

Research

Searching for complexity. Application of the set-theory to the analysis of urban mobility readiness index

Cayetano Medina-Molina^{1,2}  · Noemí Pérez-Macías³  · María Coronado-Vaca³ 

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Abstract

Numerous initiatives have been developed to monitor the sustainability performance of cities, with rankings and indicators emerging as crucial tools for understanding complex urban phenomena. However, these indices require deeper analytical methods to fully interpret their results. This study highlights the application of Set-Theory methods, specifically Qualitative Comparative Analysis with process-tracing in analyzing the Urban Mobility Readiness Index (UMR) across 60 cities for 2021 and 2022. Our primary achievement is the demonstration of Set-Theory's ability to unravel the causal complexity in urban dynamics. We find that urban mobility readiness and its negation are not determined by singular conditions but by a combination of conditions. Necessary conditions such as infrastructure and socioeconomic factors have been identified, which are critical for achieving a higher level of readiness in the UMR, and its negation. Cities lacking these conditions are less likely to reach the desired level for sustainable development. Additionally, we reveal that certain conditions serve beyond scope definitions, actively triggering causal mechanisms for both readiness and its negation. This insight underscores the multifaceted nature of urban sustainability, guiding cities towards effective strategies for sustainable development. Our study thus contributes a nuanced understanding of urban mobility, essential for policymakers and urban planners.

Keywords Urban Mobility Index · Set-Theory · fsQCA · Process-tracing · SMMR

1 Introduction

One of the most visible obstacles to achieving sustainable development is environmental pollution [1, 2], causing the neutrality of the ecological footprint to be among the priorities of organizations, cities, regions and governments [3]. More than two-thirds of the world's population will live in cities by 2050 [4, 5]. Examining the factors influencing CO₂ emissions is crucial to reducing them and promoting sustainable development [3, 6]. Although cities occupy less than 5% of the earth's surface, they consume more than 75% of natural resources and emit between 60 and 80% of greenhouse gases; managing a city is an important and complex task [7]. Therefore, meeting the needs of its inhabitants while ensuring the integrity of the environment has become one of the greatest challenges of our time [4].

Indeed, the sustainable development of the urban environment is introduced in the Sustainable Development Goals due to its critical role in global progress [8]. Sustainability requires a balanced development, acting simultaneously on its

✉ Cayetano Medina-Molina, cmedina@centrosanisoro.es; cayetano.medinamolina@ui1.es; Noemí Pérez-Macías, nperezmacias@comillas.edu; María Coronado-Vaca, mcoronado@comillas.edu | ¹Business Administration and Marketing Department, Centro Universitario San Isidoro, Avenida Leonardo da Vinci 17B, Isla de La Cartuja, Seville, Spain. ²Universidad Isabel I, Calle Fernán González, 76, 09003 Burgos, Spain. ³Faculty of Economics and Business, Universidad Pontificia Comillas, C. de Alberto Aguilera, 23, 28015 Madrid, Spain.



triple perspective. The complexity of the decisions to be faced makes it necessary to have tools that facilitate decision-making and optimize the allocation of resources [9]. In line with global urbanization trends and the challenges facing metropolitan areas today (climate change, pandemics, rapid urbanization and infrastructure for an aging population), city managers must recognize the need for change from traditional urban planning models to other more innovative and efficient [10]. Therefore, it is considered a priority to identify and rank the barriers that prevent progress toward sustainability in order to formulate solutions adapted to the needs of the context [11]. To leverage the learning derived from urban initiatives, it is essential to monitor and control the level achieved in different areas; evaluate previously implemented projects; identify the strengths and weaknesses of cities; and plan the future direction of the city [12]. This situation leads to the development of multiple initiatives to monitor the sustainability performance of different urban areas in order to help public decision-makers [4, 5, 12–16].

Among the initiatives developed for monitoring, rankings and indicators emerge as tools to address urban sustainability. They facilitate the quantification and understanding of complex phenomena [8, 17, 18] and can produce adequate responses to social impacts [19]. However, the challenge lies in selecting the most appropriate index due to its diversity [20]. Bearing in mind the limitations identified in these rankings and indicators [14, 21], a primary concern is whether these rankings or indicators truly capture the causal complexity that characterizes urban phenomena [4, 13, 21]. In addition, the methodology commonly used in the interpretation of sustainability-related indicators focuses on the independent influence (net effects) of isolated factors, lacking a systemic thinking and a comparative approach that would allow for deeper analysis and interpretation. Given that the independent examination of the dimensions that make up an index can provide different patterns from those that would be obtained by studying them as a whole, there is a call to use methods that allow addressing the complexity that characterizes urban systems [5, 8]. These methods would allow for a more accurate analysis taking into account the complex, multipath and non-linear interrelationships between indicators [17, 21].

In this way, it is pertinent to design studies based on an appropriate methodology to understand the heterogeneous effects that different innovations have on environmental deterioration [22]. For this reason, various tools have been used to rank the determinants of sustainability [11]. In recent years, numerous studies have analyzed environmental neutrality using different econometric methodologies that, although they highlight the causal links between the parameters, present results that are considered mixed and inconsistent [3]. Furthermore, the data used in the indicators are heterogeneous, which, together with the problem of correlation, poses a challenge to their comparability [10]. For this reason, authors have opted for the use of analysis techniques that take into account the complexity and asymmetry linked to the determinants of sustainability [11, 23]. Within them, first of all, the focus is on second-generation econometric methods that overcome the treatment of the heterogeneity and cross-sectional dependence of the variables studied [3, 22, 23]. This situation has led to the application of the (Method of Moments) Quantile Regression to different indices linked to sustainability [1, 3, 6, 22–24], as well as in other works focused on the determinants of the development of economies [25]. Due to its flexibility and efficiency, quantile regression helps understand the behavior of sustainability pillars by studying the entire distribution [24].

Nevertheless, considering the limitations linked to classical techniques for testing and making generalizations when examining and comparing cases in the social sciences, many times qualitative research approaches are chosen [26]. Particularly, keeping in mind that the city is a complex and multidimensional unit dependent on multiple internal and external factors [7]. In this sense, when opting for new techniques, different aspects that determine their choice have been taken into account: the interaction between the conditions studied [3, 27]; the asymmetry underlying such explanations [6, 25]; or the heterogeneous transition pathways that could occur [1]. Thus, sometimes multi-criteria decision-making (MCDM) (Table 1) is used due to its ability to be applied to complex and multi-dimensional decisions. Among such techniques is fuzzy set theory [28, 29]. This is the first *research gap* addressed by the present work, which consists of identifying analytical methods that make it possible to deal with causal complexity in the analysis of indices linked to rankings. Few studies have analyzed how sustainability challenges can be solved using configurational methods [30]. Answering the call to understand the interrelationships between ranking components, as well as how different configurations explain their results [31]. Despite the fact that these indicators have been pointed out as difficult to decipher and analyze because they condense messages that reflect a complex world [32], it has also been indicated that QCA can help identify scenarios among the data that are worthy of further analysis [26].

Indicators must be able to quantify change, identify and measure key processes, and provide a framework for setting targets and monitoring performance [33]. However, sustainable transitions are conditioned by the context in which they take place; meaning that the tools used to assess them must fit these contexts and reflect the specific conditions of each case studied [16, 34–36]. In this sense, Costa et al. [19] indicate that each author should choose the most feasible approach

Table 1 List of acronyms

Description	Acronyms
Complementary Conjunct	CC
Consistency for necessity	Cons.Nec
Consistency for sufficiency	InclS
Coverage for sufficiency	CovS
Enhanced standard analysis	ESA
Focal conjunct	FC
Fuzzy-set qualitative comparative analysis	FsQCA
Individually irrelevant	iir
Infrastructures	INF
Innovation	INN
Market attractiveness	MAT
Multi-criteria decision-making	MCDM
Qualitative comparative analysis	QCA
Proportional reduction of inconsistency	PRI
Relevance of necessity	RoN
Set-theoretic multi-method research	SMMR
Social impact	SIM
Sustainable urban mobility plan	SUMP
System efficiency	SEF
Urban mobility readiness	UMR
Urban mobility readiness index	UMRI

to their region, adopting different solutions depending on the existing urban situation and the reality of each region. However, the use of standardized indicators, as the indices do, hinders local context specificities, reinforcing stereotypes [21]. Therefore, it is suggested to adapt indicators to local idiosyncrasies [8], in order to establish the existence of causality between the factors identified for the cities under study. Additionally, the identification of causal mechanisms rests on the study of individual cases [39, 40]. This is the second *research gap* addressed by the present work, which consists of applying analytical methods to the indices linked to the rankings that allow for identifying the characteristic features that define the cities. The traditional approach to smart city rankings simplifies the choice of the most attractive city, but reinforces stereotypes and ignores the strengths and weaknesses of cities as well as their respective contexts [10]. This is done through systematic identification of the cities that explain the existence of causal relationships between the conditions and the studied result, which will allow us to delve deeper into the variables that trigger said relationship [3, 27].

To address the identified gaps, the objective of the present work is to establish the potential of techniques based on Set-Theory to deepen the analysis of the results presented in different indices linked to sustainability. Thus, this study employs Qualitative Comparative Analysis (QCA) and process-tracing. QCA, is a robust analytical technique particularly suited for studying sustainable transitions due to its ability to explore causal complexity and analyze combinatorial conditions influencing outcomes. While QCA involves a cross-case analysis, process-tracing involves within-case analysis. This is pivotal for understanding mobility, a multifaceted system with numerous interacting subsystems. Process-tracing, complements QCA by starting with the identification of the cases for analysis, thereby elucidating the configurational relationships of transitions to sustainability. Both QCA and process-tracing are grounded in Set-Theory. Specifically, we apply Set-Theoretic Multi-Method Research (SMMR) to the Urban Mobility Readiness Index (UMRI) values for 2021 and 2022 across 60 cities [37]. This approach unveils the diverse pathways leading cities towards (or away) from urban mobility readiness. By employing SMMR, we aim to discern effective strategies (via QCA) and their underlying reasons (via process-tracing), offering valuable insights for policy formulation in varied contexts [38]. While the use of fuzzy-set theory has been suggested as a way to address the uncertainty associated with the use of indicators and rankings [12], process-tracing helps trace the underlying arguments behind the mechanisms that explain how the cause leads to the effect; how the result is produced [39]. Moreover, the application of a systematic method in the selection of study cases allows us to overcome the challenge of bias in choice and lack of representativeness that is often attributed to case studies [40].

The choice of an index linked to mobility is due to the evolving patterns in transport utilization, its rising demand, and the global shifts in travel behaviors; there is an urgent need to delve into the study of mobility and innovation within

sustainable frameworks [41]. Tsiropoulos et al. [42] emphasized the importance of continuous monitoring and evaluation of urban mobility systems for understanding their impacts on sustainability. Such evaluations are crucial in tailoring sustainable urban mobility strategies to the unique challenges and opportunities presented by evolving urban landscapes.

As the number of smart city projects increases, so do the tools and indicators developed to evaluate their performance [3]. Given the development of different indices that can serve as a reference to monitor the progress of cities in their response to environmental challenges, the objective of this work is to establish the potential of techniques based on Set-Theory to deepen the analysis of such indices. Therefore, the suitability of QCA to explain causal complexity is shown as a response to the first gap. Likewise, the application of process-tracing makes it possible to identify the existence of causal mechanisms in the analyzed relationships, based on the defining characteristics of the cities under study. The results achieved demonstrate the suitability of applying Set-Theory methods for analyzing indices linked to sustainability. QCA shows that it is the conjunction of different conditions that explains the presence, or negation, of a result. It also clarifies that the explanation of a result and its negation not only differ in the sense of the relationship of the explanatory conditions but also in the conditions that make up that explanation. For its part, the application of process-tracing systematically identifies the cases to be used in the different comparisons. In this way, the analysis of the indices is enriched beyond the identification of the 'best' or 'worst' cases, representing the main novelty of this work. While fuzzy-set techniques had been applied in the analysis of indices linked to urban sustainability, this work presents as a novelty the exposure of the potential that SMMR presents to deepen the analysis of the evolution of different cities in their transition towards sustainability. The development of indices can help public managers design their policies and strategies towards more sustainable environments with fewer emissions. However, the application of analysis techniques that take into account the complexity of the phenomena studied and that recognize the differential characteristics of each city can be fundamental in the interpretation and analysis of said indices.

2 Literature review

2.1 Explanatory indices of the cities' readiness to adopt innovations

The journey towards sustainable urban growth is increasingly navigated through the lens of performance measurement. This strategic process entails the deployment of various indices and indicator systems, essential for cities to delineate their sustainability goals and strategies [5]. These measurement tools extend beyond mere data collection; they qualify complex urban concepts, transforming abstract ideas like sustainability into quantifiable metrics. This is especially relevant in the realm of sustainable urban mobility, where indicators not only deepen our understanding of the challenges but also enhance management proficiency, by highlighting operational obstacles and societal impacts [19, 43] (Fig. 1).

Globally, cities have embraced a diverse toolkit comprising rankings, benchmarking, and indices, to gauge their performance and address sustainability challenges [3, 21, 33]. In real life, it is often necessary to choose between alternatives and rank them based on a certain criterion [44]. City rankings, for instance, offer a hierarchical representation of urban centers, assessing them on a spectrum of economic, social, and geographical characteristics [13, 15, 21]. These rankings do more than just compare; they inject a competitive edge into urban development and governance, prompting cities to aspire towards higher standards of development and sustainability [14].

Benchmarking tools and indices serve as critical instruments for cities to set and monitor measurable sustainability goals [1, 4, 18, 22, 24]. These tools offer a dual perspective: They not only provide insights into current urban phenomena but also enable a longitudinal analysis of progress over time and a cross-sectional comparison among cities [4, 14, 21]. The role of sustainable urban mobility indices in bordering managerial knowledge has been particularly emphasized by Tsiropoulos et al. [42] highlighting their value in offering a nuanced understanding of urban mobility challenges. These indices are developed either as neutral data carriers or as message carriers, reflecting the multifaceted nature of urban development [4]. Moreover, urban performing indicators vary in their scope, with two main typologies identified: single indicators related to a specific city aspect, and composite indicators designed to measure complex and intangible matters [33]. Integrated indices, based on the interaction of values achieved in different previous indices, further complement these [45].

In most cases, an option could have a better rating according to one of the criteria, while other options in the comparison set could have a better rating according to another of the criteria used. Therefore, if we want to consider both criteria we could build an indicator that summarizes the information in a single number [44]. Since development cannot be exclusively measured in economic terms without considering its border environmental, social, and

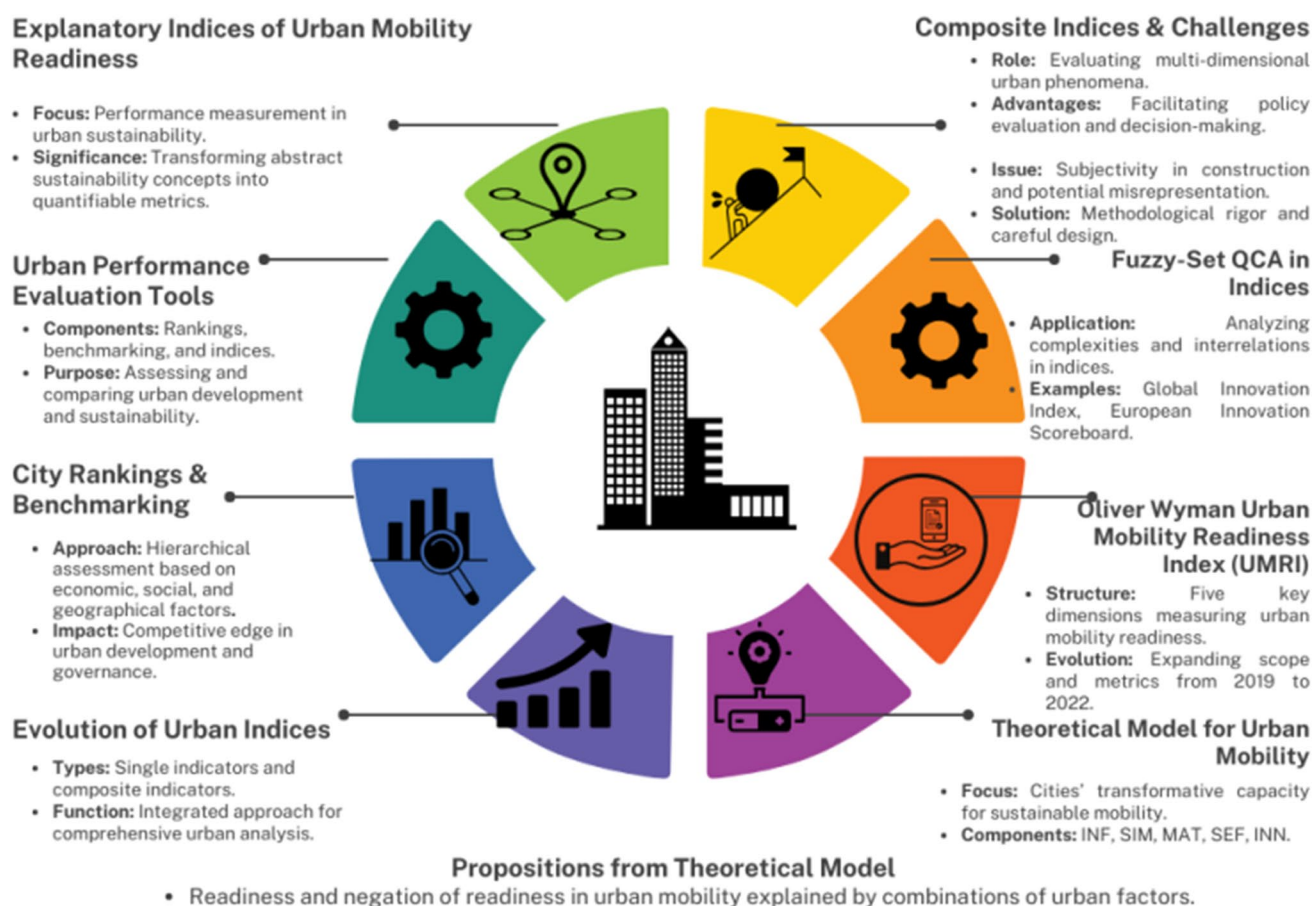


Fig. 1 Literature review

sustainable impact, there has been a push towards the development of composite indicators [32, 43]. If we want to consider two or more criteria, these are usually combined based on a particular function. The higher the value in the joint indicator, the better the option is usually. This method is referred to as the construction of composite indicators [44]. Composite indicators are a valuable tool to describe phenomena and evaluate policies and programs [46]. The evolution towards composite indices marks a significant advancement in urban performance evaluation. Composite indices, which combine individual indicators to form a single index (synthetic index), are vital for evaluating multi-dimensional phenomena related to sustainable urban development [5, 9, 16, 21]. They are constructed within a hierarchical framework, reflecting a multi-criteria composition, which is crucial for accurately depicting complex urban phenomena [47]. By aggregating diverse information about a sector and providing the basis for establishing a ranking enabling comparison of public policy performance [32], these composite indices simplify complex data, delivering a comprehensive perspective [16]. Their main advantages include ease of interpretation and the ability to facilitate comparisons on different scales [5, 21], making them invaluable decision-making tools [9]. Although composite indicators are widely exploited as valuable tools in political analysis, their appropriate methodological design is essential to avoid problems linked to misrepresentation and interpretation [47].

Building composite indices involves making a series of choices requiring subjective judgments, such as how to aggregate or weight the indicators. For this reason, it is sometimes criticized that deciding on different aggregation modes can lead to different rankings. Therefore, Marianni et al. [44] propose a method to rank countries, individuals or firms, based on two indices, which is especially useful when constructing a composite indicator that combines both dimensions is not feasible. To do this, they order the options without depending on the construction of a joint indicator [44].

2.2 The Oliver Wyman index

The Urban Mobility Readiness Index (UMRI), pioneered by the Oliver Wyman Forum in collaboration with the University of California at Berkeley, is a progressive annual ranking that gauges the preparedness of global cities to spearhead the future of mobility. Since its inception in 2019, the UMRI has expanded its scope, starting with data from 30 cities and 35 metrics in its inaugural year, progressing to encompass 50 cities in 2020 with 56 metrics, and broadening to 60 cities with 57 KPIs in both 2021 and 2022 editions.

The UMRI is structured around five pivotal dimensions: Infrastructures (INF-Has the city developed robust infrastructure and expanded connectivity to support future mobility?), Social impact (SIM-Does the city maximize societal benefits while minimizing harmful qualities like poor air quality?), Market attractiveness (MAT-How well does the city engage the private sector and secure diverse investments to build out mobility?), System efficiency (SEF-How well does the municipal government coordinate and enhance the city's mobility network through things like traffic management systems or investment in e-charging stations?), and Innovation (INN-How well does the city leverage local talent and resources to drive technological advances?). These dimensions explain Urban Mobility Readiness (UMR-Level of readiness of cities to excel in meeting their future mobility challenges).

Excelling across these dimensions is indicative of a robust mobility ecosystem. Cities are ranked on a scale of 1 to 100 based on their performance across the five core dimensions [37]. The weighting of each KPI within these dimensions is determined based on its relative importance, with a focus on factors that reflect a city's potential to build a sustainable urban mobility ecosystem. As part of the construction and testing of the 2019 UMRI, a principal component analysis was performed on the data to determine alternative weights. However, these weights were subsequently established based on expert assessments. Finally, convex optimization techniques were used to understand the weights that allow the cities to be compared to each other [37].

The recent additions are: 1) 2021: Introduction of a 'Sustainable Mobility' sub-index, comprising of 16 indicators from the UMRI, to gauge how cities prioritize sustainable urban mobility. 2) 2022: A new 'Public Transit' sub-index was added, based on 13 UMRI metrics, highlighting the management and utilization of public transit systems in cities [37]. See Table 2 for a detailed evolution of the number of cities and KPIs across the index's editions from 2019 to 2022.

2.3 Application of fuzzy-set qualitative comparative analysis to ranking and indices

Despite their comprehensive scope, it's crucial to recognize the potential limitations of composite indices in capturing specific nuances of urban contexts, as highlighted by Menini et al. [43]. The multidimensional nature of urban smartness calls for specific evaluation techniques capable of capturing the various dimensions of urban development. These techniques should consider the interaction between a city's social, political, economic, cultural aspects, and its physical infrastructure, as emphasized by Vanli [10]. In this context, the efficacy of ranking systems to accurately reflect the outcomes of interest is questioned, primarily due to their reliance on symmetric statistical techniques and linear variable relationships. This has led to the adoption of QCA to clarify interrelations and underscore the complexity presented by indices [31]. Employing QCA enhances our understanding of the behavior of index components, surpassing the constraints of analyses focused on net average effects [48], while examining multiple relationships [49].

Firstly, several studies delve deeper into the analysis of outcomes generated by rankings and indices through QCA application. This method has been used to analyze the interrelation among indices [50], or how different indices serve as precursors to analyze the complexities of achievements linked to the [51]. The fact that varied combinations of precursors lead to significant achievements in SDGs implies that the same result may be explained by different causal combinations [51]. Additionally, it's noted that despite the widespread application of the European Innovation Scoreboard, the indicator fails to highlight the existing interrelations among its components, focusing instead on the linear relationship between its explanatory conditions. Such findings emphasize the importance of equifinality and asymmetry in analyzing the European Innovation Scoreboard [31].

However, the Global Innovation Index (GII) has garnered considerable attention, with various studies applying QCA to identify relationships among its components [48, 49, 52, 53]. These studies, in addition to explaining the causal relationships that form GI's internal structure [49], combine fsQCA and structural qualitative association to further explore the relationships between GI's components [52].

Table 2 URM Index composition in 2019 and 2022 editions

Year	Cities	Dimensions	KPIs	INF KPIs	SIM KPIs	MAT KPIs	SEF KPIs	INN KPIs
2019	30	5	35	4	10	6	10	5
2022	60	5	57*	12	9	7	20	6—5 are the same as in 2019
				- 3 are the same as in 2019	- 4 are the same as in 2019	- 2 are the same as in 2019	- 4 are the same as in 2019	6—5 are the same as in 2019
				- 8 are new	- 3 are new ones	- 2 are new ones	- 13 are new ones	2019
				- 1 is relocated in INF 2022 from MAT 2019	- 2 are relocated in SIM 2022 from SEF 2019	- 3 are relocated in MAT 2022 from SEF, MAT & INN 2019	- 3 are relocated in SEF 2022 from SIM 2019	- 1 is new

Although the index textually indicates that it is made up of 57 KPIs, only 54 can be identified from its presentation

2.4 Theoretical model and justification of the propositions

Making cities sustainable depends on their transformative capacity, a measure of the systematic dynamics of the city that describes different parameters related to actors, institutions, physical environment, and their interaction processes [54, 55]. Contemporary urban areas are placing a heightened emphasis on strategies that bolster urban mobility while mitigating the negative impacts of vehicular usage. For a holistic approach to sustainability, it is imperative for urban planners and designers to take into account a diverse set of indicators spanning social, economic, and environmental features [20, 56].

Promoting sustainable urban mobility involves incorporating, adaptable transportation services, modern infrastructure, traffic management tools, awareness campaigns, well-coordinated mobility plans and advanced traffic intelligent transportation systems, which allow the population to meet their mobility needs [57]. This aligns with Moeinaddini et al. [56], who emphasize the importance of sustainable mobility in achieving a sustainable urban environment. Following a configurational approach, cities are prepared for urban mobility by taking into account behaviors, practices and context in a combined and interconnected way [58], since mobility is a complex phenomenon that requires taking into account all these intersections [20]. This is supported by Moeinaddini et al.'s [56] discussion on the relationship between urban structure and travel behavior, highlighting the role of higher densities, mixed land use, and walkable communities in promoting sustainable urban mobility. Therefore, in this study, we use a model in which the Urban Mobility Readiness (UMR) outcome is explained by INF, SIM, MAT, SEF, and INN [37].

Effective adaptation of transportation infrastructure (INF) is crucial for making the urban environment more equitable, sustainable, and resilient to the impacts of climate change [59, 60]. In fact, it has been considered evident the relevance of INF for the implementation of sustainable mobility solutions [61], or even essential for the reinforcement of INF to determine the level of preparation of a city for transformation. Menini et al. [43] further support this by highlighting the significance of nonmotorized transportation infrastructure, such as pedestrian pathways and cycle lanes, in promoting sustainable mobility. Such infrastructure not only promotes sustainable mobility, but also fosters a culture of eco-friendly transportation among the youth, setting a precedent for future urban mobility trends. Therefore, Sáez et al. [21] refer to the importance of adapting INF for the implementation of shared automated electric vehicles. For their part, Cieřla et al. [62] show the relevance of investing in INF, such as pedestrian walkways, for progress towards sustainable mobility.

The development of sustainable and efficient mobility systems (SEF) requires the involvement of governments [63]. Mainly, because it requires promoting public transportation and collective mobility [62]. In fact, in Europe, there are several strategies and plans carried out in order to move towards more sustainable mobility models. Thus, the Sustainable Urban Mobility Plan (SUMP) is the response to the challenges of designing more efficient and environmentally friendly transport systems [64].

The implementation of smart mobility innovations implies a distribution of the benefits generated among the participating agents [61], which facilitates attracting a larger number of investors (MAT). Therefore, difficulties in finding mobility solutions that adequately meet the needs of all stakeholders, in addition to budget limitations, are barriers to be taken into account when preparing cities for sustainable mobility [57].

Creating a sustainable urban mobility network requires technology and innovation (INN), as well as advanced systems that facilitate its use [63]. Menini et al. [43] emphasize that innovation is not just about high-tech solutions but also about rethinking traditional modes of transportation and ensuring they are optimized for modern urban environments. For instance, enhancing nonmotorized transportation modes on university campuses can serve as a model for broader urban areas, showcasing how innovation can be both technologically advanced and rooted in traditional mobility solutions. In fact, some argue that in order to achieve effective maintenance of infrastructure, the use of technology (INN) is necessary [59]. Innovation and technology will be key aspects for the development of urban mobility systems [65], along with the existence of qualified labor [57].

Similarly, new technologies and innovations in mobility derived from these can improve social impact (SIM) through improved affordability, reduced emissions and air pollution [20]. Furthermore, promoting nonmotorized transportation modes, especially in specific contexts like university campuses, can have a profound positive social impact. Such modes not only reduce environmental footprints but also promote healthier lifestyles and foster community interactions, enhancing the overall quality of urban life [43]. SIM is one of the factors that affect the transformative capacity of cities, and sustainable mobility plays a key role in achieving it. In fact, the EU's plans for sustainable urban mobility, aim to improve the overall quality of life for all residents and their accessibility to urban areas in order to facilitate mobility through and within urban areas [64].

Based on the above, the following propositions are proposed:

Proposition 1_a. The combination of different conditions explains the readiness of cities in meeting their future mobility challenges.

Proposition 1_b. The combination of different conditions explains the negation of readiness of the cities in meeting their future mobility challenges.

Proposition 2_a. The combination of explanatory conditions causes the readiness of cities in meeting their future mobility challenges.

Proposition 2_b. The combination of explanatory conditions causes the negation of readiness of cities in meeting their future mobility challenges.

3 Material and methods

3.1 Data

In this study, we analyzed UMRI data to study the causal conditions that are necessary or sufficient to indicate the level of urban mobility readiness of cities. The data reflects the ratings obtained by 60 cities from different regions of the world for the UMRI editions of 2021 and 2022.

3.2 Set-Theory and the explanation of causal complexity

Set-Theory is a branch of mathematics that identifies non-statistical relationships between explanatory factors and an outcome through Boolean algebra and its fuzzy set extensions [66]. Although originally Boolean algebra uses variables that occur in two states (true/present or false/absent) that make it possible to perform set-theoretic operations, Lofti Zadhe later developed fuzzy logic as an extension of Set-Theory to face with the problem of complex and imprecise concepts [67]. Boolean algebra determines which combinations of attributes lead to specific outcomes; the influence of certain attributes on an outcome is assumed to depend on their combination and not on their individual prevalence [68, 69].

Set-Theoretic methods share three features. First, they operate based on the membership scores of the cases to sets. A set is a group to which objects that share a particular characteristic belong; membership indicates the degree to which a case belongs to the set. Second, they perceive relations between social phenomena as set relations, where we are interested in knowing whether particular sets of cases are subsets of another case. Third, set relations are interpreted in terms of necessity and sufficiency [60, 66–73]. The Set-Theoretic approach offers a useful tool for analyzing complexity in small-sized samples. From its origins, the Set-Theoretic approach facilitates the construction of conceptual frameworks that allow studying complexity beyond recognizing patterns and processes, and classifying information [30].

The method most directly associated with Set-Theory is QCA. It differs from other Set-Theoretic approaches by pursuing a causal interpretation; employing truth tables and applying logical minimization [70, 73, 74]. Since QCA relies on Boolean algebra, it can use its rules to systematically evaluate the relationships between the outcome and the conditions (isolated or combined). For this, it uses the following logical operators: AND (*), referring to the intersection; OR (+), referring to the union; NOT (~), which describes the negation or complement of a set [54, 67]. Mathematical rules of commutation, relationality, and distributive law apply to the Boolean operators AND and OR [26]. While regression analysis methods identify 'the effect of causes', QCA is especially valid for explaining the 'cause of effects' [66]. Using a traditional regression can cause overestimation or underestimation of the coefficients and, in this way, not considering the heterogeneity of the data [23]. Thanks to QCA, one can elucidate how a particular outcome of interest is generated [26]. In the QCA framework, social phenomena are rarely conceived in isolation in terms of their net additive effects (as in a conventional perspective) but rather, it is the complex combination of conditions (a configurational approach) that explains a specific outcome by endowing cases with uniqueness [66, 68, 69, 71, 72, 75–78]. Configurations that, from a systemic perspective, are a constellation of connected elements [71]. A configurational approach assumes that causally related variables in one configuration might be interrelated, or even inversely related, in others [76, 79]. This approach enhances understanding of theories by showing their complexity, heterogeneity and multidimensional nature [58].

However, a configurational approach faces challenges. At the theoretical level, different antecedents could lead to multiple configurations with comparable outcomes. That is, the approach moves from the net effect of isolated conditions to the study of the effect of multiple configurations [67]. From an empirical level, configurational arguments face the challenge of modeling multiple and complex relationships between their components [79]. Therefore, limitations associated

with the use of QCA are highlighted in the literature, such as the sensitivity of the results to the calibration process or the complexity of analyzing the results [80], causing the latter to work with a reduced number of conditions [26]. Other limitations include QCA not identifying the impact that each of the conditions presents on the outcome under study, its uses of negative cases [81], or the implications that limited diversity has for the different solutions it can generate [82].

QCA is optimal for explaining causal complexity characterized by equifinality, conjunctural causation and asymmetry [67, 69]. Equifinality is linked to the analysis of different alternative causes that may lead to the outcome [83]. Unlike traditional regression methods that focus on the net effects of the independent variables on the dependent variable, QCA focuses on the consequences of the conjunction of conditions, the conjunctural causation [75]. Finally, QCA identifies asymmetrical causal relationships. That is, the presence of an outcome cannot be directly inferred from the study of the negation of the variables that explain its lack of presence. Given that social reality is complex, QCA is particularly suitable for its study [84]. Indeed, QCA has become a promising approach to explaining complexity in an era when environments are disruptive, volatile, uncertain, complex and ambiguous [30]. The application of QCA allows, through an innovative perspective, to reach richer and deeper evidence [77].

When exploring causal processes, a group or chain of events is considered that leads to specific effects; a combination of conditions, limitations, or social circumstances that jointly generate a causal effect [85]. While it is relevant to establish regularities (as QCA does through cross-case analysis), it does not expose the complete history of the causal relationship. Instead, it should be complemented by applying process-tracing at the case level through a within-case analysis [81]. This is because the evidence linked to the existence of mechanisms is found in individual case studies [40].

When causal relationships are conceptualized in terms of Set-Theory, QCA's cross-case analysis is highly compatible with process-tracing [72, 86]. SMMR (the combination of QCA and process-tracing) capitalizes on the fact that QCA and process-tracing are based on Set-Theory [87] (Fig. 2). Such a combination allows for the integration of cross-case and within-case inferences in multimethod research designs [67, 87]. Indeed this relationship enables a causal understanding, as set-based relational patterns do not automatically reflect causality, as QCA does [75, 82]. Such causality is reflected in the existence of causal mechanisms, a generative process product of abstract combinations adduced from multiple concrete and contextually embedded instantiations [72, 88]. Process-tracing helps to follow the underlying arguments

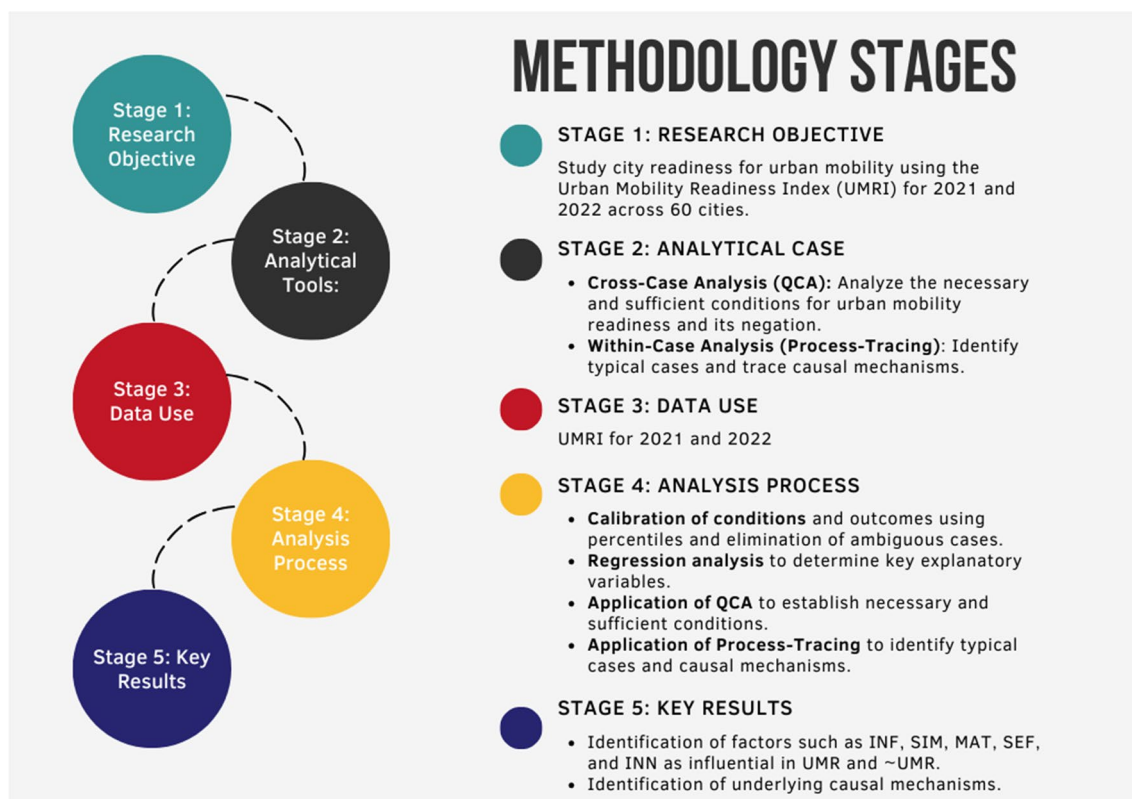


Fig. 2 Methodology

behind the mechanisms, which ultimately explain how the cause leads to the effect; how the result is produced. In this way, the causal force rests on a causal influence within-case (identified through process-tracing), among all the cases that are within the scope identified in the cross-case analysis (identified through QCA) [39]. The analysis of mechanisms via process-tracing is one of the most fruitful methods to establish causal claims and configurational relationships of transactions towards sustainability [67].

3.3 Social benefits of the research

It's crucial to highlight the significant societal benefits this research offers. These benefits underscore the study's relevance beyond the academic sphere, illustrating its practical applicability in enhancing urban life quality. Our findings contribute to the sustainable development of cities. Highlighting the significance of factors such as system efficiency, innovation, and societal impact, the research underlines key areas crucial for urban mobility readiness and sustainable city life. Likewise, emphasizing the importance of accessibility and efficiency in urban mobility, the study supports initiatives to make cities more inclusive and accessible for all residents. This is key to creating equitable urban environments where everyone can benefit from improved mobility solutions. Additionally, the study's findings have the potential to significantly influence public policies. By demonstrating the importance of a holistic approach that combines diverse conditions beyond individual investments, our research provides a roadmap for policymakers to achieve urban mobility. Likewise, the results of this work aim to help cities use innovations in a way that allows them to reduce their consumption of natural resources and their greenhouse gas emissions to help them progress in their transition towards sustainability.

4 Results

For the analysis, the SetMethods package of R was used [66, 89]. For the calibration of the conditions and the outcome, the 95th percentile (total inclusion), the 5th percentile (total exclusion) and the mean (maximum ambiguity) were used. Four cases with a membership of 0.5 (Warsaw, Milan, Zurich and Houston) were eliminated.

As can be observed, the regression analysis drawn from the Ordinary Least Squares (Table 3) shows how in the model presented, UMR is explained by five explanatory variables accounting for a significant percentage of the variance of the dependent variable ($R^2 = 0.993$). In addition, the five independent variables account for a significant effect and are positively related to the dependent variable, as extracted from the values of the estimated coefficients (INF = 0.119, SIM = 0.305, MAT = 0.164, SEF = 0.396, INN = 0.133). The regression was calculated from the calibrated variables in order to serve as a reference from the Set-Theoretic analysis in line with Ragin [81].

4.1 Cross-case analysis through QCA

Next, those conditions that are necessary for both the presence of UMR and its negation ($\sim$ UMR) were calculated (Table 4). INF (Cons.Nec = 0.917, RoN = 0.957), SIM (Cons.Nec = 0.913, RoN = 0.889), MAT (Cons.Nec = 0.936, RoN = 0.873) and SEF (Cons.Nec = 0.923, RoN = 0.934) were necessary for UMR. On the other hand, for $\sim$ UMR, $\sim$ INF (Cons.Nec = 0.952, RoN = 0.921), $\sim$ SEF (Cons.Nec = 0.928, RoN = 0.928) and $\sim$ INN (Cons.Nec = 0.946, RoN = 0.843) were necessary (Table 4). This is because the consistency, coverage and RoN are above the established limits of 0.9, 0.5, and 0.6 respectively [56, 66].

Table 3 Ordinary Least Squares regression analysis

Variable	Coefficient (standard error)	Standardized coefficient
INF	0.119*** (0.024)	0.112
SIM	0.305*** (0.022)	0.299
MAT	0.164*** (0.030)	0.149
SEF	0.396*** (0.035)	0.386
INN	0.133*** (0.024)	0.128
Constant	− 0.047*** (0.008)	–

*** $p < 0.01$, $R^2 = 0.993$, $F = 1444.070$ *** (d.f. 54)

Table 4 Analysis of the necessary conditions

	Outcome UMR			Outcome ~ UMR		
	Cons.Nec	Cov.Nec	RoN	Cons.Nec	Cov.Nec	RoN
INF	0.917	0.957	0.957	0.325	0.295	0.574
SIM	0.913	0.896	0.889	0.362	0.309	0.547
MAT	0.936	0.888	0.873	0.399	0.329	0.535
SEF	0.923	0.937	0.934	0.337	0.297	0.561
INN	0.836	0.947	0.955	0.314	0.309	0.618
~ INF	0.324	0.356	0.620	0.952	0.909	0.921
~ SIM	0.297	0.349	0.648	0.878	0.897	0.921
~ MAT	0.292	0.359	0.669	0.864	0.922	0.943
~ SEF	0.307	0.348	0.631	0.928	0.913	0.928
~ INN	0.390	0.396	0.597	0.946	0.834	0.843

Truth tables and parsimonious solutions to explain outcomes (Table 5) were calculated. Although, to avoid untenable assumptions that standard analysis does not take into account, an Enhanced Standard Analysis (ESA) is carried out. This process excludes from the minimization process those remainders that could contradict the statements of necessity [33, 73]. Thus, UMR is explained by $INF*SIM*MAT*SEF$, while ~ UMR by $\sim INF*\sim SEF*\sim INN$. These solutions have high parameters for both UMR (InclS = 1.000, PRI = 1.000, CovS = 0.782) and ~ UMR (InclS = 0.982, PRI = 0.974, CovS = 0.860). In presenting the sufficient conditions QCA depends principally on its consistency and coverage. While the consistency of the solution offers a similar interpretation to the test of significance, coverage will be closer to R^2 .

FsQCA offers theory-testing, an alternative method to evaluate the overlap between the theoretical arguments and the solution achieved. To do this, it starts by expressing theoretical arguments in Boolean terms and applies a formal evaluation of the Set-Theoretic theory proposed by [90] that reveals those aspects of the theory that are empirically corroborated by the solution and which are not [66, 79, 89].

Neither for UMR nor for ~ UMR (Table 6) are least likely cases identified -those covered by the solution but not by the theory-, which would pose an extension of the theory. On the contrary, there are uncovered likely cases -cases not covered by the solution but covered by the theory-. For UMR they are expressed in the following terms $\sim INF*SIM + \sim INF*MAT + \sim INF*SEF + \sim INF*INN + INF*\sim SIM + INF*\sim MAT + INF*\sim SEF + \sim SIM*MAT + \sim SIM*SEF + \sim SIM*INN + SIM*\sim MAT + SIM*\sim SEF + \sim MAT*SEF + \sim MAT*INN + MAT*\sim SEF + \sim SEF*INN$ (InclS = 0.738; PRI = 0.508; CovS = 0.442). For ~ UMR they are expressed under the following conjunctions $\sim INF*SEF + \sim INF*INN + INF*\sim SIM + INF*\sim MAT + INF*\sim SEF + INF*\sim INN + \sim SIM*SEF + \sim SIM*INN + \sim MAT*SEF + \sim MAT*INN + \sim SEF*INN + SEF*\sim INN$ (InclS = 0.606; PRI = 0.251; CovS = 0.411). In both cases, despite being a high number of terms, given that they have a coverage close to 0.4 and a very low PRI value, we decided not to incorporate them in the solution as this can help achieve greater consistency (Fig. 3).

Table 5 Conservative solutions

Outcome UMR	inclS	PRI	covS	covU
$INF*MAT*SEF$	0.997	0.996	0.831	0.111
$\sim INF*\sim SIM*\sim SEF*INN$	0.864	0.235	0.186	0.005
$\sim INF*SIM*MAT*\sim SEF$	0.941	0.618	0.247	0.006
$\sim INF*SIM*SEF*\sim INN$	0.959	0.677	0.241	0.011
$INF*SIM*\sim SEF*\sim INN$	0.951	0.545	0.230	0.002
$INF*SIM*SEF*INN$	1.000	1.000	0.719	0.020
Model	0.944	0.921	0.910	
$\sim INF*\sim SIM*\sim SEF$	0.985	0.979	0.801	0.452
$\sim INF*SIM*\sim INN$	0.899	0.608	0.328	0.004
$\sim INF*MAT*\sim SEF$	0.923	0.743	0.354	0.001
$SIM*\sim SEF*\sim INN$	0.911	0.649	0.328	0.006
$INF*\sim SIM*MAT*SEF*\sim INN$	0.904	0.026	0.206	0.008
Model	0.914	0.874	0.889	

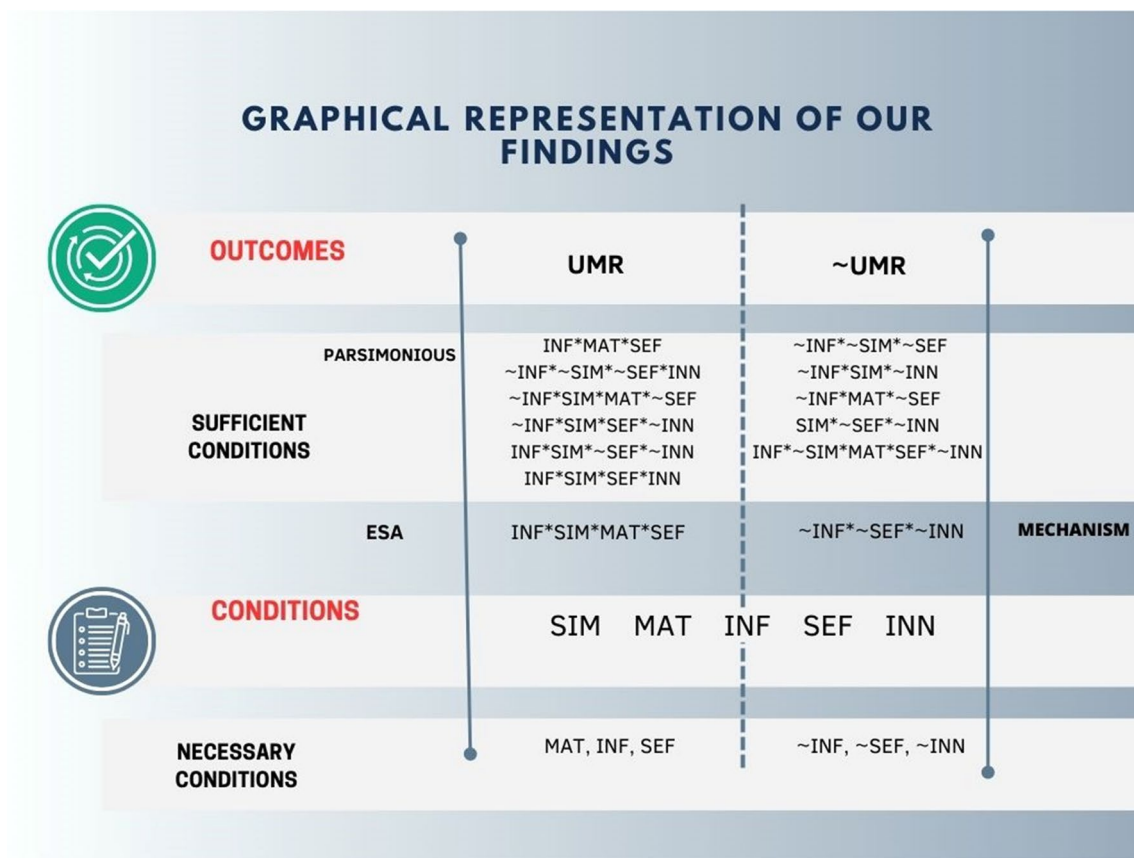


Fig. 3 Findings

Table 6 Theory Testing

Outcome UMR		inclS	PRI	covS
Model	INF*SIM*MAT*SEF	1.000	1.000	0.782
theory	INF + SIM + MAT + SEF + INN	0.809	0.753	1.000
model*theory	INF*SIM*MAT*SEF	1.000	1.000	0.782
model*~theory	–	–	–	–
~model*theory	~INF*SIM + ~INF*MAT + ~INF*SEF + ~INF*INN + I NF*~SIM + INF*~MAT + INF*~SEF + ~SIM*MAT + ~SIM*SEF + ~SIM*INN + SIM*~MAT + SIM*~S EF + ~MAT*SEF + ~MAT*INN + MAT*~SEF + ~S EF*INN	0.738	0.508	0.442
~model*~theory	~INF*~SIM*~MAT*~SEF*~INN	0.283	0.001	0.179
Outcome ~UMR		inclS	PRI	covS
model	~INF*~SEF*~INN	0.982	0.974	0.860
theory	~INF + ~SIM + ~MAT + ~SEF + ~INN	0.743	0.662	1.000
model*theory	~INF*~SEF*~INN	0.982	0.974	0.860
model*~theory	–	–	–	–
~model*theory	~INF*SEF + ~INF*INN + INF*~SIM + INF*~MAT + I NF*~SEF + INF*~INN + ~SIM*SEF + ~SIM*INN + ~MAT*SEF + ~MAT*INN + ~SEF*INN + SEF*~INN	0.606	0.251	0.411
~model*~theory	INF*SIM*MAT*SEF*INN	0.298	0.000	0.240

4.2 Within-case analysis through process-tracing

The application of process-tracing begins with the identification of the different typical cases based on their membership in the outcome and in the term (typical cases and deviant consistency in kind) or in the solution (deviant coverage and individually irrelevant cases). In their identification, a single within-case analysis is applied followed by a comparative analysis, each with its specific objectives. The SetMethods command smmr systematically identifies the cases to be used in process-tracing [66, 89].

The single within-case analysis begins with the identification of typical cases. These cases belong to the term and present the outcome with a higher membership in the result. Their identification allows us to verify the existence of a mechanism. For each conjunction, the effect of the different conjuncts (conditions that compose it) is analyzed, differentiating the conjunct under study (Focal Conjunct FC) from the rest of the conjuncts that make up the conjunction (Complementary Conjunct, CC). In typical cases, the FC must define the membership of the case in the term (the attribution principle) and be only covered by one solution term (be uniquely covered). They are better as their membership in the sufficient term is higher and they conform to the corridor principle (their inferential value increases as the difference between the membership in the result and the FC is smaller). Based on the results, we can affirm the existence of typical cases for the single term that composes the enhanced conservative solution of UMR (Table 7) and of ~UMR (Table 8).

Table 7 Typical cases UMR

	FC	Outcome	CC	Term	UniqCov	Best
Focal Conjunct INF						
Helsinki2022	0.93	0.95	0.95	0.93	TRUE	0.11
Amsterdam2021	0.90	0.95	0.91	0.90	TRUE	0.20
Chicago2022	0.87	0.91	0.90	0.87	TRUE	0.21
London2022	0.87	0.92	0.88	0.87	TRUE	0.23
Oslo2021	0.82	0.87	0.84	0.82	TRUE	0.28
SanFrancisco2022	0.87	0.96	0.89	0.87	TRUE	0.31
Tokyo2021	0.76	0.89	0.78	0.76	TRUE	0.50
Focal Conjunct SIM						
Stockholm2021	0.94	0.97	0.96	0.94	TRUE	0.12
Berlin2022	0.90	0.93	0.94	0.90	TRUE	0.16
Berlin2021	0.87	0.94	0.91	0.87	TRUE	0.27
Boston2022	0.84	0.90	0.86	0.84	TRUE	0.28
Washington.D.C.2022	0.82	0.88	0.87	0.82	TRUE	0.30
Madrid2021	0.77	0.82	0.84	0.77	TRUE	0.33
NewYork2022	0.83	0.91	0.85	0.83	TRUE	0.33
Focal Conjunct MAT						
Stockholm2022	0.94	0.96	0.95	0.94	TRUE	0.10
Madrid2022	0.80	0.82	0.83	0.80	TRUE	0.24
Singapore2021	0.88	0.96	0.94	0.88	TRUE	0.28
Amsterdam2022	0.86	0.94	0.87	0.86	TRUE	0.30
Munich2021	0.79	0.94	0.89	0.79	TRUE	0.51
Vancouver2022	0.70	0.82	0.78	0.70	TRUE	0.54
Montreal2021	0.67	0.79	0.71	0.67	TRUE	0.57
Focal Conjunct SEF						
Helsinki2021	0.91	0.95	0.93	0.91	TRUE	0.17
London2021	0.90	0.94	0.91	0.90	TRUE	0.18
Chicago2021	0.84	0.92	0.87	0.84	TRUE	0.32
Boston2021	0.80	0.92	0.82	0.80	TRUE	0.44
Vancouver2021	0.74	0.84	0.77	0.74	TRUE	0.46
SanFrancisco2021	0.78	0.96	0.86	0.78	TRUE	0.58
Dublin2021	0.60	0.69	0.67	0.60	TRUE	0.58

Table 8 Typical cases ~ UMR

	FC	Outcome	CC	Term	UniqCov	Best
Focal Conjunct ~ INF						
Quito2021	0.94	0.95	0.96	0.94	TRUE	0.08
Bogota2021	0.90	0.91	0.94	0.90	TRUE	0.12
MexicoCity2021	0.85	0.86	0.86	0.85	TRUE	0.17
CapeTown2021	0.74	0.83	0.82	0.74	TRUE	0.44
Bangkok2021	0.77	0.88	0.88	0.77	TRUE	0.45
Casablanca2021	0.79	0.92	0.88	0.79	TRUE	0.47
CapeTown2022	0.72	0.82	0.78	0.72	TRUE	0.48
Focal Conjunct ~ SEF						
Jakarta2021	0.88	0.88	0.89	0.88	TRUE	0.12
Bogota2022	0.91	0.93	0.92	0.91	TRUE	0.13
Lima2021	0.91	0.93	0.95	0.91	TRUE	0.13
Manila2021	0.91	0.95	0.92	0.91	TRUE	0.17
MexicoCity2022	0.84	0.87	0.87	0.84	TRUE	0.22
Lima2022	0.87	0.93	0.95	0.87	TRUE	0.25
Mumbai2022	0.85	0.92	0.93	0.85	TRUE	0.29
Focal Conjunct ~ INN						
Nairobi2022	0.97	0.98	0.98	0.97	TRUE	0.05
Lagos2021	0.97	0.99	0.99	0.97	TRUE	0.07
Cairo2021	0.92	0.92	0.95	0.92	TRUE	0.08
Cairo2022	0.92	0.93	0.95	0.92	TRUE	0.10
Lagos2022	0.93	0.98	0.99	0.93	TRUE	0.17
Riyadh2022	0.82	0.89	0.88	0.82	TRUE	0.32
Jeddah2022	0.82	0.92	0.92	0.82	TRUE	0.38

In the single within-case analysis, the existence of deviant consistency cases is analyzed, which allow us to identify missing conjuncts in the solution term. There are no cases of deviant consistency for UMR. In the case of ~ UMR we have the case of Dubai2021, which belongs to the conjunction ~ INF* ~ SEF* ~ INN. Although, despite having a membership in the term of 0.63, it does not reach 0.5 in the result (0.34). This discovery suggests the need to identify a condition in the conjunction that explains why the result under study is not achieved.

The single within-case analysis ends with the identification of the deviant coverage cases, which identifies missing conjunctions. These are cases belonging to rows of the truth table not included in the logical minimization process because they do not reach the required level of consistency. The cases corresponding to UMR belong to different conjunctions: ~ INF*SIM* ~ MAT*SEF* ~ INN (AbuDhabi2022), ~ INF*SIM*MAT* ~ SEF* ~ INN (Dubai2021), ~ INF*SIM*MAT* ~ SEF*INN (Moscow2022), ~ INF*SIM*MAT*SEF* ~ INN (Moscow2021; Dubai2022), INF* ~ SIM*MAT*SEF* ~ INN (Barcelona2021), INF* ~ SIM*MAT*SEF*INN (Beijing2021; Beijing2022; Shanghai2021; Shanghai2022), and INF*SIM* ~ MAT*SEF*INN (HongKong2022). The cases corresponding to ~ UMR are as follows ~ INF* ~ SIM* ~ MAT* ~ SEF*INN (Doha2021), ~ INF* ~ SIM*MAT* ~ SEF*INN (KualaLumpur2021), INF*SIM* ~ MAT* ~ SEF* ~ INN (Istambul2022), and INF*SIM*MAT* ~ SEF* ~ INN (Istambul2021).

The first comparison made in the comparative within-case analysis is between typical and individually irrelevant (iir) cases for each of the FC of the terms in which the existence of mechanisms was identified. Typical cases must be uniquely covered and the iir globally uncovered for it to be possible to assert that the identified mechanisms trigger the presence of the outcome under analysis. In the case of UMR (Table 9) the typical-iir case pairs are FC INF Helsinki2022-Lima2022; FC SIM Stockholm2021-Manila2022; FC MAT Stockholm2022-Johannesbourg2022; FC SEF Helsinki2021-Istanbul2021. For the first three FCs, the rank is 3, while for FC SEF it is 1. As we can see, the typical cases correspond to the results for the different study years (2021 and 2022) for Helsinki and Stockholm.

In the case of ~ UMR (Table 10), pairs of cases are also identified that meet the established requirements FC ~ INF Quito2021-Munich2021; FC ~ SEF Bogota2022-Moscow2021; FC ~ INN Nairobi2022-Moscow2022. The first pair presents a rank 3, while the remaining two present a rank 1.

Table 9 Comparison of typical-IIR UMR

Typical	IIR	UniqCov	GlobUncov	Best	PairRank
Focal Conjunct INF					
Helsinki2022	Lima2022	TRUE	TRUE	1.13	3
Helsinki2022	Lima2021	TRUE	TRUE	1.16	3
Helsinki2022	Jakarta2022	TRUE	TRUE	1.17	3
Amsterdam2021	Lima2022	TRUE	TRUE	1.18	3
Helsinki2022	Mumbai2022	TRUE	TRUE	1.18	3
Focal Conjunct SIM					
Stockholm2021	Manila2022	TRUE	TRUE	1.15	3
Stockholm2021	Manila2021	TRUE	TRUE	1.16	3
Stockholm2021	Riyadh2021	TRUE	TRUE	1.19	3
Berlin2022	Manila2022	TRUE	TRUE	1.21	3
Stockholm2021	Mumbai2021	TRUE	TRUE	1.21	3
Focal Conjunct MAT					
Stockholm2022	Johannesburg2022	TRUE	TRUE	1.10	3
Stockholm2022	Casablanca2021	TRUE	TRUE	1.14	3
Stockholm2022	Quito2022	TRUE	TRUE	1.14	3
Stockholm2022	Casablanca2022	TRUE	TRUE	1.16	3
Stockholm2022	CapeTown2022	TRUE	TRUE	1.23	3
Focal Conjunct SEF					
Helsinki2021	Istanbul2021	TRUE	TRUE	1.52	1
London2021	Istanbul2021	TRUE	TRUE	1.52	1
Chicago2021	Istanbul2021	TRUE	TRUE	1.64	1
Boston2021	Istanbul2021	TRUE	TRUE	1.71	1
Vancouver2021	Istanbul2021	TRUE	TRUE	1.76	1

Table 10 Comparison of typical-IIR ~ UMR

Typical	IIR	UniqCov	GlobUncov	Best	PairRank
Focal Conjunct ~ INF					
Quito2021	Munich2021	TRUE	TRUE	1.11	3
Quito2021	Paris2022	TRUE	TRUE	1.11	3
Quito2021	Stockholm2021	TRUE	TRUE	1.11	3
Quito2021	Berlin2021	TRUE	TRUE	1.12	3
Quito2021	Munich2022	TRUE	TRUE	1.14	3
Focal Conjunct ~ SEF					
Bogota2022	Moscow2021	TRUE	TRUE	1.40	1
Jakarta2021	Moscow2021	TRUE	TRUE	1.41	1
Manila2021	Moscow2021	TRUE	TRUE	1.42	1
Lima2021	Moscow2021	TRUE	TRUE	1.43	1
MexicoCity2022	Moscow2021	TRUE	TRUE	1.50	1
Focal Conjunct ~ INN					
Nairobi2022	Moscow2022	TRUE	TRUE	1.41	1
Lagos2021	Moscow2022	TRUE	TRUE	1.43	1
Cairo2021	Moscow2022	TRUE	TRUE	1.47	1
Cairo2022	Moscow2022	TRUE	TRUE	1.48	1
Lagos2022	Moscow2022	TRUE	TRUE	1.54	1

The comparison of two typical cases allows extrapolating the identified mechanism for all typical cases explained by the solution. The results show that there are pairs, both for UMR (Table 11) and ~UMR (Table 12), that meet the requirement that both typical cases are uniquely covered, presenting in all cases a rank 1. Likewise, on this occasion the pairs

Table 11 Comparison of Typical-Typical UMR

Typical1	Typical2	UniqCov1	UniqCov2	Best	PairRank
Focal Conjunct INF					
Helsinki2022	Dallas2022	TRUE	TRUE	0.84	1
Amsterdam2021	Dallas2022	TRUE	TRUE	0.89	1
London2022	Dallas2022	TRUE	TRUE	0.92	1
Focal Conjunct SIM					
Stockholm2021	Madrid2021	TRUE	TRUE	0.96	1
Berlin2022	Madrid2021	TRUE	TRUE	1.02	1
Stockholm2021	Berlin2022	TRUE	TRUE	1.06	1
Focal Conjunct MAT					
Stockholm2022	Madrid2022	TRUE	TRUE	0.92	1
Stockholm2022	Toronto2022	TRUE	TRUE	1.02	1
Stockholm2022	Vancouver2022	TRUE	TRUE	1.07	1
Focal Conjunct SEF					
Helsinki2021	Dublin2021	TRUE	TRUE	0.95	1
London2021	Dublin2021	TRUE	TRUE	0.95	1
Chicago2021	Dublin2021	TRUE	TRUE	1.07	1

Table 12 Comparison of Typical-Typical ~ UMR

Typical1	Typical2	UniqCov1	UniqCov2	Best	PairRank
Focal Conjunct ~ INF					
Quito2021	MexicoCity2021	TRUE	TRUE	0.96	1
Quito2021	Bogota2021	TRUE	TRUE	0.98	1
Quito2021	CapeTown2021	TRUE	TRUE	1.02	1
Focal Conjunct ~ SEF					
Bogota2022	MexicoCity2022	TRUE	TRUE	1.02	1
Bogota2022	BuenosAires2022	TRUE	TRUE	1.03	1
Jakarta2021	MexicoCity2022	TRUE	TRUE	1.03	1
Focal Conjunct ~ INN					
Nairobi2022	Doha2022	TRUE	TRUE	0.92	1
Nairobi2022	Cairo2021	TRUE	TRUE	0.94	1
Lagos2021	Doha2022	TRUE	TRUE	0.94	1

identified correspond to cases from the same year. The pairs identified for UMR are FC INF Helsinki2022-Dallas2022; FC SIM Stockholm2021-Madrid2021; FC MAT Stockholm2022-Madrid2022; FC SEF Helsinki2021-Dublin2021. In addition to the relevance mentioned above for Helsinki and Stockholm, the two cases corresponding to Madrid are also relevant, as they correspond to the Stockholm cases of the same year. For ~ UMR the pairs identified for each FC are: FC ~ INF Quito2021-MexicoCity2021; FC ~ SEF Bogota2022-MexicoCity2022; FC ~ INN Nairobi2022-Doha2022.

Finally, a comparison between typical cases and deviant consistency for ~ UMR was performed, pointing out the relevance of the Lagos2021-Dubai2021 pair to identify a missing conjunct in the ~ INF* ~ SEF* ~ INN term.

4.3 Research problems, solutions and theoretical contribution

The primary challenge addressed in this study is the limited ability of existing urban sustainability indices to capture the causal complexity of urban phenomena. Traditional methods, often focusing on isolated factors, fail to recognize the multifaceted and interconnected nature of urban systems. To address this, our study research employs Set-Theory methods, specifically QCA combined with process-tracing. This approach enables a more nuanced understanding of the UMR across 60 cities for 2021 and 2022. The application of Set-Theory based methods allows us to complement others traditionally applied to the analysis of rankings and indices, responding to the complexity involved in the urban transition towards sustainability. In its analysis, the focus shifts to the way in which the different explanatory conditions are

combined, respecting the integrity of each case, something fundamental for urban managers. That is, at all times, we know the cities explained by each of the terms of the different recipes. In this way, we can identify the combination of conditions that has caused a specific result to be obtained. Likewise, process-tracing systematically identifies the cases to be taken as reference both for different situations and for the corresponding comparisons.

Through QCA, we establish that urban mobility readiness is not a result of a singular condition but a synergy of multiple factors. In this way, it is highlighted that to achieve high levels of readiness for the adoption of urban mobility innovations, cities must combine different conditions. Likewise, it is confirmed how an analysis from an asymmetric perspective allows us to recognize that explaining a high level of readiness requires combining different conditions than explaining the negation of the aforementioned level of readiness. For his part, process-tracing further aids in identifying and understanding typical cases and mechanisms driving urban mobility readiness. Thanks to this identification, those cases that serve as a reference to achieve the pursued objective can be recognized; and, in this way, the solutions can be adapted to the specific context of each city.

5 Discussion and policy suggestions

5.1 Discussion of the results

Urban mobility planning in cities is a complex process, due to the interrelation of dynamic and specific conditions. QCA allows for understanding the combination of conditions that explains UMR and $\sim$ UMR, capturing the complexity of the phenomenon under study. Both for UMR (INF, SIM, MAT, and SEF) and $\sim$ UMR ($\sim$ INF, $\sim$ SEF, and $\sim$ INN).

Both UMR and $\sim$ UMR are explained by a conjunction after applying ESA. UMR through $\text{INF}^* \text{SIM}^* \text{MAT}^* \text{SEF}$, which includes European, American/Canadian, and Asia–Pacific cities for both 2021 and 2022 except for Barcelona which only accounts for 2022. This implies that UMR requires INF to make urban mobility more efficient, affordable, sustainable, and resilient [59, 60]. Furthermore, the establishment of urban mobility plans allows for better traffic management through measures that promote shared mobility and public transport [62–64]. All of this can improve accessibility, reduce costs, decrease pollution, and noise levels; and increase attractiveness to potential users, having a positive impact on society (SIM). This reiterates the importance of the interrelation of conditions in moving towards sustainable urban mobility. Similarly, it can make cities more attractive to investors (MAT) [57]. It is surprising that INN, considered a key condition for city preparation, does not appear in the recipe. This may be due to the fact that it is necessary in less developed countries where its absence can lead to $\sim$ UMR.

On the other hand, $\sim$ UMR is explained by $\sim \text{INF}^* \sim \text{SEF}^* \sim \text{INN}$, reflected in cities in Africa, Latin America, Middle East, and the less developed cities of Asia–Pacific. This demonstrates how technology and innovation are essential for both the social development of cities and the urban mobility of the future [65]. In fact, the countries that are part of this recipe are countries with minimum levels of innovation, with the maximum being Sao Paulo (18.5/100) and the minimum being Nairobi (0.7/100). Similarly, $\sim$ INF affects all of these cities, except Santiago (57.1), which are below 51 points. This is coupled with $\sim$ SEF. In fact, Latin American cities are below the average in the UMRI, as well as African and some Middle-East cities. Regarding Asia–Pacific cities, there are those that are at the forefront of the UMRI with some of the most efficient public transport systems in the world, as well as those that are part of this recipe but are lagging behind in terms of UMRI and need to take more action, such as Manila, which despite having active mobility and a large cycling infrastructure, has points for improvement such as waiting times, affordability, and station density, among others [37].

These solutions for UMR and $\sim$ UMR show the suitability of QCA to complement the traditionally made evaluations of indices with the study of the causal complexity characteristic of urban phenomena [4, 13, 21]. In this way, since the union of different conditions explains UMR and $\sim$ UMR we accept propositions 1_a and 1_b .

On the other hand, with process-tracing, we test through the analysis of typical cases the existence of a mechanism for both UMR and $\sim$ UMR, allowing us to accept propositions 2_a and 2_b , noting that the combination of the explanatory conditions causes UMR and $\sim$ UMR.

The comparative analysis between pairs of typical and iir cases, confirms that the mechanisms trigger the appearance of UMR and $\sim$ UMR through the conjuncts that form the solutions (INF, SEF, MAT, and SIM; $\sim$ INF, $\sim$ SEF, and $\sim$ INN). For FC INF, the pair Helsinki2022–Lima2022 appears. In fact, Helsinki2022 appears in 4 of the 5 comparison pairs, by having one of the highest scores in 2022 in INF. This is because it is a very walkable city. In addition, it has very diverse public multimodal transportation, occupying the third position in the UMRI. On the other hand, Lima2022 has a KPI in infrastructure below 33.9 and occupies one of the last positions in the UMRI (56/60). It needs to improve aspects such as

levels of noise and light pollution. For FC SIM we have Stockholm2021-Manila2022. Stockholm2021 occupied the first position compared to 58/60 of Manila. Manila has room for improvement in waiting times, affordability or station density, however Stockholm presents a high road safety and one of the lowest emissions levels [91]. The pairs for the FC MAT are Stockholm2022-Johannesbourg2022. Stockholm2022 occupies the second position in the UMRI compared to 47/60 of Johannesbourg2022. In fact, Stockholm2022 made strong investments in electric vehicles, but Johannesbourg2022 has undertaken few investments and few companies operate in shared mobility. Finally FC SEF Helsinki2021-Istanbul2021. Helsinki is a pioneer in innovative approaches and advances in new forms of public transportation such as the autonomous bus. In addition, it has very efficient plans and management by its government. Istanbul, despite having a strategic plan in place for the period 2020–2024, is working on improvements and has much to learn from cities like Helsinki [92].

For ~UMR the same comparison is made. In the FC ~INF we have Quito2021-Munich2021. Quito2021 ranks in one of the last positions, 57/60, in the UMRI. This is because in Quito, only light infrastructure was introduced, and the subway line was expected to be opened by the end of 2022. In contrast, Munich ranks 9/60. The city maintains a robust, affordable, and multimodal public transit system, and bike lanes received a huge boost during the pandemic in Munich. Thanks to its extensive bikeways, Munich has the second highest percentage share of cycling journeys in UMRI (after Amsterdam). FC ~SEF Bogota2022-Moscow2021. This is because Bogota2022 ranks at a position 53/60 in contrast to Moscow2021 intermediate position. Neither are spectacular in SEF, Bogota suffers significant delays in freight transport. Furthermore, Bogota international connections from the airport as well as supply chain infrastructure are lacking. Moscow has problems, but it is ranked among the cities that offer a higher quality of life, having risen in the ranking if we consider the 2020 report (29/50) compared to 2022 (34/60) [45, 93]. Finally, FC ~INN Nairobi2022-Moscow2022. These cities rank 59/60 and 34/60 respectively. Despite Nairobi having a smaller population than Moscow 5,760,596 versus 14,962,626, its GDP is 4,112 compared to Moscow's 22,796 which may result in lower levels of investment and inclusion of new technologies. Furthermore, Nairobi lacks proper integration between planning and urban transport. Moscow, on the other hand, has great ambitions as established above, and has an app launched in 2019 that allows for faster and more efficient multimodal user transportation. Additionally, it has launched a Transport Innovation Accelerator' to help start-ups [37, 92].

Finally, it is possible to extrapolate the mechanisms between all the typical cases obtained in the solution thanks to the comparison of the typical cases for each FC. Thus, for UMR the pairs that were identified were several. FC INF Helsinki2022-Dallas2022, which are cities that despite being distant in the UMRI 3/60 vs 28/60, in the INF KPI are not very different with a 77.4 and a 61.9 respectively. This is the result of strong investments in infrastructure [37, 94] or the strengths that the public transport system in Helsinki has with its new modes of shared and active transportation that are very safe, reliable and accessible [92]. FC SIM Stockholm2021-Madrid2021. As already mentioned above, Stockholm occupied the first position in UMRI 2021 and although Madrid only occupied 24/60, both cases are similar in SIM. This is because Madrid provides affordable public transit through a strong multimodal network and its 360 Sustainable Mobility Plan is advancing multiple clean air initiatives [37]. FC MAT Stockholm2022-Madrid2022. Both cities occupy fairly close positions in the UMR 2/60 versus 14/60. Both, very active in sustainable urban mobility, with a wide variety of public transport means, and significant penetration of the shared economy. Although Madrid is one of the European cities with the lowest number of electric charging points per capita, something that can make the KPI in MAT lower 60.8 compared to 70.1 in Stockholm [45]. FC SEF Helsinki2021-Dublin2021. These are cities that ranked 4/60 and 30/60 respectively in the UMRI 2021. Helsinki2021 is a pioneer in innovative approaches and has strong government support to improve the city's network [92]. Although Dublin, thanks to government support, is improving its connectivity through improvements to its railway network to open accessibility to public transport and new plans for the new metro. On the other hand, it is worth noting that both have a high market share of electric vehicles.

Regarding ~UMR, the identified pairs for each FC are as follows: FC ~INF Quito2021-MexicoCity2021. As previously mentioned, the lack of infrastructure in Quito2021 makes the case comparable to Mexico2021, which also had a low ranking at 44/60. Despite this, Mexico has implemented temporary cycling infrastructure in strategic corridors as a response to Covid-19 that are now permanent [92]. FC ~SEF Bogota2022-MexicoCity2022. These cities are very similar in terms of their position in the UMR ranking -53/60 and 45/60 respectively. The value of the SEF KPI is also very similar at 38.6 and 43.1 respectively. This is because despite government incentives for the adoption of electric vehicles, which would improve their rating in the aforementioned KPI, more investments are needed to allow for the adoption of a greater number of charging points [37]. Finally, for FC ~INN Nairobi2022-Doha2022 with low values in the INN KPI of 0.7 and 34.7 respectively and somewhat different positions in the UMR -59/60 vs. 38/60-. Doha's low score on this KPI is due to low network coverage, although it is making strong investments to improve autonomous transit.

The present work confirms the potential of the application of Set-Theoretic methods to the analysis of the results presented in the different indices. Consequently, its application to other indices will depend on the approach adopted and

the research question asked. Regarding the approach, the application of Set-Theoretic methods adapts to those studies that focus analysis on the cases (cities), rather than on the explanatory conditions. This distinction is often referred to as a case-oriented vs. variable-oriented analysis. Second, as indicated above, the focus should be on the research question addressed. In this way, it is appropriate to identify the ‘causes of effects’ rather than attending to the ‘effects of the causes’.

5.2 Policy suggestions

Given that rankings and indices are widely utilized as benchmarks in the assessment of urban projects and programs, a deeper analysis of their outcomes can significantly aid public managers in their planning processes. This is particularly crucial in the realm of sustainability, where a vast array of indices has been developed. Firstly, urban managers should acknowledge that simply reversing the values of conditions that explain achieving an optimal outcome does not necessarily serve as a reference for explaining a less favorable outcome. In fact, these solutions may not even consist of the same conditions. For instance, while social impact contributes to explaining a high level of preparedness, innovation plays a crucial role in the negation of such a level.

Furthermore, our results highlight the existence of multiple solutions for the phenomenon under study. Hence, the notion that one solution fits the reality of different cities should be discarded. With the identification of six and five combinations of conditions in the parsimonious solution, it is evident that there are multiple ‘recipes’ for cities to be prepared (or not) for the implementation of innovations linked to sustainability. This finding underscores the necessity for diverse solutions to urban problems, tailored to the specific context in which they are developed.

Finally, public managers must be cognizant of the distinct roles that conditions can play in explaining the phenomenon under study. Firstly, there are necessary conditions. If these are not adequately addressed, they may act as bottlenecks in various contexts, hindering the achievement of a high level of preparedness for the implementation of innovations related to sustainable mobility. Without reaching a minimum level in such conditions, cities will face challenges in advancing towards their desired outcomes. Secondly, sufficient conditions are identified, acting as scope conditions that explain why the result occurred. Since QCA always maintains a case-referenced approach, urban managers can discern which conditions combined to explain the achievement (or lack thereof) of the targeted objective in each of the studied cities. Lastly, if managers seek to identify the existence of causal mechanisms, the application of process-tracing facilitates this. It enables the recognition not only of the conditions present in certain cities but also how these conditions triggered the achievement of the targeted outcome.

6 Conclusions, contributions and limitations

6.1 Conclusions

Different studies called for the joint study of the dimensions that make up the indices due to their complexity [5, 8]. Therefore, this study has been carried out with the aim of establishing the potential that Set-Theory based methods have to deepen and complement the analysis of indices linked to urban rankings.

The first gap that the study responds to is to apply Set-Theory methods to the analysis of indices linked to rankings in order to deal with causal complexity. Thus, through the application of QCA (a cross-case analysis), it is established how from a Set-Theoretic perspective $INF^*SIM^*MAT^*SEF$ explains UMR and $\sim INF^* \sim SEF^* \sim INN$ explains $\sim UMR$. It stands out that the explanation of a result and its negation do not respond to an inversion of its explanatory conditions, thus demonstrating asymmetry. Likewise, of the conditions initially included in the index, INN is not part of the conjunction of conditions that explains UMR. Similarly, SIM and MAT are not part of the explanation of $\sim UMR$. Nevertheless, SMMR shows the existence of deviant coverage cases of UMR and of $\sim UMR$. This implies the presence and negation of the conditions, as well as the need to deepen the analysis of the explanation of $\sim UMR$ that suggests adding a missing conjunct to the obtained solution— $\sim INF^* \sim SEF^* \sim INN$ -. In this way, responding to [30], the challenges related to sustainability have been studied through the application of configurational methods. The application of methods linked to Set-Theory makes it possible to analyze the values provided by the UMRI through the study of causal complexity.

The second research gap addressed by this study has been to apply methods of analysis to the indices linked to rankings that allow identifying the characteristic features that define the cities. Through the application of process-tracing (within case analysis) cases are identified that differ in their relevance to the explanation of the phenomenon under study, as well as possible extensions of the explanation of these results are proposed. In this way, the systematic

identification of cases through process-tracing allows us to take into account the specific conditions of each case under study [15, 34–36]. In response to the criticism received by the indices for not taking into account the cases that remain in intermediate positions, the application of process tracing provides relevance to cities that occupy intermediate positions such as Barcelona (25), Beijing (27), Shanghai (29), Dubai (32), Moscow (34), Istanbul (37), Kuala Lumpur (38) and Doha (39) for the 2021 Index. In the case of the 2022 Index, Hong Kong (16), Beijing (29), Dubai (30), Shanghai (33), Abu Dhabi (34), Moscow (35) and Istanbul (36) are highlighted. In this way, the goal is to overcome the limitation of indicators not paying attention to the specificities of the local context. Additionally, the existence of a causal mechanism for both the UMR and $\sim$ UMR cases shows that the solution reached is not limited to identifying the scope conditions that explain the presence of the result under study or its absence, but also confirms the existence of a mechanism that triggers the effect of these conjunctions on the result and that is extrapolable to all typical cases explained by the term. Thus, by taking into account the specific features of each city, we establish the existence of causality.

6.2 Contributions

The present work's theoretical contributions include the use of Set-Theory in urban indices to analyze the causal complexity of urban phenomena. Since SMMR involves the application of QCA and process-tracing, we start from this differentiation when presenting the contributions of this study.

Starting with the contributions linked to the application of QCA:

- It is noteworthy, first, that the readiness of cities for the implementation of mobility innovations and their negation are explained by different combinations of conditions (reflecting asymmetry). The use of Set-Theoretic techniques, rather than symmetrical techniques, explain the presence of the phenomenon under study and its negation through different solutions. Thanks to this asymmetry, local managers will be able to know how the explanation that a city is prepared to sustainable mobility ($\text{INF}^* \text{SIM}^* \text{MAT}^* \text{SEF}$) differs from the explanation of the city not being prepared ($\sim \text{INF}^* \sim \text{SEF}^* \sim \text{INN}$).
- Second, the reason underlying the differences in the level of readiness between cities is not the value they reach according to some conditions, but rather the conjunctural causation between different combinations of conditions. While classical models based on variance or regression identify the net effect of different variables, Set-Theoretic methods reveal how conditions should be combined to generate a given result (not contemplating the same components in both cases). Thus, while MAT is part of the UMR solution, it is not the case for $\sim$ UMR. Also, while $\sim$ INN is part of the $\sim$ UMR solution, it is irrelevant to UMR. These results again show differences with the regression-based models. While UMR and $\sim$ UMR are explained by different combinations of conditions, in regression-based methods the explanation of a high and low result (which would be synonymous with Boolean effects) would imply that the identified variables obtained a high or low score.
- To the above, it should be added that the application of Set-Theoretic methods allows for the identification of the necessary and sufficient conditions for the achievement of the result under analysis. Such necessary conditions are those without which the phenomenon under study would not occur. Likewise, sufficient conditions have been identified that explain the phenomenon under study. Although these sufficient conditions are presented by some of the techniques commonly used and supported by regression models, the use of Set-Theoretic techniques allows us to explain their joint effect (through conjunctural causation). The results show how the conditions that are necessary, in this case, are combined to explain the appearance of the results under analysis. That is, the absence of any of the necessary conditions for UMR and $\sim$ UMR would determine that the cities do not reach the result under study. In this way, city managers can recognize with greater precision the conditions that must be present for cities to be ready for the implementation of innovations in sustainable urban mobility. Likewise, explicitly the presence of a significant proportion of the identified conditions is not enough, but instead all the conditions that were already necessary must be present simultaneously. This situation is another difference with regression-based analysis models, in which the different variables under analysis can compensate for each other.

Among the main contributions linked to the application of process-tracing we identify:

- The selection of cases in process-tracing places the focus of the analysis beyond the mere interpretation of the best and worst. The application of process-tracing allows for a systematic identification of the cases to be selected as a reference for the different comparisons. In this way, public managers have a method of analysis that makes it possible

to identify the cases to be taken as a benchmark. For example, if within the causal mechanism that explains UMR we want to deepen the analysis of reference cases that stand out in infrastructure management, the within-case analysis does not point to the cases of Helsinki and corresponding to the year 2022. Likewise, its relevance has been verified to value the lessons that can be drawn from cases that hold intermediate positions in the different indices, overcoming the valuations limited to the choice of the 'best' and the 'worst'.

- Furthermore, beyond just identifying associations, as many of the classical models of analysis do, the application of process-tracing unveils causal mechanisms that underpin the relationships between conditions and outcomes. In this way, the application of process-tracing makes it possible to identify causal mechanisms, indicative of the existence of a causal relationship. This is another difference with the classical methods of regression or those based on variance that are limited to exposing the existence of association or correlation relationships between variables. The identification of a causal mechanism allows us to affirm that the presence of the mechanisms in the terms in which they are identified (INF*SIM*MAT*SEF for UMR and $\sim$ INF* $\sim$ SEF* $\sim$ INN for $\sim$ UMR) reflects the existence of a causal relationship between the conditions and the outcome. That is, sufficient conditions not only explain the presence of the result, but bring about its existence.

The application of Set-Theory to the information conveyed through the UMRI allows public managers to better assess the situation of each city. This is critical as these indices play a very important role in evaluating the performance of cities, setting goals, and planning urban mobility to achieve more sustainable cities. Additionally, it strengthens the possibilities of benchmarking with cities that are more similar or different to the one being studied. Furthermore, in city management, it is relevant for city managers to be aware of how the conditions that explain UMR and $\sim$ UMR are interrelated.

6.3 Limitations

Our research has made strides in elucidating the complexity of urban mobility readiness, primarily through the lens of infrastructure, social impact, market attractiveness, system efficiency, and innovation. However, the intricate tapestry of urban mobility also weaves in threads of user behavior, cultural nuances, and socio-economic dynamics. To fully capture this multifaceted domain, future research must pivot towards a more integrative model that synergizes these diverse elements. This endeavor could fruitfully integrate our findings with additional indices probing these layers, thus sculpting a more comprehensive mosaic of urban mobility readiness.

A critical oversight in our study is the dimension of inclusivity within mobility services. As the digital revolution reshapes urban mobility, it is imperative to safeguard the interests of Vulnerable Social Groups—notably the elderly, individuals with disabilities, and those from lower socio-economic backgrounds. Future scholarly efforts must interrogate how digital innovations in urban mobility can transcend barriers and be universally accessible. This necessitates a thorough exploration of indices that prioritize inclusivity and equity in urban mobility, ensuring that technological progress uplifts every stratum of urban society.

Our analysis did not sufficiently delve into the nuanced concerns surrounding Mobility as a Service (MaaS) platforms, especially regarding equity and accessibility. As urban centers increasingly integrate MaaS into their mobility landscape, it's crucial to be vigilant about potential disparities in access. Future studies should critically examine the design and operational modalities of MaaS platforms to champion equitable and universal access for urban dwellers. This would entail an extensive evaluation of diverse indicators that encapsulate the equity facets of urban mobility, thereby fostering more inclusive urban mobility frameworks.

Despite these gaps, our study stands as a foundational piece in understanding urban mobility readiness through Set-Theory methods. The insights distilled lay a robust groundwork for future research, particularly in crafting models of urban mobility readiness that are inclusive, equitable, and holistically representative. By spotlighting these limitations, we chart new directions for research that can bridge these divides, contributing to the evolution of urban spaces that are more sustainable, accessible, and inclusive for all.

Author contributions All authors whose names appear on the submission (1) made substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data; or the creation of new software used in the work; (2) drafted the work or revised it critically for important intellectual content; (3) approved the version to be published; and (4) agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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Declarations

Competing interests Not applicable.

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