



Smart cities in Italy: measuring smartness for sustainable urban development of Italian municipalities

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Received: 30 June 2025 / Accepted: 24 January 2026
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Abstract

Urbanisation is accelerating globally, with 70% of the population expected to reside in cities by 2050, presenting significant challenges for sustainable urban planning. Smart cities provide potential solutions by integrating digital technologies, participatory governance, and innovative strategies to tackle urban issues such as climate change, inequality, and quality of life. In Italy, smart city development gained institutional momentum in 2012 with the National Smart Communities Plan and the Italian Digital Agenda, which established objectives for urban smart transitions, including mobility, environment, economy, security, citizen participation, and digital services. The National Recovery and Resilience Plan has further emphasised the importance of smart cities, framing their development as an ongoing process supported by targeted measures. Building on this premise, this study examines the smart city phenomenon in Italy by developing a composite Smartness Index for Italian municipalities. Existing measures emphasise infrastructure development and digitalisation, but dimensions more focused on social and environmental aspects are often overlooked. In addition, measures are often defined only for the most populous municipalities (usually provincial capitals), neglecting smaller municipalities, which constitute the majority in Italy (according to data from the 2021 ISTAT Census, municipalities with a population of less than 5000 inhabitants represent 70% of all Italian municipalities). To address these gaps, this research proposes a new index by exploiting the Structural Equation Modelling framework. Building on the existing literature, the core dimensions of smartness are identified, and a composite measure is derived from selected indicators. Furthermore, by using spatial analysis tools, the work examines the territorial heterogeneity of the phenomenon, mapping results at the municipal level to provide deeper insights into the dynamics of smart city development in Italy.

Keywords Smart cities · Sustainable urban development · Composite indicators · Spatial analysis

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1 Introduction

Currently, more than half of the global population resides in urban areas, with 4.61 billion people in 2023, according to the most recent data available from the World Bank Group. The remaining portion, approximately 3.5 billion individuals, lives in rural areas and small towns. According to the latest projections, by 2050, the urban population is expected to double, with nearly 70% of the global population living in cities (World Bank 2023). Across global regions, the European Union ranks among the most urbanised areas worldwide. It is estimated that 75% of the EU's 447 million inhabitants live in urban areas. Projections further suggest that this figure will exceed 80% by 2050 (United Nations 2019).

In this context, urban planning emerges as a critical component of governmental and European policies aimed at ensuring a high quality of life for citizens, reducing inequalities in access to basic services and mobility (dos Santos Figueiredo et al. 2022), mitigating the impacts of climate change and environmental pollution, and fostering civic and political participation.

In response to these challenges, urban development paradigms grounded in the principles of environmental, economic, and social sustainability have become central in institutional and political discourse, culminating in the United Nations' 2030 Agenda for Sustainable Development (United Nations 2015), which aims to make cities and human settlements inclusive, safe, resilient, and sustainable. Ongoing transformations, rapid urbanisation, and the need to plan and develop urban centres in accordance with sustainability principles have led in recent years to a growing interest in the concept of the smart city, particularly within the domains of urban planning and governance (De Falco and Romeo 2022).

Smart cities are increasingly framed as potential responses to the social, economic, and political challenges facing contemporary urban environments. Through the integration of digital technologies and new governance models, they aim to foster sustainable urban development and improve the quality of life of citizens (Silva et al. 2018).

In the literature, various definitions of smart cities have been proposed over the years, each highlighting the different dimensions of the concept. Although there is consensus on key characteristics, such as the use of technology, a sustainability-oriented development, the mitigation of human impact on the environment, and the central role played by human capital in defining urban planning strategies, differences arise in the emphasis placed on specific components (Ciacci et al. 2023).

For example, some definitions are primarily technology-oriented. In contrast, others adopt a holistic approach that views cities as interconnected systems (social, economic, and technological) working in synergy to achieve sustainable development and enhance citizen well-being. This diversity reflects the evolving and multidimensional nature of the smart city concept.

A strand of the literature points out the fundamental role of information and communication technologies (ICT), along with the Internet of Things (IoT), in the development of smart cities. Scholars such as Bakıcı et al. (2013) and Su et al. (2011) conceptualise the smart city as a highly technological environment in which sensors, networks, and digital infrastructures collect and use real-time data to optimise urban services, logistics, transport, and resource management. In this sense, a city becomes 'smart' by learning, adapting, and improving itself through technological integration and leveraging the information gathered from big data.

By adopting a more comprehensive view (Hall et al. 2000; Harrison et al. 2010), a smart city can be defined as one capable of integrating its digital (ICT) and social (community, governance) infrastructures to enhance, through system monitoring and data collection, the efficiency of services to citizens. Here, the ‘smartness’ emerges from the integration and interoperability of previously isolated systems, enabled by the widespread adoption of new technologies.

Other scholars, instead, stress the importance of human and social capital in promoting strategies that utilise extensive knowledge and creativity to enhance the performance of urban areas (Kourtit et al. 2012), thereby making a city ‘smart’. These approaches are based on a virtuous combination of human, infrastructural, social, and entrepreneurial capital. From this perspective, a city is considered ‘smart’ not only when it invests in traditional and digital infrastructure, but also in human and social capital, promoting sustainable economic growth, quality of life, and participatory and responsible governance of resources (Caragliu et al. 2011).

To capture the essence of the smart city concept, several authors have proposed a systematic vision to define a city’s smartness (Thuzar 2011; Zygiaris 2013). However, regardless of the components that constitute the terms of integration and the degree to which they are achieved, other authors have adopted a more pragmatic, results-oriented approach. According to Giffinger and Lu (2015), a city is ‘smart’ if it excels across multiple dimensions—economy, mobility, environment, governance, human capital—through an integrated and strategic approach to sustainable urban development. From this standpoint, the smartness lies in the coherence and interconnectedness among various spheres.

However, despite the diversity of definitions, a smart city should tend toward a set of shared objectives: improving citizens’ quality of life, increasing urban competitiveness, and promoting inclusion, participation, well-being, and sustainable development (Nam and Pardo 2011; Ivaldi et al. 2020; Gracias et al. 2023).

A nearly transversal component across the definitions of a smart city is sustainability. A smart city is typically associated with its ability to address environmental challenges and drive sustainable urban development. In this sense, ‘smartness’ aligns with the ability to harmonise economic growth and quality of life with the protection of the environment (Bakıcı et al. 2013).

Furthermore, scholars underscore the importance of political and institutional dimensions. Participatory governance emerges as a key feature, where collective intelligence is mobilised through the co-production of urban policies (Caragliu et al. 2011). Lastly, citizen well-being occupies a central place in the smart city discourse. The goal is to enhance the quality of life by making cities more attractive, inclusive, and safe. In this context, technology and governance are not ends in themselves but instruments to meet social needs and foster greater urban cohesion (Chang and Smith 2023).

A growing body of literature has developed a critical perspective on the smart city paradigm, highlighting a range of problematic issues associated with its diffusion. Kitchin et al. (2019) argue that smart city development is shaped by a strong techno-solutionist orientation, characterised by technocratic forms of governance that reconfigure the relationships between institutions, markets, and citizenship. Central to this process is the expanding role of digital technologies in the production, collection, and processing of large volumes of data. However, the process of datafication raises significant ethical and political concerns related to surveillance and predictive profiling, with the potential to reinforce pre-exist-

ing social and territorial inequalities. The use of such social sorting mechanisms may give rise to forms of 'data determinism', whereby individuals and social groups are governed not based on their actual behaviour, but on anticipated or inferred future actions, thereby increasing the risks of exclusion and stigmatisation.

Similarly, Kitchin et al. (2018) observe that a substantial share of smart city initiatives has been developed and implemented without adequate critical reflection on their medium- and long-term implications. The smart paradigm would tend to privilege approaches that address complex urban problems primarily through technological solutions, while overlooking political, institutional, and participatory dimensions. This orientation contributes to the consolidation of instrumental and technocratic forms of governance, often characterised by top-down logics in which decisions are taken for citizens rather than with citizens.

Kolotouchkina et al. (2024) identify the risk of amplifying digital and social inequalities as one of the limitations of the smart city paradigm, underscoring its impact on vulnerable groups. The authors posit that a new rationale of urban governance underpins smart development, operating on the implicit assumption that citizens are equipped with sufficient digital skills and resources to participate fully in the digital urban experience. Within this framework, the digital smart city tends to include young, highly educated, digitally competent, and professionally qualified individuals, while groups such as low-income workers, older adults, people with disabilities, and citizens with limited digital skills face an increased risk of exclusion or marginalisation. This dynamic could ultimately reinforce the divide between 'connected' and 'non-connected' citizens.

In Italy, the discourse on smart cities began and consolidated institutionally in 2012, as part of a national strategy, the National Smart Communities Plan, defined within the framework of European digital development, to capitalise on the digital revolution to promote economic growth (Smigiel 2019). In parallel, the Italian Digital Agenda (ADI) is established, tasked with defining objectives and development axes for the smart transition of cities. These include mobility, environment, economy, security, citizen participation, and the digitisation of services (De Santis et al. 2014).

In practice, the implementation of programs and initiatives for the smart transition has followed a bottom-up approach. In this process, municipalities have played a key role in promoting coordination, planning, and the formation of public-private partnerships oriented towards smartness (Dameri et al. 2019). It is worth reporting that, according to the National Association of Italian Municipalities (ANCI), smart initiatives have spread not only in major Italian cities but also in small urban centres (Sidani et al. 2022).

The importance of investing in innovative city development has been further emphasised in the context of the National Recovery and Resilience Plan (PNRR) and its Missions. Significant funding has been allocated to support various initiatives, including the digitalisation of Public Administration (Mission 1), the ecological transition and the promotion of the green ecosystem (Mission 2), Integrated Urban Plans (Mission 5), and projects aimed at urban regeneration. These numbers, together with measures implemented in recent years, demonstrate that the transition to the smart city paradigm is not just a future perspective but rather a set of changes and processes already underway. Moreover, several smart city rankings have been developed to assess the level of smartness of Italian cities. Among the most prominent are the EY Smart City Index (EY 2025) and the iCity Rank (Forum PA 2025). The former adopts a multidimensional framework that combines readiness (public/private investments in infrastructure and services) and citizen behaviour (use of smart services

and participation), across the areas of Digital Transition, Ecological Transition, and Social Inclusion. The latter focuses on the digital transformation of Italian cities along three core dimensions: digital administrations (the digitisation of administrative activities, including municipal websites, online services, and the adoption of national digital platforms), open municipalities (use of social media, availability of open data, and the presence of city apps), and connected cities (development of connectivity networks, deployment of sensors and connected devices, and the use of data analytics for urban planning). Both rankings rely on sets of quantitative indicators that are aggregated into composite scores, thereby contributing to the public debate on smart city development in Italy. However, both initiatives are characterised by limited territorial coverage—restricted to Italian provincial capitals—and by aggregation procedures that do not explicitly account for the multidimensional nature of the underlying construct.

Based on these considerations, this paper explores the smart city phenomenon in Italy by developing a composite measure of smartness at the municipality level. Specifically, the work combines a model-based statistical approach to construct an index derived from ISTAT (National Institute of Statistics) data, along with spatial autocorrelation analysis to identify significant clusters of municipalities with high or low levels of smartness, providing insights into the geographical distribution of the phenomenon. The structure of the paper is as follows. Section 2 introduces the dataset used in the analysis and provides a detailed description of the selected dimensions and indicators, while Section 3 outlines the methodology employed. Section 4 reports the results, focusing on the key findings that emerged from the study. Finally, Section 5 discusses the main contributions of the work and outlines potential avenues for future research.

2 Data

The project relies on multiple data sources: *ISTAT - A misura di Comune*¹, *ISTAT - Censimento sulle biblioteche pubbliche e private*², *ISTAT - Basi territoriali (macro-aree)*³, *Corine Land Cover Data*⁴, and *ISTAT - Administrative boundaries data*⁵.

A misura di Comune is a multi-source system developed by ISTAT in collaboration with ANCI and UPI, integrating high-resolution, harmonised indicators at the municipal level. It provides information on demographic, environmental, social, and economic aspects, with a focus on sustainable and equitable well-being. Data are drawn from multiple open sources within the national statistical system (Sistan), including ministries and environmental agencies and updated annually from 2014 onward.

The *Censimento sulle biblioteche pubbliche e private* collects detailed data on more than 9,000 libraries across Italian municipalities. Conducted by ISTAT in collaboration with MIBACT, ICCU, and CEI, it encompasses aspects such as management models, collections, services provided, and user activity.

¹ www.istat.it/.../aggiornamento-degli-indicatori-del-sistema-informativo-a-misura-di-comune/.

² www.istat.it/.../censimento-sulle-biblioteche-pubbliche-e-private-microdati-ad-uso-pubblico/.

³ www.istat.it/.../caratteristiche-territoriali-sezioni-censimento-2021-raggruppate-in-macroaree/.

⁴ land.copernicus.eu/en/products/corine-land-cover.

⁵ www.istat.it/.../confini-delle-unita-amministrative-a-fini-statistici-al-1-gennaio-2018-2/.

The *Basi territoriali (macro-aree)* provide a refined spatial subdivision of the Italian territory by introducing, for the year 2021, a land-use and land-cover classification system. Each census section is assigned a specific code, which is then grouped into 11 macro-areas, enabling more detailed territorial analysis.

The *Corine Land Cover (CLC)* data, a project coordinated by the European Environment Agency and implemented by national institutions, provides harmonised land cover and land use data across Europe. Available in both raster and vector formats, it enables tracking of environmental changes over time through a standardised classification system.

Lastly, the *ISTAT - Administrative boundaries* data provides the territorial limits of administrative units, consisting of three hierarchical levels (regions, provinces, and municipalities) and one statistical level (geographical divisions), covering the entire country.

The indicators were selected for all 7,904 Italian municipalities as of 2022, based on the relevant literature on the topic. In particular, the selection was guided by the model proposed by Giffinger et al. (2007), which identifies six key domains for measuring the smartness of a city: Smart Economy, Smart Governance, Smart People, Smart Living, Smart Mobility, and Smart Environment. From this framework, the relevant and critical dimensions for evaluating and monitoring a city's level of smartness were selected.

In particular, four dimensions were retained—Smart Economy, Smart Environment, Smart Governance, and Smart People—while the others were excluded. This choice was primarily motivated by empirical and operational considerations related to data availability, comparability, and consistency at the municipal level across the national territory. The operationalisation of the Smart Living and Smart Mobility dimensions would have required indicators that are either not systematically available in official administrative data sources or are measured non-homogeneously across Italian municipalities, particularly smaller ones. Given the aim of this study—to propose a consistent, nationwide measure of urban smartness—the analysis was restricted to indicators uniformly available for all of them. On this basis, it was possible to operationalise the dimensions most widely recognised in the literature as core components of smart cities (Neirotti et al. 2014; Albino et al. 2015). These dimensions capture key structural features of urban smartness, including economic competitiveness, environmental sustainability, institutional capacity, and human and social capital. Accordingly, the following indicators were selected to represent each domain.

- *Smart Economy*, referring to competitiveness and economic development, is operationalised through the following indicators: (1) Density of local business units, (2) Employment rate, (3) Entrepreneurship rate, (4) Number of local business services units, (5) Production specialisation in high-tech sectors (6) Taxable income per taxpayer.
- *Smart Environment*, relating to environmental sustainability, efficient resource management, and environmental protection, is assessed using the following indicators: (1) Share of vehicles with emission standards below Euro 4, (2) Accessibility index to essential services, (3) Motorization rate, (4) Share of municipal waste that is separately collected, (5) Urban green space ratio.

Since the ISTAT dataset *A misura di comune* provides data on green spaces only for provincial capitals, an ad hoc indicator was constructed to estimate the availability of green areas for all Italian municipalities. This indicator—the Urban green space ratio (Ugsr)—represents the percentage of a municipality's total area that is occupied by urban green spaces.

The indicator was computed by integrating two data sources to improve the accuracy of the estimate: ISTAT macro-area shapefiles (2021) and CLC 2018 data, using Geographic Information System (GIS) techniques. The procedure entailed a multi-step process: From the ISTAT macro-area shapefile, polygons with the attribute COD_TIPO_S = 5 were extracted. These polygons represent green areas in urban settings (e.g., parks, gardens) intended to improve residential living conditions. Similarly, polygons classified as ‘Green urban areas’ (code 141), which fall under the category ‘Artificial, non-agricultural vegetated areas’, were selected from the 2018 CLC shapefile. These areas typically include vegetation within or partially surrounded by urban fabric and serve recreational or ornamental functions accessible to the public.

Next, the municipal boundaries shapefile (ISTAT, 2022), which included resident population data for the same year, was used to calculate the area of each municipality in hectares. Then, a spatial intersection was performed between the ISTAT green areas and municipal boundaries to compute the total surface area of ISTAT green spaces within each municipality. Subsequently, to integrate the CLC data, the portions of CLC green spaces that did not overlap with ISTAT green areas were identified through a spatial intersection between the two datasets. The CLC non-overlapping areas were then intersected with municipal geometries to calculate their surface area for each municipality.

Finally, the total green space for each municipality was obtained by summing the areas derived from the ISTAT and CLC datasets. The Ugsr index was then calculated as:

$$Ugsr_i = \frac{GA(istat)_i + GA(clc)_i}{MA_i} \cdot 100 \quad (1)$$

where $Ugsr_i$ is the Urban green space ratio of the municipality i , expressed as percentage; $GA(istat)_i$ is the surface area of ISTAT urban green areas in the municipality i , expressed in hectares; $GA(clc)_i$ is the surface area of CLC urban green areas in the municipality i , expressed in hectares; MA_i is the total administrative area of the municipality i , expressed in hectares.

- *Smart Governance* refers to inclusive forms of citizen participation in decision-making processes, the quality of public administration, and the provision of services to citizens. It is measured by the following indicators: (1) Children taken into care by municipal child welfare services, (2) Expenditure on social interventions and services per family and minors, (3) Expenditure on social interventions and services per inhabitant, (4) Share of women in municipal decision-making bodies (Municipal Councils).
- *Smart People* relates to aspects connected to human capital and, more broadly, the demographic structure of the population. It is captured by the following indicators: (1) Active users per library, (2) Aging index, (3) Incidence of tertiary education attainment, (4) Population growth rate, (5) Share of resident foreign population.

The Active Users per Library (Aul) indicator was constructed using microdata from *ISTAT - Censimento sulle biblioteche pubbliche e private*. It is defined as the ratio between the total number of active users registered in libraries located within a given municipality and the total number of libraries operating in that municipality. Active users are defined as indi-

viduals who are either registered or regular visitors and who have performed at least one formalised transaction (e.g., a book loan) during the reference year. Formally:

$$Aul_i = \frac{\text{Total Active Users}_i}{\text{Number of Libraries}_i} \quad (2)$$

where i denotes each municipality.

Table 1 shows the indicators selected for each dimension in detail, together with information on how they were calculated, their source, and the year.

3 Method

To address our research aims, we implemented a multi-step methodological approach integrating data preprocessing, composite index construction, spatial analysis, and visualisation techniques.

First, we processed the selected indicators to ensure data quality and comparability. Descriptive statistical analysis of each elementary indicator enabled the identification of outliers. These values were replaced with less extreme values of the distribution corresponding to $Q1 - 1.5 \times IQR$ and $Q3 + 1.5 \times IQR$, where $Q1$, $Q3$, and IQR are the first quartile, the third quartile and the interquartile range, respectively. Subsequently, all indicators were normalised using the min-max method to align them on a common measurement scale. In the presence of missing data, imputation was carried out using the k -nearest neighbours algorithm, which estimates missing values based on the similarity between observations. The procedure was applied separately for each dimension: for incomplete observations, the $k = 10$ most similar cases (neighbours) were identified based on the available indicators; the missing value was then replaced by a weighted average of the neighbours' observed values, with weights inversely proportional to the Euclidean distance. Indicators with negative polarity were reversed to ensure interpretative coherence across all items.

Second, we adopted a model-based approach to construct a composite index of smartness for Italian municipalities, yielding a meaningful synthesis of elementary indicators and a global description of the phenomenon.

Third, we employed cartographic representation techniques to visualise the distribution of the Smartness Index across Italian municipalities. These maps enabled the identification of territorial disparities and facilitated the analysis of the spatial distribution of the phenomenon.

Finally, we applied Exploratory Spatial Data Analysis (ESDA) techniques to detect the presence of significant clusters of municipalities characterised by high or low levels of smartness. This step enabled us to assess the presence of a spatial structure in the data and identify local spatial patterns of index values across the territory.

In the following subsections, we provide a detailed description of the methodological steps, including index construction and spatial analysis.

Table 1 Selected indicators for the construction of the Smartness Index

Dimensions	Indicators	Definition/calculation	Source	Year
Economy	Density of local units [dens_loc_unit]	Number of local units/ Municipal area (square kilometres)	ISTAT – A misura di comune	2022
	Employment rate [empl_rate]	Employed population aged 15 and over/Resident population aged 15 and over $\times 100$	ISTAT – A misura di comune	2022
	Entrepreneurship rate [entr_rate]	Number of businesses/ Average resident population $\times 1000$	ISTAT – A misura di comune	2022
	Local business services units [loc_bus_serv_unit]	Number of local business service units/Total local units $\times 100$	ISTAT – A misura di comune	2022
	Production specialisation in high-tech sectors [high_tech_spec]	Employees in high- tech manufacturing and services sectors/ Total employees in local units $\times 100$	ISTAT – A misura di comune	2022
	Taxable income per taxpayer [income]	Taxable income/ Taxpayers with taxable income	ISTAT – A misura di comune	2022
Environment	Cars in circulation with emission standards lower than Euro 4 class [cars_below_euro4]	Number of cars in Euro 0–3 class in circulation/Cars in circulation $\times 100$	ISTAT – A misura di comune	2022
	Index of accessibility to essential services [ind_acc_ess_serv]	Average travel time by road to reach the nearest municipal centre, identified on the basis of the simultaneous presence of three essential services (education, health and transport)	ISTAT – A misura di comune	2019
	Motorisation rate [motor_rate]	Number of cars in circulation/Average resident population $\times 100$	ISTAT – A misura di comune	2022
	Separate collection of municipal waste [sep_waste_coll]	Municipal waste subject to separate collection/Total municipal waste collected $\times 100$	ISTAT – A misura di comune	2022
	Urban green space ratio [urb_green_space]	Total green area/ Total municipal area $\times 100$	Corine Land Cover Data/ ISTAT macro-areas	2018/ 2021

Table 1 (continued)

Dimensions	Indicators	Definition/calculation	Source	Year
Governance	Children taken into care by municipal child welfare services [child_serv]	Children aged 0–2 who have used childcare services offered by municipalities/ Annual average number of resident children aged 0–2 × 100	ISTAT – A misura di comune	2022
	Expenditure on social interventions and services per family and minors [exp_fam_min]	Municipal expenditure per family and minors/ Total municipal expenditure × 100	ISTAT – A misura di comune	2021
	Expenditure on social interventions and services per inhabitant [exp_inhab]	Municipal expenditure/ Average resident population	ISTAT – A misura di comune	2021
	Women in decision-making bodies by municipality (Municipal councils) [wom_mun_coun]	Women in municipal councils/ Total number of municipal council members × 100	ISTAT – A misura di comune	2022
People	Active users per library [active_libr_user]	Total active users/ Number of libraries	ISTAT – Censimento sulle biblioteche pubbliche e private	2022
	Aging index [aging_index]	Residents aged 65 and over on 1 January/Residents aged 0 to 14 on 1 January × 100	ISTAT – Indice di fragilità comunale	2022
	Incidence of tertiary qualification attainment [inc_tert_edu]	Percentage of people aged 25–49 who have obtained a tertiary qualification (ISCED 5, 6, 7 or 8)/ Total number of people aged 25–49	ISTAT – Indice di fragilità comunale	2022
	Population growth rate [pop_gro_rate]	Total net migration for the period observed/Resident population as at 31 December 2011	ISTAT – Indice di fragilità comunale	2021

Table 1 (continued)

Dimensions	Indicators	Definition/calculation	Source	Year
	Resident foreign population [resid_for_pop]	Foreign population residing as of 31 December. The foreign resident population consists of persons of non-Italian citizenship who have their habitual residence in the municipality where they are registered	ISTAT – Indice di fragilità comunale	2022

3.1 Constructing a composite index of smartness

Smartness is a complex theoretical concept that encompasses several dimensions, each capturing a distinct aspect of the phenomenon. From a modelling point of view, it can be described as a multidimensional construct that is not directly observable (latent) but can be inferred from a set of manifest indicators. Several analytical approaches have been proposed in the literature to estimate the relationships between constructs and their related indicators and obtain a composite index. Among them, Structural Equation Modelling (SEM; Hair et al. 2021) stands out, as it captures the entire system of causal relationships between latent and observed variables based on a theoretical model, rather than simply aggregating elementary indicators. In such a modelling framework, multidimensional constructs are represented as hierarchical structures, where a higher-order construct capturing the general concept is related to several first-order constructs that represent its distinct dimensions, each of which is measured by a set of observed indicators. To estimate the relationships between constructs and their associated indicators, either a reflective or formative measurement model can be adopted (Henseler 2020). In reflective models, indicators are viewed as manifestations of the latent construct, whereas in formative models, the latent construct is defined as a composite of its indicators. Similarly, the relationships between the higher-order construct and the first-order constructs can be specified as either reflective or formative, depending on whether the higher-order construct is seen as causing or being caused by its dimensions.

In the present work, we defined *Smartness* as a second-order construct formatively related to the four first-order dimensions of *Economy*, *Environment*, *Governance*, and *People*, each reflectively measured by its observed indicators (see Table 1). The corresponding path diagram is shown in Fig. 1.

To examine the relationships underlying our composite index and obtain a smartness score for each Italian municipality, we employed the Partial Least Squares Path Modelling (PLS-PM; Tenenhaus et al. 2005), a component-based SEM approach exploiting Ordinary Least Squares regression. This approach proved to be particularly useful for the construction of composite indices, not relying on strong assumptions about data distribution, number of indicators, and sample size. Moreover, this method offers researchers great flexibility by supporting both formative and reflective measurement models, thus allowing for a more nuanced assessment of theoretical concepts (Hair et al. 2011). For this reason, it is well

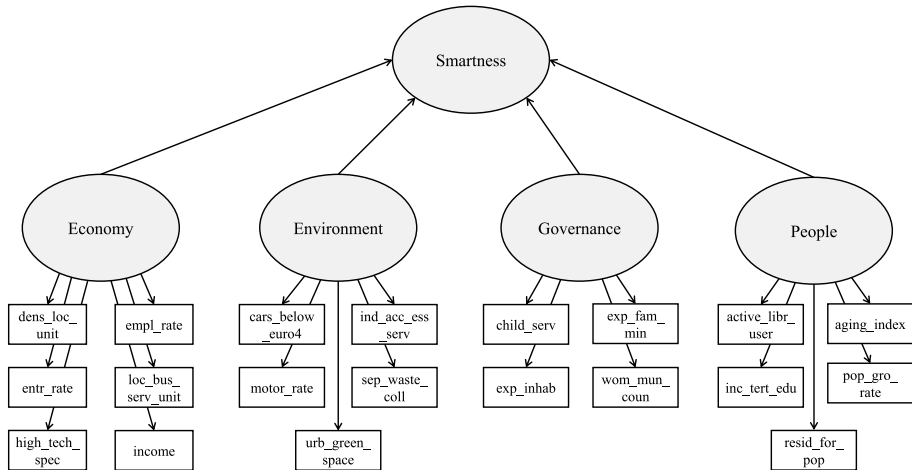


Fig. 1 Path diagram of the Smartness Index

suitable to estimate complex models that involve many latent and observed variables, especially in contexts aimed at theory development (Chin 1998). Within social research, relevant applications of PLS-PM in the construction of composite indices for higher-order constructs can be found in Cataldo et al. (2017), where it is employed to develop a multidimensional index of poverty; in Cataldo et al. (2021), for measuring sustainable development; and in Davino et al. (2018), where it is used to study equitable and sustainable well-being of the Italian provinces.

Various approaches have been proposed in the literature to estimate parameters in models involving hierarchical constructs (Higher-Order PLS-PM). Among the most commonly used are the Repeated Indicator Approach (Lohmöller 2013), the Two-Step Approach (Sanchez 2013), the Mixed Two-Step Approach (Cataldo et al. 2017), and the PLS Components Regression Approach (Cataldo et al. 2017). We employed the Mixed Two Step Approach because it proved to be particularly effective when a reflective-formative measurement model has been defined for the hierarchical construct, as in our study. This method divides the analysis into two steps:

Step 1. Implementation of the PLS-PM in the case of the Repeated Indicators Approach, namely using the indicators of the first-order constructs as manifest variables of the second-order construct. More formally, let $Y = (Y_1, Y_2, \dots, Y_J)$ be the vector of J observed variables measuring K first-order latent variables ξ_k^I ($k = 1, \dots, K$). Moreover, ξ^{II} denotes the second-order latent variable. The measurement or outer model connecting the observed variables to the corresponding latent construct is then specified as follows:

$$Y = \Lambda^I \xi^I + \delta \tag{3}$$

$$Y = \Lambda^{II} \xi^{II} + \epsilon \tag{4}$$

where Λ^I and Λ^{II} are the matrices of factor loadings linking the manifest variables to the first-order and second-order latent variables, respectively. Moreover, δ and ϵ are the

measurement errors terms. The structural or inner part of the model, specifying the relationships between the first-order and second-order latent variables, is instead described by the following equation:

$$\xi^{II} = \mathbf{B} \xi^I + \zeta \quad (5)$$

where \mathbf{B} is the matrix of path coefficients linking the first-order and second-order latent variables, and ζ is the structural error term. At the end of this step, the scores for each latent variable are obtained.

Step 2. The estimated scores of the first-order latent variables $\hat{\xi}_k^I$ obtained at Step 1 are used as manifest indicators of the second-order construct, and a PLS-PM algorithm is implemented. At this stage, the structural model in Eq. (5) and the measurement model of the first-order constructs in Eq. (3) are the same as before, whereas the measurement model of the second-order construct in Eq. (4) is updated, becoming a function of the components obtained at step 1:

$$\xi^{II} = \sum_{k=1}^K \omega_k \hat{\xi}_k^I + \epsilon \quad (6)$$

where ω_k is the weight associated to the k -th component (dimension), which expresses the strength of the relationship with the second-order construct.

The R package `plmpm` (Sanchez et al. 2024) was used to obtain parameter estimates. The PLS-PM algorithm determines the construct scores by an iterative process between inner and outer models. As the name ‘partial’ suggests, the outer estimation is independently obtained for each block (construct) as a linear combination of the corresponding observed variables. Conversely, the construct’s inner estimation considers its relations with the other constructs in the model. This iterative procedure runs until convergence, aiming at computing the outer model weights to get construct scores. Thereafter, the path coefficients can be estimated through an ordinary least squares regression between the obtained constructs. For more details about the PLS-PM algorithm see Henseler (2010).

The assessment of model fit involves measures of quality for both the measurement and structural parts of the model. For reflective measurement models, the evaluation focuses on the indicators’ reliability and validity. In particular, we considered the Cronbach’s α indicator to assess internal reliability and the Dillon-Goldstein’s ρ for composite reliability. Values above 0.70 are generally interpreted as evidence of good reliability. To evaluate indicator reliability, we examined the corresponding outer loadings (Hair et al. 2006). Loadings should be higher than 0.70, but indicators with lower outer loadings do not necessarily need to be removed if they are relevant for content validity and do not compromise convergent validity and composite reliability (Hair and Alamer 2022). To evaluate convergent validity, we used the Average Variance Extracted (AVE), which measures the extent to which the latent variable captures the variance of the indicators. AVE values equal to or greater than 0.5 are generally acceptable, although values as low as 0.4 may be tolerated (Hair et al. 2016). Concerning the structural part linking the first-order dimensions to the second-order construct, the sign and size of the path coefficients are evaluated. Finally, we considered the Goodness-of-Fit measure (GoF; Tenenhaus et al. 2005) and the Redundancy for the global

model assessment. Their values range from 0 to 1, with a higher value indicating a better model fit.

3.2 Spatial analysis

After defining the smartness measure, a spatial analysis was conducted to examine the geographical distribution of the index and to identify potential spatial clustering of similar values. The objective was to assess the presence of spatial autocorrelation (or spatial dependence), namely the tendency for observations of a variable to be correlated across geographic space. In such cases, the value observed at a given location is not independent but is influenced by values observed in neighbouring locations. This notion is grounded in Tobler's First Law of Geography (Tobler 1970), which posits that 'everything is related to everything else, but near things are more related than distant things'. Accordingly, when spatial autocorrelation is present, the distribution of the variable departs from spatial randomness and exhibits an underlying spatial structure, potentially reflecting different degrees of spatial heterogeneity.

More formally, spatial autocorrelation occurs when the values of a variable observed in a given areal unit are (linearly) correlated with those observed in neighbouring units (Getis 2010). Its empirical assessment requires the specification of a reference scenario corresponding to the absence of spatial dependence. Under this null hypothesis of spatial randomness, the observed values are assumed to be independent of their geographic location; consequently, permuting the values across space should not affect the overall structure of the data.

To test for the presence of this phenomenon, the null hypothesis is compared against two alternative hypotheses: (1) Positive spatial autocorrelation: low (or high) values tend to be surrounded by other similarly low (or high) values, (2) Negative spatial autocorrelation: high values are surrounded by low values and vice versa, indicating strong contrast between neighbouring locations (Dubé and Legros 2014).

Spatial relationships among observations are formally described by the spatial weights matrix, which defines which units are considered neighbours based on their geographic proximity, thereby specifying the structure of spatial connectivity.

In order to analyse the spatial structure of the Smartness Index data, spatial autocorrelation was assessed through both the global and local Moran's I indices (Moran 1948; Anselin 1995). Connectivity among municipalities was defined according to the Queen contiguity criterion, under which two units are considered neighbours if they share a common border or vertex.

The Moran's I index is a statistical measure used to quantify spatial autocorrelation. Conceptually, it is a cross-product statistic that compares the value of a variable at a given location with a spatially weighted average of values from neighbouring areas (spatial lag) (Wei 2022).

$$I = \frac{W}{\sum_{i=1}^N \sum_{j=1}^N w_{ij}} \cdot \frac{\sum_{i=1}^N \sum_{j=1}^N w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^N (x_i - \bar{x})^2} \quad (7)$$

where N is the total number of spatial units, x_i and x_j are the values of the variable at locations i and j , \bar{x} is the mean of the variable, w_{ij} is the element of the spatial weight matrix

W representing the connectivity between units i and j ; $W = \sum_{i=1}^N \sum_{j=1}^N w_{ij}$ is the sum of all spatial weights.

A positive value of the global Moran's I indicates clustering of similar values, whereas a negative value suggests the presence of dissimilar values in neighbouring units.

After calculating the Global Moran's I , a local measure—the Local Moran's I —is employed to capture spatial heterogeneity and the local structure of spatial autocorrelation. This indicator decomposes the global statistic, allowing for the assessment of each spatial unit's contribution to the overall result. As such, it enables the detection of spatial clusters and spatial outliers within the study area. Importantly, Local Moran's I can reveal significant localised spatial patterns even when no global autocorrelation is observed (Sokal et al. 1998). The local Moran's I for each unit i is calculated as:

$$I_i = (x_i - \bar{x}) / m_2 \sum_{j=1}^N w_{ij} (x_j - \bar{x}) \quad (8)$$

where x_i is the attribute value of the variable at location i ; x_j is the attribute value of the variable at location j ; \bar{x} is the mean value of the variable; w_{ij} is the element of the spatial weight matrix W representing the connectivity between areal unit i and areal unit j ; $m_2 = \sum_{i=1}^n (x_i - \bar{x})^2 / n$; N denotes the total number of areal units.

The Local Moran's statistic I_i expresses the degree of covariation between the value observed at location i and the values of its neighbouring units j , weighted by spatial proximity. Positive values of I_i indicate that location i is surrounded by units with similar values (i.e., spatial clusters), while negative values reflect the presence of spatial outliers.

The statistical significance of I_i can be assessed through conditional randomisation. In this method, the observed value x_i remains fixed, while the remaining $N - 1$ values are randomly permuted. This process generates a pseudo-reference distribution of I_i from which the empirical significance of the observed statistic can be evaluated.

Based on the statistically significant values of Local Moran's I , municipalities were classified into distinct spatial clusters. Municipalities with high values of the Smartness Index, surrounded by neighbours with similarly high values, were identified as High–High (HH) clusters, or hot spots. Conversely, municipalities with low Smartness Index values surrounded by similarly low values were categorized as Low–Low (LL) clusters, or cold spots.

Spatial outliers were also detected: municipalities with high Smartness Index values surrounded by neighbours with low index values were classified as High–Low (HL) clusters. Similarly, municipalities with low index values surrounded by neighbours with high Smartness Index values were classified as Low–High (LH) clusters.

Lastly, municipalities that did not exhibit statistically significant local spatial autocorrelation were classified as Not Significant, indicating that their Smartness Index values were not significantly different from the mean scores of their surrounding areas.

4 Results

In this section, we first describe the results on the composite Smartness Index for Italian municipalities, examining the PLS-PM model parameters and model fit. Subsequently, insights from spatial analysis are discussed, with cartographic representation describing the distribution of the Smartness Index and the spatial structure of the data.

4.1 Smartness index

We obtained a composite index of smartness by implementing a PLS-PM with a second-order construct formatively related to the four first-order dimensions of economy, environment, governance, and people, each reflectively measured by a set of observed indicators.

The results related to the assessment of the measurement model, which links each construct to the observed variables, are first presented. As shown in Fig. 2, most indicators exhibit satisfactory reliability, with factor loadings above or near 0.70. The indicator `inc_tert_edu`, although below the minimum threshold of 0.40, was retained to preserve content validity. Note that indicators with negative polarity were reversed before implementing the PLS-PM algorithm.

Table 2 shows the reliability and validity measures for the latent variables. Cronbach's α and Dillon-Goldstein's ρ are generally close to the recommended threshold of 0.7, with the only exception of the governance dimension, which reports a low Cronbach's α , suggesting limited internal reliability, though its composite reliability remains adequate. Moreover, the AVE measure indicates an acceptable convergent validity, assuming values above or near the minimum threshold of 0.40 for the considered constructs.

Regarding the structural part of the model, Table 3 displays the estimated path coefficients connecting the first-order dimensions to the global Smartness construct. The corresponding 95% bootstrap confidence intervals are also provided to evaluate the statistical

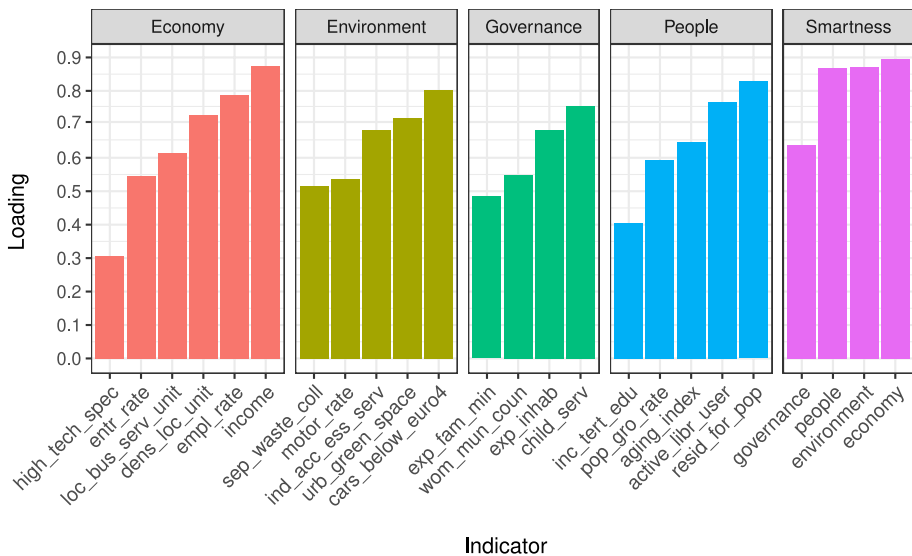


Fig. 2 Indicators' factor loadings for the considered latent variables

Table 2 Reliability and validity measures

Construct	Cronbach's α	Dillon-Goldstein's ρ	AVE
Economy	0.73	0.82	0.45
Environment	0.67	0.79	0.44
Governance	0.47	0.71	0.39
People	0.66	0.79	0.44
Smartness	0.84	0.89	0.68

Table 3 Path coefficients with standard errors and 95% bootstrap confidence intervals

First-Order Construct	Path	Std. error	95% bootstrap CI
Economy	0.327	0.002	[0.323; 0.329]
Environment	0.315	0.002	[0.312; 0.318]
Governance	0.249	0.001	[0.247; 0.251]
People	0.316	0.001	[0.313; 0.319]

significance of each relationship. Results show that all path coefficients are statistically significant, with Economy emerging as the most influential dimension ($\beta = 0.327$, 95% CI = 0.323 to 0.329), while Governance appears to have the weakest impact among the considered factors ($\beta = 0.249$, 95% CI = 0.247 to 0.251). The path diagram of the Smartness Index, along with the estimated factor loadings and path coefficients, is shown in Fig. 5 in Appendix A.

Finally, the GoF and Redundancy measures suggest an adequate global model fit, with values of 0.69 and 0.68, respectively. Overall, the results support the good quality of the Smartness Index.

4.2 The geography of smartness in Italy

The results of the ESDA allow us to assess whether—and to what extent—the distribution of Smartness Index exhibits a spatial structure. Firstly, to facilitate interpretation, we mapped the index scores. This visualisation provides insights into the geographical distribution of smartness across Italian municipalities, revealing distinct territorial patterns of high and low index values.

Several significant findings emerge from the map in Fig. 3. First and foremost, the analysis highlights persistent territorial disparities, notably the historical North–South divide that characterises the Italian context. Northern regions, such as Emilia-Romagna, Lombardy, and Veneto, exhibit a higher concentration of municipalities with elevated smartness scores. This suggests that these areas perform well across various dimensions of smart development, including governance, environmental sustainability policies, economic growth and competitiveness, and human capital⁶. These factors are further supported by stronger digital and technological infrastructures, which are markedly more developed than those in the South (Savi et al. 2024).

Central Italy occupies an intermediate position. While some municipalities in the Lazio and Toscana regions record high index values, the overall spatial distribution is more heterogeneous. Municipalities located in inland areas tend to score lower than those in coastal areas. These findings indicate that although central Italy shows signs of smart advancement,

⁶See Appendix B for the cartographic representations of the scores for each dimension of the Smartness Index.

Italian municipalities – Smartness Index map

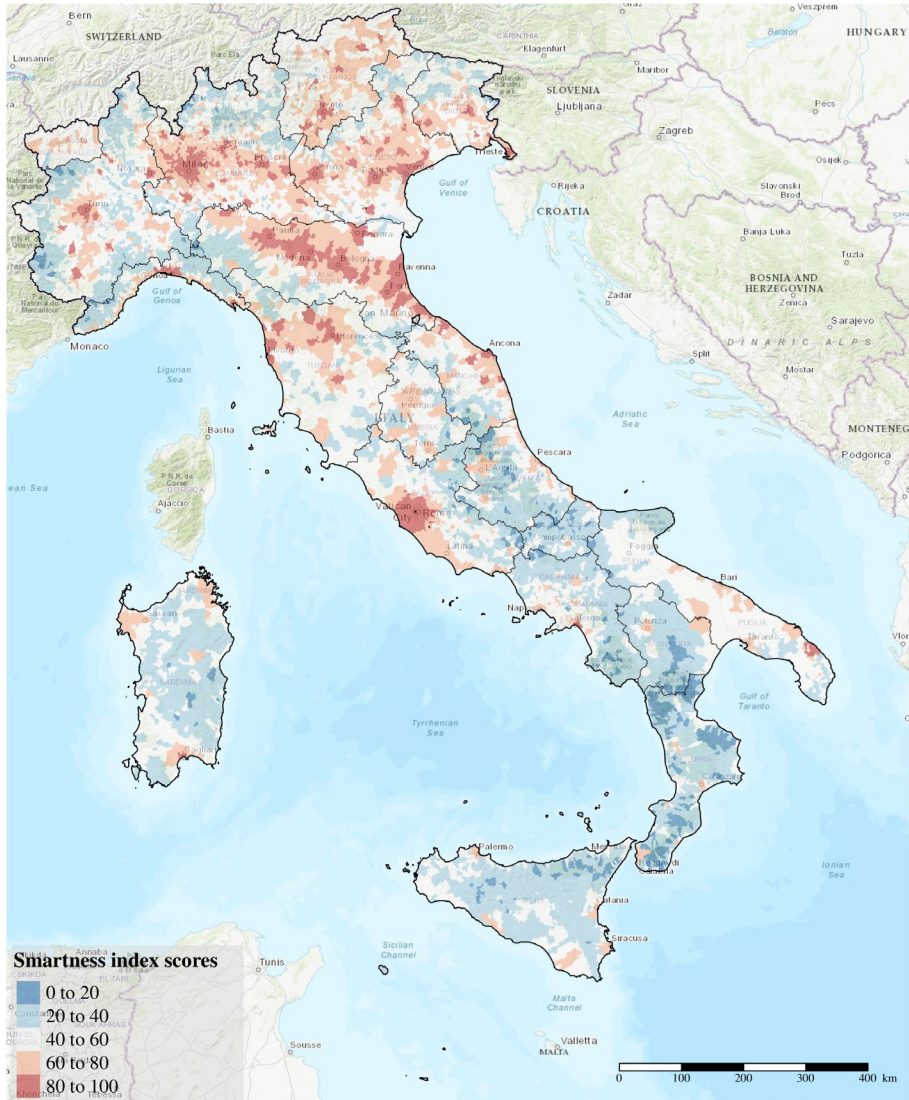


Fig. 3 Smartness Index score map of Italian Municipalities

the process is uneven, with significant internal disparities between coastal and hinterland municipalities.

In contrast, Southern Italy and the Islands display a predominantly homogeneous pattern of low performance levels, with the exception of a few regional capitals. Particularly low values are observed in regions such as Basilicata, Calabria, and Sicily. These results reflect a broader picture of structural fragility in these territories, characterised by lower GDP levels, weaker business competitiveness (especially in highly value-added sectors focused on innovation), and limited technological development (Morlicchio 2020; Saraceno et al. 2020).

Furthermore, reduced levels of human capital often characterise these areas, which are considered crucial pre-conditions for fostering smart municipal development and for promoting inclusive, citizen-oriented local governance and service delivery (Giffinger and Lu 2015).

With regard to the results of the spatial autocorrelation analysis, the global Moran's I coefficient (0.74 under the randomisation hypothesis) reveals a statistically significant and non-random spatial distribution of the index values (p -value < 0.001). This finding rejects the null hypothesis of spatial randomness and indicates a clear pattern of spatial clustering where municipalities with similar levels of smartness tend to be geographically concentrated.

Figure 4 displays the local Moran map for the Smartness Index, providing a visual representation of its spatial configuration across Italian municipalities. In essence, the local Moran's I allows the detection of spatial clusters where municipalities with similar values are concentrated, as well as spatial outliers that diverge from their local neighborhood. The analysis revealed the presence of municipalities surrounded by neighboring units with similar (High–High or Low–Low) or contrasting (High–Low or Low–High) index values.

Focusing first on the High–High clusters (comprising 1,555 municipalities), it is evident that they are predominantly located in the northern regions of the country, with a more limited presence in central Italy. On the contrary, clusters of high values are almost absent in the South, with a few exceptions in regions such as Campania, Puglia, and Sardinia. In contrast, Low–Low clusters (1,276 municipalities) are mainly concentrated in the southern areas (particularly Basilicata, Calabria, and parts of Campania) and the Islands (Sicily and Sardinia). Notably, Puglia does not show significant concentrations of low index values. It is also worth highlighting the presence of low–low clusters in central Italy's inland areas. These municipalities, often characterised by low population density and affected by depopulation processes, are among those identified as priority intervention zones in Italy's National Strategy for Inner Areas (Carrosio et al. 2020). This strategy aims to foster a sustainable transformation of such regions through the reallocation of local resources and the revitalisation of their socio-economic fabric.

The analysis also identifies the presence of spatial outliers: High–Low (61 municipalities) and Low–High (19 municipalities). High–Low municipalities, primarily located in the South and the Islands, may represent isolated smart municipalities with relatively strong performance across the measured dimensions. Yet, they are embedded in structurally weaker contexts. These municipalities include a heterogeneous set of urban centres, ranging from medium-sized cities to small towns with specific functional roles, such as tourist destinations (e.g., Taormina, Cefalù, Agrigento), the presence of universities (e.g., Cassino, L'Aquila), administrative centres, or local service hubs (e.g., Ventimiglia, Rieti, Sulmona, Reggio Calabria, Messina). Conversely, Low–High municipalities are fewer in number and are mostly represented by small-sized municipalities located in Northern (e.g., Lagnasco, Villafalletto) and Central (e.g., Galliciano nel Lazio, Mombaroccio) Italy. These cases may reflect underperforming localities, potentially due to demographic factors, local governance, institutional, or infrastructural constraints that hinder their alignment with the surrounding territory. Their functional role is limited, being typically subordinate to metropolitan areas or larger urban centres. In general, the presence of High–Low and Low–High outliers highlights that smartness does not diffuse uniformly across the national territory and that local institutional, functional, and socio-economic characteristics play a crucial role in

Italian municipalities–Smartness Index Moran map

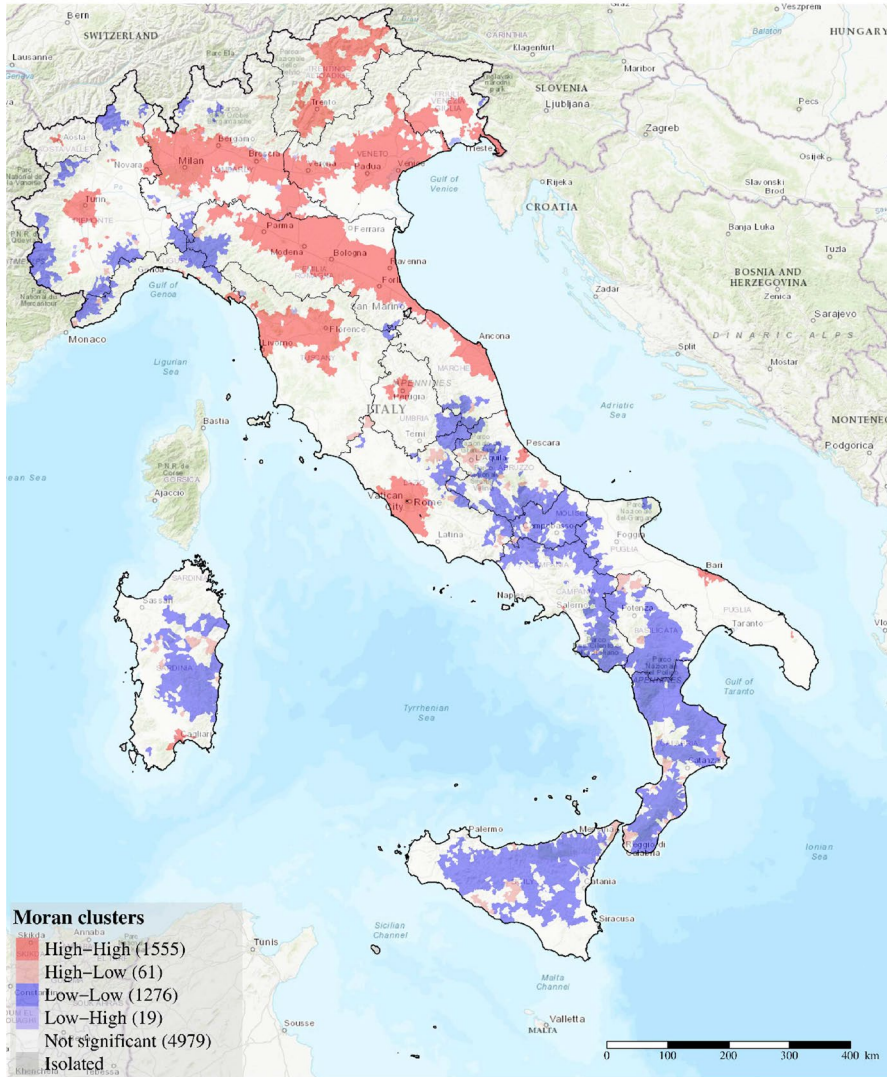


Fig. 4 Local Moran map of Smartness Index scores for Italian municipalities

shaping municipal trajectories, resulting in a heterogeneous portfolio of projects that often lacks a common strategic plan (Dameri et al. 2019).

In conclusion, the results emerging from the local Moran's I analysis suggest the presence of a marked North–South divide in the geography of smartness. Clear patterns of spatial concentration emerge. In the North, the findings indicate the existence of cohesive territorial systems where smartness appears to be well-established and regionally diffused. By contrast, the South is characterised by widespread structural weaknesses. Central Italy

occupies an intermediate position, with more limited clusters of smart municipalities, particularly along coastal areas, and greater internal disparities in inland regions.

5 Conclusion

This study proposed a new composite Smartness Index for Italian municipalities, grounded in a robust methodological framework that combines structural equation models with spatial analysis indices. The development of this integrated approach made it possible, on the one hand, to define a meaningful measure for capturing the multifaceted nature of smartness, and on the other hand, to spatially represent its territorial distribution and structure through ESDA tools, identifying patterns of high and low smartness across the territory.

Specifically, we exploited a Higher-Order PLS-PM approach as it is particularly effective in describing the complexity of this multidimensional phenomenon, while also providing a rigorous assessment of measurement quality. The application of the PLS-PM framework to construct a composite Smartness Index offers a novel contribution in comparison to traditional aggregation methods, as it allows for the modelling of the entire system of causal relationships between latent constructs and manifest indicators, structured according to a theoretical framework. The obtained Smartness Index exhibits a good model fit and appears to provide a reliable measurement of the phenomenon. Moreover, results suggest that the economic dimension is the most influential in determining smartness levels. This is not surprising, as economic development is increasingly intertwined with infrastructural growth and the diffusion of advanced digital technologies. These interdependencies contribute to strengthening the role of the economic dimension in shaping smartness, although the other dimensions also exert a significant influence.

While the overall measurement quality of the proposed Smartness Index is satisfactory, the Smart Governance dimension requires cautious interpretation. This component displays comparatively lower internal consistency, reflecting the partial empirical operationalisation of a theoretically complex construct. Such limitations are primarily driven by data constraints, as several conceptually relevant indicators are not currently available from official statistical sources at the municipal level. To mitigate this issue, future research could strengthen the Smart Governance dimension by exploiting improved data availability at the local scale and by incorporating additional or alternative indicators, such as measures of political engagement, civic participation, perceived institutional transparency, and citizens' satisfaction with public services. These extensions would allow for a more comprehensive and robust representation of governance-related processes within the index.

Our findings reveal significant territorial heterogeneity in the distribution of smartness across Italy, confirming the persistence of long-standing structural divisions, most notably the pronounced North–South polarisation. Northern municipalities exhibit high performance levels, while the South remains characterised by widespread structural weaknesses that hinder the transition toward a smart development paradigm. Central Italy occupies an intermediate position, although internal disparities—especially between coastal and inland areas—are particularly notable.

Overall, these findings underscore the need for substantial investments aimed at bridging the North–South divide through targeted resource allocation, including not only the development of infrastructure but also the growth of economic, human, and social capital.

Crucially, these efforts should be framed within a strategic vision of sustainable development to strengthen the resilience of urban systems in the face of growing challenges such as rapid urbanisation and climate change.

An additional contribution of this study lies in the inclusion of small municipalities in the analysis of the smart development process in Italy. Often overlooked in previous research, these municipalities play a crucial role not only in the national transition toward smart development but also in relieving demographic pressure on large urban centres. To the best of our knowledge, the index proposed here represents one of the first attempts to extend the analysis to all Italian municipalities. Existing studies have focused on provincial capitals (see Ciacci et al. (2021)) and almost exclusively on infrastructural and digitalisation aspects (e.g., EY Smart City Index, ICity Rank).

Given its comprehensive territorial coverage, the proposed measure can serve as an effective monitoring tool for public decision-makers at both national and local levels. Owing to its multidimensional structure and the availability of harmonised data at the municipal scale, the Smartness Index—particularly when combined with cartographic representations—offers a clear and easily interpretable synthetic overview of the level of smart development across Italian municipalities.

Beyond its descriptive capacity, the index enables a more nuanced assessment by highlighting municipalities' strengths and weaknesses across the different dimensions of smartness, thereby providing a robust empirical basis for the design of targeted and territorially differentiated policy interventions.

The cartographic representation of the index and its constituent dimensions allows for a detailed monitoring of the spatial distribution of smart development, while the Local Moran's *I* analysis adds an additional analytical layer by identifying spatial clusters of high and low smartness and assessing their spatial extent. Taken together, these tools can effectively support policy design.

At the national level, the index may inform the allocation of public resources by identifying municipalities and geographic areas lagging behind in the transition towards smart development. At the local level, it can function as a self-assessment and monitoring instrument to support the formulation and evaluation of strategic plans aimed at strengthening key pillars of the smart transition, such as environmental sustainability, human capital, and participatory governance.

One of the primary limitations of this study is the scarcity of harmonised territorial data, which hindered the inclusion of all dimensions typically associated with the smart city paradigm. Nevertheless, the effort made in this work to construct a consistent dataset, which is aligned with dimensions identified in the literature and based on the integration of multiple data sources and ad hoc indicators, has helped mitigate this issue.

In particular, components related to quality of life, accessibility, and transport systems—namely Smart Living and Smart Mobility—were excluded from the analysis. Although these components represent important elements of the framework originally proposed by Giffinger et al. (2007), their operationalisation at the municipal level was not feasible due to limitations in data availability and comparability across the national territory. However, this choice does not undermine the validity of the analysis; rather, the proposed Smartness Index should be interpreted as a measure capturing the structural dimensions of urban smart development - such as economic competitiveness, environmental sustainability, institutional

capacity, and human and social capital - instead of a fully comprehensive representation of all aspects of urban smartness.

An additional aspect to be considered concerns the temporal dimension of the analysis. The proposed approach aims to provide a snapshot of the current state of smart development by relying on the most recent data available for the selected indicators. While this strategy allows for a clear description of the present conditions of Italian municipalities with respect to the smart transition, it does not capture the dynamic nature of smart development, which evolves over time in response to economic, technological, institutional, and environmental changes that affect territories with varying intensity. However, longitudinal analyses of smartness are dependent on the availability of data that are both regularly updated and comparable over time. Changes in statistical definitions, data collection methodologies, and data availability over time may hinder the ability to consistently trace the evolution of smart development and the identification of temporal trends.

Within this context, the present study may serve as a starting point for future longitudinal research. Extending the Smartness Index across multiple years would enable the monitoring of development trajectories, the assessment of policies aimed at fostering smart transitions, and the observation of differentiated pathways across municipalities. Given its reliance on official and comparable statistical sources, the Smartness Index provides a robust tool for consistent longitudinal analysis.

Smartness index: estimated factor loadings and path coefficients

See Fig. 5.

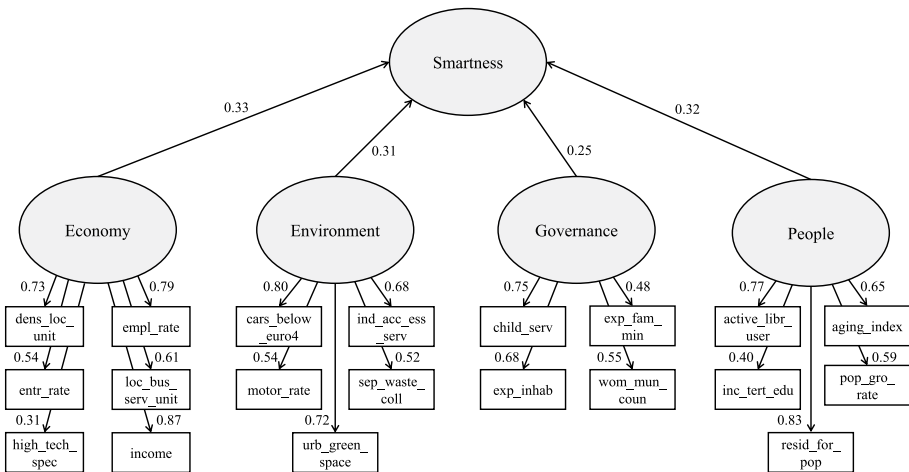


Fig. 5 Path diagram of the Smartness Index showing the estimated factor loadings and path coefficients. All coefficients are significant at $\alpha = 0.05$

Cartographic representations of the scores for each dimension of the smartness index

See Figs. 6, 7, 8 and 9.

Italian municipalities – Smart Economy Index map

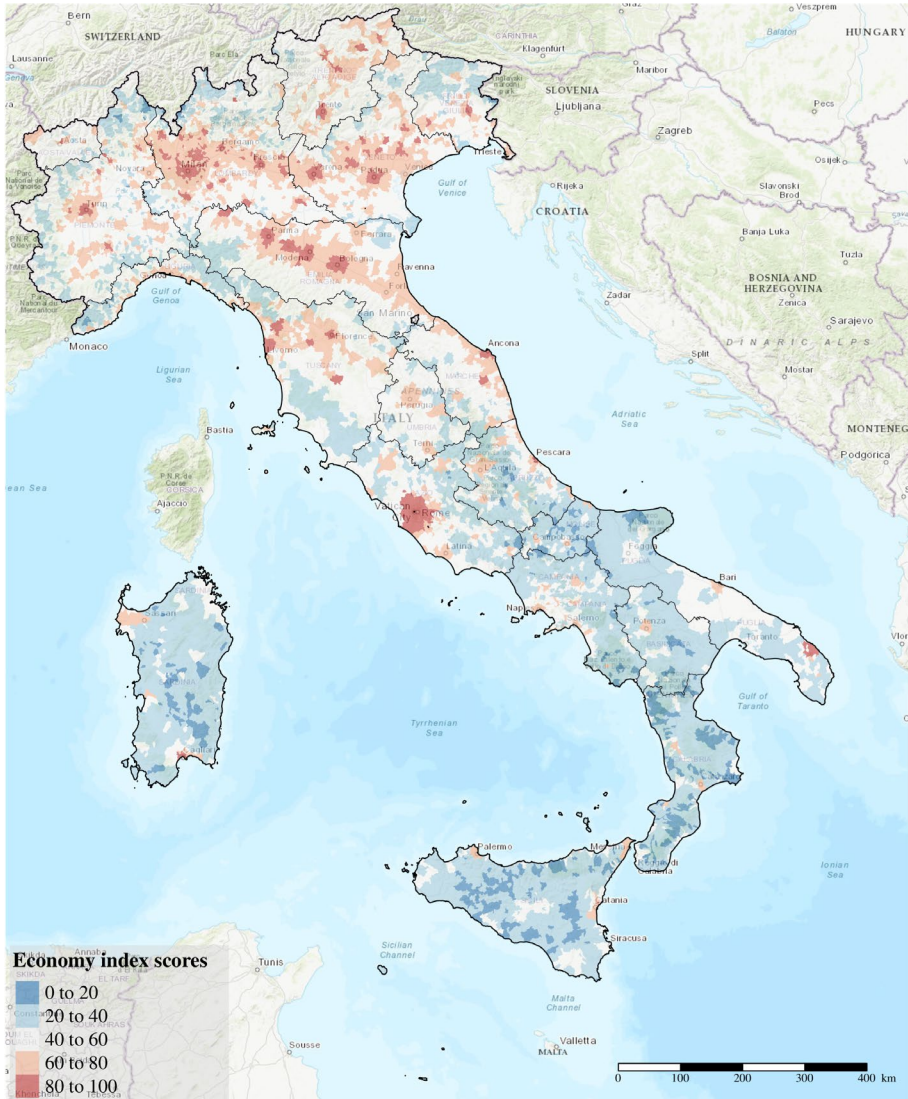


Fig. 6 Smart Economy Index score map of Italian Municipalities

Italian municipalities – Smart Environment Index map

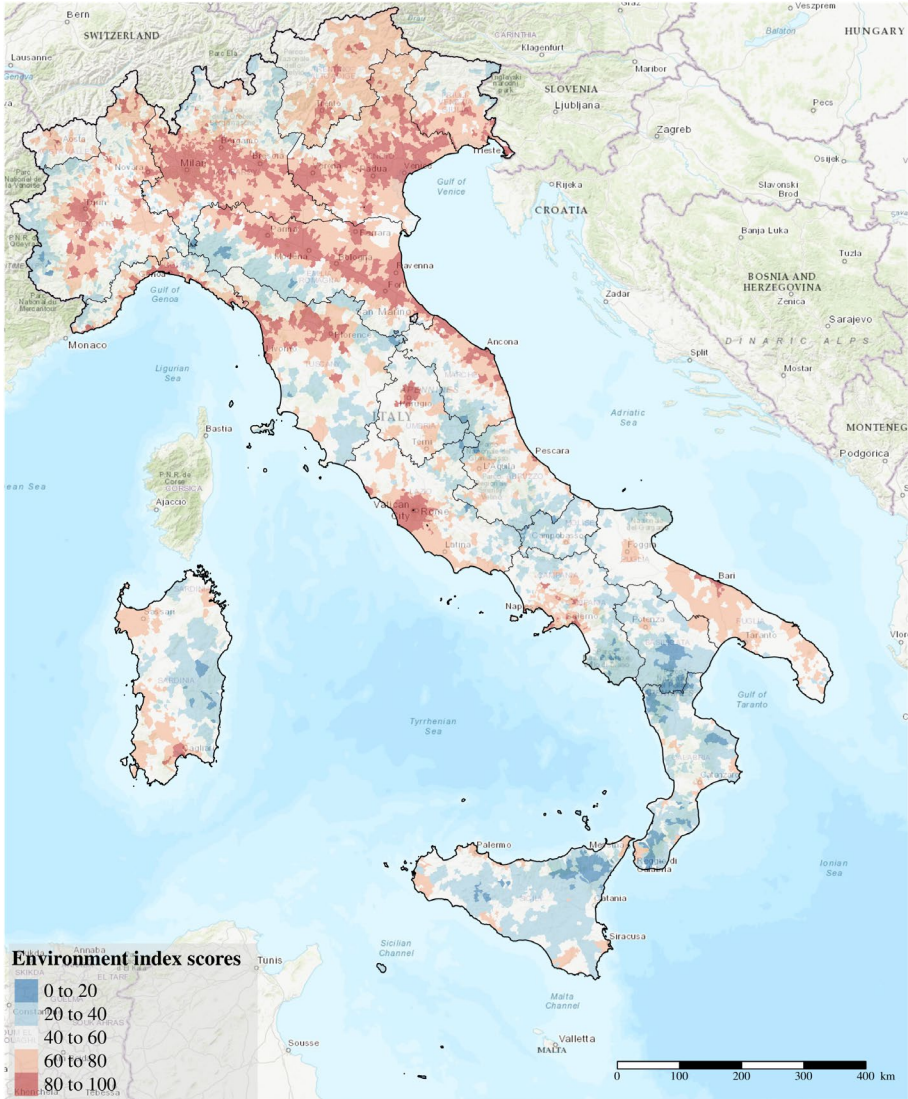


Fig. 7 Smart Environment Index score map of Italian Municipalities

Italian municipalities – Smart Governance Index map

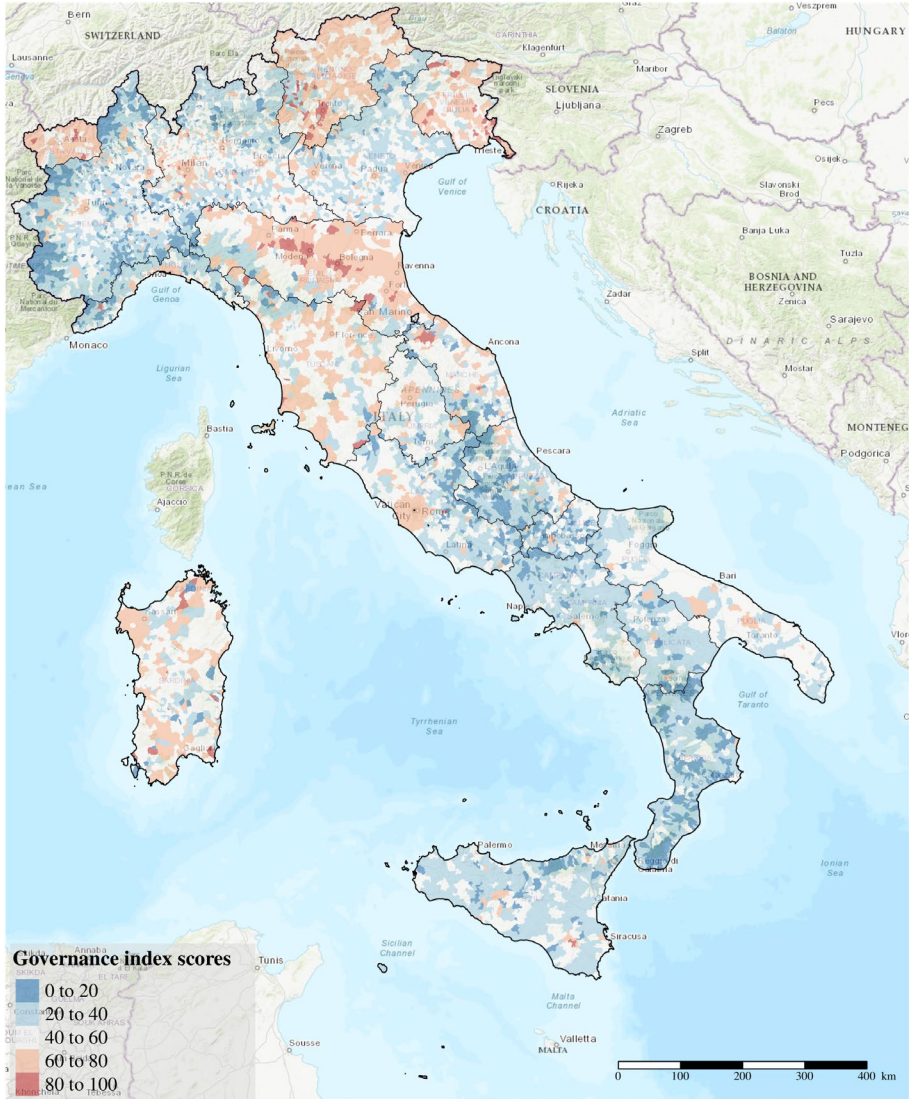


Fig. 8 Smart Governance Index score map of Italian Municipalities

Italian municipalities – Smart People Index map

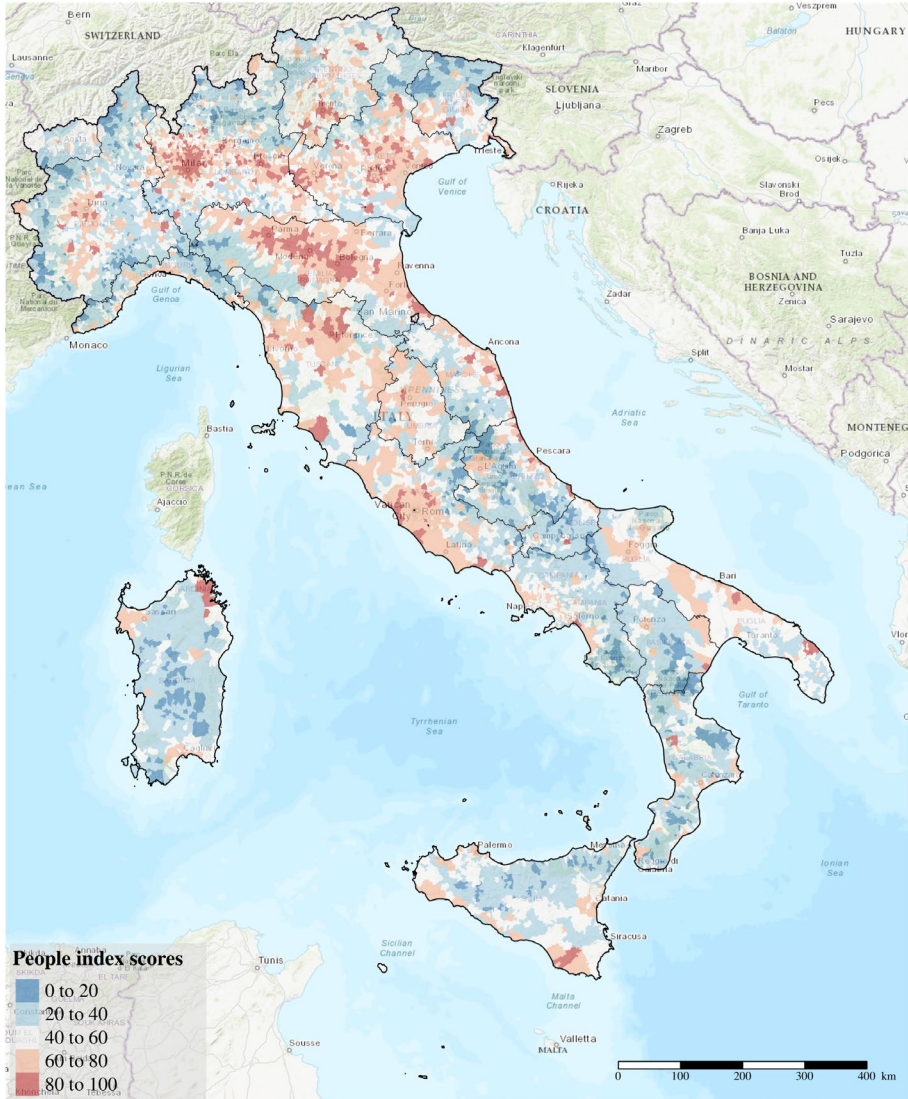


Fig. 9 Smart People Index score map of Italian Municipalities

Author contributions All the authors contributed equally to this work.

Funding Open access funding provided by Università degli Studi di Napoli Federico II within the CRUI-CARE Agreement. Rosa Fabbriackore acknowledges the financial support provided by the European Union - NextGenerationEU, in the framework of the GRINS - Growing Resilient, Inclusive and Sustainable project (GRINS PE00000018 - CUP E63C22002140007). The views and opinions expressed are solely those of the authors and do not necessarily reflect those of the European Union, nor can the European Union be held responsible for them.

Data availability No datasets were generated during the current study.

Declarations

Conflict of interest The authors declare no Conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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