci	
Bus Rapid Transit (BRT)	0.3008
Light Rail Transit (LRT)	0.3541
Electric Scooters (E-Scooters)	0.6505
Shared Ride-Hailing Services	0.5905
Bicycle Sharing Systems	0.8373

Bus Rapid Transit (BRT) has the lowest Ci value of 0.3008, indicating that it is the closest option to the best solution. This means BRT is the best performer across the four categories—Cost Efficiency, Environmental Impact Reduction, Implementation Cost, and Congestion Contribution—making it a well-rounded and balanced option for sustainable urban mobility. Light Rail Transit (LRT), with a Ci value of 0.3541, also performs well but is slightly further from the ideal. LRT likely excels in areas like environmental impact but may have higher implementation costs, making it a strong but slightly more expensive option. Electric Scooters (E-Scooters), with a Ci of 0.6505, and Shared Ride-Hailing Services at 0.5905, are midrange performers. They might excel in cost efficiency or congestion reduction but fall short in other areas such as environmental impact or implementation cost .

TABLE 9. Rank

Rank	
Bus Rapid Transit (BRT)	5
Light Rail Transit (LRT)	4
Electric Scooters (E-Scooters)	2
Shared Ride-Hailing Services	3
Bicycle Sharing Systems	1

Bicycle Sharing Systems, ranked 1st, emerge as the top performer. This suggests that despite some challenges, such as possible congestion contribution or implementation costs, the benefits—such as high cost efficiency and lower environmental impact—outweigh the drawbacks, making it the most effective mode in this evaluation. Electric Scooters (E-Scooters) rank 2nd, likely excelling in areas like cost efficiency and congestion contribution. Their relatively low implementation cost also contributes to their high ranking, even if they may have room for improvement in environmental impact. Shared Ride-Hailing Services, ranked 3rd, perform reasonably well across all categories. They may offer a balanced solution but fall short of outperforming the top two modes, potentially due to higher implementation costs or environmental concerns.Light Rail Transit (LRT), ranked 4th, likely performs well in environmental impact but faces higher implementation costs, which affects its ranking despite its strengths.

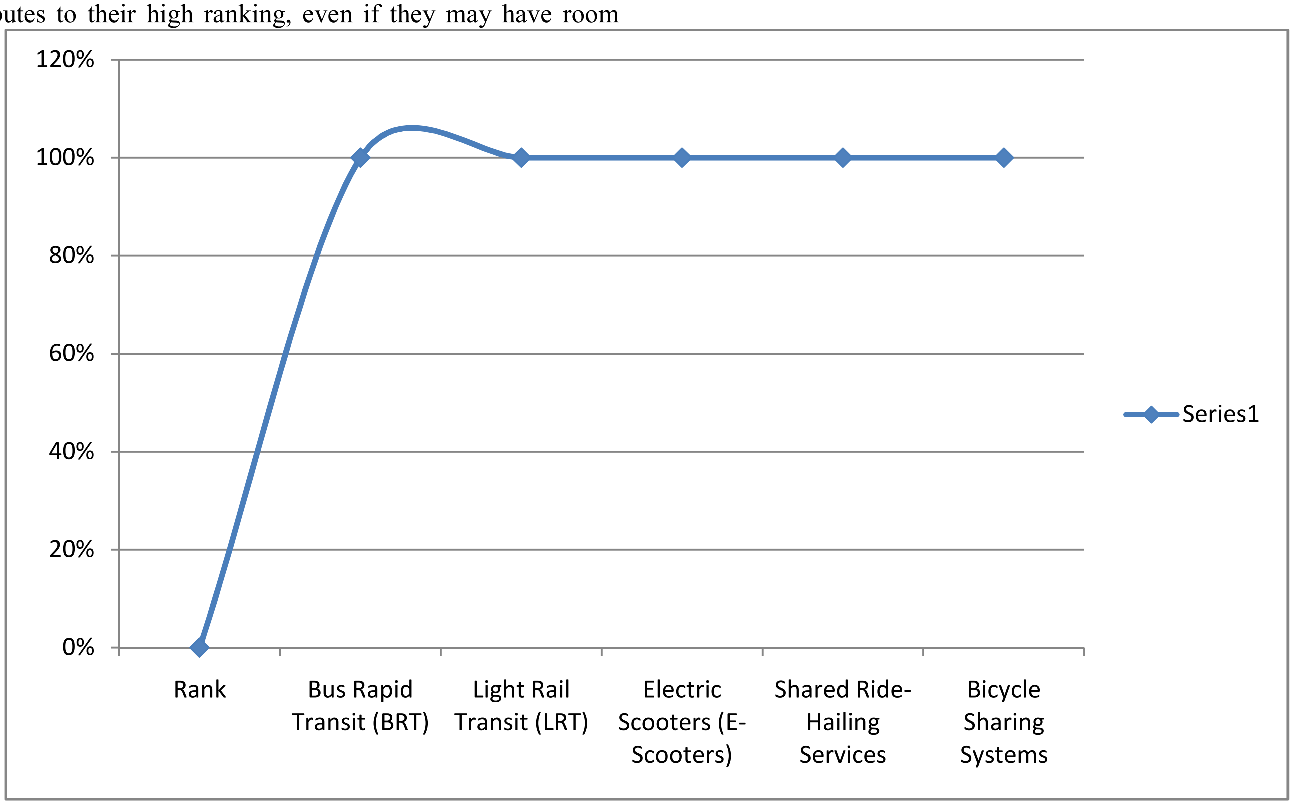


FIGURE 2. Rank

The graph shows a steep initial rise with Bus Rapid Transit (BRT) achieving the highest rank, close to 100%. This suggests that BRT leads significantly according to the metric being evaluated. After this peak, the graph flattens out, indicating that the remaining transportation modes—Light Rail Transit (LRT), Electric Scooters (E-Scooters), Shared Ride-Hailing Services, and Bicycle Sharing Systems—share relatively similar rankings, hovering just below the 100% mark. The relatively flat nature of the line after the BRT ranking indicates that the other modes of transport exhibit comparable performance in the metric. However, none of these modes surpass BRT in the evaluation, making it the dominant option in terms of whatever factor or combination of factors is being measured.

CONCLUSION

The analysis highlights inconsistencies in current literature on smart urban mobility, emphasizing the need for a comprehensive understanding of smart technologies and their role in achieving sustainable transport systems. Effective transport and mobility planning require integrated strategies that consider land use, mobility demand, and alternative transport modes. Technological advances such as Intelligent Transportation Systems (ITS) and Artificial Intelligence (AI) for real-time traffic monitoring and forecasting are critical to achieving greater levels of autonomy in transportation services. However, many cities face challenges like the cost of developing transit models, which limits their ability to optimize mobility planning. In conclusion, while smart mobility offers a promising future for low-emission and efficient transportation, its successful implementation requires clear frameworks, integrated technologies, and policies that address economic, social, and environmental concerns.

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