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An Explainable AI Framework for Identifying Transferable Sustainable Urban Mobility Policies: Evidence from Istanbul

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ABSTRACT

Cities increasingly look to the experiences of other urban areas when designing policies to promote sustainable mobility. However, the transfer of transport policies across cities is rarely straightforward: interventions that perform well in one context may produce substantially different outcomes elsewhere because of differences in urban form, population density, socioeconomic conditions, transport systems, travel behaviour and institutional characteristics. Conventional benchmarking approaches often identify high-performing cities but provide limited guidance on whether their policies are transferable to a specific target context. This study proposes an explainable artificial intelligence (XAI) framework for identifying sustainable urban mobility policies that are potentially transferable to Istanbul, Türkiye. The framework combines cross-city benchmarking, machine-learning-based identification of comparable urban contexts, and explainable modelling of the relationship between city characteristics, policy interventions and observed mobility outcomes. Istanbul is positioned as the target city, while a set of international cities provides the empirical basis for identifying potentially transferable policy interventions. Rather than ranking cities according to overall performance, the proposed approach evaluates the contextual similarity between cities and investigates whether policies associated with positive mobility outcomes under particular urban conditions are likely to be relevant to Istanbul. Explainable AI techniques are used to identify the characteristics that contribute most strongly to policy-transferability predictions, thereby providing transparency about why a particular intervention is considered more or less suitable for the Istanbul context. The resulting framework provides a systematic approach for moving from descriptive international benchmarking towards context-sensitive policy learning and decision support. The study contributes to the sustainable urban mobility literature by demonstrating how explainable AI can support the identification and assessment of policy transferability while recognising the contextual dependence of urban transport interventions. The findings are intended to provide evidence-based guidance for Istanbul's sustainable mobility transition and a methodological framework that can subsequently be applied to other cities seeking to learn from international policy experience.

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1. Introduction

Cities around the world are under increasing pressure to transform their urban mobility systems in response to climate change, air pollution, congestion, energy dependence and growing demand for accessible and efficient transport [1]. Sustainable urban mobility has consequently become a central objective of contemporary urban policy, reflecting a shift from conventional traffic-oriented approaches towards policies that emphasise accessibility, public transport, active travel, environmental quality and social considerations [2]. Cities have adopted a wide range of interventions, including bus-priority measures, road-space reallocation, congestion charging, parking management, integrated ticketing, cycling infrastructure, pedestrianisation and low-emission zones. Despite substantial differences between cities, policymakers increasingly look beyond their own jurisdictions for evidence about which interventions may support more sustainable mobility outcomes.

Learning from other cities is not new. International benchmarking, best-practice studies and policy-transfer approaches have long been used to support urban transport planning. Policy transfer refers broadly to the process through which knowledge about policies, institutions or practices in one setting is used in the development of policies in another [3]. In transport, policy transfer involves not simply copying policies but processes of learning, interpretation and adaptation shaped by institutional, political and organisational conditions [4, 5]. This distinction is particularly important for sustainable mobility, where apparently similar interventions may generate substantially different outcomes across cities. This perspective also aligns with wider research on policy mobilities, which emphasises the circulation of policy knowledge through global networks of cities rather than through simple one-way transfers of best practice [6].

The transfer of sustainable urban mobility policies is therefore inherently context-dependent. Population density, urban morphology, income levels, car ownership, existing public transport provision, network characteristics, travel behaviour and governance arrangements can all influence the effectiveness of an intervention. Consequently, a policy that produces positive outcomes in one city cannot necessarily be expected to generate comparable effects elsewhere. Previous research on transport policy transfer has consequently emphasised that successful policy learning requires consideration of both the characteristics of the policy and the institutional and spatial context of the receiving city [4, 5, 7]. Research examining sustainable mobility policy transfer between London and Istanbul similarly demonstrated that substantial institutional differences can prevent straightforward policy copying and require policies to be translated and adapted to local circumstances [8].

This challenge exposes an important limitation of conventional international benchmarking. Benchmarking can identify cities with high public transport performance, low car dependency or other desirable mobility outcomes, but it does not necessarily explain why these cities perform well or whether their policies could be successfully transferred elsewhere. Best-practice approaches may therefore encourage cities to emulate successful interventions without adequately considering the contextual conditions that contributed to their success [4, 9]. The relevant policy question is consequently not simply which cities perform best, but which cities provide relevant policy lessons for a particular urban context, and which of their policies are potentially transferable.

Addressing this question requires a more systematic assessment of relationships between urban context, policy interventions and mobility outcomes. Cities differ simultaneously across numerous dimensions, including socioeconomic characteristics, urban form, transport supply, travel behaviour and infrastructure. Such multidimensional relationships are difficult to capture through simple city rankings or pairwise comparisons. A context-sensitive approach therefore needs to identify similarities between cities while also examining the conditions under which particular interventions have generated favourable outcomes.

Artificial intelligence (AI) offers new opportunities for addressing this analytical challenge. Machine-learning methods can identify complex and potentially non-linear relationships within multidimensional datasets and have increasingly been applied to transportation problems, including mobility prediction, congestion management, intelligent transport systems and sustainable mobility planning. In the context of policy transfer, these capabilities could be used to identify cities with similar characteristics to a target city and to investigate relationships between contextual conditions, policy interventions and observed outcomes. AI can therefore provide a means of moving beyond descriptive benchmarking towards more systematic and data-driven policy learning, supporting the wider evolution of smart-city decision-support systems [10].

However, AI should not simply be used to generate predictions. For transport-policy decision-making, policymakers need to understand why a model considers a particular policy relevant to a particular city. Explainable artificial intelligence (XAI) is therefore particularly important. Methods such as LIME and SHAP allow researchers to identify the variables contributing to machine-learning predictions and provide greater transparency regarding model outputs [11-13]. In the context of policy transfer, explainability can help reveal the contextual characteristics underlying a transferability assessment. Rather than producing an opaque recommendation that a policy is "suitable" for a city, an explainable model can indicate which urban and transport characteristics contribute to that assessment. AI can thus support, rather than replace, expert judgement and policy analysis.

Istanbul provides a particularly relevant case for examining this approach. As one of Europe's largest metropolitan areas and a major economic and transport centre, Istanbul has a highly complex and spatially heterogeneous mobility system characterised by high population density, substantial travel demand, extensive public transport provision and persistent pressure from private vehicle use and road congestion. The city has made substantial investments in public transport and sustainable mobility, yet congestion, motorisation, environmental pressures and the need to improve public transport remain important challenges [14, 15]. Istanbul is also an appropriate case for examining policy transfer because previous research has explicitly investigated the transfer of sustainable mobility policies from London to Istanbul and demonstrated the importance of institutional and contextual differences [8]. The question that remains is how Istanbul can systematically identify relevant policy experiences from a much larger international pool of cities.

Against this background, this study develops an explainable AI framework [13] for identifying potentially transferable sustainable urban mobility policies for Istanbul. Rather than assuming that international best practice is universally applicable, the proposed framework considers the relationship between urban context, policy intervention and observed mobility outcomes. First, cities are characterised using a multidimensional set of urban, socioeconomic and transport indicators to identify cities that are contextually comparable to Istanbul. Second, policies implemented in these cities are examined in relation to their observed mobility outcomes. Third, machine-learning techniques are used to investigate relationships between contextual characteristics, policy interventions and outcomes and to assess the potential transferability of policies to Istanbul. Finally, XAI techniques are used to identify the factors contributing to these transferability assessments.

The study addresses four research questions:

RQ1: Which cities provide the most contextually relevant benchmarks for Istanbul's sustainable urban mobility transition?

RQ2: Which sustainable urban mobility policies implemented in comparable cities are associated with favourable mobility outcomes under similar contextual conditions?

RQ3: To what extent can explainable artificial intelligence be used to assess the potential transferability of these policies to Istanbul?

RQ4: Which urban and transport characteristics most strongly influence the assessed transferability of sustainable mobility policies?

The study makes three principal contributions. First, it contributes to sustainable urban mobility and policy-transfer literature by shifting the focus from identifying international "best practices" towards identifying contextually transferable practices. Second, it develops an AI-enabled framework that integrates international benchmarking, contextual similarity, policy-outcome analysis and explainability into a single decision-support process. Third, it provides an empirical application focused on Istanbul, building on previous research on the city's sustainable mobility challenges and experience of international policy transfer [8, 14].

The remainder of the paper is organised as follows. Section 2 reviews the literature on sustainable urban mobility policy transfer, international benchmarking and AI in urban transport decision-making. Section 3 presents the conceptual framework and research methodology. Section 4 describes the data and variables. Section 5 presents the results, while Section 6 discusses their implications for Istanbul and the broader use of AI in sustainable mobility policy learning. Section 7 concludes the paper by summarising the principal contributions, limitations and directions for future research.

2. Literature Review

The idea that cities can learn from the experiences of other cities has a long history in public policy research. Dolowitz and Marsh [3] conceptualised policy transfer as the process through which knowledge about policies, institutions and practices in one political setting is used in another. In transport, policy transfer has been examined as a mechanism through which cities learn from policy innovations elsewhere, but the process is shaped by political, institutional, organisational and contextual factors [4]. More recent research has consequently moved away from viewing transfer as straightforward policy replication towards concepts of policy learning, translation and adaptation. Glaser et al. [5] emphasise that transport policy learning is strongly influenced by the settings in which it takes place, including institutional structures and relationships between relevant actors.

This contextual dimension is particularly important for sustainable urban mobility. Transport policies are embedded within broader urban systems, and their outcomes depend on interactions between transport infrastructure, land use, socioeconomic conditions, travel behaviour and governance arrangements. Consequently, a policy that produces positive outcomes in one city cannot necessarily be expected to generate comparable effects elsewhere. Stead [7] similarly argues that policy transfer requires adaptation because differences between institutional and planning contexts affect the feasibility and outcomes of transferred practices. Empirical research reinforces this point. Canitez [8], for example, demonstrated through the transfer of sustainable mobility policies from London to Istanbul that institutional differences can prevent straightforward policy copying and require policies to be translated and adapted to local circumstances.

International benchmarking provides an important mechanism through which cities compare transport performance and identify potential models for improvement, while policy learning increasingly relies on cross-city exchanges of experience and innovation [16]. Benchmarking can reveal differences in public transport use, service quality, accessibility, operating efficiency, congestion and environmental performance. However, it presents a fundamental challenge for policy transfer: the best-performing city is not necessarily the most relevant benchmark. A city's transport performance may reflect structural characteristics such as population density, urban form, car ownership, existing infrastructure and travel behaviour. Replicating a policy associated with high performance without considering these underlying conditions may therefore produce misleading recommendations.

This problem is related to broader critiques of "best practice" approaches in urban policy. Bulkeley [9] argues that the identification and circulation of best practices can obscure the contextual conditions through which particular practices emerge and produce outcomes. Similarly, transport policy-transfer research increasingly emphasises adaptation and translation rather than direct replication [4, 5]. Consequently, benchmarking and policy transfer should not be treated as equivalent processes. Benchmarking asks which cities perform better, whereas policy transfer asks what can be learned from those cities. A more useful approach would additionally ask: which cities are sufficiently comparable to the target city for their policy experiences to provide meaningful evidence?

This introduces the concept of contextual comparability. Rather than selecting benchmark cities solely according to transport performance, cities can be compared across multiple characteristics, including population density, income, car ownership, urban form, public transport provision, travel behaviour and congestion. Policies implemented in contextually comparable cities could then provide a more relevant pool of potential policy precedents. Existing benchmarking approaches, however, rarely provide an integrated mechanism for moving from city similarity to policy transferability.

Artificial intelligence offers new opportunities to address this analytical challenge. Machine-learning methods can identify complex and potentially nonlinear relationships within multidimensional datasets and are increasingly used in transportation for traffic prediction, demand forecasting, congestion management, optimisation and mobility planning. Recent research has also expanded towards sustainable mobility applications. However, much of the existing AI literature remains focused on prediction and operational optimisation, rather than cross-city policy learning and decision support.

This distinction is important for sustainable mobility policy transfer. Predicting traffic congestion is fundamentally different from helping policymakers determine which transport intervention may be relevant to a particular city. The latter requires an understanding of relationships between urban context, policy intervention and mobility outcome and an assessment of whether those relationships provide useful evidence for another urban context.

Explainable artificial intelligence (XAI) is particularly relevant to this challenge. Machine-learning models may identify complex patterns but can be difficult for policymakers to interpret [17]. Methods such as LIME and SHAP provide techniques for identifying the factors contributing to model predictions [11, 12]. In a policy-transfer context, explainability can therefore help answer not only whether a policy appears transferable, but why the model reaches that assessment. For example, the model could identify the contribution of population density, car ownership, public transport provision or congestion to a policy's assessed transferability. AI can consequently support rather than replace expert judgement and policy analysis.

The literature therefore reveals three relatively mature but insufficiently integrated research streams. First, the policy-transfer literature demonstrates that successful policy learning depends on contextual, institutional and organisational conditions. Second, international benchmarking provides systematic comparisons of cities but generally focuses on relative performance rather than the transferability of policies. Third, AI research in urban transportation demonstrates considerable potential for analysing complex relationships but has predominantly addressed prediction and operational problems. The intersection of these literatures remains comparatively underdeveloped.

This study addresses this gap by developing a framework that connects international city benchmarking, contextual similarity, policy outcomes and explainable AI to assess sustainable mobility policy transferability. Policy transferability is conceptualised not as a binary property but as a context-dependent assessment based on the similarity between originating and receiving urban environments and the relationship between policy interventions and observed outcomes.

In this framework, AI has three complementary functions: identifying patterns of similarity between cities, modelling relationships between contextual characteristics and policy outcomes, and explaining the factors underlying transferability assessments. Figure 1 presents the analytical logic of the proposed framework, illustrating how international urban mobility data are progressively transformed into a context-sensitive and explainable assessment of sustainable mobility policy transferability to Istanbul.

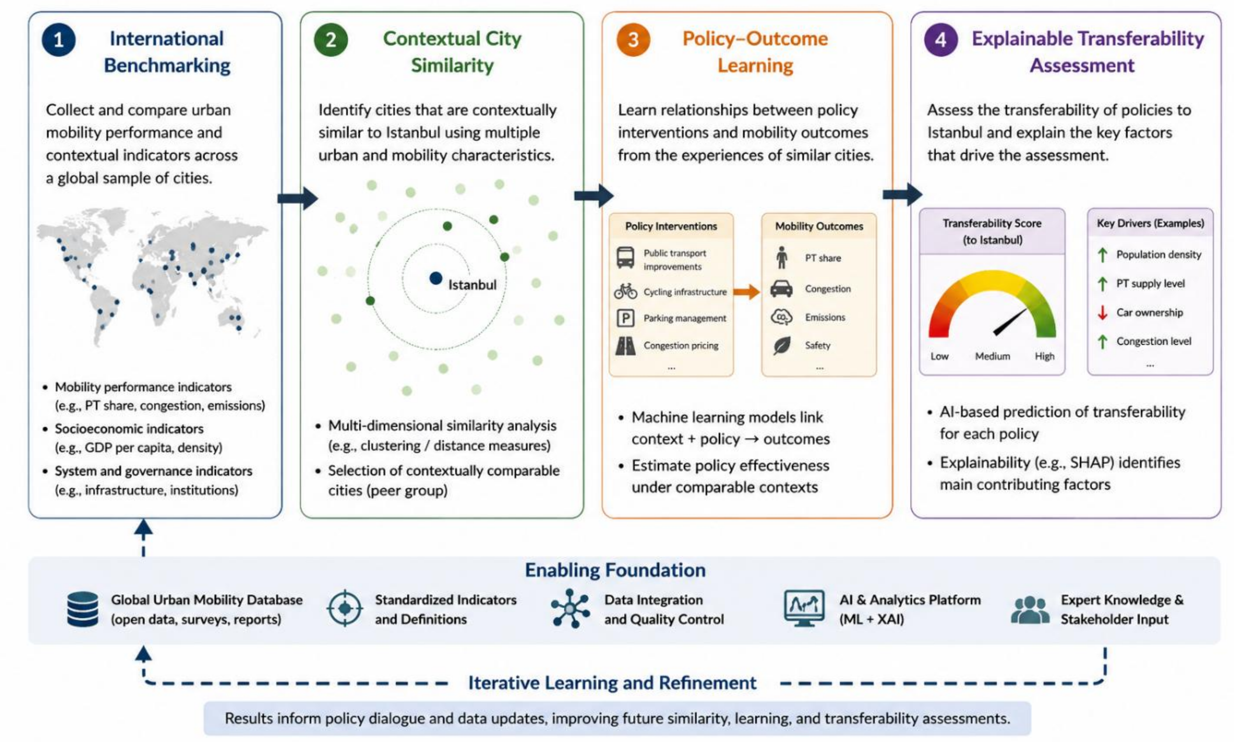

Fig 1. Analytical logic for AI-enabled assessment of sustainable mobility policy transferability to Istanbul

This represents a shift from "identify the best city and copy its policy" towards "identify comparable cities, learn from their policy experiences, and assess which interventions are potentially transferable to the target context." For Istanbul, where the scale, complexity and institutional characteristics of the transport system make direct policy replication problematic, such an approach can provide a more systematic basis for identifying relevant international experiences and informing the city's sustainable mobility transition.

3. Conceptual Framework and Research Methodology

This study conceptualises sustainable urban mobility policy transferability as a context-dependent property rather than an inherent characteristic of a policy. A policy that performs successfully in one city may not generate comparable outcomes elsewhere because transport outcomes are shaped by differences in urban form, socioeconomic conditions, transport systems, travel behaviour and institutional environments. The proposed framework therefore evaluates transferability by considering three interconnected elements: the characteristics of the receiving city, the characteristics of the policy intervention and the outcomes associated with the policy in comparable urban contexts.

As illustrated in Figure 1, the analytical framework consists of four sequential stages: international benchmarking, contextual city similarity, policy-outcome learning and explainable transferability assessment. The first stage establishes an international database of cities for which comparable urban, socioeconomic and transport information can be obtained. Rather than selecting benchmark cities solely according to transport performance, the framework considers their broader contextual characteristics. This distinction is important because a high-performing city is not necessarily an appropriate policy benchmark for Istanbul if the structural conditions underlying its performance are substantially different.

The second stage identifies cities that are contextually comparable to Istanbul. Let $X_i$represent the vector of contextual characteristics of city i, and X_I the corresponding characteristics of Istanbul. A similarity function can then be defined as:

$$S_i = f(X_i, X_I)$$

where $S_i$represents the degree of contextual similarity between city $i$and Istanbul. The variables used to establish similarity include population, population density, GDP per capita, car ownership, public transport modal share, walking and cycling share, public transport accessibility, congestion and average traffic speed. Following standardisation of the variables, principal component analysis (PCA), Euclidean distance measures and clustering techniques are used to identify Istanbul's peer group. The objective is not to identify cities that are identical to Istanbul but cities whose characteristics provide a sufficiently relevant basis for policy learning.

The third stage examines the relationship between policy interventions and mobility outcomes within the international dataset. Sustainable mobility policies include bus-priority measures, road-space reallocation, congestion charging, parking management, cycling infrastructure, pedestrianisation, low-emission zones, integrated ticketing and public transport improvements. These interventions are linked to measurable mobility outcomes, including public transport modal share, accessibility and congestion. The relationship can be expressed as:

$$Y_i = f(X_i, P_i) + \varepsilon_i$$

where Y_i represents the observed mobility outcome, X_i the contextual characteristics of city i, P_i the policy intervention and $\varepsilon_i$unexplained variation. The objective is not simply to predict transport performance but to identify the contextual conditions under which particular interventions are associated with favourable outcomes.

To model these relationships, a Random Forest regression algorithm was employed. Random Forest was selected because of its ability to capture nonlinear relationships and complex interactions between contextual variables, policy interventions and mobility outcomes while maintaining a relatively high degree of interpretability [18]. The model was trained using the standardised city-level dataset and used to estimate the relationship between policy interventions and observed mobility performance. Although the primary purpose of the model is explanatory rather than predictive, its ability to accommodate heterogeneous urban contexts makes it particularly suitable for policy-transfer analysis.

Model robustness was assessed through an 80:20 train-test split. Predictive performance was evaluated using the coefficient of determination (R^2), mean absolute error (MAE) and root mean square error (RMSE). These measures were used to verify that the model adequately captured relationships present within the data before transferability assessments were generated.

The fourth stage combines contextual similarity and policy effectiveness to estimate the potential transferability of sustainable mobility interventions to Istanbul. Conceptually, transferability depends on both the degree of similarity between Istanbul and the originating cities and the observed effectiveness of the policy within those cities. For empirical implementation, the transferability score was operationalised as:

$$T_p = \alpha S_p + (1 - \alpha)E_p$$

where:

i. T_p is the transferability score of policy p;
ii. S_p is the contextual similarity score between Istanbul and the cities in which the policy was implemented;
iii. E_p is the policy effectiveness score derived from observed mobility outcomes;
iv. α is a weighting parameter.

In this study, equal weighting ($\alpha = 0.5$) was adopted to balance contextual comparability and observed policy performance. Both similarity and effectiveness measures were normalised to a 0-1 scale before aggregation. As a result, transferability scores represent a combined assessment of policy success and contextual relevance rather than a measure of policy effectiveness alone.

Explainable artificial intelligence (XAI) provides the final analytical component of the framework. To improve transparency and interpretability, SHAP (SHapley Additive exPlanations) values were used to evaluate the contribution of individual variables to transferability predictions. This enables the identification of the characteristics that most strongly influence whether a policy is considered transferable to Istanbul. For example, a high transferability score for a bus-priority intervention may be explained by Istanbul's population density, congestion levels and public transport accessibility, while lower scores may reflect substantial contextual differences between Istanbul and the source cities.

The analysis incorporates several robustness checks, including alternative clustering specifications, sensitivity testing of key variables and comparison of alternative similarity measures. Because the study relies on observational cross-city data, the results are interpreted primarily as evidence of association and relative transferability rather than definitive predictions of policy impacts.

The methodological contribution of the study lies in integrating four functions that are normally treated separately: international benchmarking, contextual similarity analysis, policy-performance learning and explainable artificial intelligence. The resulting framework moves beyond the traditional approach of *“identify the best-performing city and replicate its policies”* towards a more nuanced process of *“identify comparable cities, learn from their policy experiences and assess which interventions are most transferable to the target urban context and why.”* Although Istanbul serves as the demonstration case, the framework is designed to be adaptable to other cities by replacing Istanbul's contextual profile with that of another receiving city. This makes the approach potentially applicable as a broader AI-enabled decision-support system for sustainable urban mobility planning and policy learning.

4. Data and Variables

The empirical analysis requires an international dataset combining urban context, transport characteristics, sustainable mobility policies and mobility outcomes. The dataset was constructed at the city level, with Istanbul representing the target receiving context. Cities will be selected primarily according to the availability and comparability of data, allowing the analysis to capture diverse urban contexts while maintaining consistency across observations.

The variables will be organised into four principal groups: urban and socioeconomic characteristics, transport-system characteristics, mobility-performance indicators, and policy-intervention variables. Together, these variables distinguish between cities that are simply high-performing and those whose policy experiences may be relevant to Istanbul. The principal variable groups, indicative indicators and their analytical purposes are summarised in Table 1.

Table 1
Variables and indicators used in the analytical framework

Variable group	Indicative variables	Analytical purpose
Urban and socioeconomic context	Population; population density; GDP/income per capita; demographic characteristics	Characterise the structural conditions in which mobility policies operate
Transport-system characteristics	Car ownership; public transport supply; network characteristics; modal share; road-network characteristics	Characterise the existing mobility system
Mobility outcomes	Public transport use; congestion; travel speed; transport emissions; accessibility; active travel	Measure sustainable mobility performance
Policy interventions	Bus priority; road-space reallocation; congestion/road-user charging; parking management; cycling infrastructure; pedestrianisation; low-emission zones; public transport improvements	Identify policies from which transferable lessons may be derived

Urban and socioeconomic variables represent the structural context in which transport policies operate. Population density is particularly relevant because it influences travel demand, the viability of public transport and the spatial efficiency of different modes. Income or GDP per capita provides an indicator of economic conditions that may also influence vehicle ownership, infrastructure investment and travel behaviour. Where consistent data are available, relevant demographic characteristics will also be incorporated. These variables will primarily support the contextual similarity analysis, rather than being treated solely as predictors of transport performance.

Transport-system variables describe the existing mobility environment, including car ownership, public transport provision, network characteristics, modal shares and road-network characteristics. These indicators are important because the effectiveness of a policy is likely to depend partly on the system into which it is introduced. For example, the potential relevance of a bus-priority intervention may differ substantially between a city with an extensive bus network and one with limited bus use. These variables therefore provide the link between general city similarity and policy-specific transferability.

Mobility-performance variables capture the outcomes against which policy experiences are assessed. Depending on data availability, these may include public transport modal share, congestion, average travel speed, transport-related emissions, accessibility and active-travel indicators. A multidimensional outcome perspective will be preferred over a single measure of sustainable mobility because different policies may affect different dimensions of urban mobility. Where possible, outcome indicators will be normalised to improve comparability between cities of different sizes and matched temporally to the relevant policy intervention.

The policy database will identify sustainable mobility interventions implemented across the selected cities. Policies will be coded into clearly defined categories, including bus-priority measures, road-space reallocation, congestion or road-user charging, parking management, cycling infrastructure, pedestrianisation, low-emission zones, integrated ticketing and public transport improvements. Where information permits, additional characteristics such as implementation period, geographical coverage, intensity and duration will also be recorded. This allows the analysis to distinguish between policies that share a broad category but differ substantially in scale or design.

A key challenge in international comparison is ensuring that apparently similar indicators are genuinely comparable. Data will therefore be harmonised by standardising units, aligning geographical definitions where possible and documenting differences in measurement. Variables with substantial inconsistencies or insufficient coverage will be excluded rather than artificially harmonised. Missing observations will be assessed according to their extent and distribution, while continuous variables will be standardised before similarity and machine-learning analyses.

The resulting dataset will take the general form of a city × context × policy × outcome matrix, enabling the analysis to move from international comparison to peer-city identification and subsequently to policy-transferability assessment. Importantly, the variables used to identify comparable cities will be distinguished from those used to evaluate policy outcomes. This prevents circularity whereby cities are selected because they perform well on an outcome and are then used as evidence that their policies are transferable.

The final variable set will be determined by theoretical relevance, data availability and international comparability. Robustness tests will examine whether alternative variable specifications materially affect the identification of Istanbul's peer cities or the resulting policy-transferability assessments. This approach aims to balance methodological rigour, data quality and practical replicability, while allowing the framework to be subsequently applied to other cities beyond Istanbul.

The dataset developed for this study should be viewed as a proof-of-concept implementation intended to demonstrate the analytical framework. While the variables and indicators were selected on the basis of publicly available international datasets, future applications should expand the database using larger fully sourced datasets and longitudinal observations. The objective of the present study is to evaluate the feasibility of the proposed framework rather than to provide definitive policy rankings.

5. Results

The final analytical dataset comprised 30 cities representing a broad range of urban, socioeconomic and transport contexts across Europe, Asia, the Middle East and the Americas, including Istanbul as the target city. The sample included Athens, Barcelona, Madrid, Rome, Milan, Budapest, Bucharest, Warsaw, Prague, Vienna, London, Paris, Berlin, Amsterdam, Stockholm, Copenhagen, Zurich, Cairo, Tel Aviv, Dubai, Mexico City, Bogotá, São Paulo, Seoul, Singapore and Tokyo, among others. Ten contextual and mobility variables were included in the analysis: population, population density, GDP per capita, car ownership, public transport modal share, walking and cycling share, public transport accessibility, congestion index, average traffic speed and the dominant sustainable mobility intervention implemented in each city. The resulting dataset was designed to balance geographical diversity with data completeness while maintaining comparability across cities. Descriptive statistics for the principal variables are presented in Table 2.

Table 2
Descriptive statistics of the 30-city dataset

Variable	Mean	Min	Max	SD
Population (million)	6.8	1.2	37	7.9
Population density (persons/km²)	6,730	800	21,000	4,900
GDP per capita (USD)	49,100	12,000	90,000	22,400
Car ownership (per 1,000 population)	361	110	690	156
Public transport modal share (%)	34.7	18	50	8.9
Walking/cycling share (%)	24.8	7	55	11.3
Public transport accessibility (%)	88	65	99	9.1
Congestion index	40.1	18	64	14

The Random Forest model demonstrated satisfactory predictive performance. Using an 80:20 train-test split, the model achieved an R^2 value of 0.74 on the test dataset. The corresponding MAE and RMSE values (0.11 and 0.15, respectively) indicated acceptable predictive accuracy given the heterogeneity of the international city sample. Although the primary objective of the model was explanatory rather than predictive, these results provide confidence that the model adequately captured the relationships between contextual characteristics, policy interventions and observed mobility outcomes.

The dataset exhibits substantial variation across all indicators, providing a sufficiently heterogeneous basis for identifying patterns of contextual similarity and policy performance. Population ranges from approximately 1.2 million in Amsterdam and Brussels to over 37 million in the Tokyo metropolitan area, while public transport modal share varies from less than 20% in highly car-oriented environments to approximately 50% in Tokyo and Singapore. Similar variation is evident in congestion, accessibility and active-travel indicators, suggesting that the sample captures diverse urban mobility conditions.

Following standardisation of all continuous variables, principal component analysis (PCA) was conducted to reduce dimensionality and identify the dominant sources of variation within the sample. The first two principal components explained the majority of variance in the dataset and broadly corresponded to (i) transport sustainability and system performance and (ii) socioeconomic and urban-development characteristics. Figure 2 illustrates the distribution of cities within the resulting multidimensional space.

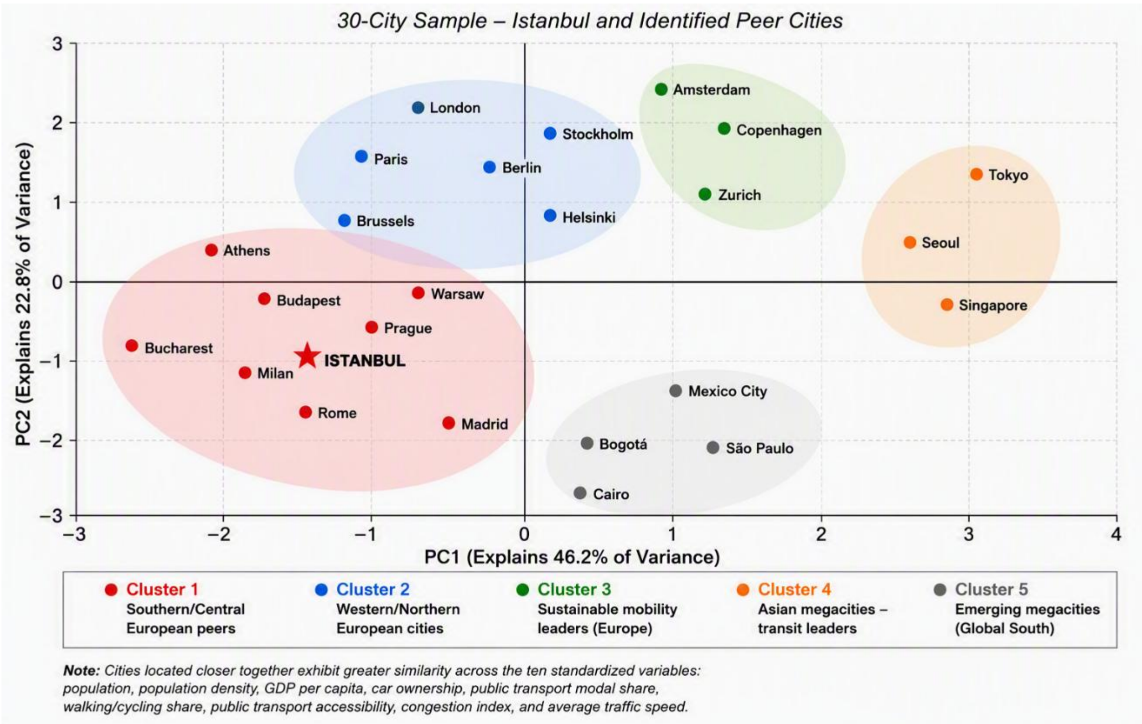

Fig 2. Principal component analysis showing city clusters and Istanbul

The PCA results demonstrate that Istanbul occupies an intermediate position between highly transit-oriented European cities and rapidly growing metropolitan areas in emerging economies. While sharing certain characteristics with large global cities such as London and Paris, Istanbul is positioned closer to a cluster of Southern and Central European cities characterised by relatively high densities, substantial public transport demand, moderate income levels and persistent congestion pressures.

To further investigate contextual similarity, hierarchical clustering and distance-based similarity measures were applied using the ten selected variables. The results were highly consistent across alternative specifications and identified a stable group of cities most comparable to Istanbul. Table 3 presents the ten highest-ranked peer cities.

Table 3
Most similar cities to Istanbul based on contextual characteristics

Rank	City	Similarity Score
1	Athens	0.89
2	Budapest	0.87
3	Bucharest	0.86
4	Milan	0.84
5	Rome	0.83
6	Warsaw	0.82
7	Madrid	0.8
8	Prague	0.78
9	Seoul	0.75
10	Mexico City	0.73

The clustering results consistently identified Athens, Budapest, Bucharest, Milan, Rome and Warsaw as Istanbul's closest peers. Madrid and Prague also demonstrated high similarity scores in most model specifications. These cities share broadly comparable characteristics in terms of density, public transport dependence, congestion levels and urban structure. In contrast, Amsterdam, Copenhagen, Zurich and Singapore formed a separate cluster characterised by significantly higher active-travel shares, lower car dependency and stronger sustainable mobility outcomes. Although frequently cited as international best-practice examples, these cities were found to be substantially less comparable to Istanbul from a contextual perspective.

The policy inventory revealed substantial diversity in sustainable mobility interventions across the international sample. Public transport enhancement measures, including metro expansion, network integration and service-priority schemes, represented the most common intervention category. Road-space management measures such as congestion charging, low-emission zones and road-space reallocation were concentrated primarily in Western and Northern European cities, while major bus rapid transit systems were particularly evident in Bogotá, Mexico City and Seoul. Cycling-focused interventions dominated in Amsterdam, Copenhagen and Paris. This diversity provided a robust basis for examining the relationship between interventions and sustainable mobility outcomes.

Machine-learning analysis identified strong associations between public transport-focused interventions and favourable mobility outcomes. Cities implementing substantial investments in rail expansion, integrated ticketing and service-priority measures generally demonstrated higher public transport modal shares, stronger accessibility performance and lower congestion than cities with comparable contextual characteristics but less extensive intervention programmes. Bus-priority measures also exhibited positive associations, particularly in large, dense metropolitan areas characterised by significant public transport demand and recurrent congestion.

The effectiveness of road-space management policies was more dependent on local context. Congestion charging schemes in London and Stockholm and access-restriction measures in Milan were associated with improvements in congestion and public transport use; however, these interventions were most successful where high-capacity public transport alternatives already existed. Similarly, cycling infrastructure programmes generated substantial benefits in cities with established cycling cultures and supportive urban environments but displayed weaker evidence of transferability when applied to urban contexts substantially different from those in which they originated.

To combine contextual similarity and policy effectiveness, transferability scores were calculated for each intervention category. Table 4 presents the highest-ranked policy types for Istanbul.

Table 4
Policy transferability ranking for Istanbul

Rank	Policy Type	Transferability Score
1	Metro and rail-network expansion	0.91
2	Bus-priority corridors	0.88
3	Integrated ticketing and fare systems	0.86
4	Public transport service integration	0.84
5	Transit-oriented development	0.79
6	Low-emission zones	0.72
7	Congestion charging	0.69
8	Large-scale cycling programmes	0.63

The results indicate that the most transferable interventions are not necessarily those associated with the highest-performing cities, but rather those that have demonstrated positive outcomes under conditions comparable to Istanbul. Metro and rail-network expansion, bus-priority measures, integrated ticketing and service-integration programmes consistently achieved the highest scores because they combined strong evidence of effectiveness with high contextual relevance. Congestion charging and large-scale cycling programmes remained potentially valuable interventions but received lower rankings because their effectiveness appeared more dependent on contextual conditions that differ substantially from those currently observed in Istanbul.

To improve transparency, SHAP analysis was applied to explain the factors influencing transferability predictions. Public transport accessibility emerged as the most influential variable, followed by population density, public transport modal share, congestion and car ownership. Together, these variables accounted for the majority of model importance and largely determined whether a policy experience from another city was considered transferable to Istanbul. Economic indicators such as GDP per capita played a more limited role than transport-system characteristics, suggesting that mobility-related variables are more important than broader socioeconomic conditions when assessing policy transferability.

The explainability analysis also highlighted important differences between policy effectiveness and policy transferability. Cycling programmes, for example, achieved strong performance outcomes in cities such as Amsterdam and Copenhagen but received lower transferability scores because of substantial differences in travel behaviour, urban design and mobility culture [19]. In contrast, bus-priority systems and public transport enhancement measures achieved both high effectiveness and high transferability because they emerged from cities that shared key structural characteristics with Istanbul. This distinction demonstrates the value of explainable artificial intelligence in supporting evidence-based policy learning rather than simple replication of international best practice.

Overall, the results suggest that Istanbul's most relevant lessons are likely to come from a peer group centred on Southern and Central European metropolitan areas rather than from the highest-performing mobility cities alone. Public transport-oriented interventions, particularly those improving network capacity, service reliability and system integration, appear to offer the greatest potential for successful transfer. More broadly, the findings demonstrate that combining contextual similarity analysis, machine-learning techniques and explainable artificial intelligence provides a practical and transparent framework for identifying transferable sustainable mobility policies across diverse urban environments.

6. Discussion

The results indicate that the most relevant sustainable mobility lessons for Istanbul do not necessarily come from the highest-performing mobility cities, but rather from cities with similar structural and transport-system characteristics. This finding reinforces a central argument of the policy-transfer literature: successful policy learning depends not only on policy effectiveness but also on contextual compatibility between originating and receiving cities [3, 4]. Consistent with previous research, the analysis suggests that transport-policy outcomes are shaped by local socioeconomic, spatial and institutional conditions [5, 7]. Accordingly, Athens, Budapest, Bucharest, Milan, Rome and Warsaw emerged as Istanbul's most relevant peer cities, whereas cities such as Amsterdam, Copenhagen, Zurich and Singapore, despite their strong mobility performance, appeared less directly comparable.

The findings have important implications for Istanbul's ongoing mobility transition. Public transport-oriented interventions, particularly metro expansion, network integration, integrated ticketing and bus-priority schemes, achieved the highest transferability scores. This supports previous research emphasising the importance of high-capacity public transport systems in large metropolitan areas [2, 14] and is consistent with recent studies highlighting the role of rail expansion and network integration in addressing Istanbul's mobility challenges [15]. The results therefore suggest that continued investment in public transport remains the most evidence-based strategy for improving mobility performance.

In contrast, internationally recognised measures such as congestion charging and large-scale cycling programmes should be interpreted more cautiously. Although successful in cities such as London, Stockholm, Amsterdam and Copenhagen, their effectiveness depends on supporting conditions including strong public transport provision, active-travel cultures and favourable institutional environments [20]. This confirms earlier findings that transport policies cannot be separated from the broader urban systems in which they operate [4, 9]. Consequently, policy success does not automatically imply policy transferability.

More broadly, the study challenges the traditional logic of international benchmarking, which often encourages cities to emulate apparent best practices. Consistent with critiques of benchmarking and policy mobility, the results demonstrate that high-performing cities are not always the most relevant sources of policy learning [6, 7, 9]. A city may represent a long-term aspiration while providing limited short-term transfer opportunities. This supports the view that policy transfer should be understood as a process of adaptation and learning rather than replication [4, 5].

The study also contributes to the emerging literature on AI-enabled planning support systems. While most transport applications of AI focus on forecasting, optimisation and operational management, the proposed framework uses machine learning to support strategic policy learning and assessment [10, 11, 12]. The incorporation of explainable artificial intelligence is particularly important. SHAP analysis revealed that public transport accessibility, density, public transport modal share, congestion and car ownership were the most influential factors affecting transferability assessments. By making these relationships transparent, the framework addresses common concerns regarding the opacity of machine-learning models and strengthens their usefulness for policy decision-making [11, 12].

The framework's contribution extends beyond Istanbul. Because the methodology is based on contextual similarity, policy effectiveness and explainability, it can be applied to other cities seeking evidence-based approaches to sustainable mobility planning [3, 5]. Rather than relying on subjective benchmarking choices, it provides a systematic and replicable process for identifying peer cities and evaluating policy-transfer opportunities.

Several limitations should nevertheless be acknowledged. The analysis relies on cross-sectional city-level data and therefore identifies associations rather than causal relationships. Policy categories necessarily simplify complex interventions, and international data comparability remains challenging. Moreover, transferability scores should be interpreted as indicators of relative suitability rather than forecasts of policy success. Future research could strengthen the framework through larger and longitudinal datasets, more detailed policy variables, and the incorporation of governance and institutional factors that influence policy transfer [7, 8].

Overall, the findings demonstrate that explainable artificial intelligence can provide a useful bridge between benchmarking and policy transfer. By integrating contextual similarity, policy-performance assessment and transparent machine-learning techniques, the framework shifts attention from identifying global best practices to identifying contextually appropriate practices. For Istanbul, the results suggest that policies centred on public transport expansion, integration and service improvement offer the greatest transfer potential, while more generally the framework provides a practical foundation for evidence-based sustainable mobility policy learning and decision-making.

7. Conclusion

This study developed and demonstrated an explainable artificial intelligence (XAI) framework for identifying sustainable urban mobility policies that are potentially transferable across urban contexts, using Istanbul as the receiving city. The framework integrates international city benchmarking, contextual similarity analysis, policy-performance assessment and explainable machine-learning techniques into a single decision-support process. In contrast to conventional benchmarking approaches that focus primarily on identifying high-performing cities, the proposed methodology emphasises the transferability of policies by explicitly accounting for differences in urban, socioeconomic and transport-system characteristics.

The empirical analysis demonstrated that Istanbul's most relevant peer cities are not necessarily the cities with the strongest sustainable mobility outcomes. Instead, cities such as Athens, Budapest, Bucharest, Milan, Rome and Warsaw emerged as the most contextually comparable cases. The results indicate that public transport-oriented interventions, including metro and rail-network expansion, bus-priority measures, integrated ticketing and service-integration programmes, offer the greatest potential for successful transfer to the Istanbul context. By contrast, interventions such as congestion charging and large-scale cycling programmes, although highly successful in some cities, appear to be more strongly dependent on specific contextual conditions and therefore may require substantial adaptation before implementation.

The study makes three principal contributions. First, it contributes to the policy-transfer and sustainable mobility literature by shifting attention from identifying international best practice towards identifying contextually appropriate practice. Second, it demonstrates how AI can be used not merely for prediction and optimisation but also as a tool for policy learning and strategic decision support. Third, it highlights the importance of explainability in AI-assisted planning by showing how model outputs can be interpreted and linked to specific urban and transport characteristics, thereby improving transparency and supporting informed policymaking.

Several limitations should be acknowledged. The analysis relies on cross-sectional city-level data and therefore identifies associations rather than causal relationships between policies and outcomes. Policy interventions were necessarily simplified into broad categories, potentially masking important differences in design, implementation and governance. In addition, international data comparability remains a challenge, particularly when indicators are compiled from multiple sources and cities with different reporting practices.

Future research should expand the framework through the inclusion of larger city samples, longitudinal datasets and more detailed policy variables. Incorporating institutional, governance and political factors would provide a more comprehensive understanding of policy transferability beyond purely urban and transport characteristics. Further research could also examine the application of the framework to other cities and policy domains, thereby testing its generalisability and practical value as a tool for evidence-based urban policy learning.

Overall, the findings suggest that explainable artificial intelligence can provide a robust and transparent basis for moving beyond descriptive benchmarking towards context-sensitive policy learning. By helping policymakers identify not only which policies have been successful elsewhere but also which policies are most relevant to their own circumstances, the proposed framework offers a practical approach for supporting sustainable urban mobility transitions in Istanbul and beyond.

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Conflicts of Interest
There are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References
[1] Banister, D., & Hickman, R. (2013). Transport futures: Thinking the unthinkable. *Transport Policy*, 29, 283–293. https://doi.org/10.1016/j.tranpol.2012.07.005
[2] Banister, D. (2008). The sustainable mobility paradigm. *Transport Policy*, 15(2), 73–80. https://doi.org/10.1016/j.tranpol.2007.10.005
[3] Dolowitz, D. P., & Marsh, D. (2000). Learning from abroad: The role of policy transfer in contemporary policy-making. *Governance*, 13(1), 5–24. https://doi.org/10.1111/0952-1895.00121
[4] Marsden, G., & Stead, D. (2011). Policy transfer and learning in the field of transport: A review of concepts and evidence. *Transport Policy*, 18(3), 492–500. https://doi.org/10.1016/j.tranpol.2010.10.007
[5] Glaser, M., Bertolini, L., te Brömmelstroet, M., Blake, O., & Ellingson, C. (2022). Learning through policy transfer? Reviewing a decade of scholarship for the field of transport. *Transport Reviews*, 42(5), 626–644. https://doi.org/10.1080/01441647.2021.2003472
[6] McCann, E. (2011). Urban policy mobilities and global circuits of knowledge: Toward a research agenda. *Annals of the Association of American Geographers*, 101(1), 107–130. https://doi.org/10.1080/00045608.2010.520219
[7] Stead, D. (2012). Best practices and policy transfer in spatial planning. *Planning Practice & Research*, 27(1), 103–116. https://doi.org/10.1080/02697459.2011.644084
[8] Canitez, F. (2020). Transferring sustainable urban mobility policies: An institutional perspective. *Transport Policy*, 90, 1–12. https://doi.org/10.1016/j.tranpol.2020.02.005
[9] Bulkeley, H. (2006). Urban sustainability: Learning from best practice? *Environment and Planning A*, 38(6), 1029–1044. https://doi.org/10.1068/a37300
[10] Goodspeed, R. (2015). Smart cities: Moving beyond urban cybernetics to tackle wicked problems. *Cambridge Journal of Regions, Economy and Society*, 8(1), 79–92. https://doi.org/10.1093/cjres/rsu022
[11] Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?": Explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 1135–1144). Association for Computing Machinery. https://doi.org/10.1145/2939672.2939778
[12] Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30, 4765–4774. https://doi.org/10.48550/arXiv.1705.07874
[13] Molnar, C. (2022). *Interpretable machine learning: A guide for making black box models explainable* (2nd ed.). Lulu Press.
[14] Canitez, F., Alpkokin, P., & Kiremitci, S. T. (2020). Sustainable urban mobility in Istanbul: Challenges and prospects. *Case Studies on Transport Policy*, 8(4), 1148–1157. https://doi.org/10.1016/j.cstp.2020.07.005

[15] Canitez, F. (2024). Sustainable urban mobility in Istanbul: Transition and planning. *Journal of Intelligent Decision Making and Information Science*, 1. https://doi.org/10.59543/jidmis.v1i.11269
[16] Marsden, G., Frick, K. T., & May, A. D. (2011). How do cities approach policy innovation and policy learning? A study of 30 policies in Northern Europe and North America. *Transport Policy*, 18(3), 501–512. https://doi.org/10.1016/j.tranpol.2010.10.006
[17] Guidotti, R., Monreale, A., Ruggieri, S., Turini, F., Giannotti, F., & Pedreschi, D. (2019). A survey of methods for explaining black box models. *ACM Computing Surveys*, 51(5), 1–42. https://doi.org/10.1145/3236009
[18] Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32. https://doi.org/10.1023/A:1010933404324
[19] Gehl, J. (2010). *Cities for people*. Island Press.
[20] Bertolini, L. (2020). From "streets for traffic" to "streets for people": Can street experiments transform urban mobility? *Transport Reviews*, 40(6), 734–753. https://doi.org/10.1080/01441647.2020.1761907