Discriminant Analysis of Smart City Profiles Across Countries: A Multivariate Approach

Tommaso Filì[1](✉), Tiziano Pavanini[2], Enrico Ivaldi[3], and Enrico Musso[1]

[1] Italian Centre of Excellence in Logistics, Transport and Infrastructures, University of Genoa, Genoa, Italy
tommaso.fili@edu.unige.it

[2] Department of Architecture and Urbanism (DAStU), Politecnico di Milano, Milan, Italy

[3] Department of Humanistic Studies, IULM University - Faculty of Communication, Milan, Italy

Abstract. According to the United Nations, more and more people will live in cities in the coming years. This poses serious challenges to local governments in terms of pressure on transport infrastructure, waste management, lighting, sewerage systems and the environment. In such a context, city management needs to become increasingly efficient and intelligent, thanks to the fundamental support of technology, the Internet of Things (IoT) and artificial intelligence (AI). The so-called Smart Cities (SCs) are thus developing across the globe to address this profound change. This study applies linear discriminant analysis (LDA) to a dataset of 102 smart cities from around the world, each described by six key dimensions of smartness: mobility, environment, government, economy, people, and living. The aim of this paper is to assess whether smart cities from the same country tend to share similar profiles and to identify the most distinctive national patterns in smart city development. Results show high accuracy in classification, with most of the cities correctly attributed to their country based on their smart characteristics. Canonical discriminant functions yield appreciable separation between countries, highlighting stable national models and outliers. Additionally, results suggest that national agendas and regional contexts play an important role in shaping smart cities.

Keywords: Smart cities · Discriminant analysis · Multivariate statistics · Urban development · Smart governance · Canonical plot

1 Introduction

Urbanization is arguably one of the most significant trends of the 21st century. According to data from the United Nations, the urban population constituted over 56% of the global total by 2021, and it is projected to increase to nearly 70% by 2050 (United Nations, 2019). This population shift presents both opportunities and challenges. While cities are recognized as drivers of economic growth and innovation, they are also facing increased pressure on infrastructure, services and the environment (Dameri et al., 2019). The acceleration of urbanization demands new paradigms of urban development and governance that can effectively address aspects of sustainability, inclusivity, and resilience.

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To serve these requirements, the smart city was brought about as a topic of research and discussion for academics, policymakers, and citizens (Bogdanov et al., 2019). This paradigm shift resulted in a great expansion of the scale of research on smart cities, along with growth in the number of participating disciplines. These include, but are not limited to, urban studies, geography, computer science and public administration.

The smart city idea is inherently elastic, with varied interpretations based on the disciplinary context and policy issues of the observer. This has led to a failure of having a unifying definition that covers everyone (Ivaldi et al., 2020; Gracias et al., 2023). However, a consensus has been reached on a multidimensional approach including technological infrastructure, environmental sustainability, quality of governance, economic performance, human capital, and quality of life (Giffinger et al., 2007; Caragliu et al., 2011). Several studies have attempted to classify smart cities based on these dimensions, often using cluster analysis, principal component analysis, or composite indices (Lombardi et al., 2012; Neirotti et al., 2014; Eskantar et al., 2024; Penco et al., 2024), such as Pena's Distance (DP2) (Ciacci et al., 2021). According to Bogdanov et al. (2019), the definition of smart city has evolved over time, moving from an initial focus on the technological component, often defined as an intelligent city, information city, or techno city, to a broader vision that includes human and social aspects, quality of life, and sustainability. The concept of the smart city is inherently linked to the pursuit of sustainable development, defined as "*meeting the needs of the present without compromising the ability of future generations to meet their own needs*" (Maxim, 2018), which is enabled by the proper utilization of social capital and emerging technologies (Poletti and Michieli, 2018).

From the literature review of the SC concept, a development in its definition is seen, moving from a technologically focused approach to a broader view that includes sustainability principles (Shao and Min 2025).

Technology has been identified as playing a pivotal role in the advancement of SCs. Digital technologies, data, and new models of governance are used in smart cities to increase efficiency, sustainability, and quality of life in cities. According to market forecasts, global investment in smart city technology is estimated to exceed USD 820 billion by the year 2025 (Chan, 2022). Across the globe, most cities have incorporated smart approaches with the goals of enhancing mobility, reducing environmental impacts, facilitating participatory governance, and promoting economic and social innovation (Ivaldi and Ciacci 2023). Crucial in the development of SCs is the integration of information and communication technology (ICT) with conventional urban infrastructure to improve services and operational efficiency (Ahad et al., 2020; Penco et al., 2021). A wide range of enabling technologies, such as edge computing, unmanned aerial vehicles (UAVs), blockchain, and digital twins, have been seen to be critical in the development and sustainability of smart cities (Fatima et al., 2019; Agboola et al. 2023; Majeed et al., 2021; Deren et al., 2021). Edge computing, for instance, optimizes resource utilization and optimizes real-time functionality in major sectors like healthcare, transportation, energy, and water supply (Khan et al., 2019). UAVs are regularly scrutinized for their potential to advance service and city surveillance (Mohamed et al., 2020), and blockchain adoption is seen as a means of delivering secure data transfer and facilitating IoT (Internet of Things) applications in urban environments (Majeed et al., 2021).

Yet another crucial field of study in the development of smart cities is cybersecurity. Smart city systems are more interconnected and, as such, vulnerable to attacks that can undermine the integrity of the IoT infrastructure. For this reason, studies are being conducted on the use of deep learning-based approaches to overcome security challenges and enhance threat identification (Pan et al. 2021). Concurrently, the use of technical standards has become crucial in realizing interoperability across various systems and technologies (Lai et al., 2020). These technologies have also given rise to initiatives aimed at addressing significant urban issues, such as energy efficiency, data governance, and citizen privacy (Kirimtat et al., 2020; Kim and Feng 2024; Javed et al. 2022).

The establishment of smart cities also entails hard challenges on the policy and governance fronts. A significant challenge that remains to be addressed pertains to the realm of security and privacy within the ambit of smart city networks, particularly in the context of utilizing IoT and blockchain technologies. In response to these challenges, researchers have proposed nature-inspired secure data dissemination models as a potential solution. These models aim to enhance trust and ensure safe data protection (Qureshi et al., 2020). Additionally, there is a call for better legal and technical means of safeguarding citizen rights (Hernandez-Ramos et al. 2020; Xihua and Goyal 2022).

There have been advances in anomaly and intrusion detection (Houichi et al., 2022) as well, mirroring the growing complexity of cybersecurity systems. Furthermore, information systems and governance frameworks are identified as being instrumental to successful smart city strategy execution. For instance, Zhou et al. (2020) identified governance policy and ICT research as innovation drivers and future development in smart city field based on scient metric analysis with CiteSpace.

Within this context, significant research questions are raised: *Do smart cities in similar circumstances across a nation exhibit analogous characteristics? Is there one overarching national pattern of smart city development, or do cities follow divergent paths regardless of their geographical location?* These are not only theoretically significant questions but also for policymaking, as they pertain to the influence of institutional context, types of governance, and socio-economic scenarios.

The present study aims to provide answers to the questions by employing a multivariate statistical method. Specifically, we apply Linear Discriminant Analysis (LDA) to 102 SCs worldwide to examine whether they can be correctly categorized into their countries of origin based on their performance in six smartness dimensions: Smart Mobility, Smart Environment, Smart Government, Smart Economy, Smart People, and Smart Living. These dimensions have been well-rooted in the smart city literature (Marchesani et al. 2024; Grossi and Welinder, 2024; Periñán-Pascual, 2023; Mora et al., 2019; Dameri and Benevolo, 2016). and offer an overall framework of the features that define a city's smartness.

LDA offers a promising methodology for exploring the research questions above since it allows researchers to explore whether groups defined by some attributes (e.g., nations) can be distinguished consistently from multivariate profiles. Past applications of LDA in urban studies have examined regional economic performance (Steiniger et al., 2008), quality of life (Batóg and Batóg, 2019), or innovation potential (Lane 2008), but its application to the smart city case remains limited. This paper seeks to fill this gap by applying LDA to a wide and diverse dataset of smart cities worldwide. By exploring the degree of homogeneity among cities within a country and among countries, our main goal is to render transparent the structural tendencies which underline smart city development. Our results have implications for both academic scholarship and urban policy because they offer evidence of the degree to which national level variables shape local urban policy and the global geography of smart city innovation.

The study is organized into five sections. The "Introduction" delineates the significance of comprehending the factors that determine the development of smart cities and presents the literature review. The second section, entitled "Methodology", presents the dataset utilized in the study, along with a detailed exposition of the methodology employed. "Results" outlines the main findings of the analysis, while the fourth section, entitled "Discussion", discusses these findings. Finally, in "Conclusions" the implications of the findings, the limitations of this study and the future agenda are stated.

2 Methodology

This study is a quantitative multivariate design with linear discriminant analysis (LDA) as the statistical technique to determine linear combinations of variables that best distinguish between two or more groups as defined in advance (Rencher, 2002). The LDA is suited to our research question, i.e., to identify country level patterns in the smart profiles of cities.

2.1 Dataset and Variables

For the sake of this paper, publicly accessible information from the IMD Smart City Index 2024 report published by the International Institute for Management Development (IMD) has been used, which provides comprehensive data on the performance of smart cities according to significant dimensions of health, safety, mobility, and governance.

The dataset includes 102 smart cities from various regions including Europe, North America, Asia, and Oceania. Each city is described by six dimensions of smartness commonly cited in the literature:

- Smart Mobility,
- Smart Environment,
- Smart Government,
- Smart Economy,
- Smart People,
- Smart Living.

These dimensions are derived from the framework proposed by Giffinger et al. (2007), one of the most influential models in smart city studies. The raw data for the six dimensions were obtained from a standardized smart city ranking report and normalized to ensure comparability across cities.

2.2 Statistical Method

We applied LDA using the six smartness dimensions as predictors and the country of origin as the grouping variable. The LDA model computes one or more discriminant functions, linear combinations of input variables, which maximize between-group over within-group variances so that group separability is optimal (Hair et al., 2010). Model performance is assessed through percent correct classified observations, overall model significance test (Wilks' Lambda test), and investigation of posterior probabilities of group membership. The analysis also produces a canonical plot, which visualizes the discriminator scores for the first two canonical functions and allows for an intuitive assessment of group clustering. The LDA has requirements of multivariate normality and equality of covariance matrices across groups. We conducted preliminary diagnostics to check for these assumptions. While there were minimal deviations, the analysis is robust due to the quite balanced group sizes as well as the interpretive nature of our objective. Limitations are the potential biases in city and source selection, as well as excluding qualitative factors that can also contribute to smart city development. Besides, the used variables are dependent on subjective questionnaires, which can introduce cultural biases in the way individuals from various countries perceive and rate certain aspects, which can affect comparability of data. Future research can include mixed methods to resolve these limitations.

3 Results

3.1 Multivariate Significance and Canonical Functions

The data set consists of 102 cities that are unevenly distributed across nations. Italy (15 cities), Germany (14), and Finland (11) have the highest representation, while numerous others such as Austria, Slovenia, Slovakia, Belgium, and Luxembourg have a single city's representation. This unequal distribution reflects the difference in maturity and availability of smart city data in nations. While nations with greater numbers of cities contribute to strong estimations of group centroids, less-represented nations might bring about more variation.

In linear discriminant analysis (LDA), when the result is graphed (e.g., Fig. 1), there is usually the presence of axes labeled "Canonical 1" and "Canonical 2" These labels are names for the first two canonical functions, linear combinations of the original variables (in this case: smart mobility, environment, government, economy, people, and living), that the model identifies to best distinguish groups of cities by country of origin. The "Canonical 1" function is the linear combination that best separates the countries. Therefore, it is the primary discriminant axis, and it picks up the largest amount of between-group variation. If one were to use one dimension to guess a city's country, this function would give the most useful criterion. On the other hand, the "Canonical 2" function is orthogonal to the first and accounts for further variation not yet explained by Canonical 1. While it accounts for less overall variance, it offers informative details that continue to distinguish groups. The strength of this visual representation is its interpretability: it transforms a complex multivariate space to a plain, two-dimensional map, in which relationships and differences between groups are apparent and accessible.

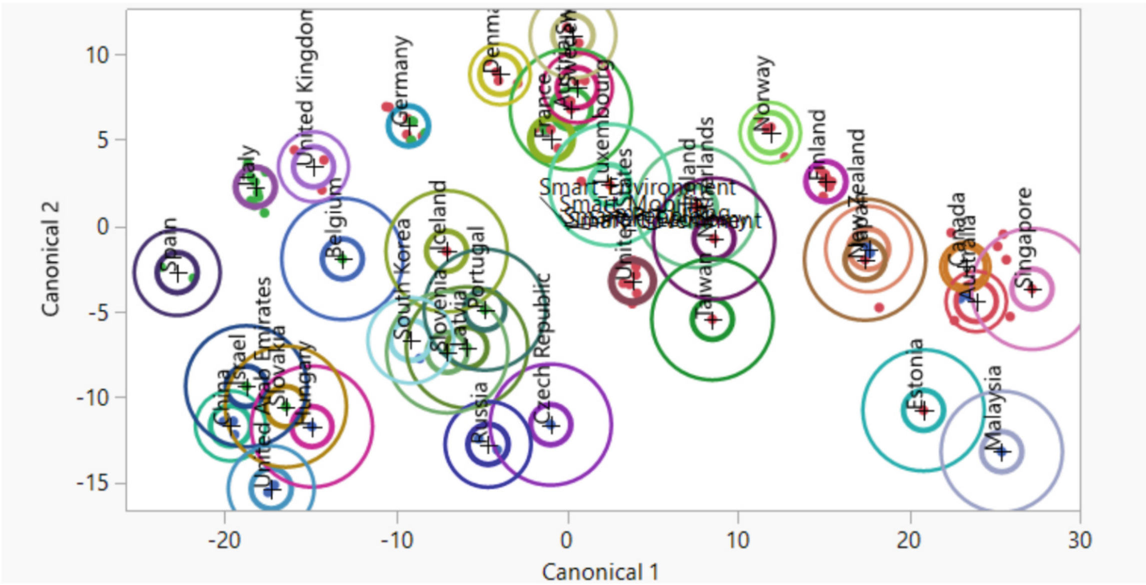

Fig. 1. Canonical plot.

In addition to the significance of discriminant functions and multivariate tests, we examined the detailed classification table to assess individual city-level performance.

Table 1. Canonical discriminant analysis results: Eigenvalues, canonical correlations, and significance tests

Countries	Eigenvalue	Percentage	Cumulative percentage	Canonical correlation	Wilks' lambda
County 1	3.163.226	80.66%	80.66%	0.998423	2.05×10^{-7}
County 2	6.167.457	15.73%	96.39%	0.99199	6.5×10^{-5}
County 3	7.238.097	1.85%	98.24%	0.937343	0.004073
County 4	3.935.297	1.00%	99.24%	0.89296	0.033556
County 5	18.802	0.48%	99.72%	0.807962	0.16561
County 6	1.096.486	0.28%	100.00%	0.723195	0.476989

Countries	Approx. F	NumDF	DenDF	p-value	
County 1	21.94	210	370.02	2.4×10^{-132}	
County 2	11.02	170	312.56	4.68×10^{-72}	
County 3	5.73	132	253.36	8.76×10^{-33}	
County 4	4.23	96	192.48	1.02×10^{-17}	
County 5	3.06	62	130	4.42×10^{-8}	
County 6	2.41	30	66	0.00	

Table 1 reports, for each city, the squared Mahalanobis distance to its group centroid, the posterior probability of correct classification, the corresponding negative log-probability, and whether the city was misclassified.

The performance of the model is quantified through percentage of well-classified observations, Wilks' Lambda test of overall model significance, and an examination of posterior probabilities of group membership. Table 1, of Canonical discriminant functions, shows that 80.7% of variance is explained by the first function with an extremely high canonical correlation (0.998). The second function accounts for the remaining 15.7%, and the two functions together explain over 96% of explained variance. That is a good discrimination ability to distinguish between groups. All functions are significant with F-values between 3.06 and 21.94, and p-values less than 0.001, indicating that the differences between group centroids are significant.

As the Table 2 reveals, all multivariate test statistics strongly reject the null hypothesis of no differences between groups. These findings stress the discriminant model's robustness and in addition that smart cities evidence strong alignment with respective national profiles. The co-occurrence of high posterior prob-abilities and minimal classification errors highlights the occurrence of strong and consistent cross-national patterns.

There were 101 of the 102 cities that were properly classified into their own country of origin, and the accuracy was 98.0% within the training set. Six dimensions of smartness were utilized to produce such high accuracy by serving as predictors. The only misclassification was when an Australian city was incorrectly classified into Singapore. This case is particularly noteworthy, as the posterior probability for the correct group (Australia) was relatively low (0.275), while the probability for Singapore was substantially higher (0.706).

Table 2. Global significance tests for the canonical discriminant function.

Test statistic	Value	Approx. F	NumDF	DenDF	p-value
Wilks' lambda	2.05×10^{-7}	21.94	210	370	2.4×10^{-132}
Pillai's trace	4.832.697	7.81	210	396	4.46×10^{-68}
Hotelling-Lawley trace	3.921.472	110.99	210	273.53	9.6×10^{-196}
Roy's greatest root	3.163.226	596.49	35	66	1.55×10^{-70}

This misclassification likely reflects a strong similarity in the smart city profiles of these two countries, especially in the dimensions of Smart Living and Smart People. Additionally, the model exhibits a remarkably high entropy R^2 value of 0.995, indicating that nearly all the variance necessary for distinguishing among countries is captured by the discriminant functions. The model's fit is also confirmed by the extremely low −2 log-likelihood value (3.15), which indicates the perfect correspondence between observed and predicted classifications. Both the input data quality and high discriminative ability of the selected smartness variables are supported by the obtained results. The linear discriminant analysis model is highly stable, accurate, and interpretable despite some instances of rare nations.

4 Discussion

The findings of this study validate the hypothesis that national context is a significant element in encouraging the development of smart cities. The strong correlation between cities and their country of origin, as evident from LDA, emphasizes the contribution of national policies, institutional setup, and financing mechanisms in the advancement of urban innovation.

Those countries with more centralized smart city strategies, such as Singapore and Norway, tend to have more uniform city profiles. This uniformity likely stems from the imposition of top-down planning, national standards, and homologous cultural or institutional values. In comparison, those countries with decentralized schemes, such as Italy or Spain, tend to have more diversified cities and thus be more likely to have more dispersed patterns in the canonical plot.

These results are consistent with the findings of Neirotti et al. (2014), who recognized national models of governance as the most significant factors to the adoption and implementation of smart city initiatives in both European and non-European nations. Similarly, in their work, Mora et al. (2017) argue that political cultures and national systems play a decisive role in local digital transformation policies and formulate convergent models in the same country. Lombardi et al. (2012) further indicate that institutional capacity differences and policy coordination at the national level have a significant effect on the performance of smart cities, especially in the fields of governance and the economy.

The use of linear discriminant analysis in this study adds to these results by statistically confirming the presence of national patterns through objective, data-based classification. As opposed to previous studies that relied on qualitative typologies or case studies based on self-report, our approach allows for a proper multivariate analysis of empirical performance data. Furthermore, the limited instances of dispersion or misclassification merit particular consideration, as they have the potential to unveil either original deviations or lacunae in local implementation. The greater the dispersion observed among certain European countries, it may be indicative of both the heterogeneity of urban traditions and the varying degrees of central government intervention in smart city policy.

The use of LDA is a powerful method for distinguishing among national smart city models and represents a valuable resource for comparative studies as well as policy evaluation. These results are likely to shape more holistic and context-sensitive smart city strategies by emphasizing the structural similarities and differences within as well as across nations.

5 Conclusions

This study demonstrates that smart cities are not isolated contexts but are deeply embedded in national scenarios. Using linear discriminant analysis (LDA), we confirmed that smart cities can be successfully separated into their respective countries on six key dimensions of smartness. The high accuracy of classification, stable posterior probabilities, and evident group separation in the canonical plot all provide strong evidence for the existence of nationally homogeneous smart city models.

These findings reinforce the hypothesis that national policies, institutions, and systems of governance significantly influence the way in which cities approach smart development, in line with New et al. (2017). In countries with centralized strategy and efficient coordination capacities, cities are more uniform in their profiles. Conversely, countries with decentralized government or fragmented urban policies tend to show greater heterogeneity among their cities.

Methodologically, the article under consideration pays particular emphasis to the strength of LDA as an empirical validation of theoretical hypotheses in smart city studies. The integration of canonical structure, classification accuracy, and multivariate significance testing is a robust platform for the discovery of latent structures in multivariate data sets. The practical applications of the research findings are highlighted. For policymakers, awareness of the degree of national cohesion in smart city development can allow for more targeted and strategic interventions. National governments can use this knowledge to better align policies, share best practices between cities, and even out disparities. Furthermore, the framework applied in this research offers researchers a convenient starting point to undertaking more comparative studies longitudinally, regionally, and across policy regimes.

It is crucial that future studies explore longitudinal trends to quantify the temporality of such national profiles and the effects of individual policy instruments and funding schemes. Furthermore, including Global South cities in the analysis would enable one to assess the formalizability of these trends and to detect potential smart city typologies in the world.

References

Agboola, O.P., Bashir, F.M., Dodo, Y.A., Mohamed, M.A.S., Alsadun, I.S.R.: The influence of information and communication technology (ICT) on stakeholders' involvement and smart urban sustainability. Environ. Adv. **13**, 100431 (2023)

Ahad, M.A., Paiva, S., Tripathi, G., Feroz, N.: Enabling technologies and sustainable smart cities. Sustain. Cities Soc. **61**, 102301 (2020)

Batóg, B., Batóg, J.: The application of discriminant analysis to the identification of key factors of the development of Polish cities. Acta Univ Lodz Folia Oeconomica. **4**(343), 181–194 (2019)

Bogdanov, O., Jeremić, V., Jednak, S., Čudanov, M.: Scrutinizing the smart city index: A multivariate statistical approach. Zb Rad Ekon Fak Rij. **37**(2), 777–799 (2019)

Caragliu, A., Del Bo, C., Nijkamp, P.: Smart cities in Europe. J. Urban Technol. **18**(2), 65–82 (2011)

Chan, G.: China's Digital Silk Road: Setting Standards, Powering Growth. Edward Elgar Publishing, Cheltenham (2022)

Ciacci, A., Ivaldi, E., González-Relaño, R.: A partially non-compensatory method to measure the smart and sustainable level of Italian municipalities. Sustainability. **13**(1), 435 (2021)

Dameri, R.P., Benevolo, C.: Governing smart cities: An empirical analysis. Soc. Sci. Comput. Rev. **34**(6), 693–707 (2016)

Dameri, R.P., Benevolo, C., Veglianti, E., Li, Y.: Understanding smart cities as a glocal strategy: A comparison between Italy and China. Technol Forecast Soc Change. **142**, 26–41 (2019)

Deren, L., Wenbo, Y., Zhenfeng, S.: Smart city based on digital twins. Comput. Urban Sci. **1**, 1–11 (2021)

Eskantar, M., Zopounidis, C., Doumpos, M., Galariotis, E., Guesmi, K.: Navigating ESG complexity: An in-depth analysis of sustainability criteria, frameworks, and impact assessment. Int. Rev. Financ. Anal. **95**, 103380 (2024)

Fatima, A., Abbas, S., Asif, M., Khan, M.: Optimization of governance factors for smart city through hierarchical Mamdani type-1 fuzzy expert system empowered with intelligent data ingestion techniques. EAI Endorsed Trans Scalable Inf Syst. **6**(23), 157795 (2019)

Giffinger, R., Fertner, C., Kramar, H., Kalasek, R., Pichler-Milanović, N., Meijers, E.: Smart Cities: Ranking of European Medium-Sized Cities. Vienna Univ Technol, Vienna (2007)

Gracias, J.S., Parnell, G.S., Specking, E., Pohl, E.A., Buchanan, R.: Smart cities—A structured literature review. Smart Cities. **6**(4), 1719–1743 (2023)

Grossi, G., Welinder, O.: Smart cities at the intersection of public governance paradigms for sustainability. Urban Stud. **61**(10), 2011–2023 (2024)

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E.: Multivariate Data Analysis, 7th edn. Pearson, Upper Saddle River (2010)

Hernandez-Ramos, J.L., et al.: Security and privacy in Internet of Things-enabled smart cities: Challenges and future directions. IEEE Secur. Priv. **19**(1), 12–23 (2020)

Houichi, M., Jaidi, F., Bouhoula, A.: Analysis of smart cities security: Challenges and advancements. In: 2022 15th Int Conf on Security of Information and Networks (SIN), pp. 01–05. IEEE, New York (2022)

Ivaldi, E., Ciacci, A.: Smart Sustainable Cities and knowledge-based economy: Policy implications. Springer, Cham (2023)

Ivaldi, E., Penco, L., Isola, G., Musso, E.: Smart sustainable cities and the urban knowledge-based economy: A NUTS3 level analysis. Soc. Indic. Res. **150**(1), 45–72 (2020)

Javed, A.R., et al.: Future smart cities: Requirements, emerging technologies, applications, challenges, and future aspects. Cities. **129**, 103794 (2022)

Kim, J.S., Feng, Y.: Understanding complex viewpoints in smart sustainable cities: The experience of Suzhou. China. Cities. **147**, 104832 (2024)

Kirimtat, A., Krejcar, O., Kertesz, A., Tasgetiren, M.F.: Future trends and current state of smart city concepts: A survey. IEEE Access. **8**, 86448–86467 (2020)

Lai, C.S., et al.: A review of technical standards for smart cities. Clean. Technol. **2**(3), 290–310 (2020)

Lane, B.W.: Significant characteristics of the urban rail renaissance in the United States: A discriminant analysis. Transp. Res. A Policy Pract. **42**(2), 279–295 (2008)

Lombardi, P., Giordano, S., Farouh, H., Yousef, W.: Modelling the smart city performance. Innov. Eur. J. Soc. Sci. Res. **25**(2), 137–149 (2012)

Majeed, U., Khan, L.U., Yaqoob, I., Kazmi, S.A., Salah, K., Hong, C.S.: Blockchain for IoT-based smart cities: Recent advances, requirements, and future challenges. J. Netw. Comput. Appl. **181**, 103007 (2021)

Marchesani, F., Masciarelli, F., Ceci, F.: Digital trajectories in contemporary cities: Exploring the interplay between digital technology implementation, the amplitude of social media platforms, and tourists inflow in cities. Cities. **146**, 104749 (2024)

MarketsandMarkets (2021) Smart Cities Market by Focus Area–Global Forecast to 2025.

Maxim F (2018) The objectives of sustainable development, ways to achieve a better life for current and future generations. In: Conferința Internațională de Drept, Studii Europene și Relații Internaționale, 6(VI):11–23.
Mohamed, N., Al-Jaroodi, J., Jawhar, I., Idries, A., Mohammed, F.: Unmanned aerial vehicles applications in future smart cities. Technol. Forecast Soc. Change. **153**, 119293 (2020)
Mora, L., Bolici, R., Deakin, M.: The first two decades of smart-city research: A bibliometric analysis. J. Urban Technol. **24**(1), 3–27 (2017)
Mora, L., Deakin, M., Reid, A.: Exploring current trends in scientific research on smart specialisation. Sci. Reg. **18**(3), 397–422 (2019)
Nations United: World Population Prospects. Economic and Social Affairs Department, New York (2019)
Neirotti, P., De Marco, A., Cagliano, A.C., Mangano, G., Scorrano, F.: Current trends in smart city initiatives: Some stylised facts. Cities. **38**, 25–36 (2014)
New, J., Castro, D., Beckwith, M.: How National Governments can Help Smart Cities Succeed. Center for Data Innovation, Washington, DC (2017)
Pan, S., Zhou, W., Piramuthu, S., Giannikas, V., Chen, C.: Smart city for sustainable urban freight logistics. Int. J. Prod. Res. **59**(7), 2079–2089 (2021)
Penco, L., Ciacci, A., Ivaldi, E.: The entrepreneurial ecosystem in the European Union smartcities. In: Territorio, inteligencia y sostenibilidad: claves para los espacios regionales, pp. 39–54. Asociación Española de Geografía, Madrid (2024)
Penco, L., Ivaldi, E., Ciacci, A.: Entrepreneurial ecosystem and well-being in European smart cities: A comparative perspective. TQM J. **33**(7), 318–350 (2021)
Periñán-Pascual, C.: From smart city to smart society: A quality-of-life ontological model for problem detection from user-generated content. Appl. Ontol. **18**(3), 263–306 (2023)
Poletti, C., Michieli, M.: Smart cities, social media platforms and security: Online content regulation as a site of controversy and conflict. City Territ. Archit. **5**, 1–14 (2018)
Qureshi, K.N., Rana, S.S., Ahmed, A., Jeon, G.: A novel and secure attacks detection framework for smart cities industrial internet of things. Sustain. Cities Soc. **61**, 102343 (2020)
Rencher, A.C.: Methods of Multivariate Analysis, 2nd edn. Wiley, New York (2002)
Sajjad, M., et al.: Raspberry Pi assisted face recognition framework for enhanced law-enforcement services in smart cities. Futur. Gener. Comput. Syst. **108**, 995–1007 (2020)
Shao, J., Min, B.: Sustainable development strategies for smart cities: Review and development framework. Cities. **158**, 105663 (2025)
Steiniger, S., Lange, T., Burghardt, D., Weibel, R.: An approach for the classification of urban building structures based on discriminant analysis techniques. Trans. GIS. **12**(1), 31–59 (2008)
United Nations Department of Economic and Social Affairs (UN DESA): World Urbanization Prospects: The 2018 Revision. United Nations, New York (2019)
Xihua, Z., Goyal, S.: Security and privacy challenges using IoT-blockchain technology in a smart city: Critical analysis. Int. J. Electr. Electron Res. **10**(2), 190–195 (2022)