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A Quantitative Model of Innovation Readiness in Urban Mobility: A Comparative Study of Smart Cities in the EU, Eastern Asia, and USA Regions

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Abstract: The smart cities paradigm has gained significant attention as a tool to address the multifaceted challenges posed by contemporary urban mobility systems. While cities are eager to integrate cutting-edge technologies to evolve into digital and intelligent hubs, they often deal with infrastructure and governance bottlenecks that prevent the rapid adoption of industry-driven innovations. This study introduces a three-step methodological approach to forecast a city's innovation readiness in urban mobility, thus facilitating city-led innovation and identifying key areas within urban mobility systems that require attention. Initially, a comprehensive literature review was undertaken to ascertain the most impactful innovation indicators influencing a city's ability to embrace new technologies. Subsequently, Principal Component Analysis (PCA) was applied to identify these indicators, highlighting the primary markers of innovation for each city. The final step involved the application of both random and fixed-effects regression models to quantify the influence of distinct unobserved variables—such as economic, cultural, and political factors—on the innovation readiness of various cities. The methodology's effectiveness was tested using data from cities across diverse regions. The findings underscore that merely 7 out of 21 innovation indicators are critical for assessing a city's innovation readiness. Moreover, the random-effects model was identified as the most suitable for capturing the nuances of unobserved variables in the studied cities. The innovation readiness scores at the city level revealed a diverse range, with cities like Madrid, Gothenburg, and Mechelen demonstrating high readiness, while others like Kalisz and Datong showed lower scores. This research contributes to the strategic planning for smart cities, offering a robust framework for policymakers to enhance innovation readiness and foster sustainable urban development, with a newfound emphasis on city-specific analysis.

Keywords: smart city; innovation readiness; principal component analysis; unobserved variables

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1. Introduction

Cities are gradually embracing technologies to address societal, environmental, and mobility-related challenges. By encouraging the integration of sensors and Big Data through the Internet of Things (IoT), the notion of smart cities contributes to this endeavour [1]. To ensure the delivery of services and sustainable development, smart cities aim to improve the quality of life of their residents and foster economic growth [2,3]. It is essential to understand and effectively address the needs and desires of citizens as a step toward improving their happiness [4]. However, the success and viability of smart city services do not depend solely on the city's stakeholders' readiness to uptake innovations, but also on the city's local capacity, thus, each city may perform differently and appearing with different smart city structures and characteristics [3]. A city with high levels of innovation readiness can indeed be considered an intelligent city, with a primary objective to continuously foster and adopt innovation, as suggested by [5]. This implies that greater readiness for technology adoption can significantly enhance the likelihood of a successful smart city adoption process. However, it is important to note that innovation, while essential, is not the only determinant of smart city development. Another critical factor involves the governance of smart cities, which focuses on promoting innovation through the adoption of technology while jointly controlling the unpredictable adverse effects of such advanced technologies to maintain the quality and benefit of city services for the public [6]. Similarly, smart tourism uses the characteristics of smart cities to improve the standard of tourism services and experiences. This technological improvement adds social value for both locals and visitors [7]. The Healthy Cities concept also constitutes a critical factor as it aims to maintain the balance of social, economic, and environmental advances to guarantee ongoing health and wellness for city residents [8]. Finally, smart human capital management has also emerged as a critical factor, since cities depend on well-educated individuals for innovation and economic expansion. The working conditions of the local job market and the available facilities play a significant role in their choices to move and settle in a city [9]. Cities often face critical challenges, as they may not always be fully prepared to adopt and adapt to new and innovative solutions. This is mainly a result of the fact that innovations driven by the private sector can move faster than the public sector's ability to adapt. To successfully address this issue, it is important for local authorities to evaluate how ready the city is for these changes. The Smart City Readiness Model, created by Hidayanto in 2018, deals with this issue a detailed method to check if a city is prepared to become a smart city [10]. This model looks at the city's technology, management, and environment performance indicators and not specifically on urban mobility indicators. This model can help the cities smooth transition to becoming smart cities by making sure they are ready to embrace new innovative solutions. To assess the city's readiness for innovation adoption, specific data should be analysed on different aspects of the city's urban mobility system. As cities incorporate multiple innovation indicators, a challenge arises in effectively analysing and understanding the intricate relationships and significance of each element in shaping a city's technological landscape. Principal Component Analysis (PCA) was used here to choose the city's major innovation indicators in order to simplify the process of choosing from among the many available city innovation indicators. However, the data collected are considered cross-sectional as they are associated with a sample of city ranks of specific geographical regions with similar characteristics taken at a specific point in time [11]; these characteristics cannot be easily quantified but may have an impact on each city's readiness level and can be captured by the unobserved variables that need to be encapsulated for deriving generalized predictive models of the innovation readiness of each city's geographical region [12]. Fixed-effects models are employed if the effects of the unobserved variables are correlated with the independent variables of a predictive model [13], while the random-effects model is used if these effects are uncorrelated [14]. To conclude, we initially examine a comprehensive set of innovation indicators derived from the literature, and apply Principal Component Analysis (PCA) to select the most critical indicators. This approach allows for a nuanced understanding of the factors that contribute to a city's readiness for innovation. We then quantify the readiness for innovation, considering the impact of unobserved variables that may affect this readiness. We also provide a comparative analysis across different geographical regions, which adds to the understanding of how context-specific factors influence a city's ability to innovate. The methodology used is based on the following three novel methodological steps:

1. Identifying significant variables that address the maturity of a city to adopt innovative solutions through an extensive literature review process.
2. Employing PCA to select the most vital indicators, thus defining the main innovation parameters for each urban environment.
3. Assessing both random- and fixed-effects regression models to capture the impact of various unobserved variables, such as economic, cultural, and political factors, enables a precise calculation of the level of innovation readiness for each region.

The rest of the paper is organized as follows: Section 2 provides a comprehensive literature review of academic research efforts that deal with the development of methodologies that capture the city's readiness to adopt smart or innovative mobility solutions; Section 3 provides the methodology used to predict the level of innovation readiness of a city; Section 4 examines the applicability of the selected methodology in the dataset of 30 stakeholder ranks in 21 predictors of innovation readiness. Finally, Section 5 concludes the main insights derived from the implemented methodology.

2. Smart Cities and Innovation

The process of turning metropolitan areas into smart cities is complex and involves more than simply integrating cutting-edge technology. These urban ecosystems embody a holistic approach to development, striving for sustainability, inclusion, and improved quality of life for their inhabitants. Qualitatively, smart cities are characterized by their responsiveness and interconnectedness, fostering citizen engagement and social wellbeing as central tenets of their growth [2,3]. They are defined by their ability to leverage a plethora of technologies, such as smart homes (SHs) and vehicle-to-grid (V2G) systems, to offer diverse services and address urban challenges, with internet technology providing the essential backbone for innovation [15]. Quantitatively, the success of smart cities can be measured through various indices that assess aspects like innovation readiness, sustainability, and quality of life, offering a benchmark for their intelligent infrastructure and services. The evaluation criteria used to measure the success of cities include their ability to promote environmental sustainability, economic efficiency, and inclusion in society [16]; while smart cities have the potential to enhance efficiency and sustainability, they also bring challenges like privacy concerns, data security, and ensuring access to benefits for everyone [17]. In summary the concept of cities represents a holistic approach to urban development that values both the qualitative experiences of citizens and the quantitative outcomes of urban initiatives [18]. This perspective highlights the complexity of smart city development and emphasizes the need for a comprehensive understanding of its different dimensions. The importance of innovation in shaping cities is well-documented. Smart cities are not just about integrating advanced technologies; they represent a holistic approach to urban development that seeks sustainability, inclusion, and improved quality of life for their inhabitants [19]. A key component of this transition is the incorporation of internet technology, which offers the necessary framework for innovation to thrive. The backbone of smart cities is sustainability, which drives their growth and ensures resource-efficient and environmentally friendly urban solutions [20]. Sustainable smart cities aim to enhance quality of life while minimizing their ecological footprint, integrating smart technology to achieve these goals. The role of citizens is paramount in smart cities, with citizen engagement and social wellbeing being crucial dimensions of their development [19]. Smart cities strive to be inclusive, ensuring that the benefits of urban innovation are accessible to all. They place citizens at the centre of their initiatives, valuing their participation and prioritizing their wellbeing. The idea of a smart city that prioritizes the needs and values of its citizens, known as a citizen-centred smart city (CCSC), highlights the significance of incorporating thinking and social wellbeing in smart city development [21]. However, it is important to acknowledge that the journey towards cities comes with its fair share of challenges. Issues related to privacy, data security, and the digital divide need to be addressed to ensure equitable access to smart city benefits [18]. The integration of smart homes (SHs) and vehicle-to-grid (V2G) technologies are examples of how smart cities are evolving, showcasing the potential for increased efficiency and sustainability. However, overcoming the challenges associated with these developments is crucial to realize the full potential of smart cities [15]. In conclusion, smart cities represent a holistic approach to urban development, integrating innovation, sustainable practices, citizen engagement, and addressing challenges to create intelligent, liveable, and inclusive urban spaces. The multifaceted nature of smart cities underscores the complexity of their development, highlighting the need for a comprehensive understanding of their various dimensions to fully realize their potential [22].

3. Literature Review

The recent rapid development of technology has recently catalysed the transformation of urban centres into smart cities, improving the wellbeing of citizens by improving their quality of life and fostering greener urban environments. However, the pace of industry-led innovation often outweighs that of city-led innovation, which presents challenges in the adoption of new solutions due to infrastructural and governance maturity issues. Adding to this discourse, ref. [23] introduced a novel approach to assessing drone-based logistics concepts in cities, which could significantly impact urban mobility and delivery systems. Their work suggests that the integration of such advanced technologies requires a city to be flexible and innovative, not just in the adoption of technology but also in regulatory frameworks. Similarly, ref. [24] explores the diffusion of urban innovations across the global city network, highlighting the contagious nature of such innovations and the importance of connectivity between cities. This study underscores the need for a collaborative approach to innovation, where cities can learn from each other's successes and failures. Furthermore, ref. [25] provide a critical perspective on the environmental impacts of green innovations at the city level in China. Their findings indicate that while green innovations can lead to improved carbon emission performance, the heterogeneity of such innovations in different cities suggests that a one-size-fits-all approach may not be effective. This emphasizes the need for tailored strategies that consider the unique environmental, economic, and social contexts of each city. Our study focuses on innovative mobility solutions, defining them as novel technologies and approaches applied to urban transportation and mobility, aiming to improve efficiency, sustainability, and accessibility. We focus on understanding how cities can gauge their current maturity in adopting these innovative mobility solutions, a crucial step towards achieving the transformation into smart cities. According to [26], readiness encompasses the ability of a city to apply data-driven planning and monitoring processes using digital tools, engage various stakeholder groups, and handle the opportunities and challenges that arise with the implementation of innovative mobility solutions. Various frameworks and indicators have been developed to assess the city's readiness to implement smart city initiatives. For example, the smart readiness indicator (SRI) devised by the European Commission assesses the readiness of buildings to incorporate technologies and electronic systems to enhance energy efficiency and overall performance [27]. Research has also been conducted to assess a city's urban mobility system readiness for adopting innovation by investigating various dimensions, such as governmental, technological, environmental, socioeconomic, and political [26,28,29]. Our study contributes to this field by comparing different cities across three major regions, providing insights into how diverse urban contexts of each country might influence innovation readiness. We consider governance and stakeholder engagement as part of the innovation readiness assessment, which touches on the interplay between policy, technology, and stakeholders. The inclusion of cities from different continents and the use of regression models to account for unobserved variables address the specific cultural and political influences of cities on the adoption of innovation. In addition to the previous studies, we have identified research efforts, employing methodologies similar to ours. For example, ref. [30] used fixed and random-effects models using balanced panel data for 28 European states, focusing on the smart environment and reducing air pollution. In a similar vein, ref. [31] examined the connection between China's smart cities' capacity for innovation and their spatial structure using a fixed-effects panel data model. Our results are consistent with the broader literature on smart cities and innovation readiness, as they highlight the multifaceted nature of smart city development and the crucial role of innovation readiness in this process. The consistency of our findings with previous studies adds credibility to our results and underscores the robustness of our methodology. However, our study provides a novel effort in predicting the innovation readiness of cities using a specific set of urban mobility and urban mobility related indicators, along with additional mathematical methodologies such as the PCA. We therefore contribute to the existing literature by offering a comprehensive and tailored mathematical analysis of innovation readiness, providing valuable insights and a novel perspective on the prerequisites for smart city development. The results of the critical analysis of the state-of-the-art literature reveals the following research gaps:

1. There seems to be a lack of research efforts focusing on how to effectively scale innovation readiness models across different urban settings, considering each city's unique characteristics.
2. There is a gap in research focused on the complex interplay between policy development, technology deployment, and stakeholder engagement in the context of smart city innovations.
3. The impact of political and cultural variables on the uptake and efficacy of smart city innovations has not received enough attention in research.

This paper addresses the above research gaps as follows:

- By examining different cities across three major regions, the study aims to provide insights into how diverse urban contexts influence innovation readiness and scalability.
- The study will consider governance structures and stakeholder participation as integral parts of the assessment of innovation readiness, addressing the dynamics between policy, technology, and stakeholders.
- Utilizing regression models to account for unobserved variables, and the PCA model for dimensionality reduction, the research will address specific cultural and political influences on innovation adoption, advocating for tailored strategies that reflect the unique contexts of each city.

4. Materials and Methods

4.1. Survey Design and Data Collection

The survey design and data collection for our study were meticulously planned and executed to ensure the robustness and reliability of the findings. In the spring of 2022, specifically during March and April, we launched our survey using an online platform to facilitate ease of access and distribution. However, we encountered some challenges with the use of EU online services in China, which led us to adapt utilizing Excel files to collect responses from Chinese participants effectively. Our selection of cities was pragmatic, influenced by the willingness of cities to engage with our research and the practical constraints they faced. We sought a single, consolidated response from each city to maintain consistency across the dataset. Notably, Beijing presented a unique case where the survey reached a broader institutional base, yielding six distinct responses. Each of the participants expressed their confidence together with their responses, so a weight was assigned to each response (Table 1).

Table 1. The weight of the response of each participant from Beijing based on their perception and their confidence.

Participant	Weight
Beijing-1	19%
Beijing-2	19%
Beijing-3	13%
Beijing-4	13%
Beijing-5	19%
Beijing-6	19%

The regional distribution of cities, which included a concentration from Eastern Asia, the EU region, and the USA, mirrored our organization's network reach and collaborative ties. The survey itself was created based on a review of the latest research articles. We carefully selected a variety of innovation indicators that cover aspects such as governance, data, infrastructure, stakeholders, and climate. The survey had two sections: the first one collected general information about the participants, including their city, role and affiliation; the second section focused on exploring the innovation indicators in detail. Every indicator was given in the form of a question with a response range of 1–5, with 1 being the lowest and 5 being the highest. To facilitate scoring accuracy, we provided text alongside each score value to ensure clear understanding and enable participants to accurately reflect their city's situation. The next table (Table 2) contains the affiliation and the role of each survey participant; this information can give valuable insights to the reader about the consistency of the responses.

Table 2. The city representatives along with their affiliation and their role.

City	Affiliation	Role
Almada	Municipality of Almada	Mobility expert
Arad	City of Arad	Mobility expert
Bielefeld	City of Bielefeld	Head of Office for Mobility
Birmingham	Transport for West Midlands	Mobility Leader
Braga	City of Braga	Mobility expert
Budapest	Centre for Budapest Transport (BKK)	Head of Piloting and Modelling
Gothenburg	City of Gothenburg	Mobility expert
Guimarães	City of Guimarães	Mobility expert
Hertogenbosch	City of Hertogenbosch	Policy Maker
Ioannina	City of Ioannina	Mobility expert
Kalisz	City Hall Kalisz	Mobility expert
Madrid	Logistic Service Provider	Transport Operator
Mechelen	City of Mechelen	Mobility officer
Padua	Mobility department of Padua	Mobility expert
Région Île-de-France	Regio of Ile-de-France	Freight and Logistics Officer
Thessaloniki	Hellenic Institute of Transport	Mobility Expert
Valencia	Fundación Valenciaport	Pilot technical coordinator
College Station	Texas A&M University	Mobility expert
Minneapolis	City of Minneapolis	Mobility expert
Palm Beach	NGO	Project Manager
Beijing-1	Public Institution	Project Manager
Beijing-2	Public Institution	Mobility expert
Beijing-3	Local Authority	Project Manager
Beijing-4	Public Institution	Project Manager
Beijing-5	Public Institution	Mobility expert
Beijing-6	Regional Authority	Transport Operator
Datong	Local Authority	Project Manager
Shanghai	Local Authority	Project Manager
Tel Aviv	Technion—Israel Institute of Technology	Mobility Expert
Xi'an	Local Authority	Project Manager

To identify the prominent innovation indicators, we followed the PRISMA approach, an established method to conduct systematic literature reviews. This approach was instrumental in defining the main elements of an innovative urban mobility ecosystem across six key categories. An expert group was later convened to refine the selection of indicators, ensuring that the final list was both relevant and non-redundant. This rigorous process, combining systematic literature review and expert consultation, underpinned the development of our survey and the subsequent data collection, laying a solid foundation for our study's evaluation of city innovation readiness.

4.2. Methodology

In this research, a novel three-step methodology is applied, aimed at predicting the level of innovation readiness of a city and supporting cities towards a city-led innovation. The methodology firstly defines significant variables that can address the maturity of a city to adopt and successfully implement innovative mobility solutions. In the initial phase, a comprehensive literature review was performed, identifying and highlighting the dominant innovation indicators that influence the city's ability to embrace innovation. Subsequently, Principal Component Analysis (PCA) was adeptly utilized in the second phase to select the most vital indicators, thereby defining the main innovation parameters for each urban environments. In the last phase, both random- and fixed-effects regression models were strategically employed to capture the impact of different unobserved variables, such as economic factors, cultural aspects, and political influences, allowing the precise calculation of the level of innovation readiness for each respective region.

The above table (Table 3) includes the 21 questions that were selected to assess the innovation readiness index of a city. As mentioned already, a qualitative 5-scale descriptive score was assigned to each question, based on literature review and expert opinion. This descriptive score that was used for each question can be found on Table A1 of the Appendix A. Although indicators 9–21 of Table 3 are directly related to mobility, indicators 1–8 provide essential information on the broader innovation context within which mobility solutions are implemented. Governance and policy, for example, play a vital role in creating a conducive environment for innovation in mobility, ensuring that the city has the capability to develop and implement supportive policies [32]. Infrastructure is another critical aspect, as the availability and quality of infrastructure directly impact the feasibility and effectiveness of innovative mobility solutions [33]. Stakeholder engagement ensures that a diverse range of perspectives is considered in the innovation process, promoting inclusive and well-integrated mobility solutions [34]. By including indicators 1–8 in our assessment, we ensure a holistic evaluation of the city's readiness for innovation, taking into account not only the mobility-related aspects but also the broader innovation ecosystem [35]. This comprehensive approach enables us to provide actionable information and guidance to cities, enhancing their readiness for innovative mobility solutions [36]. Furthermore, to gain an understanding of our assessment on the readiness for innovation in smart cities, it is crucial to situate our work within the existing landscape of innovation indices and indicators. One notable example is the Innovation Cities Index (ICI) developed by 2thinknow, which ranks 500 cities worldwide based on their conditions for innovation and examines 31 different aspects of their economies using 162 indicators. Although our readiness assessment shares similarities with ICI in terms of its approach and consideration of various dimensions of innovation, it also possesses unique features. Specifically tailored to evaluate innovation readiness in the context of cities with a specific emphasis on innovative mobility solutions. This allows us to delve deeper into the challenges and opportunities related to urban mobility innovation providing focused insights and recommendations for cities seeking to enhance their readiness for innovation, in this domain [37–39]. The most significant city innovation indicators in Table 3 are then identified using the Principal Component Analysis (PCA) methodology [40]. The most critical components are selected considering the Guttman–Kaiser criterion, which dictates that components with eigenvalues greater than 1 should be selected. The underlying logic of this criterion is that any principal component should explain more variance than a single original variable [41]. The dataset examined will now consist of the selected innovation indicators of Table 3, derived from the PCA methodology in Step 2, and will be used to calculate the level of innovation readiness of each city that constitutes the dependent variable. It is assumed that the examined dataset encompasses one entity associated with the geographical region of each city. In Step 3, a Hausman test is used to decide between the fixed- and random-effects model, capturing the impact of geographical regions' unobserved variables on their respective city's innovation readiness. The Hausman test is used to investigate the null hypothesis, which states that the random-effects model is more appropriate than the fixed-effects model [42]. The fixed-effects model is chosen as the most suitable model and the null hypothesis is rejected if the p-value for the Hausman test is less than the probability of a predetermined significance level [43]. Finally, the selected model will be used to predict the probability of the level of readiness of a city to adopt innovative mobility solutions based on the different characteristics of their urban mobility system. The nomenclature of fixed regression models is represented in Tables 4 and 5 considering two entities, namely regions and geographical areas [44].

Table 3. Identified city innovation indicators.

No	Innovation Indicators
1	Coordination and adaption level for adopting innovative solutions [45]
2	Implementation level of sustainable urban mobility solutions [46]
3	Stakeholders' engagement in co-creating and co-designing innovative mobility solutions [47]
4	Competence level in fundraising for innovation and public investment in smart innovative policy making [48]
5	Collaboration levels with neutral partners and other cities and organisations to transfer knowledge [49]
6	University Town with Research and Innovation Activities level [50]
7	City's population's educational and digital competence of the city population [51]
8	Smart and transparent levels of a city's Government processes [52]
9	Open-source, safe and easily accessible level for mobility data [53]
10	Collection and data use level for understanding the current situation of passenger transport mobility [54]
11	Collection and data use level for understanding the current situation of freight transport mobility [55]
12	Reliance level on data and evidence to make passenger transport policies [56]
13	Reliance level on data and evidence to make freight transport policies [57]
14	Availability and intelligence level of multimodal passenger transport infrastructure and services in the city [58]
15	Availability and intelligence level of multimodal freight transport infrastructure and services in the city [59]
16	Skilled workforce level on innovative mobility solutions for passenger transport [60]
17	Skilled workforce level on innovative mobility solutions for freight transport [61]
18	Sustainable mobility services and green modes of transport use levels [62]
19	Openness level to new business models and the application of the triple helix of innovation to smart passenger mobility solutions [54]
20	Openness level to new business models and the application of the triple helix of innovation to smart freight mobility solutions [63]
21	Richness level in terms of the number of big innovators and high-tech companies [64]

The descriptive scale of the questions can be found in Table A1 of the Appendix A and an online version of the survey can be found in https://urbanpolicymodel.imet.gr/innovation-readiness.html [Accessed on 9 October 2023].

$$y_i^f = \alpha_i + \sum_{j \in J} b_j \cdot x_{ji} + \varepsilon_i \qquad (\forall i \in I), \tag{1}$$

$$y_i^r = b_0 + \sum_{j \in J} b_j \cdot x_{ji} + (u_i + \varepsilon_i) \qquad (\forall i \in I), \tag{2}$$

Table 4. Nomenclature of the fixed effects regression model components and maximization function.

Parameter	Nomenclature
${y_i}^F$	The dependent variable that represents the readiness level for each entity $i \in I$ considering the fixed-effects model.
b_j	The regression coefficient of the independent variable $j \in J$
$x_i j$	The value of the independent variable $j \in J$.
α_i	The individual fixed effect per entity $i \in I$.
ε_i	The normally distributed error term with zero mean and variance $\sigma^2$for each entity $i \in I$
$\phi()$	The probability density function of the normal distribution.

Table 5. Nomenclature of the additional random-effects regression model components.

Parameter	Nomenclature
${y_i}^R$	The dependent variable that represents the readiness level for each region $i \in I$ considering the random-effects model
u_i	The normally distributed random effect with zero mean and variance ${\sigma_u}^2$ for each region $i \in I$
b_o	The mean value of the unobserved heterogeneity (constant)

5. Results and Discussion

The methodology employed is being evaluated in a dataset that includes a city ranking of 30 stakeholders (see Figure 1) on twenty-one (21) innovation indicators which are constituted as the independent variables (v) of the regression model. We employed Python as the primary tool for all quantitative analyses to achieve our research objectives successfully. Python's comprehensive ecosystem, including its advanced statistical packages and machine learning libraries, provided the necessary capabilities for a range of computations and methodological applications. This versatile programming environment supported our analytical processes, from the application of advanced regression techniques to Principal Component Analysis and the computation of descriptive statistics. The choice of Python was instrumental in ensuring the rigour and precision of our study, allowing us to address the multifaceted aspects of innovation readiness within smart cities.

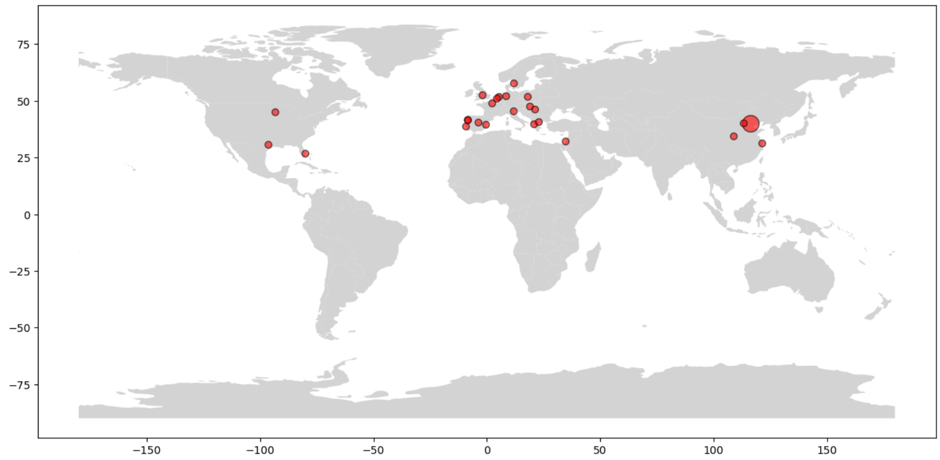

Figure 1. A total of 30 cities participated in the innovation readiness survey. The size of the circles represent the number of the participants at the specific city.

Nine (9) responses are linked to the cities of the Eastern Asia Region, specifically Xian, Beijing, Shanghai, and Datong; eighteen (18) responses are connected to the cities of the EU region, specifically Budapest, Kalisz, Padua, Valencia, Almada, Arad, Gothenburg, Hertogenbosch, Ioannina, Mechelen, Région Île-de-France, West Midlands, Braga, Madrid, Thessaloniki, Guimarães, Bielefeld, and Tel Aviv; three (3) are from cities of the USA, namely College Station, Palm Beach, and Minneapolis. The responses can be found in the following figure.

The implementation of the PCA methodology leads to the innovation indicators that have the most important impacts on the selected principal components considering the Guttman–Kaiser criterion (see Table 6).

The implementation of the PCA narrowed down the list of 21 innovation indicators into only 7; specifically, questions 1, 3, 4, 5, 9, 11, and 18 were determined to be significant (see Figure 2). The results of Table 6 reveal that the innovation indicator "Data collection and use level to understand the current situation of freight transport mobility" is the most influential for PC1, explaining 31% of its variance. Similarly, the indicator "Levels of collaboration with neutral partners and other cities and organizations to transfer knowledge" is the most impactful for PC2, accounting for 42% of its variance. The indicators "The levels of use of sustainable mobility services and green modes of transport use levels" and "Open-source, safe and easily accessible level for mobility data" have negative loadings on PC3 and PC4, respectively. This suggests that as the values of these indicators increase, the values of their respective principal components decrease. Furthermore, the indicator "Coordination and adaption level for adopting innovative solutions" has a strong negative influence on PC5, explaining −63% of its variance. On the contrary, the "Stakeholder engagement level in co-creating and co-designing innovative mobility solutions" and the "Level of competency in innovation fundraising and public investment in smart innovative policy making" have strong positive influences on PC6 and PC7, respectively, with loadings of 63% and 59%. The descriptive statistic of the finalized dataset is provided in Table 7.

Table 6. Selected principal components and respective innovation indicators.

Innovation Indicators	PCA Loadings	Principal Components	Explained Variance
Collection and data use level for understanding the current situation of freight transport mobility	31%	PC1	31%
Collaboration levels with neutral partners and other cities and organisations to transfer knowledge	42%	PC2	13%
City's sustainable mobility services and green modes of transport use levels	−39%	PC3	8%
Open-source, safe and easily accessible level for mobility data	−46%	PC4	8%
Coordination and adaption level for adopting innovative solutions	−63%	PC5	7%
Stakeholders' engagement level in co-creating and co-designing innovative mobility solutions	63%	PC6	6%
Level of competency in innovation fundraising and public investment in smart innovative policy making	59%	PC7	5%

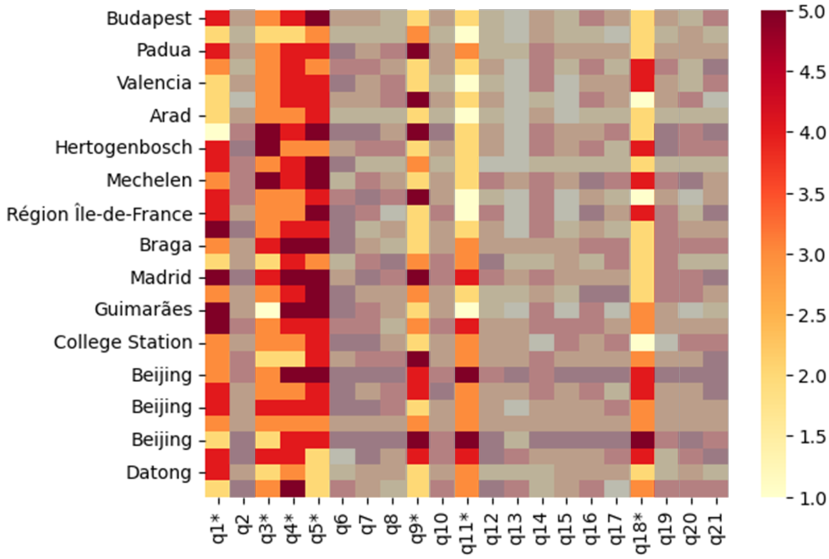

Figure 2. The responses of the 30 stakeholders to the innovation readiness survey. Questions with asterisk and grey mask are the non-significant questions that were calculate from the PCA.

The results of Table 7 reveal that the level of coordination and adaptation to adopt innovative solutions is averaged at 3.3 out of 5, with a variation (standard deviation) of 1.1, suggesting a moderate level of coordination and adaptation. Stakeholders' engagement in co-creating and co-designing innovative mobility solutions has a slightly above-average score of 3.1, but with a tighter spread, as indicated by a standard deviation of 0.9. Interestingly, the level of competence in innovation fundraising and public investment in smart policy making is relatively high, averaging 3.8 with a lesser spread of 0.8. Cities also seem to be collaborating well with neutral partners and other organizations, as evidenced by a high average score of 4. The open-source, safe, and easily accessible level for mobility data is at an average of 3.1, but with a broader spread of 1.2. The level of data collection and use to understand the current mobility situation in the transport of goods is slightly below the average of 2.5, with a variation of 1.1. The city's sustainable mobility services and green transport modes have an average score of 2.7. Lastly, when it comes to innovation readiness, cities score an average of 66.5 out of 100, with a variation of 10.6, indicating a decent level of readiness, but with some variability between cities.

Table 7. Descriptive statistics of numerical data.

Variables	Count	Mean	Std	Min	25%	50%	75%	Max
Coordination and adaption level for adopting innovative solutions	30	3.3	1.1	1	2.3	3	4	5
Stakeholders' engagement level in co-creating and co-designing innovative mobility solutions	30	3.1	0.9	1	3	3	3	5
Competence level in fundraising for innovation and public investment in smart innovative policy making	30	3.8	0.8	2	3	4	4	5
Levels of collaboration with neutral partners and other cities and organizations to transfer knowledge	30	4	1	2	3.3	4	5	5
Open-source, safe and easily accessible level for mobility data	30	3.1	1.2	2	2	3	4	5
Data collection and use level to understand the current situation of freight transport mobility	30	2.5	1.1	1	2	2.5	3	5
The levels of use of sustainable mobility services and green modes of transport use levels	30	2.7	1.1	1	2	2.5	4	5
Innovation readiness	30	66.5	10.6	40.7	62.1	65.7	71.8	89.4

We recognize that the Hausman test application and the development of the chosen fixed or random-effects model are limited by the size of our study. Furthermore we fully understand the significance of validating our findings especially considering the extent of our data. To address any concerns regarding normality we have conducted thorough tests to assess normal distribution for each response related to the cities' performances on the chosen innovation indicators and the assigned level of innovation readiness provided by the respondents. Specifically we have utilized the Shapiro Wilk test, for normality [65], to ensure that our results are reliable. A summary of the normality test results can be found in Table 8.

Table 8. Normality test results.

Indicators	*p* Value	Normality
1	1.4%	Not Gaussian
2	0.1%	Not Gaussian
3	0.1%	Not Gaussian
4	0.0%	Not Gaussian
5	0.0%	Not Gaussian
6	1.0%	Not Gaussian
7	0.4%	Not Gaussian
Innovation Readiness Level	27.6%	Gaussian

The results of the normality test indicate that none of the innovation indicators (1–7) follow a distribution. However, the composite measure of "Innovation Readiness Level" does exhibit a distribution. This is an occurrence in real-world data especially when dealing with smaller sample sizes. To overcome this issue and determine the suitable model between fixed and random-effects, we utilize a bootstrapped version of the Hausman test incorporating the Wild Bootstrap method. This approach involves resampling our data with replacement and conducting the Hausman test on each dataset using robust variance estimators. The advantage of this method is its independence from assuming normality, which makes it more resilient when faced with deviations from data distributions [66]. By aggregating the results from all the resampled datasets, we can make a informed decision on which model to employ based on a distribution of test statistics rather than relying solely on one point estimate. This approach strengthens the reliability and validity of our model selection process. The results of the Bootstrap Hausman test are summarized in Table 9.

Table 9. Bootstrapped Hausman Statistics Results.

Results	Values
Hausman_Statistic	0.26
P_Value	0.90
Decision	Random Effects
Bootstrap_Mean	0.72
Bootstrap_Median	0.62
Bootstrap_Std	0.45
Bootstrap_2.5th_Percentile	0.13
Bootstrap_97.5th_Percentile	1.93

The fixed-effects and random-effects models' coefficient estimates do not significantly differ from one another, as indicated by the computed Hasuman statistic of 0.26. Given the accompanying high p-value of 0.90, which further suggests that there is insufficient statistical evidence to reject the null hypothesis; the random-effects model is chosen as the more suitable option for the given data. This decision is underpinned by both the bootstrap mean and median, which are 0.72 and 0.62, respectively, exceeding the observed Hausman statistic and reinforcing the suitability of the random-effects model. The standard deviation of the bootstrap distribution, at 0.45, points to a considerable spread in the Hausman statistics across the bootstrap samples, yet the observed statistic falls well within the 95% confidence interval marked by the 2.5th and 97.5th percentiles. This interval, stretching from 0.13 to 1.93, does not bracket the observed statistic in its extreme tails, aligning with the high p-value and the consequent decision to not reject the null hypothesis. Given the selected random-effects model and the observed non-normality of the sample, we will similarly apply the Wild Bootstrap method, for accommodating non-normality in the residuals [67] and deriving the coefficients and random effects of the model.

Table 10 provides the mean values of the coefficients of each independent variable as these derive from 1000 iterations of the bootstrap random-effects model implementation, along with the mean random effects of each city.

Table 10. Random effect regression coefficients.

Variables	Mean Coef.
y Intercept	11.3
Coordination and adaption level for adopting innovative solutions	−0.13
Stakeholders' engagement level in co-creating and co-designing innovative mobility solutions	2.34
Competence level in fundraising for innovation and public investment in smart innovative policy making	0.18
Levels of collaboration with neutral partners and other cities and organizations to transfer knowledge	2.29
Open-source, safe and easily accessible level for mobility data	4.11
Data collection and use level to understand the current situation of freight transport mobility	−0.51
The levels of use of sustainable mobility services and green modes of transport use levels Innovation readiness	1.46
Mean Random Effects	
EU	−3.76
Eastern Asia	6.27
USA	2.63

The table of coefficients of the bootstrap random-effects model (Table 10) provides information on the factors that affect innovation readiness in different cities. The positive y-intercept of 11.3 suggests a baseline readiness for innovation that is above average when other factors are zero. However, the coordination and adaptation level for adopting innovative solutions has a small negative coefficient (−0.13), indicating that entities adept at these aspects might be slightly less prepared for innovation than expected. In contrast, stakeholders' engagement in co-creating and co-designing solutions has a significant positive effect (2.34), implying that stakeholder involvement greatly contributes to innovation readiness. A moderate positive coefficient for the competence level in fundraising and smart policy-making (0.18) indicates that these factors are somewhat influential in predicting innovation readiness, highlighting the role of financial and strategic planning in the innovation process.

The level of collaboration with neutral partners shows a strong positive influence (2.29), suggesting that entities engaging in knowledge exchange are significantly more ready for innovation. Interestingly, the coefficient for open-source and accessible mobility data is quite high and positive (4.11), which aligns with the general expectation that open data practices are associated with higher innovation capacity. This could indicate the significant benefits of open data in fostering innovation. The negative coefficient for data collection and use level to understand the current situation of freight transport mobility (−0.51) might reflect challenges in effectively utilizing such data for innovation. The levels of use of sustainable mobility services and green modes of transport have a positive effect on innovation readiness (1.46), underscoring the importance of sustainable practices in fostering innovation. These results highlight the multifaceted nature of innovation readiness and the need for targeted policies that bolster stakeholder engagement, financial competence, collaboration, and sustainable practices to create an environment conducive to innovation. Table 11 provides the mean values of the innovation readiness scores predicted in each of the 1000 bootstrap iterations for each city of the examined dataset, together with the mean absolute percentage error derived from each prediction.

Table 11. Bootstrapped predictions of innovation readiness per city.

City	Mean Predicted Innovation Readiness Score %	MAPE
Budapest	50.90	3.2
Kalisz	35.19	1.5
Padua	44.67	1.5
Tel Aviv	40.59	0.0
Valencia	45.41	1.8
Almada	42.38	1.4
Arad	44.25	4.1
Gothenburg	56.11	1.9
Hertogenbosch	46.26	0.4
Ioannina	49.96	4.0
Mechelen	56.28	0.0
Minneapolis	49.02	2.6
Région Île-de-France	48.77	1.5
Transport for West Midlands	47.39	1.6
Braga	51.75	0.5
Palm Beach	44.88	1.0
Madrid	60.62	0.1
Thessaloniki	49.59	0.6
Guimarães	52.31	3.7
Bielefeld	49.10	1.1
College Station	46.20	1.3
Xian	46.45	1.3
Beijing [1]	48.65	1.3
Shanghai	40.10	3.3
Datong	35.92	2.1

[1] The Innovation Readiness score was calculated as the weighted average of the score of each individual participant and the weight of the participant (Table 1).

The innovation readiness scores derived from Table 11 present a heterogeneous landscape across various cities. Notably, cities such as Madrid, Gothenburg, and Mechelen demonstrate exemplary readiness for innovation, with respective scores of 60.62%, 56.11%, and 56.28%. These figures indicate a robust capacity for integrating and leveraging new technologies within these urban environments. Conversely, cities like Kalisz and Datong exhibit lower innovation readiness, with scores of 35.19% and 35.92%, respectively, suggesting potential areas for development in their innovation infrastructure. The study also reveals a spectrum of readiness levels among other cities. Budapest achieves a readiness score of 50.90%, indicating a moderate level of preparedness, while Padua and Tel Aviv are positioned at 44.67% and 40.59%, respectively. In the context of the United States, Minneapolis registers a readiness score of 49.02%, closely followed by Palm Beach at 44.88%. In Eastern Asia, the scores of Beijing and Shanghai, at 48.65% and 40.10%, respectively, reflect a varied state of innovation readiness within the region. The mean absolute percentage error (MAPE) associated with these scores, such as 3.2% for Budapest and 0.1% for Madrid, provides an additional layer of insight into the predictive accuracy of these assessments. This variability in MAPE values across different cities suggests a differential in prediction reliability, which is a crucial consideration for the robustness of the readiness scores. The analysis conducted at the city level highlights the diverse nature of innovation readiness emphasizing how local factors and regional dynamics shape a city's innovation landscape. The findings of this study lay a foundation for understanding and improving a city's ability to innovate. By creating a methodology to assess innovation readiness at the city level this research opens the doors for comprehensive data collection and refined predictive models in the future. As cities continue to develop their innovation ecosystems and more data becomes available these predictions can be further refined, offering insights for policymakers, urban planners, and innovation strategists seeking to foster and monitor innovation readiness. Therefore, this study makes a contribution to ongoing research and development, in the field of urban innovation readiness.

6. Conclusions and Discussion

In this study, we introduced a novel methodological framework designed to assess the impact of unobserved variables on the innovation readiness of cities. Employing this methodology on a dataset informed by the rankings of 30 stakeholders in 21 predictors of innovation readiness, we utilized Principal Component Analysis (PCA) to effectively distil the essence of these indicators. This allowed us to concentrate on the principal innovation markers that significantly shape a city's technological profile. To ascertain the predictive accuracy for each city's innovation readiness, we conducted a rigorous evaluation of both random and fixed-effects models, applying bootstrap Hausman tests to determine the most suitable model. The insights gleaned from the application of our methodology are encapsulated in the following points:

- A selective set of 7 out of 21 innovation indicators emerged as pivotal for predicting a city's innovation readiness.
- The random-effects model was identified as more adept at capturing the influence of unobserved variables on the innovation readiness of cities, with a nuanced application at the city level.
- The city-level analysis revealed a diverse range of innovation readiness scores, with cities like Madrid, Gothenburg, and Mechelen demonstrating high readiness, while others like Kalisz and Datong showed lower scores.
- The bootstrap Hausman test was employed to validate the model selection, ensuring robustness against the small sample size limitations.
- The random-effects model was ultimately chosen for its efficacy in reflecting the diverse impacts of unobserved variables across different cities.
- The limited dataset size may constrain the generalizability of the findings, but it sets a precedent for future research in this domain.
- Variability in MAPE values across cities, such as 3.2% for Budapest and 0.1% for Madrid, suggests differential prediction accuracies, potentially affecting the reliability of the readiness scores.

These findings provide a refined lens through which to view innovation readiness, offering valuable benchmarks for urban innovation policy and a foundation for future research in the domain. To this end, we must state that our study has observed a diverse range of cities. Each of these cities has its unique characteristics, policies, and regulations that could contribute to the differences in innovation readiness. If the random effects in our model turn out to be statistically significant, it would imply that there are unobserved heterogeneities between the cities that are not captured by the observed variables in our model. These discrepancies could indeed be attributed to various factors, including but not limited to policies, regulations, governance structures, cultural aspects, and economic conditions.

- Policies and Regulations: Different regions have different policies and regulations that can significantly impact the readiness of a city to innovate. For example, cities in the

European Union might be influenced by the overarching EU policies on innovation and smart city development, whereas cities in Eastern Asia and the United States might be subject to their national and local government policies [68].

- Governance Structures: The governance structures in place can also play a crucial role. Cities with more efficient and supportive governance structures might find it easier to adopt innovative solutions and transform into smart cities [69].
- Cultural Aspects: Cultural aspects, including the society's openness to change and innovation, can also contribute to discrepancies. Cities in regions with a strong culture of innovation and adoption of technology might be more ready to embrace smart city solutions [70].
- Economic Conditions: The economic conditions of the region can also impact the innovation readiness of a city. Cities in economically stable regions might have more resources to invest in smart city initiatives, whereas cities in less stable regions might face financial constraints [71].

The significance of this study hinges upon its role as a foundational step in understanding and enhancing the innovation capabilities of cities. By establishing a methodology for assessing innovation readiness at the city level, this research opens avenues for more comprehensive and targeted data collection. As more data become available and as cities continue to develop their innovation ecosystems, these predictions can be further refined, offering a powerful tool for policymakers, urban planners, and innovation strategists to foster and track progress in innovation readiness. This study, therefore, not only contributes to our current understanding but also paves the way for ongoing research and development in the field of urban innovation readiness.

Future research perspectives could involve the addition of new indicators to the existing set of 21 innovation indicators, such as emerging technological trends, social factors, and environmental considerations, while also assessing the impacts of critical disruption events (i.e., COVID-19) on the innovation readiness of cities.

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Conflicts of Interest: The authors declare that they have no competing interests.

Appendix A

The next table contains the questions and the indicative scales that were distributed through the survey to the participants.

Table A1. Innovation Readiness questions and their descriptive scores.

Question	Score 1	Score 2	Score 3	Score 4	Score 5
Q1	Non expanded collaboration. There are no horizontal processes applied in planning and procurement in relation to mobility.	Multiple departments are involved in decision making for mobility but there are important gaps and inefficiencies.	Supporting innovation taken up in mobility is a recognized priority and the cooperation of related organizations has started (i.e., intergovernmental partnerships, innovation hubs were organized, emphasizing local innovation capacity for mobility, etc). However, no practical result yet for innovative mobility in the city.	Clear interdepartmental strategy towards implementation of innovative mobility policy exists but its implementation in practice (i.e., achieving generalization of pilots of solutions emerging by companies) is limited. Lack of knowledge and tools, legal obstacles and fragmented market initiatives create problems.	Innovative procurement process is applied and a dedicated Department or authority is responsible for coordinating the actors in speedy adoption and assessment of innovative solutions. Innovation scale up in mobility is already happening in the city.
Q2	NO SUMP, NO SULP.	SUMP Under development. SULP not really advanced.	SUMP Plan in place and under implementation. Poor SULP activities.	Monitoring of SUMP implementation impact. Good SULP measures under assessment.	Full Public involvement for SUMP and SULP Linked with available finance and Political support. Many innovative solutions being part of the applied plan.
Q3	No engagement available	Multi stakeholder platform available but no regular operation nore emphasis in emerging innovative solutions support.	Upon specific issues the stakeholders were (are) mobilized and solution was found to problems.	6-month meetings among industry and public administration for solutions definitions and measures assessment	Citizens' engagement platforms and freight partnerships available and in operation in the city.
Q4	Initiatives are low. No funding available for innovative policymaking. City capacity is low in raise funding opportunities	City is participating in networks and initiatives for exploiting smart city including mobility dedicated funds with no results until now.	City or Regional funding is used for implementing small scale initiatives in mobility innovation. City welcomes private investments in emerging mobility solutions.	City is active in raising EU and national funds (participating in EU projects, smart cities mission) for test-bending innovative mobility solutions.	City has secured funding for wide development of integrated ICT and ITS enabled solutions for mobility. A District-wide infrastructure for smart city and smart mobility is under development.
Q5	There are no (inter)national synergies with institutes.	There are national synergies with institutes and universities.	There are national and limited international synergies with institutes and universities.	There are national and international synergies with institutes and universities.	City is part of international collaborations and synergies.
Q6	There are no research institutions (unis, research centers) available. City's socioeconomical factors are not affected by the operation of institutions. It is not a university city.	Existence of small research institutions in the city (e.g., universities with low/medium reputation)	Existence of universities and research institutions in the city (e.g., universities and institutions with high national reputation). City's socioeconomical factors are affected by the operation of institutions It is a university city	Unis and research institutions in the city (e.g., universities and institutions with high national reputation). Centre for start-ups/spin-offs foundations	institutes with high reputation, start up companies, research centres, technology parks. City's socioeconomical factors are dominated by the operation of institutions It is a strong university city.

Table A1. *Cont.*

Question	Score 1	Score 2	Score 3	Score 4	Score 5
Q7	Low Educational level of citizens (International standard classification of education (ISCED = 0–2)), aged population and low intern net access capacity.	Young people well educated and capable in electronic means, however important part of the population is considered disadvantages for digital services accessibility.	Medium Educational level of citizens (International standard classification of education (ISCED = 3–4)). Citizens are sufficiently competent in digital services.	Population in full transition towards digital competencies and good level of digital competence is already achieved.	High Educational level of citizens (International standard classification of education (ISCED = 5–8)) and society fully adapted to shared and electronic economy model.
Q8	The government processes are not digitized yet (no e-governance).	Digitization government processes are under development or limited available (e-Documents, open meetings).	Data centric governance (citizen or user can proactively explore the new possibilities inherent in strategically collecting and leveraging data).	Managed (Fully Digital). The organization has fully committed to a data-centric approach to improving government, and the preferred approach to innovation is based on open data principles.	Optimizing governance (smart/innovative). Digital innovation using open data is embedded deeply across the entire government, with buy in and leadership from the top policymakers.
Q9	Data are not open and easily accessible.	Data are open but not easily accessible.	Data are open and easily accessible.	Data are open, easily accessible and safe.	Data are open, easily accessible and safe and there is legal framework for ensuring data privacy.
Q10	No data collection or rare surveys.	Traditional methods of collecting data (e.g., survey).	Smart infrastructure for data collection.	Observatories of data.	City as a living lab (e.g., Digital Twins).
Q11	No data collection or rare surveys.	Traditional methods of collecting data (e.g., survey).	Smart infrastructure for data collection.	Observatories of data.	City as a living lab (e.g., Digital Twins).
Q12	No data available and open data framework do not exist.	Open data framework accepted.	Stakeholders cooperation (PPP for data and knowledge exchange).	Observatories with cloud based data storage. Advanced data analysis techniques.	Living Labs and/or Digital Twins available. Advanced data analysis techniques. Simulation techniques for testing new innovations.
Q13	No data available and open data framework do not exist.	Open data framework accepted.	Stakeholders cooperation (PPP for data and knowledge exchange).	Observatories with cloud based data storage. Advanced data analysis techniques.	Living Labs and/or Digital Twins available. Advanced data analysis techniques. Simulation techniques for testing new innovations.
Q14	Old Modal transport infrastructure and lack of intermodal infrastructure and services. Technology penetration in Transport and mobility operation is low.	Old Modal transport infrastructures and lack of intermodal infrastructure and services. Electronic services have been introduced allowing for integrated use of mobility services.	Infrastructure of traditional modes need modernization. Emerging new mobility services (shared electric, micro mobility) are operating in the city but physical and digital infrastructure for their operation is not sufficient.	The city has modern transport and mobility infrastructure and services. There still lack of framework for their integration and lack of capacity for transition to advanced innovation taken up (i.e., autonomous automated mobility, multimodal, digital mobility services, etc). Digital infrastructure related to mobility needs further improvement.	In the city the infrastructure and services for innovative mobility are advanced and well integrated. Digital multimodal management services will follow soon. Private and Public actors capacity and collaboration is sufficient for transitioning towards innovation scale up in mobility.

Table A1. *Cont.*

Question	Score 1	Score 2	Score 3	Score 4	Score 5
Q15	Old Modal transport infrastructure and lack of intermodal infra & services. Electronic services have been introduced allowing for integrated use of mobility services.	Infrastructure of traditional modes need modernization. Emerging new mobility services (shared electric , micro mobility) are operating in the city but physical & digital Infrastructure for their operation is not sufficient.	The city has modern transport & mobility infrastructure and services .There still lack of framework for their integration & lack of capacity for transition to advanced innovation taken up (ie autonomous automated mobility, multimodal digital mobility services, etc). Digital infrastructure related to mobility needs further improvement.	In my city the infrastructure & services for innovative mobility are advanced & well integrated. Digital Multimodal management Services will follow soon. Private and Public actors capacity & collaboration is sufficient for transitioning towards innovation scale up in mobility.	
Q16	Lack of knowledge & expertise	Specific People in public sector with know-how	Team of experts tha can be mobilized for guiding innovation taken up in mobility. The city applies innovative policy for mobility "based on analogy results" from other cities and knowledge gained through networks.	City has acess to specialized organizations and tools for guiding decision making on mobility solutions to be adopted, assessing the solutions impact and developing dedicated policies to strengthening innovation	Capacity is sufficient in the city ecosystem (ie operation of capacity building platform with the stakeholders) and competence is available (ie mobility competence center) for innovative mobility policy & solutions taken up.
Q17	Specific People in public sector with know-how	Team of experts that can be mobilized for guiding innovation taken up in mobility. The city applies innovative policy for mobility "based on analogy results" from other cities and knowledge gained through networks.	City has acess to specialized organizations and tools for guiding decision making on mobility solutions to be adopted, assessing the solutions impact and developing dedicated policies to strengthening innovation	Capacity is sufficient in the city ecosystem (ie operation of capacity building platform with the stakeholders) and competence is available (ie mobility competence center) for innovative mobility policy & solutions taken up.	
Q18	Car is the dominant mode of transport >40%. No available New Mobility Solutions (NMS) $\sim$0%. There is no noticeable change is active modes use for the past 3 years <30%. Low use of green vehicles <10%.	Available New Mobility Solutions (NMS). Car is still the dominant mode of transport. There is a small tendency to active modes use. Increased use of green vehicles $\sim$20%.	Increased use of active modes and New Mobility Solutions (NMS). Car use is decreased Green cars are increased.	Increased use of active modes and New Mobility Solutions (NMS). Car use is decreased Green cars are increased.	Increased use of active modes and New Mobility Solutions (NMS). Conventional cars are not used $\sim$0%. Green cars are increased $\sim$100%.

Table A1. *Cont.*

Question	Score 1	Score 2	Score 3	Score 4	Score 5
Q19	No existing synergies and non previous experience as pilot city in national or EU smart mobility program.	Rare synergies between companies for urban mobility innovations. Local very small implementation of collaborative business models in smart mobility.	Participation in EU funds and/or contribution as pilot city. Occasional synergies between companies for urban mobility innovations (no formal cooperation schemes).	Clusters between the companies in urban mobility of the city preparing and demonstrating collaborative business models and smart mobility solutions (MaaS under preparation,	Synergies with big innovators, (MaaS implemented, electric shared mobility in the city, multimodal digital management services in process, etc). Participation in EU funds and/or contribution as pilot city. Research results are generalized and extended and innovation acceleration activities are implemented.
Q20	No existing synergies and non previous experience as pilot city in national or EU smart mobility program.	Rare synergies between companies for urban mobility innovations. Local very small implementation of collaborative business models in smart mobility.	Participation in EU funds and/or contribution as pilot city. Occasional synergies between companies for urban mobility innovations (no formal cooperation schemes).	Clusters between the companies in urban mobility of the city preparing and demonstrating collaborative business models and smart mobility solutions (MaaS under preparation,	Synergies with big innovators, (MaaS implemented, electric shared mobility in the city, multimodal digital management services in process, etc). Participation in EU funds and/or contribution as pilot city. Research results are generalized and extended and innovation acceleration activities are implemented.
Q21	No high tech companies and start-ups	The city has few high-tech companies and no start-ups (e.g., 100 tech companies and <10 startups)	The city has high-tech companies and start-ups (e.g., 100 tech companies and 100 startups)	The city has high-tech companies and start-ups (e.g., 400 tech companies and 200 startups).	The city is hub for technology and innovation (Big innovators and Startups) (e.g., 2.2 k tech companies and 1.6 k startups).

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