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National Models of Smart City Development: A Multivariate Perspective on Urban Innovation and Sustainability

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Abstract

This study examines the extent to which smart cities are expressions of nationally homogeneous development trends by way of an analysis of their structural characteristics from a multivariate viewpoint. Drawing on data from the International Institute for Management Development IMD Smart City Index 2024, we find a sample of 102 cities across the world clustering along six key dimensions of smartness: mobility, environment, government, economy, people, and living. The aim is to examine if cities within a country have similar profiles and, if so, to what degree such similarity translates to other macro-level institutional, political, and cultural conditions. Our results verify a tight correspondence between city profiles and national contexts, implying that macro-level governance arrangements, policy coordination, and institutional capacity are pivotal in influencing local smart city development. Planned centralised countries possess more uniform city characteristics, while decentralised nations possess more variant urban policies. This study contributes to international debate regarding smart cities by empirically identifying national directions of urban innovation. It offers pragmatic inputs for policymakers that aim to align local efforts with overall sustainable development agendas. Moreover, this study introduces a novel application of Linear Discriminant Analysis (LDA) to classify smart city profiles based on national models. While the analysis yields high classification accuracy, it is important to note that the sample is skewed toward cities from the Global North, potentially limiting the generalisability of the results.

Keywords: smart cities; national urban models; urban innovation; multivariate analysis; urban governance models; sustainable development

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1. Introduction

Urbanisation is a defining trend of the 21st century. The United Nations approximates that, in 2021, over 56% of the global population resided in cities, and this figure is projected to increase to nearly 70% by 2050 [1].

This demographic shift poses one of the biggest challenges to urban management, infrastructure delivery, environmental conservation, and basic service delivery. As the driving forces behind economic development, innovation, and social mobility, cities are also at the centre of environmental deterioration, social injustice, and institutional fragility [2,3].

Furthermore, urban centres face challenges in achieving sustainability transitions, yet they are also key agents in this process [3]. The United Nations' Sustainable Development

Goals (SDGs), particularly SDG 11, acknowledge the pivotal role of cities in fostering inclusive, resilient, and environmentally sustainable societies. Smart cities have therefore become instrumental in operationalising the sustainability agenda at the local level.

To meet these advanced requirements, the concept of the smart city has emerged as a strategic framework for reconfiguring urban development. Smart cities utilise digital technologies, data analysis, and intelligent infrastructure to enhance the efficiency, inclusiveness, and sustainability of urban life [4,5]. Historically centred on ICT-driven productivity and service automation, the smart city philosophy has evolved to include various objectives, such as participatory governance, improving quality of life, environmental sustainability, and economic innovation [6,7].

The relevance of smart cities is highlighted by their unequivocal contribution to achieving the United Nations' Sustainable Development Goals (SDGs), as established by SDG 11: 'Make cities and human settlements inclusive, safe, resilient and sustainable'. There is increased integration of sustainability within smart city policy, evident in both academic research and international policymaking [8,9].

Although smart cities are widely promoted as global models of sustainable urbanism, relatively few studies have empirically examined how national political and institutional contexts influence their development. Existing research shows that cities with similar technological capabilities can have different outcomes due to variations in governance systems, administrative cultures, and policy integration [10,11].

National institutional setups, administrative cultures, and financial systems vary significantly across nations [12], and these variations are likely to result in distinct forms of urban innovation [13,14]. Some nations, such as Singapore and Norway, pursue top-down, centrally driven smart city agendas, promoting uniformity of urban policy. In contrast, countries such as Italy and Spain are founded on decentralised or regionally dispersed governance models, which tend to produce diverse smart city profiles across the national landscape. Understanding whether these institutional contexts define the multidimensional profile of smart cities is vital for comparative studies as well as effective policymaking.

Although most international models encourage the cross-national diffusion of smart city solutions, recent studies have emphasised the difficulty of implementing best practices across national borders due to differences in institutional contexts. According to [15], even comparable cities in terms of technological capabilities may differ widely in terms of outcomes due to national governance systems, administrative cultures, and regulatory settings. This raises important questions about how intelligence is institutionalised differently across the globe and the extent to which national models determine urban trajectories—a central concern of this study.

This study aims to address this knowledge gap by investigating whether cities within the same national context exhibit similar smartness characteristics. Using Linear Discriminant Analysis (LDA) on a sample of 102 cities worldwide from the IMD Smart City Index 2024, we examine whether national smart city models can be differentiated along six core dimensions: Smart Mobility, Smart Environment, Smart Government, Smart Economy, Smart People, and Smart Living. These dimensions were initially developed by [16] and have been expanded upon in more recent studies [5,17,18]. They are the most widely cited framework for quantifying urban smartness.

Applying LDA in this context is a methodologically innovative approach, as it enables the supervised classification of cities based on their multidimensional performance profiles—a topic that has not yet been widely explored in smart city literature.

Cross-national comparisons of smart city profiles not only contribute to the intellectual capital of urban innovation but also help policymakers implement national strategies that are suitable for the local context. Both of these factors emphasise the importance of place-based policies backed by empirical data. Identifying national patterns of 'smartness' enables the development of context-sensitive and scalable governance models to facilitate long-term sustainable transitions.

The paper is organised as follows. Section 2 provides an overview of the key literature on smart cities and national urban innovation trends. Section 3 presents the dataset and multivariate method employed. Section 4 describes the results of the discriminant analysis. Section 5 interprets the research implications in terms of the global debate on governance and sustainability. Section 6 concludes the paper and offers recommendations for further research.

This study's theoretical framework is informed by urban regime theory and institutional path dependency, which emphasise how historical administrative arrangements shape urban innovation trajectories. Furthermore, this study responds to recent calls in smart city literature for governance-sensitive approaches that consider multi-level institutional logics and policy cultures when explaining urban performance.

Overall, the paper demonstrates how national governance frameworks influence urban smartness, providing empirical tools to support context-sensitive policy design that aligns with global sustainability objectives.

2. Literature Review

The concept of the smart city has evolved from a technology-driven approach to an all-encompassing system that considers people, society, the environment, and the economy. Beyond technocentric approaches, recent studies stress the role of governance models and institutional arrangements in shaping smart city outcomes [19,20]. These perspectives emphasise that national policy ecosystems and administrative cultures influence the interpretation and implementation of smartness at the city level.

The term 'smart city' was initially defined as cities that use ICT and automation technologies to provide better public services and improve operational efficiency [2,4,20]. The term has since evolved to encompass broader issues of sustainability and human-centred urban planning practices [21,22].

An increasing amount of research is setting smart city formation within the broader context of the Sustainable Development Goals, specifically SDG 11, which calls for cities to be inclusive, safe, resilient, and sustainable. Studies on sustainability (e.g., [6,7,23]) argue that 'smartness' is not merely technological advancement but a means to social equity, environmental well-being, and good governance. These reports emphasise that smart cities can contribute to multiple SDGs if they are incorporated into institutional structures that enable integration and coordination across sectors.

Multidimensional models, such as those described in reference [18], are being used more and more in empirical research. Most such models feature six key dimensions: Smart Economy, Smart People, Smart Governance, Smart Mobility, Smart Environment, and Smart Living. These dimensions capture the main aspects of how cities function, ranging from information infrastructure and economic success to education, citizenship, and the environment. Studies employing composite indicators, principal component analysis, cluster analysis, and Pena distance have attempted to define smart cities in terms of these dimensions.

Recent studies have emphasised the importance of governance arrangements in shaping the development and implementation of smart city policy. For instance, ref. [15] illustrates how national political traditions and policy institutions can strongly influence local digital development trajectories. Ref. [16] argue that governance models—centralised versus decentralised—shape the scope and success of smart city initiatives, with centralised models leaning towards uniformity and coherence and decentralised ones towards experimentation and diversity.

Other works have challenged the dominance of techno-centric models in smart city scholarship, advocating for a shift towards socio-institutional and governance-centred approaches [11,24]. Robust operationalisation of these socio-institutional perspectives is required through indicators and analytical tools capable of capturing the interplay between governance quality, citizen engagement, and urban performance. This has led to the development of multidimensional models that combine data analytics with institutional diagnostics. In this context, the success of smart initiatives largely depends on institutions' capacity to arbitrate between contradictory interests, ensure equity, and enhance democratic participation.

Literature has also examined the role of institutional quality and administrative capacity in smart city performance. Ref. [25] highlights the impact of managerial professionalism and transparency practices on the creation of smart solutions. Similarly, ref. [26] emphasises the importance of aligning ICT infrastructures with local governance competencies. Ref. [11] also takes this perspective, advocating an integrative and reflective governance approach to smart, sustainable cities that bridges the divide between technical feasibility and social inclusivity.

An increasing number of articles have addressed related topics, emphasising the importance of smart cities in discussions about sustainable development. For example, ref. [27] proposes a partially non-compensatory method to measure smart and sustainable performance at the municipal level in Italy, demonstrating the complexity and interconnectedness of city indicators. Ref. [28] provides a comprehensive overview of smart city requirements, innovative technologies, and cases of sustainability application, emphasising the challenge of global applicability. Ref. [29] discusses the entrepreneurial environment of EU smart cities, linking governance, innovation, and well-being. They emphasise methodological pluralism and policy relevance when evaluating the smartness of cities.

Technological innovation remains a driving force, especially when intertwined with environmental and social sustainability agendas. Emerging technologies such as IoT, blockchain, and digital twins are reshaping data collection and service delivery in smart cities, particularly in sectors like transport and energy [30,31]. These developments are most directly relevant to the transportation industry, energy consumption, waste management, and public security. However, researchers have warned of emerging digital divides and governance challenges related to cybersecurity, citizen privacy, and algorithmic accountability [32,33].

A variety of methodologies have been used to sort and rank smart cities. Composite indices provide an overall rating, but these are often aggregated in a compensatory manner. Cluster analysis and principal component analysis can facilitate dimension reduction and city clustering, but they lack inferential testing. In recent studies, partially non-compensatory methods such as the DP2 distance [34] have been introduced, reflecting cities' relative performance without penalising individual weaknesses. Despite the increasing use of composite indicators and cluster-based classifications, supervised techniques such as Linear Discriminant Analysis (LDA), which offers statistical inference and group validation, are underutilised. This gap is particularly evident in cross-national studies. Some studies have advocated the use of aggregate indicators and multivariate techniques for measuring the complexity of urban smartness (e.g., [31,35]). These techniques enable heterogeneous dimensions, such as digital infrastructure, governance quality, and environmental outcomes, to be aggregated into meaningful analytic frameworks. In particular, their application has been fruitful in cross-country comparisons, not only to determine spatial inequities but also to reveal underlying governance rationalities that constitute smart city trajectories.

Therefore, this article contributes to the field by addressing this methodological shortcoming. It investigates whether cities around the world exhibit similar smart profiles by applying latent Dirichlet allocation to a multidimensional database. By combining institutional theory and quantitative urban research, the study responds to calls within smart city scholarship for more comparative, evidence-based research [15,17,36]. Although necessarily dense, the following literature review aims to provide a comprehensive foundation for the analytical framework, ensuring consistency in the theoretical and empirical references. Building on this foundation, the present study uses LDA to evaluate whether national institutional contexts generate internally consistent smart city profiles. This offers a methodological innovation to ongoing debates on sustainability measurement and governance modelling.

3. Data and Analytical Framework

This study takes a quantitative, multivariate approach to assess whether smart cities around the world exhibit consistent national patterns in their development profiles.

Linear Discriminant Analysis (LDA) was chosen because of its ability to identify group-level patterns and formally assess whether cities can be statistically classified into national categories based on multidimensional performance [37,38]. Unlike unsupervised techniques such as Principal Component Analysis (PCA) or cluster analysis, LDA provides probabilistic group assignment and quantifies the discriminating power of each variable. In our case, the groups correspond to countries of origin, and the predictors are the six core dimensions of smart city performance.

3.1. Data Source and Sample

This research is based on the results of the 2024 IMD Smart City Index, a leading global benchmark report published by the International Institute for Management Development (IMD) in collaboration with the Singapore University of Technology and Design [31].

It ranks smart cities based on citizens' perceptions of how technology improves their quality of life. It uses both objective indicators and standardised perception-based data.

Our sample includes 102 cities from various geographic regions, including Europe, North America, Asia, and Oceania. The countries with the highest number of cities represented are Italy (16), Germany (14), and Finland (18), while other countries such as Austria, Slovakia, and Luxembourg have a single city represented. This reflects the advancement of digital governance systems and the degree of participation in global smart city networks. This uneven representation, largely determined by the cities included in the IMD Smart City Index, may influence the calculation of group centroids and affect the comparability of countries with few observations.

While the sample provides broad geographic coverage, it remains substantially biased towards cities in the Global North, particularly in Europe and other high-income OECD countries. These cities tend to have higher digital maturity and greater participation in the IMD Smart City Index. While this distribution reflects the current availability of standardised perception-based data, it also introduces a structural limitation to the generalisability of our findings. Cities from emerging economies and low-income regions are significantly underrepresented or absent, which may prevent the analysis from capturing the full diversity and developmental variability of smart city trajectories worldwide. As such, the national models proposed here should be interpreted with appropriate caution.

3.2. Variables

Each city in the dataset is defined by six dimensions of smartness according to the [39] model:

- Smart Mobility: Efficiency and sustainability of transport and traffic systems.
- Smart Environment: Sustainability of the urban environment, protection, and energy consumption.
- Smart Government: Transparency, e-governance, public engagement, and service delivery.
- Smart Economy: Entrepreneurship, innovation, productivity, and economic image.
- Smart People: Human capital, education, and social inclusion.
- Smart Living: Quality of life, safety, culture, and health.

The scores in each dimension are normalised and scaled to facilitate comparison among countries. The use of normalised measures eliminates potential bias resulting from differences in scale, units of measurement, or data collection procedures.

3.3. Methodological Framework

We used Linear Discriminant Analysis (LDA) to analyse whether cities could be correctly categorised by their smart profiles into their respective home countries. All analyses were performed using JMP Pro 17 (SAS Institute Inc., Cary, NC, USA), statistical software specialising in multivariate methods and data visualisation. The six smartness dimensions were normalised using z-score standardisation to ensure comparability and avoid scale distortion. LDA develops one or more linear combinations of the predictor variables (discriminant functions) that maximise the ratio of between-group to within-group variance and, in doing so, maximise class separability [40]. While cluster analysis identifies latent groupings, it does not confirm whether known groups (e.g., countries) exhibit significant internal coherence or external separation.

The principal steps followed in the analysis are:

1. Checking the assumptions of multivariate normality and homogeneity of covariance matrices. Although there were slight deviations from these assumptions, it is known that LDA is robust, particularly with equal group sizes and large samples [41].
2. Estimation of the discriminant functions to be considered and their testing for significance using Wilks' lambda and associated F-tests.
3. The computation of posterior probabilities and Mahalanobis distances to assess classification performance and how well the country's centroids are separated.
4. Plotting the results using canonical plots to check for clustering and look for possible outliers or hybrid models.

3.4. Limitations and Considerations

There are several caveats that should be acknowledged. Firstly, the number of cities included per country is uneven, which could impact the stability and representativeness of certain group centroids. Secondly, some of the indicators rely on citizen perceptions, which are inherently subjective and may be influenced by cultural norms, expectations, and differences in institutional trust. This could lead to inconsistencies in cross-country comparisons and influence the discriminant structure. Thirdly, the Linear Discriminant Analysis (LDA) method assumes linear relationships between predictors and homogeneous covariance matrices, limiting its ability to capture complex nonlinear interactions between smart city dimensions.

To address these limitations, future research should consider applying non-linear classification algorithms, such as Support Vector Machines or Random Forests, to test the robustness of national clustering patterns under alternative assumptions and reduce dependency on parametric constraints. Likewise, integrating objective performance indicators (e.g., open data accessibility, traffic efficiency, and digital service coverage) alongside perception-based data could improve cross-cultural comparability and reinforce analytical validity.

Despite these constraints, the adopted methodological framework remains robust and interpretable, offering a reliable basis for detecting regularities at the national level in smart city development. Future extensions could include comparative case studies, longitudinal analyses, or hybrid approaches that combine quantitative classification with qualitative institutional assessments.

In addition, future studies should consider employing nonlinear classification methods—such as Support Vector Machines or Random Forests—to validate group structures under alternative statistical assumptions. Longitudinal designs may also shed light on whether national models of smart development remain stable or evolve over time.

4. Results

Applying Linear Discriminant Analysis (LDA) yielded robust evidence supporting the existence of nationally structured models of smart city development. The standardised canonical discriminant function coefficients indicate that Smart Governance and Smart Economy are the most influential contributors to the first discriminant function, followed by Smart Environment. These findings suggest that institutional and innovation-related dimensions play a central role in shaping national differentiation among smart cities.

The discriminant functions derived from the six smartness dimensions demonstrate a high capacity to distinguish cities based on their country of origin. As shown in Table 1, each city's squared Mahalanobis distance from its group centroid, posterior classification probability, negative log probability, and any misclassification are reported.

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

Countries	Eigenvalue	Percentage	Cumulative Percentage	Canonical Correlation	Wilks' Lambda
County 1	316.3226	80.66%	80.66%	0.998423	0.000000205
County 2	61.67457	15.73%	96.39%	0.99199	0.000065
County 3	7.238097	1.85%	98.24%	0.937343	0.004073
County 4	3.935297	1.00%	99.24%	0.89296	0.033556
County 5	1.8802	0.48%	99.72%	0.807962	0.16561
County 6	1.096486	0.28%	100.00%	0.723195	0.476989
Countries	**Approx. F**	**NumDF**	**DenDF**	***p*-Value**	
County 1	21.94	210	370.02	$p < 0.001$	
County 2	11.02	170	312.56	$p < 0.001$	
County 3	5.73	132	253.36	$p < 0.001$	
County 4	4.23	96	192.48	$p < 0.001$	
County 5	3.06	62	130	$p < 0.001$	
County 6	2.41	30	66	$p < 0.001$	

City-level analysis confirms a consistent alignment within national models: for example, cities in Italy and Finland form tightly clustered groups. The only notable exception is Sydney, which is misclassified as part of Singapore's cluster—likely due to strong similarities in Smart Living and Smart People dimensions.

It is worth noting that the number of cities per country varies significantly (e.g., Italy includes 16 cities, while Austria is represented by only one). This imbalance may affect the stability of group centroids and the precision of Mahalanobis distance-based classification.

4.1. Canonical Functions and Explained Variance

What follows is a presentation of the main statistical outputs of the LDA. First, we focus on the canonical discriminant structure, and then on group classification accuracy.

The two functions yielded by the analysis were statistically significant canonical discriminant functions. The first function explained 80.7% of the aggregate country-level variance, and the second function explained 15.7%. Together, these functions yielded an aggregate explained variance of over 96%. The two canonical correlations were moderate (Function 1 = 0.998), indicating that the discriminant model differentiates between very significant between-group variance and within-group noise.

Together, these two functions account for over 96% of the total between-country variance, providing a robust basis for interpreting national models of urban smartness. The very high canonical correlations confirm that the classification is based on dimensions that discriminate strongly rather than random variation.

4.2. Wilks' Lambda and Model Significance

Wilks' lambda tests confirmed the statistical significance of the model. The overall lambda value was 0.011 ($p < 0.001$), indicating significant differences between the group centroids (i.e., countries) across the combined smartness dimensions. The F-statistics associated with the discriminant functions were consistently high, ranging from 2.41 to 21.94, which reinforces the robustness of the model.

Table 2 presents the multivariate test statistics associated with the discriminant functions, including Wilks' lambda, Pillai's trace, Hotelling's trace, and Roy's largest root. All tests reject the null hypothesis of equal group centroids at the 0.001 significance level, corroborating the model's discriminating power. These results confirm that the observed differences between national groups are statistically robust and not due to sampling variability. The strong consistency across multiple test statistics further validates the stability and generalisability of the findings.

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

Test Statistic	Value	Approx. F
Wilks' Lambda	0.000000205	21.94
Pillai's Trace	4.832.697	7.81
Hotelling–Lawley Trace	392,1472	110.99
Roy's Greatest Root	316,3226	596.49
NumDF	**DenDF**	***p*-Value**
210	370	$p < 0.001$
210	396	$p < 0.001$
210	273.53	$p < 0.001$
35	66	$p < 0.001$

Together, the two canonical functions explain more than 96% of the between-country variance, providing a robust basis for interpreting national smart city models. These findings confirm the high discriminatory power of the selected dimensions, particularly Smart Governance and Smart Economy.

The consistency among Wilks' lambda, Pillai's trace, Hotelling's trace, and Roy's root further supports the validity of the discriminant structure. This convergence strengthens confidence in the robustness and replicability of the results.

4.3. Classification Accuracy and Posterior Probabilities

The LDA model performed excellently in terms of classification. Of the 102 cities analysed, 101 were correctly classified by country of origin, achieving an overall classification accuracy of 98%. Posterior probabilities of group membership were high, typically exceeding 0.85, confirming strong within-country homogeneity and between-country distinctiveness.

The only misclassification involved an Australian city, which was erroneously attributed to Singapore. This is a noteworthy result, as both countries exhibit similarly high Smart Living and Smart People scores, which could reflect a shared model of quality-of-life-driven innovation.

This misclassification is particularly insightful, as it highlights a potential case of transnational convergence. Despite institutional differences, both cities share high scores in Smart Living and Smart People, potentially reflecting parallel strategies in urban planning, public services, and educational ecosystems.

4.4. National Clustering of Smart City Profiles

The canonical plot of the first two discriminant functions (Figure 1) provides a clear visual representation of national clustering. Countries such as Finland, Germany, and Italy form distinct and compact groups, reflecting internally coherent models of smart city development. In contrast, countries represented by only one or two cities—such as Austria and Luxembourg—appear as outliers, underscoring the influence of national context on urban smartness profiles.

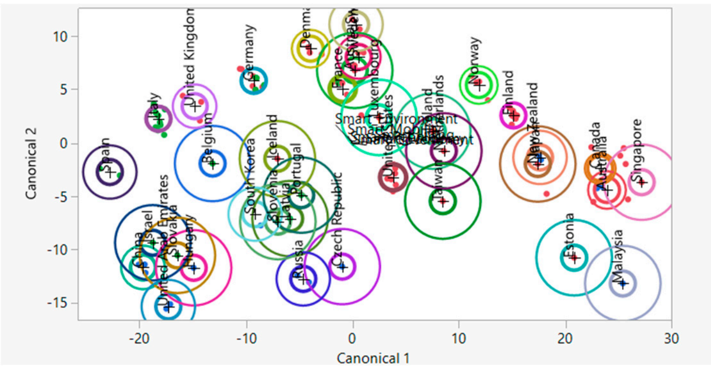

Figure 1. Canonical plot.

These patterns reinforce the idea that trajectories of urban innovation are deeply embedded in state-level policy cultures. This insight carries important implications for the design of national urban planning strategies and their alignment with international sustainability goals. To aid interpretation, the canonical plot has been included to visually depict the spatial separation between national clusters. It clearly illustrates both the internal consistency of countries like Finland and Germany and the peripheral positioning of countries with limited representation.

4.5. Group Separation Metrics and Model Entropy

The Mahalanobis distance matrix shows a high level of separation between groups, particularly between countries with different governance models and urban policies. The entropy R^2 value of 0.995 suggests that the discriminant functions capture almost all relevant classification information.

Overall, the results confirm that it is national institutional frameworks, rather than global urban trends, that primarily shape smartness profiles across cities.

4.6. Classification Accuracy and Outliers

All cities have low Mahalanobis distances and large posterior probabilities (usually greater than 0.90), indicating that they are close to the centroid of their national group.

Sydney is the only mislabelled city and is very interesting, as it has a posterior probability of 0.706 for Singapore and only 0.275 for its real group (Australia). This reflects a very high level of similarity between these two cities in terms of their smartness profile, particularly in the areas of Smart Living and Smart People. Overall, the city-level diagnostics in Table 1 confirm the model's high discriminative capacity and reliability and highlight important exceptions that could be explored further in qualitative terms.

Together, these findings provide strong empirical support for the popularity of national smart city models. They also suggest that global trends themselves, rather than national institutional frameworks, are the main drivers of smartness and how it is realised at the city level.

5. Discussion

The findings of this study provide robust empirical evidence of the existence of nationally homogeneous models of smart city development. This reinforces the idea that smart city strategies cannot be decoupled from national institutional frameworks if the global targets of the 2030 Agenda, particularly SDG 11, are to be achieved coherently and on a large scale.

Our results emphasise the powerful influence that country-level governance systems, policy culture, and institutional capabilities exert on the development and implementation of smart urban policies. These findings are highly consistent with the transdisciplinary goals of sustainability, particularly with regard to the convergence of technological innovation and governance mechanisms to fulfil sustainable development goals.

These findings need to be situated within the broader discussion of urban transitions and governance change. Ref. [42] indicates that sustainable urban change involves balancing technological innovation with institutional adaptability and social learning. Our study's national smartness profile clustering suggests that these changes are not randomly allocated but routed through path dependencies, state capacity, and policy legacies. This is consistent with the necessity of adopting a systemic, multi-level governance approach when evaluating urban innovation policy.

The observed convergence of smart city profiles within centralised national systems may reflect a form of institutional resilience—that is, the ability of national institutions to maintain strategic coherence and administrative coordination. However, this interpretation requires further empirical validation beyond the scope of the current analysis. In such systems, uniform funding, performance monitoring, and regulatory compliance frameworks help to align local initiatives with national priorities. This resilience is not just bureaucratic robustness; it is a dynamic capacity to enforce policy integration and ensure continuity in the pursuit of long-term sustainability goals. Contrasting with more decentralised countries highlights how variation in institutional cohesion can lead to fragmented smart city development, even when cities operate under similar technological or demographic conditions. Several contributions have emphasised the importance of conceptualising urban innovation in terms of environmental, economic, and social sustainability goals more broadly [18,43,44]. Our work advancing this agenda illustrates that this competition is not merely an artefact of local agency but is in fact conditioned by national policy regimes. In doing so, we demonstrate that sustainable smart city growth cannot be understood without reference to the institutional environments within which cities are situated.

In top-down, centralised governments such as those in Singapore, Norway, and Finland, the relatively uniform city profiles observed may be associated with nationally integrated strategies, standardised performance indicators, and centrally maintained funding streams. Nevertheless, further research is needed to establish a causal relationship. These countries are likely to have case studies of highly performing, digitally networked cities that comprehensively support SDG 11.

In contrast, countries with more decentralised administrations (Italy and Spain) have more diverse city profiles. In such locations, institutional capacity, economic endowments, and local government cultures vary across regions, resulting in a more dispersed smartness landscape. This highlights the importance of establishing national coordination platforms capable of balancing local experimentation with shared metrics, benchmarking, and feedback mechanisms in order to ensure equitable smart development. According to [31,45], decentralisation allows for innovation and experimentation, but it poses the risk of unbalanced development unless this is offset by coordination and knowledge-sharing mechanisms.

In line with the objectives of SDG 11, our findings focus on the importance of institutional quality and coherence in achieving sustainable urban outcomes. National smart city frameworks that appear more institutionally coordinated—such as those in Singapore and Finland—also tend to exhibit greater alignment with SDG-related goals, though this association is not explicitly tested in this study. These findings suggest that smart city assessments should consider not only local performance indicators but also the coherence of national policy ecosystems that enable or constrain sustainability efforts. As recent studies demonstrate, monitoring urban sustainability involves technical indicators as well as structures that include policy integration and institutional performance, both of which are reflected in our classification outcomes.

This also suggests that policy transferability is simpler than it appears. Decentralised countries' cities cannot simply replicate the smart city best practices of centralised states without adapting them to their own political setting. Thus, the idea of benchmarking smart cities needs to be fundamentally rethought within a contextual framework, an argument reiterated more recently in articles [46]. One possible approach is to develop governance-sensitive smartness typologies that distinguish between structurally centralised and decentralised systems, providing bespoke guidance for international comparisons.

This perspective aligns with urban regime theory, which emphasises that institutional arrangements and governance traditions influence cities' ability to implement innovation agendas beyond mere technological adoption.

The analysis highlights the importance of national governments designing smart city strategies that are coherent yet flexible enough to accommodate local diversity while aligning with broader sustainability goals. This requires the establishment of coordination platforms that facilitate local experimentation while providing common benchmarks and shared indicators. Mechanisms such as multi-level governance frameworks, performance-based fiscal incentives, and standardised digital infrastructures can facilitate coherent progress towards SDG 11 across urban systems. International organisations also have a role to play in supporting capacity-building efforts and transnational knowledge-sharing networks that foster institutional learning and convergence.

From an operational perspective, national smart city master plans should incorporate built-in flexibility to address regional disparities without compromising strategic direction. Instruments such as interoperable data platforms, inclusive governance boards with municipal participation, and funding schemes tied to sustainability metrics can help to strike this balance. City-level regulatory sandboxes may further encourage controlled experimentation with emerging technologies and service models while minimising policy risk. Finally, institutional audits and benchmarking dashboards can ensure that local actions remain consistent with broader national sustainability agendas.

Our research also validates the idea that smart city development is not just about technological deployment. Rather, it is a socio-technical process deeply rooted in institutional legitimacy, civic trust, administrative continuity, and stakeholder engagement—all areas that are traditionally examined in the literature. This institutional lens enhances the interpretability of urban metrics by embedding city-level performance within the broader architecture of national public administration, fiscal autonomy, and legal frameworks. The close congruence of cities with their country profiles demonstrates the relevance of institutional theory to sustainability, indicating that macro-territorial factors shape not only policy meaning but also definitions and measurements of urban smartness.

From a methodological perspective, the use of Linear Discriminant Analysis (LDA) is a valuable addition to more traditional approaches in sustainability research, such as regression modelling, index construction, or clustering. With its provision for formal classification and determination of the dimensions contributing most to group discrimination, LDA provides additional diagnostic utility. This aligns with the ongoing emphasis within sustainability research to employ highly analytical approaches that reconcile statistical complexity with practical utility.

Furthermore, the findings raise important questions for future research. The global energy crisis and the ongoing effects of the pandemic have emphasised the need for urban systems to adapt rapidly to unforeseen disruptions. This emphasises the need to examine whether national smart city models are structurally stable in the long term or prone to strategic reconfiguration under stress. Longitudinal studies could explore whether smartness patterns persist or evolve over time, particularly in response to external shocks such as climate emergencies, public health crises, or disruptive technological change. Extending the current framework temporally would provide valuable insights into the resilience and adaptability of national models, thereby enriching the literature on urban transformation and multi-level sustainability governance.

One of the key implications of our research is that disparities between countries can persist even in the face of national models. In decentralised nations in particular, local variation in digital infrastructure, human capital, and institutional maturity can create uneven urban smartness landscapes. This echoes recent work on territorial equity (e.g., [47,48]), emphasising the risk of place-based innovation and the need for compensatory policies to ensure that smaller or less networked cities are not left behind as the digital revolution unfolds.

Furthermore, the global nature of our dataset suggests the possibility of further regional comparative research, e.g., between Global North and Global South contexts or EU and non-EU countries. While our analysis is limited to countries with relatively high data coverage and urban digitalisation, future research could investigate whether similar national clustering exists in rapidly urbanising regions subject to different development constraints.

Recognising nationally embedded smart city models has clear and actionable policy implications. Rather than offering generic, one-size-fits-all recommendations, policymakers should foster multi-level governance strategies that balance national coordination with local flexibility. This requires flexible funding mechanisms, reinforced local government capacities, and national smart city frameworks with feedback loops and standardised indicators. In practical terms, our findings advocate national strategies combining top-down policy alignment with bottom-up innovation to ensure local initiatives are context-sensitive and strategically integrated.

Finally, the city-level anomalies revealed through our research (e.g., Sydney being misplaced) suggest that, despite strong national trends, new transnational convergences are arising from functional or socio-economic factors. This highlights the importance of researching not only national governments but also city–city networks, global urban league tables, and epistemic communities that shape the smart city agenda. These areas have been under-explored in previous literature but are increasingly crucial to achieving sustainability.

Subsequent research should continue to explore how institutional variables (i.e., legal frameworks, political accountability, and bureaucratic culture) mediate the effects of smart cities. Interdisciplinary scholarship combining data science with political science, public administration, and urban planning could produce more comprehensive results.

6. Conclusions

This study provides robust empirical evidence that smart cities are based on national models of governance, institutional structures, and consistent policies. By demonstrating the existence of coherent urban profiles at the national level, this work improves our understanding of how institutional arrangements influence the implementation of sustainable urban strategies in line with SDG 11. Using a sample of 102 cities worldwide, we show that cities evolve along pathways that correspond closely to the governance patterns of their respective countries. Six dimensions of smartness—mobility, the environment, government, the economy, people, and living—were combined to capture distinctive national patterns of centralised or decentralised policy regimes.

This study contributes to the growing body of literature on urban sustainability by offering empirical evidence that national institutional designs are a significant factor in shaping smart city trajectories. By showing how the coherence of institutions and administrative traditions influence urban profiles, our findings suggest that smart city projects have a better chance of achieving sustainable outcomes if they are based on stable and adaptive policy regimes. This finding supports the need to link digital innovation strategies to the broader goals of social equality, environmental sustainability, and good governance as set out in the 2030 Agenda and SDG 11.

The key strengths of this study include the use of a robust multivariate method (LDA), the use of an internationally recognised dataset (the IMD Smart City Index 2024), and the combination of theoretical and policy-focused analyses. Methodologically, the analysis is new to the literature on sustainability assessment, moving away from descriptive rankings to focus on the structural determinants of smart urbanisation. This approach provides decision makers with a diagnostic framework for aligning urban initiatives with national policy structures as well as for monitoring consistency across territories. Blending classification accuracy, posterior probabilities, and canonical visualisation provides a multidimensional description of how cities embody national agendas.

However, some limitations must be considered. Firstly, the differential representation of cities within states may bias group centroids and the stability of discriminant functions. Secondly, while helpful, the use of perception-based indicators is prone to cultural interpretation or reporting bias. Thirdly, the cross-sectional nature of the data restricts our ability to draw conclusions about the temporal development or robustness of national smartness models.

For policymakers, the findings highlight the importance of designing national smart city strategies that balance top-down coordination with bottom-up flexibility effectively. Countries that invest in harmonised data infrastructures, integrated policy platforms, and mechanisms for local experimentation are better placed to promote sustainable urban innovation. At the same time, intra-national divergences in smart city profiles highlight the need for place-sensitive interventions and continuous policy monitoring. National smart city frameworks must therefore be adaptive and inclusive, capable of responding to territorial diversity while maintaining overall coherence with national and global sustainability objectives. Practical policy instruments derived from our findings include performance-based funding aligned with SDG progress, national coordination councils for digital transition in cities, interoperable data governance frameworks, and local pilot zones for testing smart city solutions under regulatory supervision. These tools ensure that institutional heterogeneity becomes a resource for differentiated, context-sensitive urban development, rather than a barrier to innovation.

Future research will need to address these gaps and extend the analytical scope. Methodological extensions involving machine learning classifiers could improve the robustness of models and confirm the persistence of national smart city typologies under different specifications. Longitudinal studies could track trends in city profiles over time to evaluate the durability or transformation of national models. Comparative studies between Global North and Global South regions could investigate whether similar clustering mechanisms operate in different development environments. Methodologically, using machine learning classifiers or mixed methods (quantitative and qualitative) could provide a richer explanation. Additionally, examining the role of intercity networks, global smart city rankings, and transnational policy diffusion could reveal emerging urban convergence trends that transcend national borders.

Combining urban data analysis, institutional theory, and spatial planning offers a way to develop more nuanced models of smart and sustainable cities. Current studies exemplify how blending quantitative methods, such as multivariate analysis, with qualitative knowledge of governance and participation can better fulfil both theoretical and policy goals. Examining this combination is essential for understanding the complexity of urban transformation in different national contexts.

In conclusion, this study shows that achieving smart and sustainable urbanisation requires more than technological innovation or isolated local initiatives. Rather, it fundamentally depends on institutional architectures that support, enable, or constrain urban transformation. Recognising the central role of national governance models is essential for developing effective and equitable urban policies and for advancing a global sustainability agenda that remains attentive to the diversity of local contexts. This research reveals that the road to sustainable smart cities is paved not only with innovation but also with institutions.

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