



Unveiling Urban Smartness: Empirical Evidence from Italian Cities

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Abstract

Rapid urbanization poses significant challenges, making the development of smart cities a strategic imperative to foster sustainable economic growth and enhance urban competitiveness. Measurement and evaluation tools are useful ways to set goals and monitor the cities' progress toward smartness. There are few studies that examine the results achieved in the Italian context. This study introduces a robust multidimensional framework for evaluating the smartness of Italian cities, by providing the user with a step-by-step approach. The framework is composed of five stages: (i) a comprehensive literature review to develop a holistic understanding of smart cities and identify the criteria of the Multi-criteria decision-making (MCDM) process; (ii) the selection of indicators that serve as sub-criteria within the MCDM framework; (iii) weight assignment to each indicator by convening a panel of stakeholders and using the Analytical Hierarchy Process (AHP); (iv) normalization, assessment, and aggregation of results, producing final scores to rank cities based on their smartness levels, using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method; (v) sensitivity analysis to confirm the stability and validity of the obtained results. Indicator data are collected from the 21 Italian regional capital cities. Application of the framework has returned meaningful results, highlighting significant disparities between the sampled cities. The model provides policy makers, urban planners and researchers with a comprehensive and scalable tool to measure urban intelligence, identifying strengths and potential areas for urban improvement. This study is a key contribution to the ongoing efforts to transform urban environments into smarter, more efficient spaces that improve the well-being of citizens.

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1 Introduction

Although cities occupy only about 3% of the Earth's land, they are home to a rapidly growing proportion of the world's population, projected to reach 68% by 2050 (United Nations, 2019). This urban expansion brings significant economic challenges as cities are responsible for approximately 72% of global greenhouse gas emissions and are major consumers of the world's resources (European Commission, 2020). Indeed, the rapid urbanization growth has generated many challenges (i.e., overcrowding, degradation, pollution, energy shortage, traffic, land loss, social inequality, crime, healthcare issues, etc.) (Kabir et al. 2018; Kummitha and Crutzen 2017; Biagi and Meleddu 2024) due to the high density of the population, intensity of human activities, and inefficiency of the built environment (Bibri and Krogstie 2017). The "urban diseases" hinder cities' development, making them disordered and unorganized (Johnson 2008). In the search for solutions to these challenges, the smart city emerged as a new paradigm in the early 1990s, driven by technological advancements and the principles of sustainability (Gibson et al. 1992). The scientific literature has defined the smart city in several ways (Mora et al. 2017; Chourabi et al. 2012). Recent decades have seen a shift in the smart city paradigm: from a technology-driven focus on enhancing urban infrastructure efficiency to a broader approach that emphasizes the importance of people and soft infrastructures (Ahvenniemi et al. 2017; Stratigea et al. 2015). The smart city has acquired wide recognition thanks to extensive marketing promotion, political support and a large number of smartness initiatives embraced by many cities around the world (Masik et al. 2021). In this sense, policymakers are orchestrating joint efforts to encourage smart cities and related policies have drawn considerable interest and funding (Walravens and Ballon 2013). However, several barriers may hinder the successful implementation of smart city initiatives (Nam and Pardo 2011; Ruhlandt 2018). One of the main challenges is the lack of effective measurement and evaluation tools that can quantify and communicate cities' progress towards smartness (Dameri 2017). These tools are essential to set clear objectives and monitor the effectiveness of implemented policies, facilitating the demonstration of the added value of smart city initiatives to citizens and authorities (Caird et al. 2016). Without accurate evaluation, it is difficult to avoid the failure of initiatives and to optimize resource allocation. Evaluation tools provide crucial data for the design of targeted policies that effectively respond to specific urban challenges. By identifying a city's areas of weakness and strength, decision makers can allocate resources more effectively and introduce interventions that directly address the most pressing problems (Giffinger et al. 2010). This data-driven approach promotes more informed decision-making and can lead to the creation of more resilient and adaptable urban environments that better meet the needs of their communities. Urban rankings emerge as useful tools to comparatively assess the attractiveness of cities, stimulating competitiveness and continuous

improvement through the documentation of successes and areas of weakness (Komninos et al. 2019). Despite the growing interest in smart cities, research on measuring and evaluating their outcomes remains limited, indicating a field still in development but with significant potential for the future (Sharifi 2019). Previous research on smart city evaluations has shown that existing frameworks often fall short, providing incomplete information that is usually focused on specific urban dimensions or geographic contexts. Moreover, the indicators commonly used are not scalable or replicable, and there is a notable lack of accessible, necessary data. This has left a significant gap in holistic assessments of smart city initiatives, particularly among Italian cities. To address these shortcomings, this study proposes a new scalable model to assess the smartness of cities using a systemic approach validated in Italian regional capitals. The model is designed with two primary objectives: (i) to provide policy makers with a versatile tool that is tailored for strategic discussions and can be adapted to various urban scales and complexities; (ii) to evaluate the urban smartness of Italian cities by using an extended definition. The assessment framework was developed with Multi-Criteria Decision-Making (MCDM) methods through a structured five-phase process. The first phase involved an extensive literature review to establish a comprehensive understanding of what constitutes a smart city. This foundational work helped identify the criteria needed for the MCDM process. In the second phase, specific indicators were chosen as sub-criteria within the MCDM framework. The third phase focused on assigning weights to each indicator, which were obtained through consultations with a group of stakeholders using the Analytical Hierarchy Process (AHP). During the fourth phase, the process of normalization, evaluation and aggregation of the results was performed using the TOPSIS method. This method produced final scores that effectively ranked cities based on their overall intelligence levels. The fifth and final stage included a sensitivity analysis to ensure the stability and validity of the results. The indicator data for this in-depth analysis were carefully collected from all 21 Italian regional capitals, including the autonomous provinces of Trento and Bolzano. The remainder of the paper is structured as follows. Section 1 presents the background on the smart city, while Sect. 2 reviews previous literature on the evaluation tools. Section 3 describes the research methodologies adopted. Sections 4 and 5 present and discuss the analysis results. Finally, Sect. 6 concludes, highlighting research implications, limitations and directions for future studies.

2 Literature Review: Definitions and Metrics for Smart Cities

The scientific literature does not provide a unanimous consensus regarding the smart city idea or of what actions should be put in place to make cities smarter places (Hollands 2020; Majd et al. 2025). There are several definitions of smart cities to be found in literature and they differ greatly due to the multiple entities involved and the many functions they perform (Mora et al. 2017). Two main research trends can be identified. According to the first, technology is the major driver in the urban transformation process, enabling the creation of a smart city (Harrison and Donnely, 2011). Several technologies (e.g., Cloud and Edge computing, Cyber-Physical Systems, Sensory devices and Internet of Things, Big Data, Artificial Intelligence, Machine and Deep

learning, Wireless Sensor Networks, Blockchain, G technology, etc.) are incorporated to help with the establishment of an effective connected network of devices and entities within a smart city (Ahad et al. 2020). These technologies are used to maximize the efficiency of hard urban infrastructure, including transportation, communications, waste, energy and water. However, the univocal focus on the technological aspects is often criticized by those who argue that technology alone cannot “save” cities from urbanization challenges (Chatterton 2019; Yang et al. 2024). The second more extensive research trend is based on a people-centered perspective and recognizes the key role of soft infrastructure (e.g., citizen engagement, data, social innovation, knowledge economy, etc.) (Giffinger et al. 2007a, b; Yu et al. 2024). Following this trend, a city is smart if investments in traditional and modern infrastructures (ICT) and human and social capital promote sustainable development and a higher quality of life, by adopting participatory governance approaches (Caragliu et al. 2013). Indeed, smart city initiatives aim to optimize existing infrastructure, provide more efficient services to citizens, increase collaboration among different actors and encourage innovative business models in both private and public sectors (Marsal-Llacuna et al. 2015).

Smart city initiatives require political support and are a key focus in global policy aimed at boosting urban prosperity, innovation and competitiveness. The United Nations supports these strategies through its Sustainable Development Goal 11 and the New Urban Agenda, promoting the use of ICT to create sustainable, inclusive urban environments (Barbieri et al. 2025; Sharifi et al. 2024). The European Union integrates smart city concepts to encourage economic growth, environmental sustainability and social equity, leveraging technology and social capital to enhance local governance and community ties, as highlighted in the European Green Deal (Akuraju et al. 2020; Angelidou 2016; European Commission, 2020). Projects such as the Covenant of Mayors, Smart Cities Marketplace, Scalable Cities, CIVITAS, URBACT and the Green Digital Charter are supported by extensive funding opportunities and frameworks provided by platforms like the European Innovation Partnership on Smart Cities and Communities (EIP-SCC). However, smart city initiatives can falter without alignment with the city’s strategic needs and good governance practices. A successful smart city strategy must leverage the area’s specific strengths and weaknesses, emphasizing coordinated initiatives that combine technological solutions with holistic, both top-down and bottom-up, approaches to urban development (Angelidou 2014; Meijer and Bolivar, 2016; Mora et al. 2019). Moreover, the true value of these initiatives should be measured based on their direct and indirect benefits to the urban population (Meijer 2015; Neuroni et al. 2019; Barrutia et al. 2022). However, the implementation of smart city projects often encounters obstacles such as risk aversion, inadequate economic incentives, and conflicting stakeholder interests, which can result in high costs and limited success (Sørensen and Torfing 2011; De Vries et al. 2016; Crosby et al. 2017; Cabral et al. 2019; Nam and Pardo 2011; Ruhlandt 2018). To mitigate these risks, it is crucial to employ robust measurement and evaluation tools to monitor and guide the city’s progress towards its smart city goals.

Several previous scientific and institutional studies that introduce indicator frameworks for the evaluation and ranking of smart cities are available. In many cases, they mainly focus on specific smart city themes, e.g., environmental sustainability (Girardi

and Temporelli 2017; Abu-Rayash and Dincer 2025), energy provision (Papastamatiou et al. 2017), transportation systems (Debnath et al. 2014), public safety (De Marco 2015), housing conditions (Susanti et al. 2016) and technological solutions (Hodson et al. 2023; Diaz-Sarachaga 2025). Moreover, some studies have shown that indicators are often not representative of all smart city's dimensions (Huovila et al. 2019; Ahvenniemi et al. 2017). In addition, existing approaches have been criticized for focusing more on implementation processes and investment metrics than on outcomes and impacts of smart city programs (Caird and Hallett 2019).

Other studies attempt to propose extensive smart city evaluation frameworks but apply them to geographic contexts that are too specific (e.g., Chinese cities) (Shen et al., 2018) or too general (e.g., cities around the world) (Cohen 2014). In such cases, the indicators used may not be suitable for the European context or not comparable because of the different social, economic, natural and institutional environments in which they are applied. Based on features of the European context, Giffinger et al. (2007a, b) provided a complete set of guidelines to assess and rank European cities under six dimensions, i.e., smart economy, smart people, smart governance, smart mobility, smart environment and smart living. However, this model was applied to indicators referring to different and very dated periods. More recently, the need for uniform intelligence monitoring in European cities has also led to EU initiatives, such as CITYkeys (Bosch et al. 2017), which evaluate smart cities across five dimensions, namely people, planet, prosperity, governance and propagation. In Italy, two major smart city ranking projects are implemented annually: ICity Rank, promoted by ICity Lab of Forum PA and ANCI (National Association of Italian Municipalities), and Smart City Index, promoted by Ernst & Young. In the latest edition, ICity Rank focuses on the digital transition of Italian provincial capital cities (ForumPA 2023), while Smart City Index emphasizes the human smart city approach (Ernst & Young, 2022). Therefore, both seem to lack a holistic assessment of the smart city concept. Some scholars have also engaged in defining theoretical comprehensive assessment tools specifically for Italian cities. For instance, Lombardi et al. (2011) proposed a triple-helix network model to classify smart city performance in five urban dimensions (governance, economy, human capital, living and environment), while Dall'O' et al. (2017) provided a set of indicators consistent with the ISO 37,120 standard among six dimensions (economy, environment, energy, governance, living, mobility, people). However, the former has not yet been applied to any urban context, while the latter has only been applied to three small and medium-sized cities in northern Italy. Existing frameworks find poor application in the practice of Italian cities due to the limited scalability and replicability of the indicators, and also often struggle due to the scarce quantity of updated data on an urban scale. As a result, there is little evidence of studies that assess the smartness of Italian cities comprehensively on a national basis, allowing for appropriate policymaking based on emerging territorial gaps and specific characteristics of the national context. Finally, many assessment frameworks adopt methodologies that assign equal importance to all indicators and do not consider the use of sensitivity techniques, which are necessary to anticipate future changes and manage uncertainties caused by the evolutionary dynamics of urban systems (Marsal-Llacuna et al. 2015).

In summary, previous studies have several evident limitations: (i) they fail to comprehensively assess smart city performance across different urban sizes and indicator types (input, process, output, outcome, impacts); (ii) they carried out practical applications of theoretical models in geographic contexts which are often either too limited or too vast; (iii) they use indicators that often lack available, scalable and replicable data; (iv) they apply scientific methodologies that do not adequately differentiate the importance of various indicators; (v) they do not provide a thorough and nationally-focused assessment of smartness in Italian cities. This study addresses these gaps by offering a refined approach that enhances data scalability, indicator relevance and the scope of application.

3 Methodological Design

This section proposes a methodological model to measure the smartness level of cities, capable of incorporating the systemic effects of technological development on the environmental, social, and economic dimensions. As illustrated in Fig. 1, the

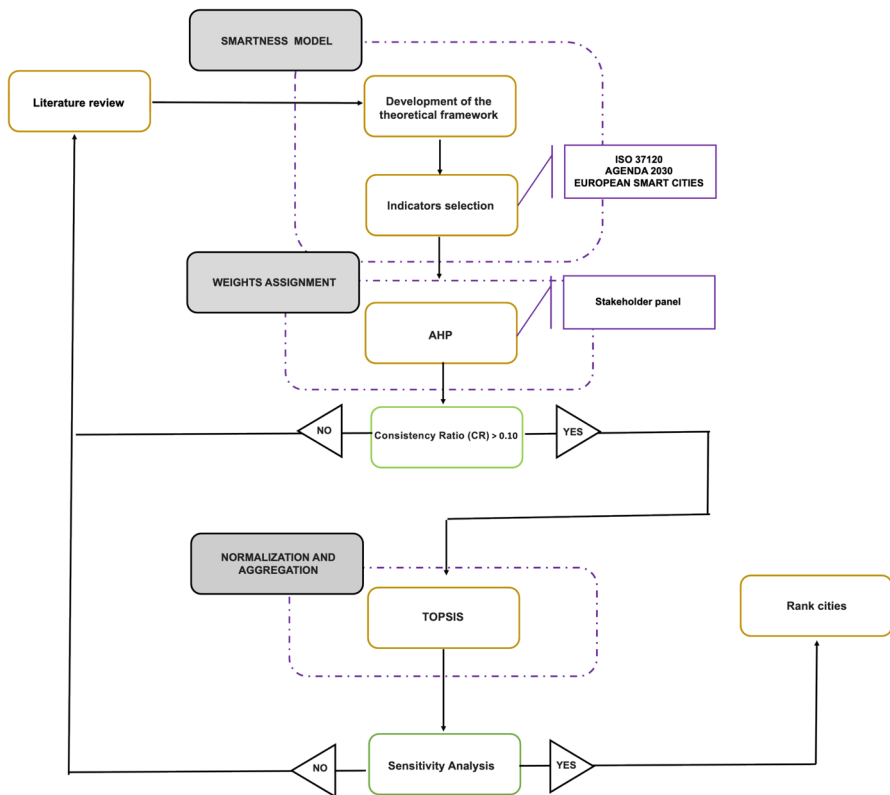


Fig. 1 Methodological design

framework follows a structured process consisting of five sequential phases.

The first phase focuses on conducting a thorough review of the existing literature to establish a strong theoretical foundation for understanding smart cities. During this stage, the main criteria for the Multi-Criteria Decision-Making (MCDM) process are carefully selected. These criteria reflect the essential dimensions of a smart city, such as technological innovation, environmental sustainability, economic development and quality of life. The selection is based on their consistent appearance in the literature and their acknowledged significance in shaping the concept of urban smartness (Sect. 3.1).

Based on the theoretical model, the second phase involves the careful selection of indicators that act as sub-criteria within the MCDM framework. These indicators are explicitly chosen to measure the specific criteria identified in the previous phase, ensuring a precise evaluation of each dimension. Importantly, the indicators are derived from secondary data sources, extracted from various databases, which are thoroughly documented in Sect. 3.2. By aligning the indicators with global objectives, such as the 2030 Agenda for Sustainable Development, and following international standards like ISO 37,120, we ensure that the selected indicators are both contextually appropriate and globally standardized. This approach allows for consistent and reliable comparisons across different urban contexts, enhancing the robustness and validity of the analysis (Sect. 3.3).

The third phase involves assigning weights to the selected indicators using the Analytical Hierarchy Process (AHP). In this step, a panel of experts conducts pairwise comparisons to assess the relative importance of each indicator. AHP translates these qualitative judgments into quantitative values, assigning weights that reflect the significance of each indicator in evaluating smart city performance. This process ensures a structured and objective determination of weights, grounded in expert knowledge (Sect. 3.3).

In the fourth phase, the TOPSIS method is applied to evaluate and rank the cities based on their smartness scores. Unlike a single composite indicator that might obscure how each dimension contributes to overall performance, TOPSIS allows us to keep these dimensions distinct. This makes it possible to assess, for example, how environmental sustainability, mobility, technological innovation or social inclusion each contribute individually to the smartness of a city. Specifically, TOPSIS ranks cities according to their proximity to a defined ideal, considering both positive (maximization) and negative (minimization) factors, thus providing a balanced and detailed view of performance across all dimensions (Sect. 3.4).

The final phase conducts a sensitivity analysis to verify the robustness and stability of the results. This analysis examines how changes in indicator weights or input data might affect the final rankings of cities (Sect. 3.5).

In summary, the proposed model follows a logical, step-by-step approach: (i) it establishes a theoretical basis, (ii) selects relevant indicators, (iii) assigns weights through a systematic process, (iv) evaluates city performance using a robust ranking method and (v) validates the results through sensitivity analysis.

3.1 Theoretical Framework

The analysis of literature on the smart city theme serves as a starting point for defining a systematic approach that allows for the measurement of urban smartness, considering its broader definition. For this purpose, Giffinger's model (2007) has been selected. This model views smart cities as ecosystems of stakeholders engaged in a process of sustainable transition and improvement of the quality of life within a given territory (urban or not), utilizing digital technologies to facilitate related actions. It is widely recognized and adopted globally by both academics and practitioners, and suggests a categorization of Smart City application fields into six domains: Smart Economy, Smart Mobility, Smart Governance, Smart Environment, Smart People and Smart Living.

Smart Economy involves fostering sustainable economic competitiveness and innovation, with a focus on sustainable entrepreneurship and economic models that integrate local and global ecosystems.

Smart Mobility aims to develop a modern and sustainable transportation system that caters to the diverse needs of all users, including citizens, workers and tourists, with a focus on improving local and international accessibility and sustainable transport systems.

Smart Governance emphasizes the importance of making public actions more open, inclusive and transparent, integrating various stakeholders in decision-making processes and utilizing new technologies for participatory governance. For instance, a city might introduce an online platform that enables citizens to vote on local issues, participate in discussions and contribute to the decision-making process on urban development projects. This digital tool could allow for real-time feedback and collaborative problem-solving, aligning with the principles of participatory governance. By doing so, the city not only democratizes its decision-making but also fosters a sense of community engagement and ownership among its residents.

Smart Environment addresses sustainable management of natural and heritage resources, including green and renewable energy production, sustainable food production and technology optimization for resource management.

Smart People corresponds to an inclusive society using new technologies and innovation to improve knowledge management and social capital. This includes the level of and access to education and training while also advocating tolerance and taking advantage of growing multi-culturality and links between local and global ecosystems.

Smart Living aims to improve the quality of life and safety in the city through the set of services offered, changes in citizens' lifestyles, social cohesion and tourist attractiveness. This also concerns everything related to e-health, culture, social services and the availability of better-quality housing services.

Within the MCDM model, the six dimensions identified above represent the criteria for evaluating the smartness of cities. These dimensions are not mutually exclusive, they interact with one another to create a holistic and sustainable urban environment that leverages digital technologies for the benefit of its citizens and the environment.

3.2 Indicators Selection and Data Management

The criteria selected in the previous section provided the basis for identifying detailed indicators, which function as sub-criteria within the Multi-Criteria Decision Making (MCDM) framework. In capturing the extensive nature of the smart city concept, we selected a total of 72 indicators, with 12 indicators dedicated to each of the six dimensions defined by Giffinger's model. These indicators represent secondary data, sourced from various databases. A comprehensive list of these indicators, including their descriptions, units of measurement, reference periods and geographical levels, is conveniently provided in Table 1. Projects like ICity Rate, Smart City Index, ISO 37,120, and the United Nations' 2030 Agenda for Sustainable Development were crucial references. Additionally, action plans from the European Covenant of Mayors were considered, especially those targeting sustainability and energy consumption reductions, reflecting the ethos of Smart City development. The methodical process of indicator selection was informed by well-established projects and protocols with an emphasis on sustainability and standardization. These indicators as sub-criteria are intended to measure how well cities perform across the smart dimensions defined in phase one. The alignment with global objectives ensures that the selected indicators are applicable in diverse urban contexts, allowing for meaningful comparisons and benchmarking internationally. This refined set of indicators thus captures a wide range of city functionalities and attributes, from economic resilience and environmental sustainability to governance transparency and social inclusivity, thereby ensuring a holistic evaluation of urban smartness.

All indicators refer to the year 2021, as it represents the most recent, fully updated reference year for the majority of the selected indicators. In cases where only regional (NUTS2) or provincial (NUTS3) data were available—rather than municipal-level data—an assumption of approximate uniformity was adopted, following established approaches found in the literature (Dall'O' et al. 2017; Sotirelis et al. 2021). This step allowed the inclusion of important indicators (e.g., net income inequality, coverage for ultra-fast internet access) that would otherwise have been excluded due to lack of city-specific information. Throughout the data collection process, missing values were carefully checked: indicators with over 10% missing data were considered for exclusion unless deemed critical for capturing a particular dimension. Where necessary, missing values below this threshold were handled through regional-average imputation (NUTS2). Potential outliers were investigated via boxplot-based analyses, and observations lying beyond the 95th/5th percentile were winsorized to reduce the distorting effects of extreme values while retaining the overall data structure (Tukey 1977; Dixon and Tukey 1968; Barnett and Lewis 1994).

3.3 Assigning Weights to Indicators Through the AHP

For the discernment of criteria and sub-criteria within AHP model, we convened an expert panel comprising 20 seasoned professionals with deep roots in urban development. The panel included an even mix of municipal policymakers - mayors and administrators - and academics with a profound grasp of economic policy, applied

Table 1 Description of the indicators/sub-criteria used in the model

Dimensions/criteria	Indicators/sub-criteria	Description	Unit of measure	Year	Territorial level	Source
Economy	EC1 <i>Unemployment rate</i>	People in the working-age population who are without a job and actively seeking employment. The indicator provides insights into the health of the labor market, the availability of job opportunities and overall economic conditions. It is calculated by dividing the number of unemployed individuals by the total labor force	Percentage values	2021	NUTS 3	ISTAT
	EC2 <i>Inactivity rate</i>	People in the working-age population who are neither part of the active labor force nor employed nor actively seeking employment. The indicator provides insights into the labor force participation and potential barriers to employment. It is calculated by dividing the number of inactive individuals by the total working-age population	Percentage values	2021	NUTS 3	ISTAT
	EC3 <i>Employment rate</i>	People in the working-age population who are employed. The measure indicates economic stability, economic participation and opportunities for income generation. It is calculated by dividing the number of employed individuals by the total labor force	Percentage values	2021	NUTS 3	ISTAT
	EC4 <i>Taxable income</i>	Average amount of taxable income received by each taxpayer. The indicator provides insights into individuals' financial situations, income distribution and tax contributions. It is calculated by dividing the total taxable income of a given population by the number of taxpayers contributing to that income	Euro	2021	NUTS 3	ISTAT

Table 1 (continued)

Dimensions/criteria	Indicators/sub-criteria	Description	Unit of measure	Year	Territorial level	Source
EC5	<i>Net income inequality</i>	Inequality in the distribution of income after taking into account taxes, transfers and other government interventions, indicating economic disparities among the population. It is calculated by dividing the total equivalent income received by 20% of the population with the highest income by that received by 20% of the population with the lowest income	Pure number - Ratio of incomes	2021	NUTS 2	ISTAT
EC6	<i>Poverty or social exclusion risk</i>	Probability of individuals experiencing at least one of the following conditions: (1) living in households at risk for poverty; (2) living in households experiencing severe material and social deprivation; (3) living in households with low labor intensity. It is calculated by dividing the number of these individuals by the total resident population	Percentage values	2021	NUTS 2	ISTAT
EC7	<i>Real GDP annual growth rate</i>	Annual percentage change in real gross domestic product (GDP) per capita, adjusted for inflation, indicating the overall economic well-being of a specific geographic area. It is calculated by dividing the annual growth rate of real GDP by the total resident population	Percentage values	2021	NUTS 2	ISTAT
EC8	<i>Entrepreneurship rate</i>	Level of entrepreneurial activity, which gives information on innovation, economic dynamism and job creation potential within a specific geographic area. It is calculated by dividing the number of active businesses by the total resident population	Percentage values	2021	NUTS 3	ISTAT
EC9	<i>Local unit density</i>	Concentration of local units of active enterprises within a specific geographical area. The measure indicates the level of economic development and attractiveness of a territory and is calculated by dividing the number of local units by the total municipal area	Values per km ²	2021	NUTS 3	ISTAT

Table 1 (continued)

Dimensions/criteria	Indicators/sub-criteria	Description	Unit of measure	Year	Territorial level	Source
Environment	EC10	<i>Specialization in high-tech sectors</i>	Concentration of activities in high-tech sectors, indicating the level of innovation and competitiveness of a specific geographical area. It is calculated by dividing the number of employees in the high-tech manufacturing and service sectors by the total number of employees in local units	Percentage values	2021	NUTS 3 ISTAT
	EC11	<i>Firms with innovative product and process activities</i>	Enterprises that engage in innovative activities related to the development of products and/or production processes, which are considered drivers of economic and technological progress. It is calculated by dividing the number of such enterprises by the total number of enterprises	Percentage values	2021	NUTS 2 ISTAT
	EC12	<i>Firms with at least 10 employees for web sales</i>	Enterprises with at least 10 employees engaged in online sales through websites or e-commerce platforms to end customers. The indicator reflects the level of adoption of digital technologies for business purposes and is calculated by dividing the number of such enterprises by the total number of enterprises	Percentage values	2021	NUTS 2 ISTAT
Environment	EN1	<i>Air pollution</i>	Presence of harmful or excessive concentrations of substances in the atmosphere resulting from human activities, which have adverse effects on human health, ecosystems, climate and air quality. It is calculated as the number of exceedances of the daily prescribed limit value for PM10 (50 µg/m ³)	Number of days	2021	NUTS 3 ISTAT

Table 1 (continued)

Dimensions/criteria	Indicators/sub-criteria	Description	Unit of measure	Year	Territorial level	Source
EN2	<i>Noise pollution</i>	Excessive or unwanted sounds that disturb the normal functioning of human activities or the environment, leading to hearing impairment, sleep disturbances, stress, communication difficulties and reduced quality of life. It is calculated by dividing the number of noise controls in which at least one exceedance of the limits was detected by the total resident population	Values per 100,000 inhabitants	2021	NUTS 3	ISTAT
EN3	<i>Municipal waste production</i>	Amount of solid waste generated by households, businesses, institutions and other sources within an urban area. The indicator helps assess waste generation trends, identify waste management strategies and promote sustainable practices. It is calculated by dividing municipal waste generated by the total resident population	Kg per inhabitant	2021	NUTS 3	ISTAT
EN4	<i>Separate collection of municipal waste</i>	Practice of sorting and collecting different types of materials (paper, plastic, glass, metals, organics) separately at the source, contributing to efficient waste management and environmental protection. It is calculated by dividing the amount of separately collected municipal waste by the total municipal waste collected	Percentage values	2021	NUTS 3	ISTAT
EN5	<i>Landfilling of municipal waste</i>	Amount of municipal solid waste disposed in landfills, posing serious environmental risks including groundwater contamination, soil pollution, greenhouse gas emissions and habitat destruction. It is calculated by dividing the amount of municipal waste sent to landfills by the total amount of waste collected	Percentage values	2021	NUTS 2	ISPRA

Table 1 (continued)

Dimensions/criteria	Indicators/sub-criteria	Description	Unit of measure	Year	Territorial level	Source
EN6	<i>Electricity from renewable sources</i>	Electricity generated from renewable energy sources (solar, wind, hydro, biomass and geothermal energy), which are considered environmentally friendly and sustainable. It is calculated by dividing the kilowatt-hours of electricity generated from renewable sources by the total resident population	Percentage values	2021	NUTS 3	Terma S.p.A.
EN7	<i>Photovoltaic systems density</i>	Concentration of photovoltaic systems in a specific geographical area, which indicates the use of solar energy technology for the production of electricity. It is calculated by dividing the number of functioning photovoltaic systems by the total municipal area	Values per 10 km ²	2021	NUTS 3	ISTAT
EN8	<i>Soil Consumption</i>	Conversion of natural soil for human settlements, infrastructure or economic activity, which can lead to land degradation and loss of biodiversity. It is calculated by dividing the consumed soil by the sum of the consumed, unconsumed and unclassified soil	Percentage values	2021	NUTS 3	ISTAT
EN9	<i>Protected areas density</i>	Territory designated and managed for the conservation and protection of natural ecosystems, biodiversity and cultural heritage. It is calculated by dividing the surface area of protected areas by the total municipal area	Percentage values	2021	NUTS 3	ISTAT
EN10	<i>Urban green density</i>	Concentration of green spaces (parks, gardens, trees, etc.) within urban areas, which allow for the improvement of air quality, temperature regulation, recreational opportunities and aesthetic value. It is calculated by dividing the area of green areas by the total municipal area	Percentage values	2021	NUTS 3	ISTAT

Table 1 (continued)

Dimensions/criteria	Indicators/sub-criteria	Description	Unit of measure	Year	Territorial level	Source
ENI	<i>Urban garden availability</i>	Accessibility of gardens (fruit, vegetables, aromatic herbs, flowers or ornamental plants) within urban environments, which contribute to food security and healthy habits. It is calculated by dividing the urban garden area by the total municipal area	Percentage values	2021	NUTS 3	ISTAT
	<i>Water loss</i>	Volume of water lost or unaccounted in the water service distribution system, which reduces the efficiency of water supply systems. It is calculated as the difference between the water injected into municipal drinking water distribution networks and the water supplied for authorized uses	Percentage values	2021	NUTS 2	ISTAT
	<i>Local public transport offer</i>	Seat-km offered by local public transport (buses, trams, trains and subways), which helps reduce congestion, pollution and dependence on private vehicles. It is calculated by dividing the product of the kilometers traveled in the year by all public transport vehicles and the average capacity of the vehicles supplied by the total resident population	Values per inhabitants	2021	NUTS 3	ISTAT
MO2	<i>Regular users of local public transport</i>	Individuals who regularly use local public transport services for their travel or travel needs, contributing to sustainability. It is calculated by dividing the number of people aged 14 and over who use public transport several times a week by the total resident population	Percentage values	2021	NUTS 2	ISTAT
MO3	<i>Speed of local public transport</i>	Average speed at which public transport vehicles travel their routes within a city, indicating the efficiency and quality of service. It is calculated by dividing the kilometers traveled by local public transport by the time taken to travel them	Kilometers per hour	2021	NUTS 3	ISTAT

Table 1 (continued)

Dimensions/criteria	Indicators/sub-criteria	Description	Unit of measure	Year	Territorial level	Source
MO4	<i>Vehicle density</i>	Motorization level of a specific area, indicating traffic congestion and road safety. It is calculated by dividing the number of vehicles in circulation by the total municipal area	Values per km ²	2021	NUTS 3	ISTAT
MO5	<i>Cars with lower emission standards</i>	Cars with emissions standards below the Euro 4 class, which contribute to air pollution and environmental degradation. It is calculated by dividing the number of such cars (euro class 0–3) by the total number of cars in circulation	Percentage values	2021	NUTS 3	ISTAT
MO6	<i>Buses with lower emission standards</i>	Buses used for local public transport with emissions standards below the Euro 4 class, which contribute to air pollution and environmental degradation. It is calculated by dividing the number of such buses (euro class 0–3) by the total number of buses in circulation	Percentage values	2021	NUTS 3	ISTAT
MO7	<i>Taxi licenses</i>	Permits issued by local authorities that allow individuals or companies to operate taxis within an area, ensuring compliance with safety standards, quality of service and fare regulations. It is calculated by dividing the number of active taxi licenses by the total resident population	Values per 10,000 inhabitants	2021	NUTS 3	ISTAT
MO8	<i>Vehicles for shared mobility services</i>	Vehicles available for car sharing, scooter sharing, bike sharing and electric micro mobility services, which allow for more efficient use of transport infrastructure. It is calculated by dividing the number of such vehicles by the total resident population	Values per 10,000 inhabitants	2021	NUTS 3	ISTAT

Table 1 (continued)

Dimensions/criteria	Indicators/sub-criteria	Description	Unit of measure	Year	Territorial level	Source
MO9	<i>Cycle paths density</i>	Extension of dedicated cycling lanes within an urban area, providing safe spaces, improving public health and contributing to environmental sustainability. It is calculated by dividing the km of cycle paths present by the total municipal area	Percentage values	2021	NUTS 3	ISTAT
MO10	<i>Pedestrian areas availability</i>	Availability of designated pedestrian zones within urban areas, designed to improve pedestrian safety and promote active mobility. It is calculated by dividing the surface area of pedestrian areas present by the total resident population	Percentage values	2021	NUTS 3	ISTAT
MO11	<i>Road accident rate</i>	Road accidents within a specific area, which indicate the effectiveness of the road policies adopted. It is calculated by dividing the number of road accidents with injuries to people by the total resident population	Values per 1.000 inhabitants	2021	NUTS 3	ISTAT
MO12	<i>Pedestrian fatality rate</i>	Pedestrian deaths due to road accidents, which provides insights into the risks and safety level of pedestrians. It is calculated by dividing the number of pedestrians killed in road accidents and the total resident population	Values per 100.000 inhabitants	2021	NUTS 3	ISTAT
G01	<i>Women and political presentation</i>	Participation of women in political positions, which indicates progress towards gender equality in governance. It is calculated by dividing the number of women elected to the City Council by the total number elected to the City Council	Percentage values	2021	NUTS 3	ISTAT

Table 1 (continued)

Dimensions/criteria	Indicators/sub-criteria	Description	Unit of measure	Year	Territorial level	Source
GO2	<i>Women in decision-making bodies</i>	Participation of women in decision-making bodies, which ensures diverse and inclusive decision-making processes. It is calculated by dividing the number of women in Municipal Board by the total number of individuals in Municipal Board	Percentage values	2021	NUTS 3	ISTAT
GO3	<i>Young people and political representation</i>	Involvement and representation of younger people in political institutions, which indicates progress towards intergenerational equity in governance. It is calculated by dividing the sum of the ages of the municipal councilors as of 31 December by the total number of municipal councilors	Years	2021	NUTS 3	ISTAT
GO4	<i>Young people in decision-making bodies</i>	Involvement and representation of younger people in decision-making bodies, which promotes youth empowerment and the inclusivity of governance processes. It is calculated by dividing the sum of the ages of the Municipal Board member as of 31 December by the total number of Municipal Board members	Years	2021	NUTS 3	ISTAT
GO5	<i>Electoral participation</i>	Level of engagement of eligible voters in the electoral process, indicating the health of democracy and the legitimacy of elected officials. It is calculated by dividing the number of people who voted in the first round (or single round) in the municipal elections by the total number of people entitled to vote	Percentage values	2021	NUTS 3	ISTAT

Table 1 (continued)

Dimensions/criteria	Indicators/sub-criteria	Description	Unit of measure	Year	Territorial level	Source
GO6	<i>Digitalization of public services</i>	Level of use of technologies for the provision of public services to citizens, that enhance service delivery and reduce bureaucracy. It is calculated as the number of online services available to citizens with a high level of digitalization, i.e. which allow the entire process relating to the service to be concluded online	Whole number	2021	NUTS 3	ISTAT
GO7	<i>Mobile applications for citizens</i>	Availability of mobile applications (for smartphones, PDAs, tablets) developed by government authorities or agencies to provide free services and information to citizens for some urban sectors (culture, tourism, waste, mobility, safety, etc.), ensuring citizens involvement and administrative efficiency. It is calculated as the number of available apps	Whole number	2021	NUTS 3	ISTAT
GO8	<i>Training in the e-Government area</i>	Training programs offered to government employees in the area of e-Government, enabling staff with the necessary skills and knowledge to effectively utilize digital tools and enhance service delivery. It is calculated by dividing the number of municipal employees who have attended training courses in the e-Government area by the total number of municipal employees	Percentage values	2021	NUTS 2	ISTAT
GO9	<i>Participatory planning</i>	Urban planning that actively involves stakeholders (through public meetings, workshops, surveys, focus groups, online platforms, etc.), ensuring transparency, accountability and inclusivity. It is calculated as the number of public interventions in different sectors (urban planning, cultural activities, mobility, etc.), implemented through the engagement and sharing of the program by all interested parties	Whole number	2021	NUTS 3	ISTAT

Table 1 (continued)

Dimensions/criteria	Indicators/sub-criteria	Description	Unit of measure	Year	Territorial level	Source	
	GO10	<i>Administrative transparency</i>	Degree to which government institutions and processes are transparent and accessible to the public, promoting government openness, integrity and good governance practices. It is calculated by the amount of open data available to citizens	Percentage values	2021	NUTS 2	ISTAT
	GO11	<i>Coverage for ultra-fast internet access</i>	Availability and accessibility of ultra-fast internet services within a specific geographic area, that enhances digital connectivity and improves the quality of life for residents. It is calculated by dividing the number of households residing in an area served by a very high-capacity new generation connection (FTTH) by the total of resident households	Percentage values	2021	NUTS 3	ISTAT
	GO12	<i>Families with internet access</i>	Households that have access to the internet at home, which inform policies to bridge the digital divide and promote digital inclusion and literacy initiatives. It is calculated by dividing the number of families with Internet access at home by the total of resident families	Percentage values	2021	NUTS 2	ISTAT
People	PE1	<i>Students' literacy skills</i>	Proficiency of students in reading, writing and comprehension, which help to develop targeted interventions to support struggling students and ensure that all students acquire the essential literacy skills. It is calculated as the average score obtained in the functional literacy tests of students in third classes of lower secondary school	Average number	2021	NUTS 3	Servizio Nazionale Valutazione Invalsi

Table 1 (continued)

Dimensions/criteria	Indicators/sub-criteria	Description	Unit of measure	Year	Territorial level	Source
PE2	<i>Students' numerical skills</i>	Proficiency of students in mathematical concepts, reasoning and problem-solving, which help to develop targeted interventions to support struggling students and ensure that all students acquire the essential mathematical skills. It is calculated as the average score obtained in the numerical competence tests of students in third classes of lower secondary school	Average number	2021	NUTS 3	Servizio Nazionale Valutazione Invalsi
PE3	<i>Incidence of tertiary qualification</i>	Population who has obtained tertiary qualifications, such as bachelor's degrees, master's degrees or doctoral degrees, assessing the educational attainment levels within a population. It is calculated by dividing the number of people aged 25–49 who have obtained a tertiary level qualification (Isced 5, 6, 7 or 8) by the total number of people aged 25–49	Percentage values	2021	NUTS 3	ISTAT
PE4	<i>Researchers</i>	Researchers employed in research and development (R&D) activities expressed in terms of full-time equivalent, helping to assess capacity for innovation and scientific productivity. It is calculated by dividing the number of researchers from various scientific disciplines engaged in the conception of new knowledge, products, processes, methods and systems by the total resident population	Values per 10,000 inhabitants	2021	NUTS 2	ISTAT

Table 1 (continued)

Dimensions/criteria	Indicators/sub-criteria	Description	Unit of measure	Year	Territorial level	Source
PE5	<i>Knowledge workers</i>	Workers with specialized skills, education, or expertise in fields such as information technology, research and development, engineering, finance and consulting, driving innovation, competitiveness and organizational performance in knowledge-based economies. It is calculated by dividing the number of employed with university education (Isced 6,7 and 8) in scientific-technological professions (Isco 2–3) by the total number of employed	Values per 100 workers	2021	NUTS 2	ISTAT
PE6	<i>Participation in ongoing training</i>	Extent to which individuals engage in continuous learning and professional development activities throughout their careers, promoting career advancement and improving job performance. It is calculated by dividing the number of people aged 25–64 who participated in education and training activities in the 4 weeks before the interview by the total population aged 25–64	Percentage values	2021	NUTS 3	ISTAT
PE7	<i>Early exit from the education and training system</i>	Individuals who leave the education system before completing their intended level of education or training, which could have limited employment opportunities and lowered earning potential. It is calculated by dividing the number of people aged 18–24 with at most a lower secondary school diploma, who do not possess regional professional qualifications obtained in courses lasting at least 2 years and not included in an education path or education, by the total population aged 18–24	Percentage values	2021	NUTS 2	ISTAT

Table 1 (continued)

Dimensions/criteria	Indicators/sub-criteria	Description	Unit of measure	Year	Territorial level	Source
PE8	<i>Not in Education, Employment or Training</i>	Individuals who are not engaged in education, employment, or training activities, which represents a vulnerable group at risk for social exclusion, economic insecurity and disengagement. It is calculated by dividing the number of these people aged 15–29 by the total population aged 15–29	Percentage values	2021	NUTS 3	ISTAT
PE9	<i>Digital skills</i>	Competencies that enable individuals to effectively use digital technologies to access, understand, create, communicate and collaborate in digital environments. It is calculated by dividing the number of people aged 16–74 who have at least basic digital skills for all 5 domains identified by the “Digital competence framework 2.0” by the total population aged 16–74	Percentage values	2021	NUTS 2	ISTAT
PE10	<i>Internet banking operations</i>	Banking transactions conducted by individuals through online banking platforms, indicating the level of financial and digital skills of population. It is calculated by dividing the number of people who have carried out online banking operations (internet banking) in the last 3 months by the total resident population	Percentage values	2021	NUTS 2	ISTAT
PE11	<i>Online purchases for private use</i>	Extent to which individuals engage in online shopping to purchase goods or services for personal or household consumption, helping to assess e-commerce trends and the digital economy’s growth. It is calculated by dividing the number of people who ordered/purchased goods or services on the internet in the last 3 months by the total resident population	Percentage values	2021	NUTS 2	ISTAT

Table 1 (continued)

Dimensions/criteria	Indicators/sub-criteria	Description	Unit of measure	Year	Territorial level	Source
Living	PE12 <i>Local institutions websites or apps usage</i>	Frequency of interactions between individuals and websites or mobile applications developed by local institutions, indicating the digital engagement of citizens. It is calculated by dividing the number of aged 14 and over who have used websites or apps of the Public Administration or public service providers in the last 12 months by the total resident population aged 14 and over	Percentage values	2021	NUTS 2	ISTAT
	L11 <i>Library availability</i>	Availability of libraries within a specific geographical area, which reflects a community's commitment to literacy, education and lifelong learning and contributes to social inclusion, community cohesion and cultural enrichment. It is calculated by dividing the number of libraries registered in the National Library Registry by the total resident population	Values per 100,000 inhabitants	2021	NUTS 3	ISTAT
	L12 <i>Historical-cultural heritage availability</i>	Availability of historical and cultural heritage sites within a specific geographical area, which reflects cultural richness, identity and heritage preservation efforts. It is calculated by dividing the number of museums, galleries, archaeological sites and monuments by the total resident population	Values per 100,000 inhabitants	2021	NUTS 3	ISTAT
Living	L13 <i>Tourist intensity</i>	Tourist activity experienced within a specific geographical area, indicating the level of tourism development, economic impact and carrying capacity of a destination. It is calculated by dividing the number of tourists at accommodation establishments by the total resident population	Values per 1,000 inhabitants	2021	NUTS 2	ISTAT

Table 1 (continued)

Dimensions/criteria	Indicators/sub-criteria	Description	Unit of measure	Year	Territorial level	Source
L14	<i>Housing cost overload</i>	Households that spend a high percentage of their income on housing expenses, leading to financial stress and housing instability. It is calculated by dividing the number of people living in families where the total cost of the home in which they live represents more than 40% of the net family income by the total resident population	Percentage values	2021	NUTS 2	ISTAT
L15	<i>Healthy life expectancy at birth</i>	Average number of years that a newborn is expected to live in good health, without experiencing significant disability or illness, reflecting overall population health and well-being	Years	2021	NUTS 2	EUROSTAT
L16	<i>Death from tumors, diabetes, cardiovascular and respiratory diseases</i>	Probability of deaths attributed to specific diseases associated with lifestyle factors, environmental exposures, genetic predisposition and access to healthcare. It is calculated by dividing the number of people who died between the ages of 30 and 69 from cancer, diabetes, cardiovascular and respiratory diseases by the total resident population aged 30–69	Percentage values	2021	NUTS 2	ISTAT
L17	<i>Beds in ordinary hospitalization</i>	Available beds specifically designated for ordinary hospitalization within public and private healthcare facilities, such as general hospitals or medical centers, which help to efficiently and effectively manage patient flow. It is calculated by dividing the number of beds by the total resident population	Values per 10,000 inhabitants	2021	NUTS 2	ISTAT
L18	<i>Doctor availability</i>	Number of qualified medical doctors available to provide healthcare services, ensuring timely access to healthcare by dividing the number of doctors by the total resident population	Values per 1,000 inhabitants	2021	NUTS 2	IQVIA ITALIA

Table 1 (continued)

Dimensions/criteria	Indicators/sub-criteria	Description	Unit of measure	Year	Territorial level	Source
LJ9	<i>Voluntary killings</i>	Killing where the perpetrator acts with premeditation and intention, but without external coercion or duress, helping to assess levels of violence, crime and public safety within a society. It is calculated by dividing the number of voluntary killings by the total resident population	Values per 100,000 inhabitants	2021	NUTS 2	Ministero dell'Interno
LJ10	<i>Violence against women</i>	Various forms of physical, sexual, psychological or economic violence perpetrated against women, typically within the context of intimate partner relationships or domestic settings, which represent a pervasive human rights violation and a significant public health issue. It is calculated by dividing the number of female victims of violence reported to the public helpline against violence and stalking 1522 by the total female resident population	Values per 100,000 women inhabitants	2021	NUTS 2	ISTAT
LJ11	<i>Crowding in prisons</i>	Level of overcrowding within prisons, leading to substandard living conditions, increased tensions and challenges in delivering effective rehabilitation and reintegration programs. It is calculated by dividing the number of prisoners by the total of available places defined by the regulatory capacity	Percentage values	2021	NUTS 3	ISTAT
LJ12	<i>Duration of civil proceedings</i>	Length of time it takes to resolve civil legal disputes through judicial proceedings, which helps to assess the efficiency, accessibility and effectiveness of the judicial system. It is calculated as the average duration in days of proceedings settled in ordinary courts	Days	2021	NUTS 2	Ministero della Giustizia

economics and public economics. Their collective insights ensured that the theoretical constructs were grounded in pragmatic urban policy and academic rigor.

The AHP method was developed by Thomas Saaty for analyzing complex problems in different decision-making scenarios (Saaty 1980). The AHP generally consists of three main steps, namely, decomposition of the problem, comparative judgment and generation of priorities (Janic and Reggiani 2002). The main aim of the AHP method is to develop a hierarchical structure with the main goal at the top level, the criteria or attributes at the second level, and the alternatives at the bottom level.

No priorities were generated for this framework, as the AHP method can only be used to define weights. Therefore, the first step in the AHP was aimed at constructing pairwise comparison matrix $P_{AHP} (w*w)$ with the criteria aligned in the first row and the first column in the same order, as seen in Table 2.

The same procedure was applied to the sub-criteria (indicators) belonging to each criterion.

In the second step, the group of experts decided the comparative relative importance of sub-criteria and criteria, to perform judgement for pairwise comparisons. This step leveraged the diversity of our expert panel, blending the tactical acumen of urban administrators with the strategic foresight of economists. By employing a standardized scale of relative importance - ranging from “Equal Importance” to “Extremely High” - the experts appraised the significance of one element in relation to the others, instilling the model with a calibrated spectrum of priority weights (Table 3). Criteria and sub-

Table 2 Pairwise comparison matrix

	Criterion 1	Criterion 2	–	Criterion 6
Criterion 1	1	1/a	–	1/b
Criterion 2	a	1	–	1/c
–	–	–	1	–
Criterion 6	b	c	–	1

Table 3 AHP intensity of importance table

Linguistic term	Intensity scale
Equal importance	1
Very low	2
Low	3
Fairly low	4
Medium	5
Fairly high	6
High	7
Very high	8
Extremely high	9

criteria (indicators) with the same relative importance were assigned 1. The others were given a number from 2 to 9, and reciprocals were assigned to the same pair of criteria and sub-criteria (indicators) when the order was reversed, as seen in Table 3.

These values represent the relative importance of one alternative when compared to others keeping one criterion or sub-criterion (indicator) fixed (Singh and Malik 2014).

A normalized element was then obtained using Eq. (1).

$$r_{ij} = \frac{P_{ij}}{\sum_{i=1}^w e_{ij}} \quad (1)$$

where p_{ij} is an element of the original matrix P_{AHP} (w^*w) and the denominator is the summation of all the elements in the respective column. Finally, the weight vector was obtained using Eq. (2).

$$w_j = \frac{1}{N \sum_{i=1}^N r_{ij}} \quad (2)$$

where $w_j \geq 0$, $\sum_{j=1}^n w_j$, and N is the number of alternatives (Singh and Malik 2014).

Subsequently, the weights obtained from the comparison between the sub-criteria (indicators) were multiplied by the weights of the respective sub-criteria and criteria, thus obtaining the final evaluations. These weights represent the consensus of the panel, translating qualitative assessments into quantitative measures. Through a series of computations, we arrived at a vector that embodies the collective wisdom of the experts, distilling it into actionable data points that reflect the relative importance of each sub-criterion within the hierarchy.

To ensure the consistency of these comparisons and to evaluate the reliability of the derived weights, a Consistency Ratio (CR) was computed (Saaty 1980). The CR assessed the probability that the matrix judgments were randomly generated. In our methodology, the CR is calculated for each matrix. If the CR is less than or equal to 0.1, the level of consistency is considered acceptable, indicating that the matrix is sufficiently consistent to proceed with the derived weights in the decision-making process. If the CR exceeds 0.1, the judgments are revisited to address possible inconsistencies, and the pairwise comparison process is repeated to improve coherence (Apostolou 2002; Chu and Liu 2002).

3.4 Normalization, Aggregation and Final Rank Using the TOPSIS Method

In order to obtain the final smartness score for each city considered, corresponding to the model alternatives, the TOPSIS method was used. Developed by Yoon and Hwang (1981), TOPSIS is a MCDM method that ranks the alternatives according to the geometric distances of the alternatives from the positive-ideal and negative-ideal solutions. “Best” is the alternative with the smallest distance from the ideal solution and the largest distance from the anti-ideal solution. The creators of the method declared the relative closeness of the alternative to the ideal solution as the overall measure of the quality of the alternative, taking into account its distance from the ideal and anti-ideal solution at the same time. The main advantages of this method are its clarity,

coherence, accuracy, adaptability and mathematical plainness (Krstić, 2022; Coluccia et al., 2024).

In the present study, after establishing the problem structure (definition of goal, alternatives, criteria and sub-criteria) (Sects. 3.1 and 3.2) and calculating the weight to be attributed to each sub-criterion (Sect. 3.3), the following steps were followed:

Step 1 create the initial decision matrix X (3), whose elements are the performance x_{ij} of alternatives i in relation to sub-criteria j , i.e., the vector magnitudes which correspond to the evaluations of alternatives in relation to indicators.

$$X = [x_{ij}]_{n \times m} \tag{3}$$

where m is the total number of alternatives and n is the total number of indicators.

Step 2 construct the normalized decision matrix R (4), by normalizing the alternatives performance using Eq. (5)

$$R = [r_{ij}]_{n \times m} \tag{4}$$

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad \forall i = 1, \dots, m, \quad j = 1, \dots, n \tag{5}$$

where r_{ij} is the normalized value of x_{ij} , i.e., the evaluation of the alternative i , in relation to the sub-criterion j .

Step 3 obtain the weighted normalized decision matrix V (6) using Eq. (7), which multiplies the elements at each column of the R matrix by their associated weights w_j .

$$V = [v_{ij}]_{n \times m} \tag{6}$$

$$v_{ij} = w_j \cdot r_{ij} \quad \forall i = 1, \dots, m, \quad j = 1, \dots, n \tag{7}$$

Step 4 determine the positive-ideal and negative-ideal solutions. The positive-ideal solution derives from Eq. (8) for benefit indicators and Eq. (9) for cost indicators.

$$v_j^+ = \max \{ v_{1j}, \dots, v_{mj} \}, \quad j \in B \tag{8}$$

$$v_j^+ = \min \{ v_{1j}, \dots, v_{mj} \}, \quad j \in C \tag{9}$$

Instead, the negative-ideal solution $V^- = (v_1^-, \dots, v_n^-)$ derives from Eq. (10) for benefit indicators and Eq. (11) for cost indicators:

$$v_j^- = \min \{ v_{1j}, \dots, v_{mj} \}, \quad j \in B \quad (10)$$

$$v_j^- = \max \{ v_{1j}, \dots, v_{mj} \}, \quad j \in C \quad (11)$$

Step 5 calculate the separation measures, i.e., the n -dimensional Euclidean distance of each alternative from the positive-ideal and negative-ideal solutions, following Eq. (12) and Eq. (13), respectively.

$$S_i^+ = \text{dist}(A_i, V^+) = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} \quad i = 1, \dots, m \quad (12)$$

$$S_i^- = \text{dist}(A_i, V^-) = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad i = 1, \dots, m \quad (13)$$

Step 6 Calculate the relative closeness coefficient of each alternative to the positive-ideal solution by adopting Eq. (14)

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^+} \quad (14)$$

where $0 \leq C_i^* \leq 1$.

Relative closeness is the decision-making rule in TOPSIS: the higher the coefficient value, the better the alternative's performance.

Step 7 rank the alternatives according to decreasing values of the relative closeness coefficient C_i .

3.5 Sensitivity Analysis

Sensitivity analysis within MCDM aims to test the robustness and reliability of results by varying the importance (weights) assigned to criteria and examining whether such changes can lead to different choices or rankings among alternatives. Such an analysis can reveal the degree to which each criterion influences the final decision and helps identify the most critical criteria for the outcome. By adjusting weights and observing the resulting shifts in alternative rankings, decision-makers can also understand potential trade-offs and prioritize criteria more effectively. This practice ensures that decision-making remains defensible and justifiable even when facing uncertainties or

differing stakeholder priorities. It acts as a check against subjective biases in weight allocation and supports the development of more balanced and resilient decisions (Krstić, 2022).

In this study, sensitivity analysis was carried out through 21 additional distinct scenarios to understand the robustness of the results against changes in the importance given to certain indicators. The approach targets smart city dimensions individually for the initial 18 scenarios, i.e., 3 scenarios were created for each the 6 dimensions (criteria). In each dimension, the weight of the most significant indicator (or the most significant indicators, having the same weight) was adjusted unevenly, decreasing corresponding weight by 15%, 30% and then 45%. Consequently, the reduced weight was equally distributed across remaining indicators for each scenario, ensuring that the sum of the weights remained equal to 1. This is a targeted examination to observe the influence of perceived crucial factors within each separate domain.

In contrast, the final 3 scenarios expanded this approach across the entire spectrum of dimensions. Here, the weights of the three most influential indicators from all 72 were modified (12 indicators for 6 dimensions). Instead of limiting the weight change within each dimension, the scenarios investigated the outcome when the importance of the most significant indicators across all dimensions were recalibrated by 15%, 30%, and 45%. This broader approach evaluates the impact of the most crucial sub-criteria overall, rather than within their respective domains (Miškić et al. 2023).

By examining the results across varied scenarios, the study aims to validate the decision-making process, ensuring that the conclusions drawn about cities smartness are not overly dependent on a few indicators and that the methodology is resilient to changes in expert judgment and priorities (Triantaphyllou et al., 1997; Stević et al. 2020).

4 Implementation of the Multidimensional Evaluation Framework

This section demonstrates the application of the multidimensional framework within the Italian context, illustrating how the assessment procedure can be used. By providing a practical example, it aims to assist users (scholars, policymakers and citizens) in interpreting the results and drawing conclusions about the level of smartness in Italian cities. It also identifies potential areas for improvement within the evaluated dimensions.

Italy, with its pronounced regional disparities, administrative decentralization and distinctive governance structure, offers a significant context for analyzing systemic approaches to urban smartness. Unlike countries characterized by more uniform development patterns, Italy demonstrates substantial socio-economic, infrastructural and technological heterogeneity across its regions (Boffa et al. 2016; Ferrara and Nisticò, 2019). These disparities present both challenges and opportunities, making Italy particularly suited for evaluating the robustness and adaptability of the proposed multidimensional framework.

From a scientific perspective, despite the growing body of literature on smart cities, limited research has addressed urban smartness in contexts as heterogeneous and decentralized as Italy, where governance is distributed across multiple administrative

levels (Chinetti 2023). This gap underscores the importance of developing a framework tailored to such complexities while contributing transferable insights applicable to other nations with similarly diverse socio-economic landscapes.

From a practical perspective, Italy's administrative decentralization and the pivotal role of regional capital cities provide an optimal setting for exploring tailored urban policies (Di Liddo et al. 2018; Dameri et al. 2019). The regional diversity in resources and socio-economic conditions demands customized strategies that leverage local strengths and address specific challenges. In this regard, Italian cities function as a laboratory for evaluating innovative governance approaches and sustainability-driven initiatives, offering lessons that are both context-specific and globally relevant (Chinetti 2023).

In this study, a sample of 21 cities was selected to support the analysis of urban smartness performance. In particular, Italian regional capitals, including the autonomous provinces of Trento and Bolzano, were chosen because of the effective accessibility and quality of the data needed. The definition of this group of 21 cities ensures that they provide valid and comparable information. The geolocation of the Italian cities sample is shown in Fig. 2.

The next step was to collect data for the 72 indicators listed in Table 1, which fall under the six dimensions of the assessment framework. Data for the 21 sample cities, referring to the year 2021, were obtained from diverse authoritative and recognized sources, including primarily ISTAT, supplemented by EUROSTAT, ISPRA, IQVIA ITALIA, Servizio Nazionale Valutazione Invalsi, Ministero dell'Interno and Ministero della Giustizia. The majority of indicators (62.5%) were locally defined (NUTS-3). To



Fig. 2 Italian cities sample

include broader contextual information beyond the city level, some indicators based on regional or provincial data (NUTS 2) were also included. This was particularly relevant in the cases of limited urban data availability.

Subsequently, weights were assigned using the AHP method, as explained in Sect. 3.3. Table 4 presents criteria and sub-criteria weights (dimensions and indicators of the evaluation framework). It also illustrates final weights, obtained by multiplying criteria and respective sub-criteria weights, and the resulting ranking.

After obtaining final weights, the TOPSIS method was used to aggregate and rank the data. The relative closeness coefficient (C_i) was computed to assess the smartness performance of the 21 sample cities. Table 5 shows the cities' rankings, based on C_i , respectively from the perspectives of smart economy, smart environment, smart mobility, smart governance, smart people and smart living. Instead, Table 6 illustrates the overall ranking of cities' smartness, considering all dimensions together. These results are also presented graphically in Fig. 3.

Finally, a sensitivity analysis was performed to verify the reliability and stability of the obtained results, as explained in Sect. 3.5. The rankings resulting from the varied scenarios were methodically compared with those derived from the baseline scenarios. Figure 4 offers a comprehensive visual representation of the sensitivity analysis outcomes. The appendix provides the overall scores and rankings for each weight scenario of the sensitivity analysis to enhance the transparency and credibility of the findings. Further explanations are available in the next paragraph.

5 Results and Discussion

5.1 Smartness Performance Across the Six Different Evaluation Dimensions

5.1.1 Smart Economy

Looking at the ranking of smart economy across the 21 sample cities, it can be observed that the top performers are Bolzano, Trento, Milano and Bologna, while the worst are Napoli, Campobasso, Potenza, L'Aquila and Catanzaro. Note that the first cities are all located in Northern Italy, while the last are in Southern Italy. This finding confirms the persistent territorial disparities in economic development, with southern territories experiencing a decline in their economic weight (Accetturo et al. 2024) and northern cities generally outperforming their southern counterparts in terms of industry, innovation and infrastructure (Barbieri et al. 2025). However, the average value of the C_i in smart economy is relatively low (0.406), indicating the general poor performance of Italian cities in this urban dimension. The exceptionally good performance of leading cities is predominantly driven by (i) a higher employment rate in high-tech industries, (ii) a higher number of firms engaging in innovative product or process development, and (iii) a higher number of firms adopting digital technologies for business purposes. Indeed, technological tools and innovation in general play a crucial role in enhancing firm performance and driving economic progress. Previous scientific literature has amply demonstrated that they lead to increased productivity

Table 4 Weights obtained using AHP method

Criteria	Weights	Sub-criteria	Weights	Final weights	Rank
EC	0.089	EC1	0.039	0.004	58
		EC2	0.039	0.004	58
		EC3	0.039	0.004	58
		EC4	0.064	0.006	48
		EC5	0.104	0.009	37
		EC6	0.104	0.009	37
		EC7	0.064	0.006	48
		EC8	0.025	0.002	68
		EC9	0.025	0.002	68
		EC10	0.166	0.015	24
		EC11	0.166	0.015	24
		EC12	0.166	0.015	24
EN	0.274	EN1	0.155	0.043	4
		EN2	0.019	0.005	52
		EN3	0.026	0.007	43
		EN4	0.155	0.043	4
		EN5	0.155	0.043	4
		EN6	0.155	0.043	4
		EN7	0.04	0.011	31
		EN8	0.04	0.011	31
		EN9	0.026	0.007	43
		EN10	0.064	0.018	20
		EN11	0.064	0.018	20
		EN12	0.099	0.027	11
MO	0.154	MO1	0.168	0.026	13
		MO2	0.105	0.016	22
		MO3	0.107	0.017	22
		MO4	0.021	0.003	61
		MO5	0.046	0.007	43
		MO6	0.168	0.026	13
		MO7	0.032	0.005	53
		MO8	0.174	0.027	12
		MO9	0.069	0.011	33
		MO10	0.069	0.011	33
		MO11	0.021	0.003	61
		MO12	0.021	0.003	61
GO	0.274	GO1	0.03	0.008	39

Table 4 (continued)

Criteria	Weights	Sub-criteria	Weights	Final weights	Rank
		GO2	0.02	0.006	50
		GO3	0.03	0.008	39
		GO4	0.02	0.006	50
		GO5	0.045	0.012	27
		GO6	0.168	0.046	1
		GO7	0.168	0.046	1
		GO8	0.069	0.019	18
		GO9	0.107	0.029	9
		GO10	0.107	0.029	9
		GO11	0.168	0.046	1
		GO12	0.069	0.019	18
PE	0.154	PE1	0.078	0.012	28
		PE2	0.078	0.012	28
		PE3	0.078	0.012	28
		PE4	0.03	0.005	54
		PE5	0.03	0.005	54
		PE6	0.021	0.003	61
		PE7	0.047	0.007	41
		PE8	0.047	0.007	41
		PE9	0.204	0.031	8
		PE10	0.13	0.020	15
		PE11	0.13	0.020	15
		PE12	0.13	0.020	15
LI	0.056	LI1	0.048	0.003	65
		LI2	0.048	0.003	65
		LI3	0.048	0.003	65
		LI4	0.031	0.002	70
		LI5	0.078	0.004	56
		LI6	0.078	0.004	56
		LI7	0.19	0.011	33
		LI8	0.19	0.011	33
		LI9	0.127	0.007	43
		LI10	0.123	0.007	47
		LI11	0.021	0.001	71
		LI12	0.021	0.001	71

Table 5 Relative closeness coefficients results and rankings of the 21 Italian cities, based on each smart city evaluation dimension individually

Economy			Environment			Mobility		
Rank	Cities	C_i	Rank	Cities	C_i	Rank	Cities	C_i
1	Bolzano	0.688	1	Bolzano	0.803	1	Milano	0.720
2	Trento	0.573	2	Aosta	0.738	2	Venezia	0.487
3	Aosta	0.541	3	Trento	0.609	3	Roma	0.485
4	Milano	0.534	4	Catanzaro	0.578	4	Torino	0.459
5	Bologna	0.516	5	Potenza	0.537	5	Firenze	0.443
6	Roma	0.498	6	L'Aquila	0.524	6	Trento	0.393
7	Ancona	0.497	7	Trieste	0.513	7	Cagliari	0.386
8	Torino	0.446	8	Bologna	0.507	8	Bolzano	0.380
9	Firenze	0.402	9	Cagliari	0.501	9	Trieste	0.369
10	Trieste	0.379	10	Perugia	0.483	10	Bologna	0.351
11	Venezia	0.363	11	Bari	0.480	11	Aosta	0.337
12	Palermo	0.361	12	Napoli	0.464	12	Ancona	0.322
13	Bari	0.350	13	Genova	0.453	13	Palermo	0.313
14	Cagliari	0.339	14	Firenze	0.452	14	Bari	0.305
15	Perugia	0.335	15	Roma	0.444	15	Perugia	0.290
16	Genova	0.329	16	Ancona	0.432	16	Genova	0.270
17	Napoli	0.307	17	Milano	0.425	17	Potenza	0.256
18	Campobasso	0.287	18	Venezia	0.408	18	L'Aquila	0.212
19	Potenza	0.277	19	Campobasso	0.407	19	Napoli	0.162
20	L'Aquila	0.267	20	Torino	0.400	20	Catanzaro	0.128
21	Catanzaro	0.243	21	Palermo	0.387	21	Campobasso	0.089

Governance			People			Living		
Rank	Cities	C_i	Rank	Cities	C_i	Rank	Cities	C_i
1	Milano	0.692	1	Trento	0.888	1	Aosta	0.675
2	Roma	0.430	2	Bologna	0.852	2	Bolzano	0.627
3	Torino	0.422	3	Milano	0.828	3	Trieste	0.581
4	Genova	0.421	4	Roma	0.795	4	Trento	0.577
5	Bari	0.405	5	Firenze	0.769	5	Firenze	0.511
6	Catanzaro	0.398	6	Venezia	0.752	6	Campobasso	0.505
7	Venezia	0.393	7	Trieste	0.751	7	Genova	0.502
8	Trento	0.370	8	Bolzano	0.703	8	Potenza	0.475
9	Trieste	0.343	9	Torino	0.687	9	Perugia	0.474
10	Bologna	0.337	10	Genova	0.677	10	Venezia	0.461

Table 5 (continued)

Governance			People			Living		
Rank	Cities	C_i	Rank	Cities	C_i	Rank	Cities	C_i
11	Palermo	0.325	11	Aosta	0.660	11	Ancona	0.458
12	Ancona	0.320	12	Perugia	0.652	11	L'Aquila	0.458
13	Napoli	0.319	13	Ancona	0.618	13	Milano	0.409
14	Bolzano	0.318	14	Cagliari	0.572	14	Bologna	0.389
15	Perugia	0.290	15	L'Aquila	0.524	15	Catanzaro	0.386
16	Firenze	0.266	16	Campobasso	0.350	16	Torino	0.377
17	Cagliari	0.250	17	Potenza	0.330	17	Cagliari	0.338
18	L'Aquila	0.232	18	Bari	0.256	18	Palermo	0.337
19	Campobasso	0.155	19	Catanzaro	0.169	19	Bari	0.296
20	Potenza	0.144	20	Napoli	0.115	20	Roma	0.284
21	Aosta	0.115	21	Palermo	0.060	21	Napoli	0.215

Table 6 Relative closeness coefficients results and overall smartness ranking of the 21 Italian cities

Rank	Cities	C_i
1	Milano	0.560
2	Bolzano	0.525
3	Trento	0.481
4	Aosta	0.469
5	Roma	0.448
6	Bologna	0.436
7	Trieste	0.435
8	Catanzaro	0.430
9	Bari	0.422
10	Torino	0.419
11	Venezia	0.418
12	Genova	0.415
13	Cagliari	0.406
14	Firenze	0.397
15	L'Aquila	0.389
15	Perugia	0.389
17	Ancona	0.375
18	Napoli	0.374
19	Potenza	0.365
20	Palermo	0.350
21	Campobasso	0.299

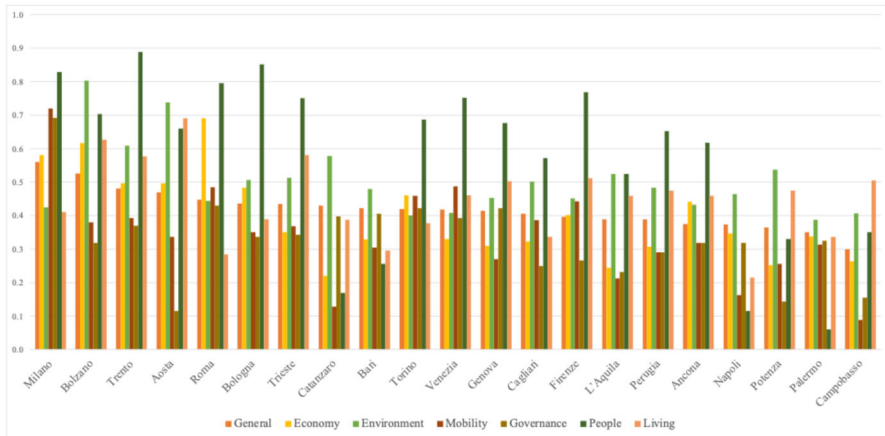


Fig. 3 Graphical visualization of MCDM process results

(Brynjolfsson and McAfee 2014), enhanced competitiveness (Porter 1990), facilitated market access (Bakos 1998) and creation of skilled jobs.

5.1.2 Smart Environment

Bolzano, Aosta, Trento, Catanzaro and Potenza lead the smart environment ranking, while Milano, Venezia, Campobasso, Torino and Palermo bring up the rear. Leading cities exhibit superior performance in terms of air quality, which is a crucial indicator for evaluating urban environmental sustainability and also affects public health (Saini et al. 2020). In addition, they excel in separate collection practices for different material types (paper, plastic, glass, metals, organic materials), contributing to efficient waste management and resource circularity (Salmenperä et al. 2021). Finally, their higher scores are also driven by their commitment to producing and distributing electricity from renewable energy sources (solar, wind, hydro, biomass and geothermal energy), characterized by low greenhouse gas emissions, abundance and renewability (Panwar et al. 2011). It is noteworthy that the top three performing cities are all located in the Alps, confirming that the geographical and climatic characteristics typical of alpine regions may foster environmental sustainability (Barbieri et al. 2025). Furthermore, larger cities are found in the lower half of the ranking, confirming that the higher concentration of people and activities in big cities generates greater anthropogenic pressure, leading to problems such as waste management, loss of biodiversity, soil, water and air pollution (Zhou et al. 2022). Despite policy efforts in recent years to promote smart environment initiatives, the average value of the C_i is 0.502, indicating that further joint efforts are still required in Italy to foster more sustainable and circular cities.

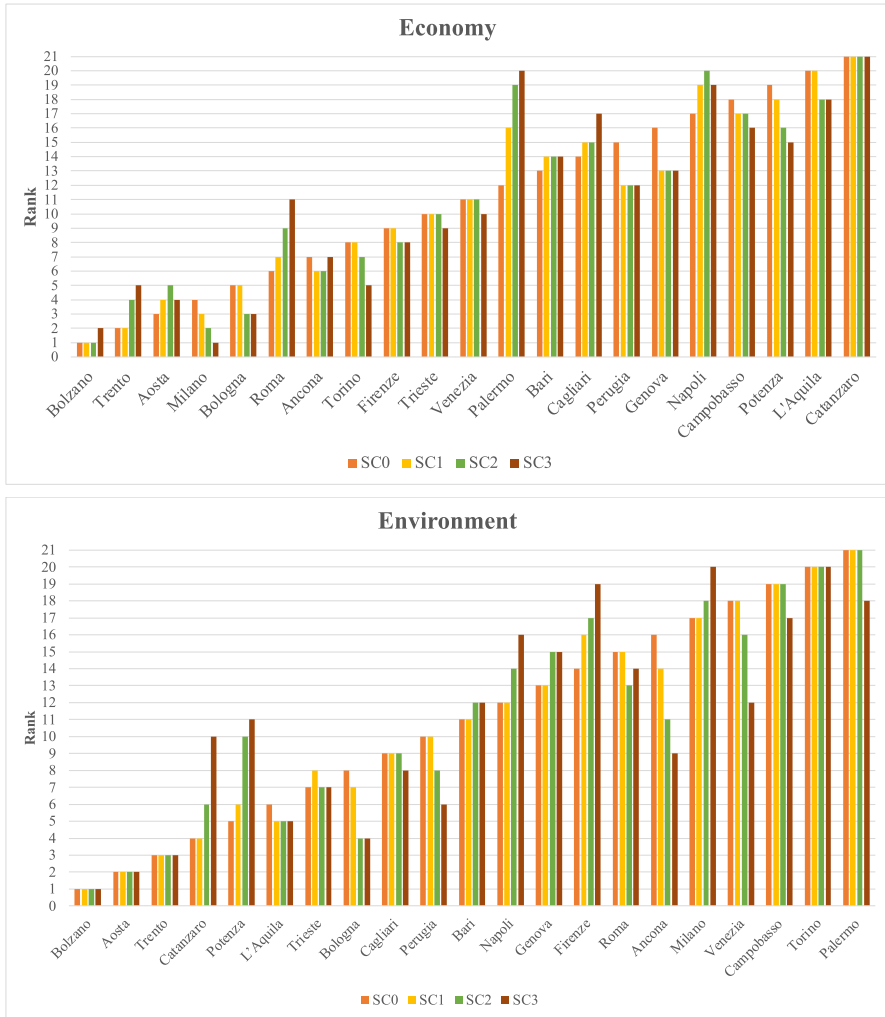


Fig. 4 Sensitivity analysis results

5.1.3 Smart Mobility

Milano, Venezia, Roma, Torino and Firenze emerge as the frontrunners in smart mobility, while Potenza, L'Aquila, Napoli, Catanzaro and Campobasso rank the lowest. Mobility issues seem to be relevant for Italian cities, as the average value of the C_i is quite low (0.341) and only the first city has a score higher than 0.5. The substantial gap between Milano and the second-ranked city underscores its exceptional performance. Moreover, the wide disparity between the first and last positions (0.631) indicates significant regional discrepancies in mobility conditions, particularly between the North and South of Italy. Northern cities predominantly occupy the upper echelons of the

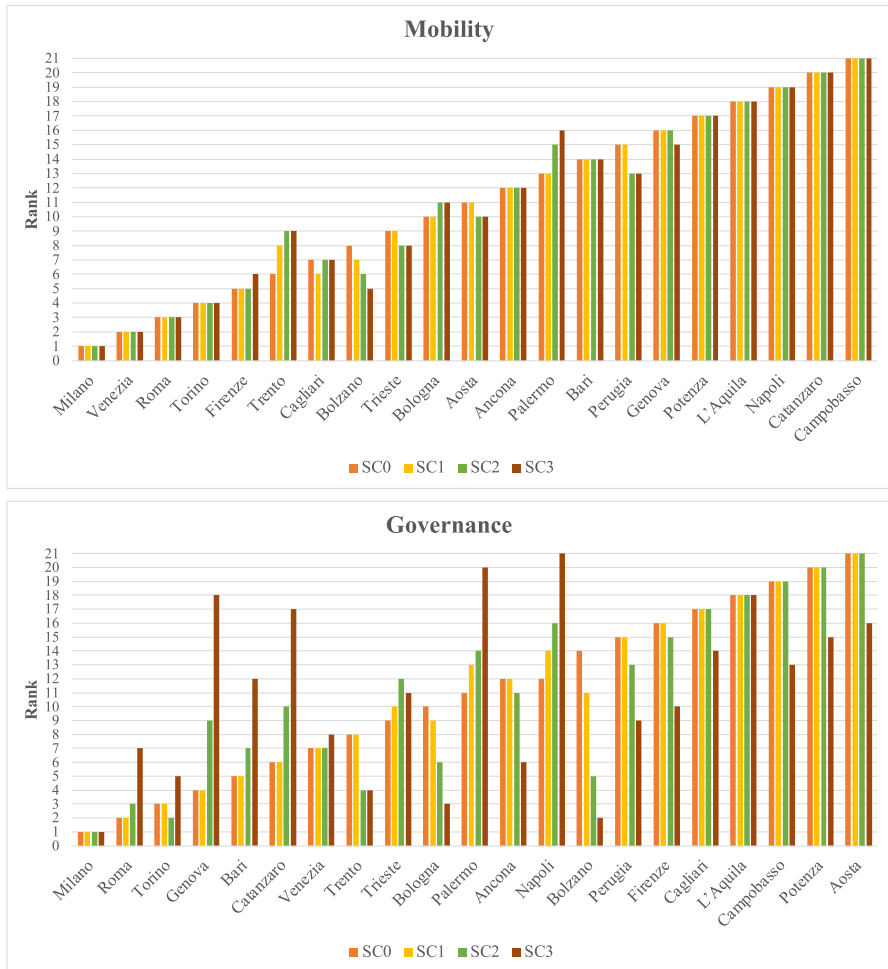


Fig. 4 continued

ranking, while Southern cities cluster at the bottom, confirming a need for increased investment and policy support in these regions (Battarra et al. 2018). Larger cities generally exhibit better smart mobility performance, likely due to greater resource availability and more developed infrastructure, despite this not always being true (Sotirelis et al. 2021). Key factors contributing to successful smart mobility initiatives include an adequate offer of local public transportation (buses, trams, trains and subways) complemented by incentive policies to increase public vehicle use, which helps reduce traffic congestion, pollution and dependence on private vehicles (Abdulrazzaq et al. 2020). Moreover, leading cities demonstrate an active commitment to modernizing their circulating vehicle fleet, i.e., (i) replacing older buses with low-emission models (below Euro 4 standard), and (ii) increasing sharing mobility options and electric micro-mobility services (cars, scooters, bikes). These strategies contribute

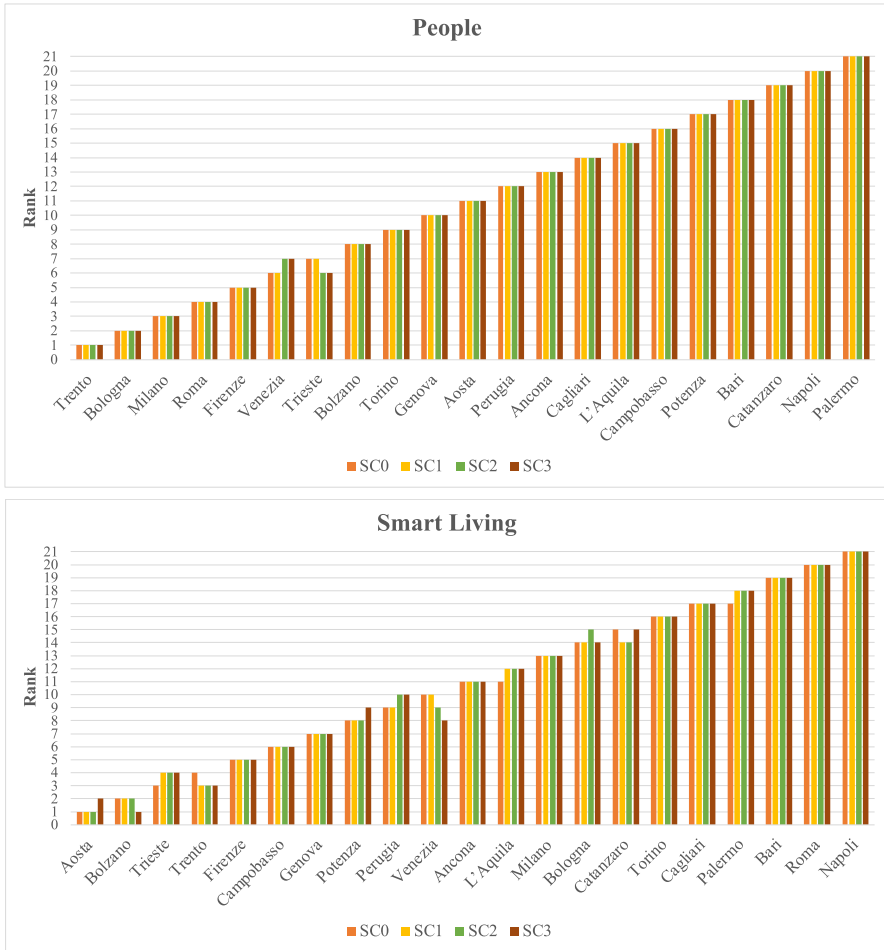


Fig. 4 continued

to the mitigation of environmental degradation, optimization of transportation infrastructure, and higher quality of public transport service (Potter 2003; Machado et al. 2018).

5.1.4 Smart Governance

Milano, Roma, Torino, Genova and Bari are the five best performers in smart governance, while Cagliari, L'Aquila, Campobasso, Potenza and Aosta are the five worst. Although governments decry many efforts to promote smart governance, further efforts are needed to improve the performance of Italian cities in this urban dimension. The average C_i is the lowest among all six smart dimensions (0.331) and, also in this case, only the first-ranked has a score above 0.5. The ranking, while highlighting a

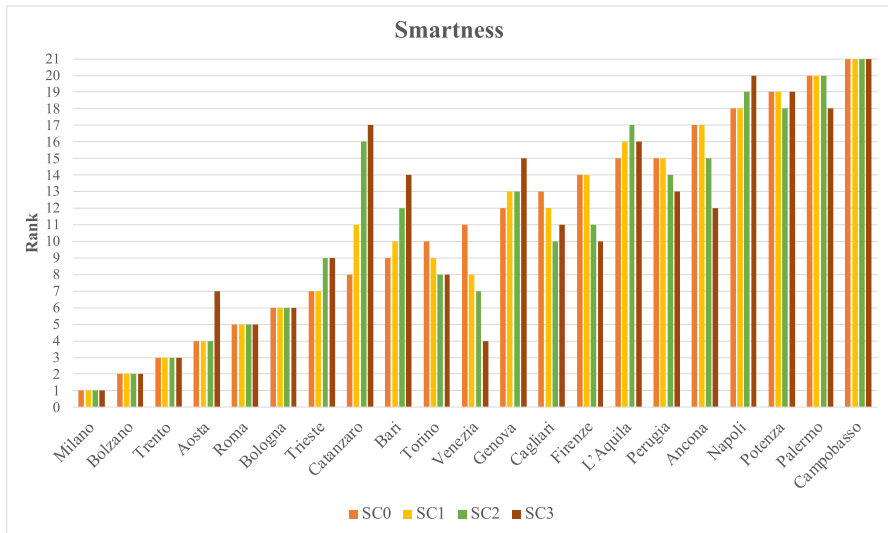


Fig. 4 continued

primacy of Milano and a general superiority of the Northern cities, shows a reduction in the traditional North-South gap in terms of smart governance. This data suggests a progressive homogenization of governance policies at the national level, although still with heterogeneous results among the different cities. High-performing cities share certain common experiences and characteristics, including (i) advanced public services digitalization, (ii) a robust suite of mobile apps providing information on various urban sectors (culture, tourism, waste, mobility, safety, etc.), (iii) comprehensive e-Government training for municipal employees, (iv) robust participatory urban planning process that actively involves stakeholders (through public meetings, workshops, surveys, focus groups, online platforms, etc.), and (v) widespread access to ultra-fast internet services. Indeed, previous literature confirms the role of technological innovation in reducing bureaucracy and improving service delivery, transparency and accountability (Sofyani et al. 2020). Additionally, the integration of ICT in governance empowers citizens by facilitating their participation in decision-making processes, ensuring that public policies better align with public needs (Oliveira et al. 2020).

5.1.5 Smart People

Top performers in smart people are Trento, Bologna, Milano, Roma and Firenze, while Potenza, Bari, Catanzaro, Napoli and Palermo are evaluated as the worst. People in the best cities demonstrate greater levels of education, skills and job specialization. Additionally, they have better access to online services due to higher digital skills in all five domains of the European DigComp 2.2. framework. Such competencies enable individuals to effectively use digital technologies to access, communicate and collaborate in digital environments (Vuorikari et al. 2016). Indeed, an increasing number of ICT-supported platforms have been integrated into people's daily lives (Bonina et al.

2021) and more people frequently carry out digital activities (e.g., internet banking operations, online purchases of goods and services, operations on local institutions websites or apps). Although the average performance in smart people is the highest among the six smart dimensions (0.572), citizens often struggle to access digital services due to insufficient digital skills, especially in Southern Italy. The ranking highlights a clear gap between the cities of Northern and Southern Italy, with the Northern cities consistently ranking at the top. Moreover, it reveals a worrying misalignment between the top and bottom positions (0.828), with such a wide gap suggesting a profound heterogeneity in smart people at the national level. These results underline how the skills, education and capabilities of the population are influenced by a series of socio-economic and cultural factors that vary significantly between different regions (Lucendo-Monedero et al. 2019), as well as the urgent need to intervene with targeted policies to bridge the existing deep disparities and promote skills development (Lamorgese and Petrella, 2019).

5.1.6 Smart Living

Looking at the smart living ranking, it can be observed that the top-performing cities are Aosta, Bolzano, Trieste, Trento and Firenze, while the bottom-ranking are Cagliari, Palermo, Bari, Roma and Napoli. The average C_i is equal to 0.445 and suggests a need for substantial improvements in the livability of Italian cities by adopting targeted urban policies. Even in this ranking, Northern cities tend to perform better than their Southern counterparts, although the correlation is not as pronounced as in other dimensions. Note that among the best cities are those located in the Alps, indicating favorable livability conditions in these areas. The ranking also seems to suggest that the smart living could be inversely linked to the size of the city, given that smaller cities often outperform larger metropolis. These results confirm that smaller cities, offering a more human-scaled environment and more personalized services, can provide a higher quality of life for their residents. Indeed, people living in larger urban areas often report having lower life satisfaction than those living in smaller urban areas or rural areas in developed countries (Biagi and Meleddu 2024). Smart living encompasses various aspects of daily life, including cultural vitality, tourist attractiveness, justice, security and healthcare provision (Giffinger and Gudrun 2010). The improvement of healthcare facilities and the availability of qualified doctors help to efficiently manage patient flow, ensuring timely access to healthcare services and thus increasing public health and quality of life (Ambrose 2001). Voluntary killing and violence (physical, sexual, psychological) against women also affect smart living performance, reducing urban safety and creating an environment of fear and insecurity (Krug et al. 2002).

5.2 Overall Smartness Performance and Sensitivity Analysis

Table 6 shows the overall smartness performance ranking across 21 sample cities. The top five cities in are Milano, Bolzano, Trento, Aosta and Roma. Instead, the five worst cities are Ancona, Napoli, Potenza, Palermo and Campobasso. Considering that

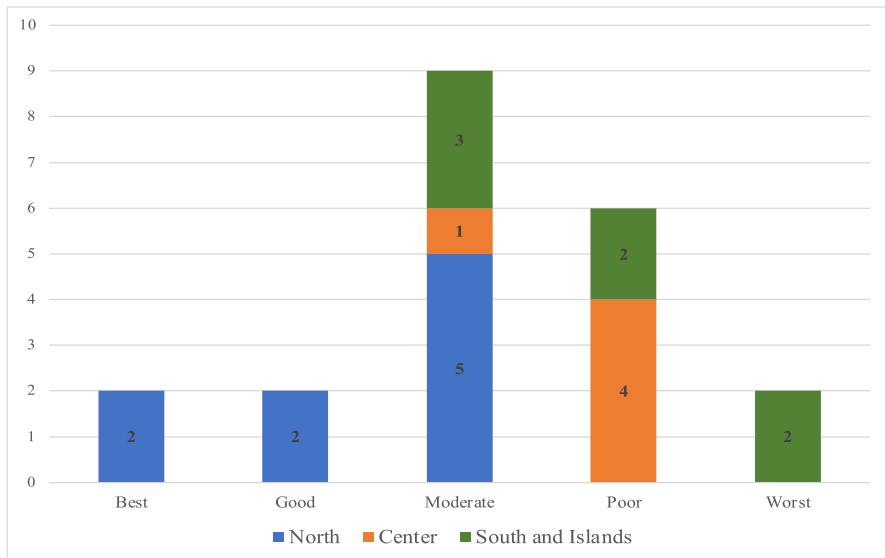
Table 7 Smartness grade classification

Best	$0.507 < C_i \leq 0.560$
Good	$0.455 < C_i \leq 0.507$
Moderate	$0.403 < C_i \leq 0.455$
Poor	$0.351 < C_i \leq 0.403$
Worst	$0.299 \leq C_i \leq 0.351$

smartness scores (C_i) vary from 0.299 to 0.560 (minimum and maximum values), by dividing this range to obtain equal intervals of scores, five categories that define the different grades of smartness performance can be obtained (Table 7).

By incorporating the above grading criteria with the results in Table 6, the cities in each category can be obtained. 9.52% of cities exhibited the worst performance, followed by 28.57% in poor performance, 42.86% in moderate performance, 9.52% in good performance, and 9.52% in the best performance. Figure 5 graphically reports these results, also considering the geographical division of Italian regions into North, Central and South and Islands.

The best-performing cities, Milano and Bolzano, lead the ranking thanks to significant investments in advanced infrastructure, digital services and sustainability policies. Trento and Aosta follow closely with good performance. Their commitment to adopting innovative solutions for urban challenges has enabled them to create innovative and attractive urban ecosystems. However, the leading cities still have room for improvement. For example, Milano should focus on environmental protection and urban safety, while Bolzano and Aosta need to strengthen participatory governance and citizen

**Fig. 5** Division of cities into smartness grades and by geographic area

involvement. Note that all the best and good performing cities are from the North, confirming the excellence of this area in smart city initiatives.

The majority of cities fall into the moderate category, indicating a medium level of smartness. This category is the most heterogeneous, including cities with varying characteristics and located in different areas of the country (Bologna, Trieste, Torino, Venezia and Genova in the North, Roma in the Center, and Catanzaro, Bari and Cagliari in the South). Each of them has specific smartness challenges to be addressed, but there is still good growth potential to be exploited.

Cities categorized as poor exhibit significant delays in adopting smart solutions, concentrated in Central (Firenze, L' Aquila, Perugia and Ancona) and Southern (Napoli and Potenza) Italy. Finally, the worst performing cities are Southern ones: Palermo and Campobasso, which present the most critical issues. These results confirm the challenges that the South and parts of Central Italy face in the innovation process, due to a number of factors: lower public investment, lower ability to attract private investment, poor innovation culture, lack of digital skills, etc. These issues are exacerbated by historical socio-economic inequalities between North and South that still affect the development of these areas (Salvati et al. 2017).

Looking beyond the categorization above, the average value of C_i (0.428) indicates that the smartness level of Italian cities is relatively low and confirms that further efforts are needed to improve their overall performance (Boscacci et al. 2014). In any case, cities with best and good smartness performance can be considered satisfactory in smart city practice and can share the good experience they have generated with other cities.

Furthermore, according to the data illustrated in Fig. 3, each city performs differently in the analyzed dimensions. For instance, Milano ranks first from an overall smartness perspective, but places 2nd, 17th, 1st, 1st, 3rd and 13th in smart economy, environment, mobility, governance, people, and living, respectively. These findings demonstrate that the development of smart city programs in Italian cities is often not well balanced among the six urban dimensions. This imbalance can be blamed on many factors, but the most significant is that each city implements its strategies and plans to promote smart city practices based on its specific functions, characteristics, needs and contexts (Angelidou 2014). Therefore, although cities prioritize different urban dimensions, in the long run smart city development across the six domains must be balanced to achieve higher levels of smartness (Albino et al. 2015).

The results of the sensitivity analysis, as illustrated in Fig. 4, revealed how responsive the final rankings are to changes in initial input concerning indicator weights.

With reference to the separate urban dimensions, note that the smart mobility, people and living rankings show no significant variations between the different weighting scenarios (SC0, SC1, SC2, SC3). This consistency suggests that the rankings obtained in the baseline scenario accurately reflect the smartness performance of Italian cities in these domains, strengthening the credibility, reliability and stability of the study.

On the other hand, the final rankings are more unstable for smart economy, environment and governance dimensions. In economy there is a progressive worsening of the positioning of Roma and Palermo as the weight of indicators EC10, EC11 and EC12 decreases. This means that their performance is strongly influenced by the innovative capacity and digital dynamism of the local productive fabric. In environment,

a major downgrading of some cities (i.e., Catanzaro, Potenza, Napoli and Firenze) is observed in favor of a climb in the rankings of other cities (i.e., Bologna, Perugia, Ancona and Venezia). This result indicates that the importance placed on air pollution, waste management and renewable energy (EN1, EN2, EN3, EN4) largely determines the success or failure of a smart environment. The governance ranking shows the most significant variations, especially in the last scenario (SC4). In fact, cities such as Genova, Bari, Catanzaro, Palermo and Napoli have experienced a significant decline in performance, while many other cities, especially Bolzano, have seen significant improvements. Smart governance is strongly affected by the weighting of digital indicators, including digitization of public services, mobile apps and internet connection speed (GO6, GO7, GO11). Although the sensitivity analysis results obtained in these dimensions need careful evaluation by readers, they can still be considered solid and robust. Indeed, what matters most for stability is that the top and bottom positions remain relatively unchanged across the different scenarios. It should also be noted that the least stable rankings are those in which the weight of more indicators has been changed (three for Economy and Governance and four for Environment). The greater the number of indicators varied, the greater the likelihood of obtaining different results. This is because more complexity is introduced into the model, the more the relationships between indicators are altered and the degree of arbitrariness in evaluation is increased.

Finally, the sensitivity analysis on overall smartness performance has shown no major changes in the rankings compared to the baseline scenario. Despite some changes in the middle part of the rankings, the top and bottom positions remain firm in the varied scenarios. This consistency indicates that the model is robust to changes in parameter estimates and assumptions and further confirms the robustness of the results. To further support the validity of the study, the CR was calculated after the AHP. It is observed to be less than 0.1, which indicates consistency in the judgments made during the weighting process and further supports the robustness of the derived rankings.

The appendix provides the overall scores and rankings for each sensitivity analysis weight scenario to improve the transparency and credibility of the results.

6 Conclusion

The rapid pace of urbanization presents complex challenges from environmental, economic and social points of view. The smart cities paradigm appears to be a valid solution to address them. In this context, identifying models to measure how cities are aligned with smart cities policies is an essential tool for policy makers. These models allow for the evaluation of the effectiveness of the adopted policies, identification of priority areas of intervention and optimization of the allocation of resources.

In response, this study introduces a comprehensive multidimensional framework to assess the smartness of cities, applied to 21 Italian regional capitals. By evaluating six critical dimensions—smart economy, smart environment, smart mobility, smart governance, smart people and smart living—we provide a nuanced picture of urban

intelligence that captures the interplay between technology, society, economy and the environment.

Our findings reveal significant disparities in smartness performance among Italian cities, highlighting a pronounced north-south divide. Northern cities like Milano, Bolzano and Trento lead the rankings, showcasing strengths in technological innovation, sustainable practices, and advanced governance models. Conversely, southern cities such as Palermo and Campobasso lag behind, underlining persistent regional inequalities that require targeted policy interventions.

A key insight from our analysis is the uneven development across the six smart city dimensions within individual cities. For instance, while Milano excels in smart governance and economy, it faces challenges in environmental sustainability and urban safety. This imbalance suggests that cities often prioritize certain areas over others, potentially undermining overall progress toward comprehensive smartness. Addressing this requires a balanced, integrated approach that concurrently advances all dimensions.

For urban planners, policymakers and regulators, our framework offers a practical and scalable tool for diagnosing city performance. It enables stakeholders to benchmark against peers, identify areas for improvement, and allocate resources more effectively. By utilizing readily available data and robust analytical methods like the Analytical Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), the framework ensures accuracy while remaining accessible for various urban contexts.

Moreover, this study fills a critical gap in existing literature by providing a holistic assessment tailored to the Italian context, overcoming limitations of previous models that suffered from poor scalability and data availability. The stability of our results, confirmed through extensive sensitivity analysis, underscores the reliability of our approach. In practical terms, adopting this framework can guide policy makers in developing targeted strategies that improve their levels of smartness, building on identified strengths and addressing weaknesses.

In conclusion, our multidimensional framework serves as both a diagnostic tool and a strategic roadmap for cities aspiring to become smarter. It bridges the gap between theory and practice, offering actionable insights that can drive meaningful transformation. As urban areas continue to evolve, leveraging such comprehensive assessment models will be crucial in shaping cities that are not only technologically advanced but also sustainable, equitable and responsive to the needs of their citizens.

Appendix

(See Table 8)

Table 8 Sensitivity analysis results

SC0			SC1			SC2			SC3		
Rank	Cities	C_i	Rank	Cities	C_i	Rank	Cities	C_i	Rank	Cities	C_i
Economy											
1	Bolzano	0.688	1	Bolzano	0.676	1	Bolzano	0.658	1	Milano	0.655
2	Trento	0.573	2	Trento	0.573	2	Milano	0.606	2	Bolzano	0.638
3	Aosta	0.541	3	Milano	0.564	3	Bologna	0.572	3	Bologna	0.598
4	Milano	0.534	4	Aosta	0.553	4	Trento	0.567	4	Aosta	0.570
5	Bologna	0.516	5	Bologna	0.543	5	Aosta	0.563	5	Torino	0.558
6	Roma	0.498	6	Ancona	0.515	6	Ancona	0.532	5	Trento	0.558
7	Ancona	0.497	7	Roma	0.492	7	Torino	0.513	7	Ancona	0.543
8	Torino	0.446	8	Torino	0.475	8	Firenze	0.493	8	Firenze	0.539
9	Firenze	0.402	9	Firenze	0.444	9	Roma	0.482	9	Trieste	0.483
10	Trieste	0.379	10	Trieste	0.413	10	Trieste	0.450	10	Venezia	0.472
11	Venezia	0.363	11	Venezia	0.400	11	Venezia	0.439	11	Roma	0.470
12	Palermo	0.361	12	Perugia	0.377	12	Perugia	0.421	12	Perugia	0.458
13	Bari	0.350	13	Genova	0.367	13	Genova	0.408	13	Genova	0.447
14	Cagliari	0.339	14	Bari	0.364	14	Bari	0.380	14	Bari	0.394
15	Perugia	0.335	15	Cagliari	0.339	15	Cagliari	0.339	15	Potenza	0.357
16	Genova	0.329	16	Palermo	0.336	16	Potenza	0.332	16	Campobasso	0.351
17	Napoli	0.307	17	Campobasso	0.309	17	Campobasso	0.331	17	Cagliari	0.339
18	Campobasso	0.287	18	Potenza	0.303	18	L'Aquila	0.304	18	L'Aquila	0.322
19	Potenza	0.277	19	Napoli	0.297	19	Palermo	0.303	19	Napoli	0.283

Table 8 (continued)

SC0			SC1			SC2			SC3		
Rank	Cities	C _i	Rank	Cities	C _i	Rank	Cities	C _i	Rank	Cities	C _i
20	L'Aquila	0.267	20	L'Aquila	0.284	20	Napoli	0.289	20	Palermo	0.266
21	Catanzaro	0.243	21	Catanzaro	0.237	21	Catanzaro	0.229	21	Catanzaro	0.219
Environment											
1	Bolzano	0.803	1	Bolzano	0.771	1	Bolzano	0.729	1	Bolzano	0.676
2	Aosta	0.738	2	Aosta	0.717	2	Aosta	0.689	2	Aosta	0.654
3	Trento	0.609	3	Trento	0.616	3	Trento	0.627	3	Trento	0.644
4	Catanzaro	0.578	4	Catanzaro	0.552	4	Bologna	0.532	4	Bologna	0.554
5	Potenza	0.537	5	L'Aquila	0.525	5	L'Aquila	0.529	5	L'Aquila	0.538
6	L'Aquila	0.524	6	Potenza	0.519	6	Catanzaro	0.519	6	Perugia	0.535
7	Trieste	0.513	7	Bologna	0.517	7	Trieste	0.518	7	Trieste	0.524
8	Bologna	0.507	8	Trieste	0.513	8	Perugia	0.510	8	Cagliari	0.516
9	Cagliari	0.501	9	Cagliari	0.503	9	Cagliari	0.507	9	Ancona	0.499
10	Perugia	0.483	10	Perugia	0.493	10	Potenza	0.498	10	Catanzaro	0.481
11	Bari	0.480	11	Bari	0.474	11	Ancona	0.468	11	Potenza	0.475
12	Napoli	0.464	12	Napoli	0.456	12	Bari	0.466	12	Venezia	0.459
13	Genova	0.453	13	Genova	0.448	13	Roma	0.449	12	Bari	0.459
14	Firenze	0.452	14	Ancona	0.447	14	Napoli	0.442	14	Roma	0.457
15	Roma	0.444	15	Roma	0.445	15	Genova	0.440	15	Genova	0.429
16	Ancona	0.432	16	Firenze	0.444	16	Venezia	0.435	16	Napoli	0.419

Table 8 (continued)

SC0	SC1			SC2			SC3		
	Rank	Cities	C _i	Rank	Cities	C _i	Rank	Cities	C _i
14	Bari	0.305	0.311	14	Bari	0.316	14	Bari	0.321
15	Perugia	0.290	0.305	15	Perugia	0.315	15	Genova	0.318
16	Genova	0.270	0.287	16	Genova	0.303	16	Palermo	0.315
17	Potenza	0.256	0.269	17	Potenza	0.282	17	Potenza	0.292
18	L'Aquila	0.212	0.212	18	L'Aquila	0.212	18	L'Aquila	0.213
19	Napoli	0.162	0.166	19	Napoli	0.172	19	Napoli	0.177
20	Catanzaro	0.128	0.138	20	Catanzaro	0.148	20	Catanzaro	0.157
21	Campobasso	0.089	0.094	21	Campobasso	0.102	21	Campobasso	0.107
Governance									
1	Milano	0.692	0.762	1	Milano	0.822	1	Milano	0.851
2	Roma	0.430	0.318	2	Torino	0.216	2	Bolzano	0.174
3	Torino	0.422	0.317	3	Roma	0.204	3	Bologna	0.166
4	Genova	0.421	0.308	4	Trento	0.200	4	Trento	0.157
5	Bari	0.405	0.298	5	Bolzano	0.199	5	Torino	0.152
6	Catanzaro	0.398	0.292	6	Bologna	0.197	6	Ancona	0.136
7	Venezia	0.393	0.291	7	Venezia	0.189	7	Roma	0.124
8	Trento	0.370	0.280	7	Bari	0.189	8	Venezia	0.120
9	Trieste	0.343	0.263	9	Genova	0.187	9	Perugia	0.119
10	Bologna	0.337	0.258	10	Catanzaro	0.178	10	Firenze	0.110

Table 8 (continued)

SC0			SC1			SC2			SC3		
Rank	Cities	C_i	Rank	Cities	C_i	Rank	Cities	C_i	Rank	Cities	C_i
11	Palermo	0.325	11	Bolzano	0.254	11	Ancona	0.175	11	Trieste	0.109
12	Ancona	0.320	12	Ancona	0.246	12	Trieste	0.169	12	Bari	0.107
13	Napoli	0.319	13	Palermo	0.234	13	Perugia	0.151	13	Campobasso	0.099
14	Bolzano	0.318	14	Napoli	0.231	14	Palermo	0.141	14	Cagliari	0.089
15	Perugia	0.290	15	Perugia	0.216	15	Firenze	0.140	15	Potenza	0.088
16	Firenze	0.266	16	Firenze	0.200	16	Napoli	0.137	16	Aosta	0.087
17	Cagliari	0.250	17	Cagliari	0.188	17	Cagliari	0.126	17	Catanzaro	0.081
18	L'Aquila	0.232	18	L'Aquila	0.169	18	L'Aquila	0.112	18	L'Aquila	0.079
19	Campobasso	0.155	19	Campobasso	0.124	19	Campobasso	0.103	18	Genova	0.079
20	Potenza	0.144	20	Potenza	0.115	20	Potenza	0.094	20	Palermo	0.069
21	Aosta	0.115	21	Aosta	0.098	21	Aosta	0.087	21	Napoli	0.056
People											
1	Trento	0.888	1	Trento	0.883	1	Trento	0.877	1	Trento	0.873
2	Bologna	0.852	2	Bologna	0.849	2	Bologna	0.846	2	Bologna	0.844
3	Milano	0.828	3	Milano	0.818	3	Milano	0.810	3	Milano	0.803
4	Roma	0.795	4	Roma	0.784	4	Roma	0.775	4	Roma	0.769
5	Firenze	0.769	5	Firenze	0.763	5	Firenze	0.756	5	Firenze	0.752
6	Venezia	0.752	6	Venezia	0.743	6	Trieste	0.735	6	Trieste	0.729
7	Trieste	0.751	7	Trieste	0.742	7	Venezia	0.734	7	Venezia	0.728

Table 8 (continued)

SC0	SC1			SC2			SC3		
	Rank	Cities	C _i	Rank	Cities	C _i	Rank	Cities	C _i
8	Bolzano	0.703	0.696	8	Bolzano	0.689	8	Bolzano	0.684
9	Torino	0.687	0.679	9	Torino	0.672	9	Torino	0.666
10	Genova	0.677	0.668	10	Genova	0.661	10	Genova	0.656
11	Aosta	0.660	0.644	11	Aosta	0.630	11	Aosta	0.620
12	Perugia	0.652	0.639	12	Perugia	0.627	12	Perugia	0.618
13	Ancona	0.618	0.616	13	Ancona	0.614	13	Ancona	0.612
14	Cagliari	0.572	0.568	14	Cagliari	0.565	14	Cagliari	0.562
15	L'Aquila	0.524	0.526	15	L'Aquila	0.529	15	L'Aquila	0.530
16	Campobasso	0.350	0.362	16	Campobasso	0.373	16	Campobasso	0.380
17	Potenza	0.330	0.342	17	Potenza	0.353	17	Potenza	0.360
18	Bari	0.256	0.258	18	Bari	0.260	18	Bari	0.261
19	Catanzaro	0.169	0.177	19	Catanzaro	0.184	19	Catanzaro	0.188
20	Napoli	0.115	0.122	20	Napoli	0.129	20	Napoli	0.133
21	Palermo	0.060	0.063	21	Palermo	0.066	21	Palermo	0.068
Living									
1	Aosta	0.675	0.668	1	Aosta	0.662	1	Bolzano	0.660
2	Bolzano	0.627	0.641	2	Bolzano	0.652	2	Aosta	0.656
3	Trieste	0.581	0.578	3	Trento	0.579	3	Trento	0.579
4	Trento	0.577	0.574	4	Trieste	0.569	4	Trieste	0.563

Table 8 (continued)

SC0	SC1			SC2			SC3		
	Rank	Cities	C_i	Rank	Cities	C_i	Rank	Cities	C_i
5	Firenze	0.511	5	Firenze	0.507	5	Firenze	0.503	0.499
6	Campobasso	0.505	6	Campobasso	0.493	6	Campobasso	0.484	0.474
7	Genova	0.502	7	Genova	0.484	7	Genova	0.472	0.460
8	Potenza	0.475	8	Potenza	0.467	8	Potenza	0.461	0.455
9	Perugia	0.474	9	Perugia	0.463	9	Venezia	0.457	0.453
10	Venezia	0.461	10	Venezia	0.459	10	Perugia	0.455	0.449
11	Ancona	0.458	11	Ancona	0.451	11	Ancona	0.445	0.439
11	L'Aquila	0.458	12	L'Aquila	0.447	12	L'Aquila	0.439	0.430
13	Milano	0.409	13	Milano	0.396	13	Milano	0.386	0.377
14	Bologna	0.389	14	Catanzaro	0.381	14	Catanzaro	0.376	0.372
15	Catanzaro	0.386	14	Bologna	0.381	15	Bologna	0.375	0.37
16	Torino	0.377	16	Torino	0.366	16	Torino	0.359	0.352
17	Cagliari	0.338	17	Cagliari	0.327	17	Cagliari	0.321	0.316
18	Palermo	0.337	18	Palermo	0.324	18	Palermo	0.314	0.304
19	Bari	0.296	19	Bari	0.289	19	Bari	0.285	0.280
20	Roma	0.284	20	Roma	0.265	20	Roma	0.251	0.241
21	Napoli	0.215	21	Napoli	0.210	21	Napoli	0.206	0.202
Smartness									
1	Milano	0.560	1	Milano	0.582	1	Milano	0.606	0.630

Table 8 (continued)

SC0			SC1			SC2			SC3		
Rank	Cities	C _i	Rank	Cities	C _i	Rank	Cities	C _i	Rank	Cities	C _i
2	Bolzano	0.525	2	Bolzano	0.494	2	Bolzano	0.462	2	Bolzano	0.429
3	Trento	0.481	3	Trento	0.457	3	Trento	0.433	3	Trento	0.410
4	Aosta	0.469	4	Aosta	0.443	4	Aosta	0.415	4	Venezia	0.394
5	Roma	0.448	5	Roma	0.431	5	Roma	0.412	5	Roma	0.393
6	Bologna	0.436	6	Bologna	0.422	6	Bologna	0.407	6	Bologna	0.391
7	Trieste	0.435	7	Trieste	0.417	7	Venezia	0.402	7	Aosta	0.388
8	Catanzaro	0.430	8	Venezia	0.410	8	Torino	0.397	8	Torino	0.385
9	Bari	0.422	9	Torino	0.409	9	Trieste	0.396	9	Trieste	0.375
10	Torino	0.419	10	Bari	0.396	10	Cagliari	0.373	10	Firenze	0.357
11	Venezia	0.418	11	Catanzaro	0.392	11	Firenze	0.371	11	Cagliari	0.356
12	Genova	0.415	12	Cagliari	0.391	12	Bari	0.366	12	Ancona	0.339
13	Cagliari	0.406	13	Genova	0.390	13	Genova	0.361	13	Perugia	0.335
14	Firenze	0.397	14	Firenze	0.384	14	Perugia	0.353	14	Bari	0.334
15	L'Aquila	0.389	15	Perugia	0.371	15	Ancona	0.351	15	Genova	0.330
15	Perugia	0.389	16	L'Aquila	0.366	16	Catanzaro	0.350	16	L'Aquila	0.313
17	Ancona	0.375	17	Ancona	0.364	17	L'Aquila	0.340	17	Catanzaro	0.304
18	Napoli	0.374	18	Napoli	0.348	18	Potenza	0.317	18	Palermo	0.293
19	Potenza	0.365	19	Potenza	0.342	19	Napoli	0.316	19	Potenza	0.292
20	Palermo	0.350	20	Palermo	0.332	20	Palermo	0.313	20	Napoli	0.280
21	Campobasso	0.299	21	Campobasso	0.281	21	Campobasso	0.260	21	Campobasso	0.239

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Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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