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Assessing Smart City Maturity Through a Multidimensional DP2-Based Clustering of the IMD Smart City Index

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Abstract

The growing number of smart city rankings and composite indices has improved cross-city comparability, but often at the cost of blurring the distinction between technological advancement and structural urban development. In particular, the notion of smart city maturity is frequently used implicitly and conflicted with overall rank position, providing limited insight into how different dimensions of urban performance interact and balance each other. This study looks at city maturity as a multiple-dimension setup that shows the degree of integration across key urban policy domains. The study uses perception-based indicators from the IMD Smart City Index 2024. The study builds six domains: Digital Readiness, Infrastructure and Mobility, Environmental Quality, Community and Economic Resilience, Proximity and Livability and Circular Economy and Resource Management. Indicators are aggregated within each domain using a non-compensatory distance-based approach (DP2), which limits redundancy among correlated indicators and avoids excessive compensation across domains. Hierarchical clustering applied to the resulting domain scores identifies four distinct smart city maturity profiles: Digital, Smart-Sustainable, Resilient, and Circular. These categories are interpreted as descriptive archetypes rather than normative rankings. These profiles capture different configurations of strengths and weaknesses across domains and point to heterogeneous development paths among global cities. The proposed framework facilitates comparative interpretation and analytical discussion across urban policy domains by shifting the analytical focus from linear rankings approaches to multidimensional profiling. Limitations related to data structure and cross-sectional design are acknowledged, and directions for future longitudinal and integrative research are outlined.

Keywords: Smart city maturity; Multidimensional profiling; non-compensatory composite indicators; Peña Distance (DP2); Hierarchical clustering; Perception-based indicators; Urban policy domains

Introduction

Over the past twenty years, the idea of the smart city has become a key focus in urban studies and policy [1-4]. It brings together digital innovation, efficient infrastructure, environmental sustainability, good governance, and social inclusion [5-6]. Researchers have published a wide range of studies on how to measure and compare smart cities, often using composite indices, rankings, and dashboards that pull together different types of indicators into a single score [7-10]. Well-known examples include rankings [11], composite indicators based on principal component analysis (PCA) [12], and dashboards modelled after ESG or ISO standards [13-14].
Notwithstanding the widespread adoption of these strategies, these are presented with three inherent pitfalls. The first inherent contradiction of these smart city reviews lies in their ranking-driven nature, and in the implicit belief they contain concerning the ability of cities to be ranked along a linear scale of "smartness" [15]. Second issue comes from the possibility of compensatory aggregation strategies, in which strong performance in some realms, that are usually digital and connectivity or transportation, can compensate for weakness in other realms of smart cities, which include liveability and the quality of the environment [16]. Thirdly, the concept of smart city maturity often remains implicit, failing to provide a clear, theoretical definition [17].
As such, existing assessments can give limited information about the way that the urban development structures of cities are arranged. Urban areas with very different types of city development can be placed in similar ranking positions and the inter-balance (or lack thereof) between the strategic domains of urban areas is hidden or lost within these rankings. Thus, the ability for an analytical basis or policy relevance to these types of tools that use rank-based measures will be restricted when the purpose of the ranking is to determine how different dimensions associated with urban performance interact with one another.
To fill these gaps, the present paper reframes the paradigm of maturity in the assessment of a smart city. According to this paradigm, the maturity level of a smart city refers to the level to which a given smart city aligns with a balanced and well-rounded development about a range of domains, according to ITU-T's report (2018) [18]. These domains of a smart city maturity model range from digital readiness, infrastructure and mobility, environmental quality, community and economic resilience, proximity and liveability, and the management of resources: a smart city's maturity level cannot thus be measured using technology intensity and ranking position.

Conceptual Framework: Smart City Maturity

From "smartness" to maturity

Already, early models of a smart city have argued that technology needs to be used to fulfil citywide agendas, and that efficiency, as a sole goal, was a limited objective. Key works that have shaped this area of research, such as [19] and [20], have identified that a smart city can be effectively described through the paradigm of a socio-technical system, where information technology combines with governance, human capital, and sustainability.
Based on this approach, there has been a growing concept, albeit intuitive, regarding smart city maturity that has developed with regards to the degree to which smart city initiatives are integrated. Nevertheless, this is a point that is sometimes simplified and perceived as a reflection of more advanced technology or simply smart cities with positive performance rankings. On this basis, many papers apply the so-called "maturity models", i.e. models that represent the level of development of an organization, according to the definition provided by [21], to smart cities [see 22-24].
For this research, smart city maturity is viewed as a structural quality of smart city systems, which depends on how well-balanced and integrated different strategic domains are. This means that a mature smart city is one that may not necessarily be highly technologically developed, but one where technology, environment, and physical structure are well-integrated and not separately developed.

Maturity as multidimensional balance

Based on this definition, maturity is seen as a complex and non-compensatory criterion. Development in one area cannot compensate for shortcomings in other domains. In this regard, for instance, developments in information services cannot compensate for shortcomings in governance, environmental qualities, or liveability. High social cohesion without sufficient infrastructural development or information access can limit adaptability.
In contrast, rankings are assessed in a way that allows compensatory aggregation mechanisms, wherein strong performance in a few indicators outweighs low performance in others. In a maturity model framework, focus shifts not only to the level of performance, but also the way performance is distributed.
Therefore, smart city maturity is a profile location in a multidimensional space, not a scalar measure, although in academic literature SCs are often evaluated using ordinal or nominal scaling systems [25]. Cities are compared based on how close their specific performance patterns are to each other and clustered into groups that represent a specific profile of maturity.

Analytical domains of smart city maturity

To make this definition operationally meaningful, there are six strategic areas which are explored:

1. Digital Readiness, including a measure of digital infrastructure, e-government services, and digital inclusion.
2. Infrastructure and Mobility, which highlights efficiency, accessibility, and digital integration of transport and essential services.
3. Environmental Quality, including the environmental factors of air, public spaces, cultural dynamism, and environmental transparency.
4. Community & Economic Resiliency; dealing with capacity for governance, community engagement, security, and adaptable societal structures.
5. Proximity and Livability, including issues related to accessibility, housing, inclusion, and urban life.
6. Circular Economy & Resource Management, which encompasses recycling, reusing, sharing, and green employment.

The domains above are policy-oriented constructs. They fit the IMD Smart City Index structure and the body of literature on smart city governance. They do not address any psychological or behavioural constructs. It is essential to note that the domains are not hierarchical. They can be considered interactive dimensions, and their combination influences the maturity level of the urban system. **Table 1** lists the domains that show maturity levels for smart cities together with their respective indicators based on the IMD Smart City Index.

Table 1 *“Macro-categories and Indicators from the IMD Smart City Index 2024”*

Strategic Domains	Variable (IMD Index)	Conceptual Justification
Digital Readiness	Free public Wi-Fi has improved access to city services	Facilitates digital inclusion and access to municipal services
	Online reporting of city maintenance problems provides a speedy solution	Enhances responsiveness and efficiency in urban management
	A website or App allows residents to effectively monitor air pollution	Digital environmental monitoring promotes awareness and transparency
	Online access to job listings has made it easier to find work	Technology reduces barriers to labour market access

	Online services provided by the city has made it easier to start a new business	E-government platforms streamline administrative procedures
	Processing Identification Documents online has reduced waiting times	Digitalization accelerates service delivery and reduces bureaucracy
Infrastructure & Mobility	CCTV cameras have made residents feel safer	Intelligent surveillance systems improve public security
	Medical services provision is satisfactory	Reflects access to essential urban health services
	Arranging medical appointments online has improved access	E-health systems enhance efficiency in care provision
	Employment finding services are readily available	Technological platforms support job matching
	Public transport is satisfactory	Efficient, accessible public transport is a core component of smart cities
	Apps that direct you to an available parking space have reduced journey time	Real-time tools optimize traffic flow and reduce travel time
	Car-sharing Apps have reduced congestion	Shared mobility reduces individual car use and road congestion
	Bicycle hiring has reduced congestion	Promotes active mobility and sustainable transport options
	Online scheduling and ticket sales has made public transport easier to use	Digitalization of mobility services increases usability and ridership
	The city provides information on traffic congestion through mobile phones	Informed mobility enables route optimization and travel planning
	The current internet speed and reliability meet connectivity needs	Robust digital infrastructure supports smart services
	IT skills are taught well in schools	Digital literacy is essential for inclusive smart city participation
Environmental Quality	Air pollution is not a problem	Indicates effective environmental policies and low emissions
	Green spaces are satisfactory	Urban greenery improves liveability and public health
	Cultural activities (shows, bars, and museums) are satisfactory	Cultural vitality contributes to quality of life
	Online purchasing of tickets to shows and museums has made it easier to attend	E-culture tools increase access and participation
	Most children have access to a good school	Educational quality is a pillar of sustainable urban development
	Online public access to city finances has reduced corruption	Digital transparency enhances institutional accountability
	Corruption of city officials is not an issue of concern	Clean governance is essential to sustainable growth
	Basic sanitation meets the needs of the poorest areas	Inclusive infrastructure improves adaptive capacity

Community & Economic Resilience	Public safety is not a problem	Secure environment support social resilience
	Residents provide feedback on local government projects	Participatory governance strengthens community trust
	Information on local government decisions are easily accessible	Transparency enhances institutional legitimacy
	Residents contribute to decision making of local government	Civic engagement fosters responsiveness and resilience
	Lifelong learning opportunities are provided by local institutions	Continuous education supports adaptability to change
	Online voting has increased participation	E-democracy expands civic inclusion and legitimacy
Proximity & Livability	Traffic congestion is not a problem	Low congestion indicates accessibility and proximity of services
	Finding housing with rent ≤ 30% of salary is not a problem	Housing affordability ensures spatial inclusion
	Minorities feel welcome	Inclusive urban environments support social cohesion
	An online platform where residents can propose ideas has improved city life	Digital co-creation strengthens local democracy
Circular Economy & Resource Management	Businesses are creating new jobs	Circular innovation stimulates green employment
	A website or App allows residents to easily give away unwanted items	Digital sharing platforms reduce waste and support reuse
	Recycling services are satisfactory	Effective waste management is key to circular sustainability

Descriptive typologies, not normative rankings

Based on the above framework, the clusters that emerge from the empirical study are to be considered descriptive maturity profiles rather than value statements and prescriptive stages. “Digital”, “Smart-Sustainable”, “Resilient” and “Circular” are to be considered shorthand notations for the purposes of summarizing the most apparent data, rather than suggesting that there is a hierarchy of “better” cities. There may be some maturity profiles that show a higher degree of overall integration in the given areas, although maturity in this case is a construct that is of a comparative and diagnostic rather than an evaluative nature.

Methodology

Methodologically, the paper is positioned on a non-compensatory aggregation approach [26-27] articulating perception-based indicators from the IMD Smart City Index 2024 into six analytical domains through the Peña Distance. This study adopts a quantitative, multivariate, longitudinal perspective to identify and compare smart city maturity profiles at the city level [28-29].
By controlling redundancy among correlated indicators and avoiding arbitrary weighting schemes, DP2 maintains the multidimensional structure of urban performance intact [30].
Hierarchical clustering applied to these domain scores allows for the identification of distinct maturity profiles interpreted as descriptive archetypes rather than normative rankings. This paper contributes on three different fronts: first, by developing a clear conceptualization of smart city maturity founded on notions of balance and integration across domains; second, by introducing a DP2-based aggregation and clustering framework that contrasts with both ranking and PCA based approaches in reducing compensability while enhancing interpretability

[31]; and third, by deducing an empirically based typology of smart city development profiles that offers a comparative tool through which to identify domain-specific strengths and weaknesses across cities.

The empirical strategy combines non-compensatory aggregation of perception-based indicators with hierarchical clustering, with the aim of deriving descriptive archetypes of smart city development rather than linear rankings. Using this approach, it is possible to compare cities based on the six fundamental dimensions of smart city performance via the examination of the intra-country aggregation of data using the meaning of the clusters. The study makes use of the IMD Smart City Index 2024, which is the internationally accepted database released jointly by the International Institute of Management Development, along with the Singapore University of Technology and Design. Smart city performance is measured almost exclusively via citizens' views on the impacts of urban infrastructure and technology on their daily lives [32].

The use of perception-based indicators is consistent with the objective of capturing citizens' experienced quality of urban services and governance, rather than infrastructural capacity alone [33].

The index captures the globe's smart cities based on the perceptions of their citizens regarding how they utilize technology to increase the quality of their lives. While a limited number of contextual indicators are included, the index is predominantly based on standardized perception-based measures collected from city residents.

Based on the conceptual framework for the maturity of a smart city, the original IMD indicators were categorized into six domains which are policy-oriented, representing major dimensions of the development of a city. Each set represents a certain dimension of the transformation of a city, which may be technology, infrastructure, environment, society, and economy, and comprises a set of perception indicators supplied by the citizens residing in the cities. The indicators included in each domain are reported in **Table 1**.

Non-compensatory aggregation via the DP2 index

For synthesizing data found in every analytical domain, this research uses a distance metric, namely Peña Distance DP2, that has been established as appropriate for a multidimensional setting [30, 34-35]. The application of DP2 has been chosen because of its non-compensatory nature and ability to account for information redundancy by considering correlation between indicative elements, which become important when evaluating a level of smart city maturity.

$$DP2(j) = \sum_{i=1}^{n} \frac{d_{ij}}{\sigma_i}\left(1 - R^2_{i,i-1,i-2,\ldots,1}\right);$$

where

- $i = 1, \ldots, n$; (variables) and $j = 1, 2, \ldots, m$ (areas),
- $d_{ij} = \left|x_{ij} - x^*_{ij}\right| \left|x_{ij} - x^*_{ij}\right|$ is the difference between the value taken by the i-th variable in area j and the minimum of the variable in the least desirable theoretical scenario, namely the reference value of matrix X, and,
- σ_i is the standard deviation of variable i.

Contrary to the arithmetic average or weighted averages, the DP2 method does not depend on weighting factors, which could result in a situation where superior performance in some areas of the index overshadows the overall score. This fits the conceptual approach used in the study, whereby advancements in one area, such as digital readiness, do not compensate for weakness in other areas, including governance, liveability, and environment. Operationally, the DP2 index calculates the generalized distance of each unit of observation (city) to a unit of reference that represents worst performance on a set of indicators. For each domain, a set of indicators is reduced to a composite score through calculation of corrected distances that consider inter-indicator correlations through partial correlation coefficients. This allows indicators to contribute to the composite score solely since they supply distinct information.

In relation to this investigation, DP2 is done independently for each analytical domain and is used to produce a set of six domain-specific synthetic scores for each city. These capture the

relative multidimensional intensity of performance for each domain and are the inputs for the next stage analysis.
Here, the DP2 index is employed to create domain-specific synthetic variables that maintain the overall multivariate equilibrium and are then fed into the clustering procedure for maturity profiles. The six DP2 domain indices derived represent the input variables for the hierarchical clustering procedure discussed in the next subsection.

Hierarchical clustering procedure

Hierarchical cluster analysis was carried out for the six domain scores of DP2 for every city. The distance measure was Euclidean distance, with Ward's criterion for forming the clusters, which is the most congruent with variance minimization [36-37]. Indications of the number of clusters came from inspecting the dendrograms as well as the elbow method. All this fits well with looking for homogeneous maturity profiles rather than optimizing predictivity.
For descriptive reasons, an aggregated DP2 score was also calculated for the six domain-specific DP2 scores for each city. Cluster-level means for the aggregated DP2 score are employed in the Results section to provide descriptions of multifaceted performance trajectories for the maturity profiles that have been distinguished.

Results

Domain-specific DP2 scores

For each city included in the IMD Smart City Index 2024, six domain-specific DP2 scores were computed: Digital Readiness, Infrastructure and Mobility, Environmental Quality, Community and Economic Resilience, Proximity and Livability, and Circular Economy and Resource Management.
These scores are intended to summarize the relative multidimensional intensity of performance within each domain, while limiting redundancy among correlated indicators. As illustrated in Table 2, the DP2 values are reported according to domain and city, thus providing the empirical basis for the subsequent clustering analysis.

Table 2 *"DP2 Scores by Macro-category and City"*

City	Country	Digital Readiness	Infrastructure & Mobility	Environmental Quality	Community & Economic Resilience	Proximity & Livability	Circular Economy & Resource Management
New York	United States	17.61	29.07	14.91	12.11	12.5	9.45
Tallinn	Estonia	16.9	24.86	17.51	13.79	9.18	9.17
Ankara	Turkey	17.74	28.5	12.72	12.77	12.76	7.73
Zurich	Switzerland	13.88	26.17	16.86	15.28	10.45	10.11
Warsaw	Poland	18.53	23.69	13.15	12.13	11.19	9.56
Seoul	South Korea	20.02	31.07	10.42	11.94	7.89	9.06
Canberra	Australia	13.66	20.24	17.13	12.62	12.93	10.81
Bilbao	Spain	13.47	27.49	16.38	11.45	11.95	7.54
Helsinki	Finland	12.78	22.82	15.59	11.9	12.1	11.61
Krakow	Poland	17.68	22.98	12.53	11.77	10.56	8.47
Oslo	Norway	9.78	26.15	16.94	13.1	11.36	12.1
Bologna	Italy	13.68	22.88	14.75	10.21	13.2	7.54

Copenhagen	Denmark	10.92	23.9	15.48	13.35	9.92	11.6
Zaragoza	Spain	11.09	23.92	15.96	10.08	11.62	7.57
Vilnius	Lithuania	17.21	24.36	12.95	9.43	6.51	11.18
Sydney	Australia	14.4	24.59	13.63	11.61	9.18	10.34
Brisbane	Australia	13.69	23.71	14.63	11.63	8.64	9.75
London	United Kingdom	14.77	24.37	13.29	9.64	8.76	9.03
Prague	Czech Republic	13.87	25.15	12.63	11.27	8.18	10.34
Los Angeles	United States	14.61	23.02	12.56	10.61	9.66	9.18
Vienna	Austria	12.15	22.32	14.41	11.63	9.69	10.41
Lausanne	Switzerland	10.46	24.14	15.99	12.31	9.78	8.37
Lille	France	13	25.73	13.38	9.19	9.82	7.67
Munich	Germany	11.91	22.51	14.76	12.06	7.88	9.71
Melbourne	Australia	14.17	22.23	13.75	10.33	7.99	8.18
Madrid	Spain	13.72	26.91	13.1	8.98	7.75	7.16
Washington D.C.	United States	12.01	22.42	13.37	10.68	9.93	9.41
Aukland	New Zealand	12.52	20.56	14.57	11.86	6.69	9.8
Amsterdam	Netherlands	11.81	25.43	12.59	10.09	9.82	8.31
Geneva	Switzerland	10.6	21.68	15.53	13.03	7.53	8.19
Düsseldorf	Germany	11.7	21.83	13.2	11.23	9.7	8.41
Lyon	France	12.61	25.39	13.2	8.46	7.83	7.98
Luxembourg	Luxembourg	10.94	21.47	14.99	11	7.47	8.81
Rotterdam	Netherlands	12.1	22.88	11.63	9.92	9.79	8.68
Stockholm	Sweden	9.92	21.32	14.67	9.9	8.41	9.68
Bordeaux	France	10.84	24.27	14.11	8.7	7.79	8.12
Gothenburg	Sweden	10.06	20.86	14.6	8.99	8.64	9.19
Leeds	United Kingdom	11.12	20.25	11.27	10.24	9.86	9.99
Ottawa	Canada	9.68	13.59	15.33	11.69	9.17	10.27
Newcastle	United Kingdom	9.63	21.06	12.51	10.38	10.49	9.36
The Hague	Netherlands	10.57	22.22	12.03	10.44	9.32	8.3
Boston	United States	9.42	21.21	13.65	10.67	7.9	9.72
Hamburg	Germany	10.57	20.61	12.74	10.64	8.1	9.05
Manchester	United Kingdom	10.98	20.09	11.7	10.27	9.16	9.24
Wellington	New Zealand	10.73	16.97	14.44	10.36	7.49	9.03
Reykjavík	Iceland	10.3	14.98	14.33	11.01	8.67	9.31
Birmingham	United Kingdom	10.58	21.01	11.9	9.02	9.56	8.68
Chicago	United States	10.55	22.02	11.3	8.66	10.05	7.65
Brussels	Belgium	11.24	22.45	11.51	8.01	8.37	7.3
Milan	Italy	11.31	20.58	11.28	7.04	9.76	7.76
Barcelona	Spain	11.15	22.73	11.31	8.07	7.17	6.1
Paris	France	10.98	22.35	11.28	7.09	6.72	7.5
Busan	South Korea	16.9	26.46	7.62	10.13	8.27	6

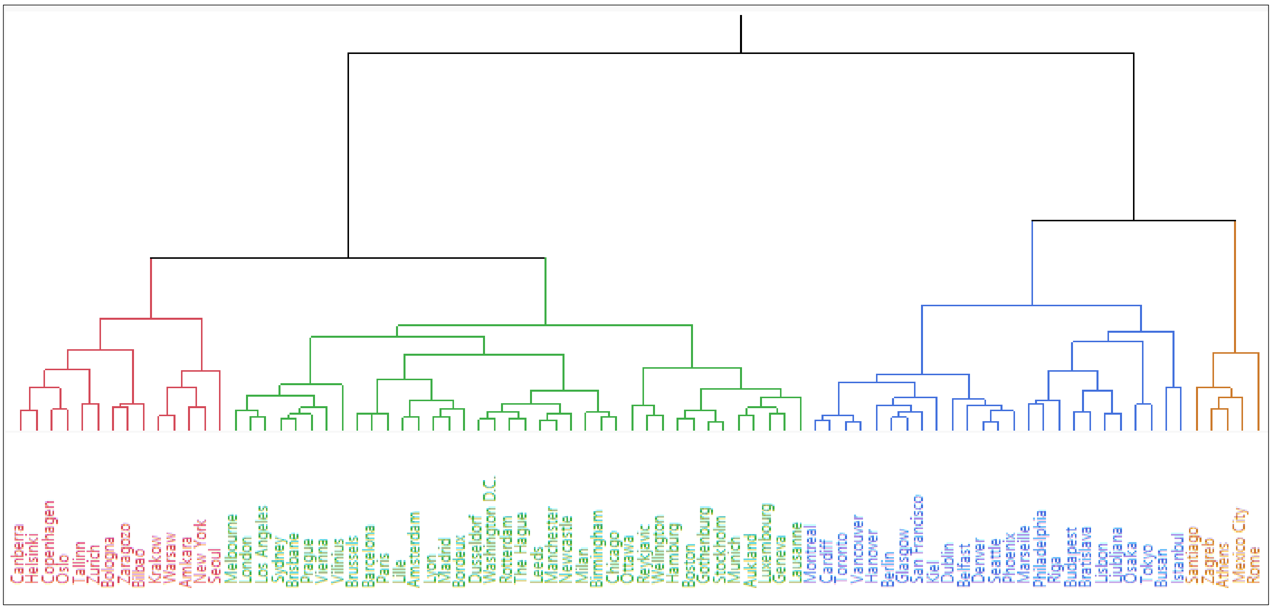
Vancouver	Canada	11.31	18.16	13.71	9.79	7.42	8.44
Toronto	Canada	10.67	18.4	13.38	9.82	6.67	8.02
Montreal	Canada	9.8	18.1	13.05	9.54	7.08	8.81
Lisbon	Portugal	13.75	16.94	11.65	6.22	5.48	5.85
Cardiff	United Kingdom	9.8	17.13	12.26	9.12	7.2	8.27
Belfast	United Kingdom	10.36	17.21	11.49	7.28	6.49	10.22
San Francisco	United States	9.14	20.15	11.74	8.32	7.28	7.69
Ljubljana	Slovenia	12.31	16.33	11.47	8.06	5.65	5.67
Glasgow	United Kingdom	9.04	17.53	11.29	8.86	8.12	8.02
Berlin	Germany	8.32	19.02	10.37	9.02	8.43	8.7
Hanover	Germany	6.62	17.98	12.78	9.5	8.91	7.94
Istanbul	Turkey	14.37	21.32	6.4	7.39	5.52	5.65
Denver	United States	8.2	17.94	11.68	9.23	6.03	8.72
Seattle	United States	7.8	18.41	11.35	8.32	6.04	9.06
Phoenix	United States	9.24	16.92	9.71	8.26	6.53	9.02
Riga	Latvia	10.84	19.14	9.69	4.69	6.6	6.27
Budapest	Hungary	10.92	18.18	9.45	6.68	4.61	7.55
Bratislava	Slovakia	9.94	18.03	9.35	8.35	5.88	7.04
Dublin	Ireland	8.27	14.92	10.69	6.61	4.39	8.89
Kiel	Germany	6.6	14.42	9.98	9.86	7.87	7.64
Philadelphia	United States	7.18	18.61	9.24	6.56	7.67	6.8
Marseille	France	6.63	19.2	8.34	4.3	6.24	5.28
Tokyo	Japan	5.86	15.8	5.36	7.05	6.7	7.19
Osaka	Japan	3.45	13.8	5.11	6.91	7.54	5.41
Mexico City	Mexico	10.93	15.32	7.85	2.93	5.33	3.44
Zagreb	Croatia	9.37	10.66	9.01	3.77	4.24	4.07
Athens	Greece	9.31	11.21	6.73	4.22	2.64	3.71
Santiago	Chile	8.52	15.12	5.45	0.84	2.18	3.23
Rome	Italy	2.22	7.66	8.02	1.27	4.39	0.46

Identification of smart city maturity profiles

Hierarchical clustering applied to the six DP2 domain scores resulted in a four-cluster solution (**figure 1**). The selection of four clusters was supported by dendrogram inspection and the elbow criterion, which together indicate a clear reduction in within-cluster variance beyond this threshold.

The resulting clusters represent distinct smart city maturity profiles, defined by specific configurations of domain-level performance rather than by a single linear ordering.

Figure 1 *"Hierarchical Clustering Dendrogram of Smart Cities"*



Source: Author's calculations.

Cluster-level descriptive comparison

The average DP2 scores by cluster and analytical domain, together with the number of cities included in each group, are presented in Table 3. The cluster-level averages provide a descriptive summary of multidimensional performance patterns across the identified profiles.

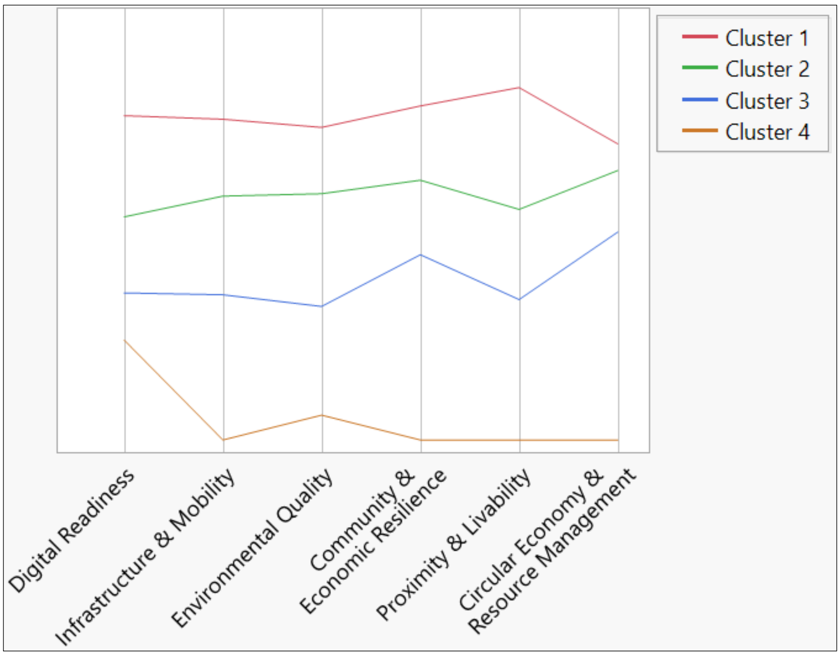
Table 3 *"DP2 Scores by Cluster and Macro-category"*

Cluster	Cities within the cluster	Digital Readiness	Infrastructure & Mobility	Environmental Quality	Community & Economic Resilience	Proximity & Livability	Circular Economy & Resource Management	DP2 Overall for cluster
1	14	14.84	25.27	15.02	12.32	11.26	9.45	12.83
2	38	11.79	22.09	13.27	10.16	8.66	8.87	10.27
3	25	9.49	18.00	10.29	7.99	6.75	7.53	7.53
4	5	8.07	11.99	7.41	2.60	3.76	2.98	3.81

Source: Author's calculations.

To facilitate comparison across domains, the information (except for DP2 Overall) is summarized graphically in **Figure 2**.

Figure 2 *"Cluster Analysis of Global Smart Cities"*



Source: Author's calculations.

Cluster 1 has shown relatively elevated and balanced scores in all six areas, with particularly strong performance in Environmental Quality and Circular Economy and Resource Management. Cluster 2 has intermediate to elevated values in the various dimensions, and relatively stronger scores in Infrastructure and Mobility and Community and Economic Resilience. Cluster 3 exhibited intermediate scores, accompanied by greater variation across the various dimensions. Conversely, Cluster 4 demonstrated lower values across the majority of dimensions, especially in Proximity and Livability and Circular Economy. As a more descriptive measure, the cluster-level averages of the total DP2 value are provided. These measures do not attempt to grade cities or profiles on a normative scale but rather distil multidimensional intensity.

Discussion

The study approached the issue of smart city ranking differently than listing cities from a best to worst perspective. Instead, this study's approach is to assess the maturity of smart cities along multiple levels, representing their performance in numerous policy domains, as per [38]. The results of this analysis suggest that there are multiple types of cities that can be grouped together along similar paths of development, in accordance with [39] and [40]. These groupings provide a holistic view of the maturity levels of smart cities because they account for both the imbalance and complements of the various domains. This clearly shows that high levels of performance in individual domains do not mean that a city is highly mature overall [41]. For example, some cities may have high levels of digital preparedness and infrastructure but may not be performing as well as cities that exhibit a high degree of proximity, livability, or circular economy practices. The results of this analysis demonstrate that the concept of maturity for smart cities requires consideration of the degree of integration and balance across the multiple domains, not just the maximization of individual indicators.
The established patterns of the identified maturity profiles have further elucidated upon the discrepancy with the IMD overall ranking, where the significant correlation between the overall DP2 scores by cluster level and position as ranked showed ($r = -0.71$) an inverse coding of the ranking (lower rank = higher position) demonstrates a relatively high correlation between the two methods of assessing cities at the aggregate level. This confirms that maturity profiles are not orthogonal to ranking outcomes, but conceptually non-equivalent: while rankings impose a

linear ordering, clustering reveals multidimensional configurations of strengths and weaknesses that may coexist at similar rank positions, as per [42]. However, the strong correlation does not imply equivalence; while rankings give a linear organization of cities from least to most ideal, the cluster structure shows how different combinations of the strengths and weaknesses among the various domains can create different maturity profiles across different ranks, and highlight other combinations of strength or weakness that otherwise would not be visible in ordinal rankings. Analysis of the results also indicates that non-compensatory aggregation of data in this instance has provided value-add to the assessment of smart cities by inhibiting redundancy through the correlation of indicators and eliminating the full compensation of dimensions using the DP2 model. The use of the DP2 model to create a multi-dimensional assessment of smart cities minimizes the likelihood that a dimension like Digital Infrastructure dominates other dimensions (Governance, Environmental Quality, Daily Livability) when using perception-based indicators, which frequently demonstrate correlated response patterns and may artificially inflate composite measures [9].

It is important to note that Cluster Profiles are not normative stages in terms of how cities should develop, nor are they prescriptive in terms of what each city ought to be. Rather, they reflect dominant characteristics that were found in the clusters based on the data gathered. Therefore, when using labels such as “Digital”, “Smart/Sustainable”, “Resilience” and “Circular” it does not mean that they represent some type of hierarchy, nor does it indicate that cities move from one cluster to another in a pre-defined manner. As per [43], clusters may represent an amalgamation of different types of conditions, such as the institutional arrangements that exist within a city, the type of welfare regime utilized within the city, the nature of urban form, and the types of historical influences affecting how the cities have developed, none of which are considered in this analysis. Because there are limitations to the study, it is important to consider the following points: a) Because data are cross-sectional (taken from just one point in time), researchers cannot determine how mature a city has become or what type of city is becoming over time; b) The use of perception-based indicators may not accurately reflect the true nature of a city's quality of services and/or governance because they may be influenced by cultural expectations or the way individuals respond to these types of surveys; c) When clustering methods are used, researchers tend to simplify the level of heterogeneity within clusters in order to identify dominant characteristics.

All these limitations suggest that there are numerous opportunities for future research. We agree with [44] stating that using multiple waves of perception data would allow researchers to study cities over time through the path of transition between cluster profiles. Furthermore, incorporating objective indicators (such as environmental performance, mobility performance, and governance metrics) to validate results would lead to a greater effect and the potential for using various methods for measuring a city's development.

Finally, comparing maturity to other institutional, economic, or geographic characteristics can help us determine the reasons for why some configurations develop and remain in existence. The results also indicate that evaluating smart cities by a multidimensional maturity profile is a supplement to the existing ranking process. Comparative analysis allows for the use of various aspects and their configuration rather than a single linear ranking, thus providing additional information for the successful analysis and discussion of urban development strategies.

Conclusions

In this work, we put forth an alternative method to measuring maturity of smart cities, which takes into consideration multiple dimensions of how smart cities are creating value in different policy relevant areas independently of traditional ranking systems. Maturity represents a combination of outcomes in different areas that cities create based on their resources and priorities [24]. Based on the perception-based data collected through the IMD Smart City Index 2024 survey, the researchers defined six (6) domains, and used a method known as DP2 to combine them in a manner that does not compensate for weakness in one area by creating value in another area. To conduct the cluster analysis of the resulting domain scores, the researchers applied hierarchical clustering techniques, identifying and defining four (4) profiles of smart city maturity. These profiles represent types of smart cities based on characteristics and demonstrate the heterogeneity of strengths and weaknesses within the smart city community, as opposed to presenting a linear path of development or a universal hierarchy of maturity. While the aggregate results of the rank-order and profile match are comparable, they reveal significant structural implications that would have gone undetected had rankings been the only basis for comparison. Cities that are ranked similarly may have very different maturity profiles [45], revealing important implications for research and practice regarding the value of profiling and understanding the complexity of urban development in the 21st century as it relates to the transition to smart cities.

Methodologically, our research offers methodical examples of how multi-level data aggregation and clustering can aid the advancement of previously developed composite indices by balancing the different domains involved in the assessment and by minimizing the potential for distortion due to overlapping measures within a given domain. Substantively, our results, in accordance with [46], demonstrate that the level of maturity associated with an urban area labelled as a “smart city” does not merely stem from technology but rather reflects the extent to which various policy domains associated with urbanization are coordinated. Several limitations are worth noting. First, the research design was cross-sectional and the ability to examine transitions over time is not currently possible; second, perception-based measures may include respondents’ cultural norms and styles of answering as well as their actual performance; and third, while these limitations do not invalidate the findings, it is important to understand how to interpret the results relative to those limitations.

There are multiple opportunities to expand upon the work in this study via future research. Conducting longitudinal studies would allow an examination of changes in maturity and how urban development evolves from one maturity profile to another. Integrating both objective and perception-based measures of urban performance would increase the robustness of the research validation process and create new opportunities to employ mixed-methodology approaches [44,42]. Additionally, studying how maturity profiles may correlate with or be influenced by institutional, economic, or spatial dimensions could shed light on how urbanization is framed within the broader context of each of these areas.

Rather than replacing existing ranking exercises, the proposed maturity-based framework complements them by revealing structural configurations of urban development that are otherwise concealed by linear ordering.

Data Availability Statement

All data are public and published by IMD Smart City Index 2024. Readers can access them on https://www.coit.es/sites/default/files/imd_-smartcityindex-2024-full-report.pdf

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