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ANÁLISE DE CIDADES INTELIGENTES EM MINAS GERAIS: UMA ABORDAGEM BASEADA EM CLUSTERIZAÇÃO K-MEANS

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ABSTRACT

This study analyzes the relationships between clusters generated from the six dimensions of Mokarrari and Torabi's (2021) smart cities ranking, applied to municipalities in Minas Gerais with more than 100,000 inhabitants. The research employed the K-Means clustering algorithm, the elbow method to determine the optimal number of clusters, and the silhouette index to validate the cluster performance. The results revealed significant asymmetries between the dimensions analyzed, with emphasis on the Governance dimension, which presented the best clustering structure, while dimensions such as Mobility and Living showed greater overlap between groupings. The results indicate that urban intelligence in Minas Gerais municipalities depends on the interaction between structural and institutional dimensions, reinforcing the need for integrated public policies for regional development. In addition, the study showed that adapting the ranking to the Brazilian context allows a more realistic assessment of intermunicipal inequalities, contributing to municipal and state strategic planning.

Keywords: Multicriteria Analysis. Smart Cities. K-Means Clustering. Urban Development. City Ranking.

RESUMO

Este estudo analisa as relações entre os clusters gerados a partir das seis dimensões do ranking de cidades inteligentes, de Mokarrari e Torabi (2021), aplicados aos municípios mineiros com mais de 100.000 habitantes. A pesquisa utilizou o algoritmo de clusterização *K-Means*, o método do cotovelo para definição do número ideal de *clusters* e o índice de silhueta para validação dos agrupamentos. Os resultados revelaram assimetrias relevantes entre as dimensões analisadas, com destaque para a dimensão governança, que apresentou melhor estrutura de clusterização, enquanto dimensões como mobilidade e vida evidenciaram maior sobreposição entre agrupamentos. Os resultados indicam que a inteligência urbana nas cidades mineiras depende da interação entre dimensões estruturais e institucionais, reforçando a necessidade de políticas públicas integradas para o desenvolvimento regional. Além disso, o estudo evidenciou que a adaptação do ranking ao contexto brasileiro possibilita uma leitura mais realista das desigualdades intermunicipais, contribuindo para o planejamento estratégico municipal e estadual.

Palavras-chave: Análise Multicritério. Cidades Inteligentes. Clusterização *K-Means.* Desenvolvimento Urbano. Ranking de Cidades.

INTRODUCTION

Urban expansion has directly impacted urban planning and management, intensifying challenges related to mobility, access to services, and sustainability. This process, driven by population growth and increased life expectancy, requires continuous investment in technology and urban management (Albino *et al.*, 2015). Data published by the United Nations (UN, 2019) indicate that more than half of the world's population lives in urban areas, with projections indicating continued growth through 2050.

To mitigate the consequences of population growth in urban areas, the concept of Smart Cities emerged in the mid-1990s. According to Giffinger and Gudrun (2010), smart cities embody a forward-looking perspective structured around dimensions such as people, governance, quality of life, environment, economy, and mobility. These dimensions are characterized by the integration of decisive, independent, and conscious behaviors among key stakeholders.

To fully realize the benefits of Smart Cities initiatives, it is imperative to monitor and evaluate the level of urban intelligence, categorize proposed initiatives, identify the strengths and weaknesses of each municipality, and formulate future development plans (Mokarrari; Torabi, 2021). The European Smart Cities Ranking (Giffinger *et al.*, 2007), developed by the TU Wien research group, represents a comprehensive analysis of the fundamental characteristics present in national and international rankings. This ranking is structured around six dimensions: a) Smart People, b) Smart Environment, c) Quality of Life, d) Smart Governance, e) Smart Economy, and f) Smart Mobility, each based on multiple factors and indicators (Giffinger *et al.*, 2007). The integration of these dimensional results enables the construction of an overall city ranking.

Mokarrari and Torabi (2021) identified a research gap highlighting the need to develop a smart cities classification framework adapted to developing countries, such as Iran. The researchers analyzed five Iranian cities using several techniques from Multiple Attribute Decision Making (MADM This method is considered one of the most appropriate approaches for assessing smart cities. For classification purposes, the authors developed, based on a review of the literature, a smart cities evaluation framework (ranking) comprising 28 indicators (variables) distributed across six main dimensions: people, environment, governance, economy, living, and mobility.

Given the relevance of Minas Gerais, this study applies the Iranian ranking developed by Mokarrari and Torabi (2021) to municipalities in the state using a clustering approach. This study aimed to analyze the relationships among clusters across the six dimensions identified by the authors when applied to cities in Minas Gerais. According to the Census (IBGE, 2022), Minas Gerais is the second most populous state in Brazil, with a population of 20,539,989 inhabitants distributed across 853 municipalities. The state also plays a significant role in the national economy, ranking third in Gross Domestic Product (GDP) in the country (IBGE, 2023).

Considering the importance of the state of Minas Gerais, the ranking proposed by Mokarrari and Torabi (2021) is applied to municipalities with more than 100,000 inhabitants. Although smart city classification models are widely adopted, the literature indicates that rankings present methodological and structural limitations, which may lead to reduced or decontextualized results when applied directly (Leyva, 2013). In particular, international rankings tend to be developed on the basis of distinct institutional, historical, and socioeconomic realities, often disregarding regional specificities and territorial inequalities (Giffinger; Gudrun, 2010; Berrone *et al.*, 2018).

Within this context, an adaptation of the variables to the Brazilian context was necessary, drawing on available indicators from official national databases, such as IBGE (2019, 2022, 2023) and the Connected Smart Cities Ranking (2022), as well as following the clustering methodology proposed by Schelings *et al.* (2023) using the K-Means algorithm. This adaptation enabled the incorporation of the state's socioeconomic, cultural, and institutional particularities, overcoming the limitations of directly applying international frameworks and providing a more context-sensitive analysis aligned with regional realities and municipal asymmetries.

This study contributes to the field of regional development and management by highlighting how urban intelligence is unevenly distributed among municipalities with different institutional, economic, and structural capacities. The analysis of interrelationships among strategic dimensions broadens the debate on territorial planning and provides insights for the formulation of integrated public policies aimed at reducing intermunicipal asymmetries and defining investment priorities at the municipal and state levels.

SMART CITIES

According to Komninos (2002), Smart Cities are geographical areas—such as communities, neighborhoods, districts, cities, or regions—capable of embracing technological progress, innovation, information processing, knowledge exchange, and technological resources. Caragliu *et al.* (2011) indicate that a city is considered smart when investments in human and social capital, as well as modern urban mobility, foster sustainable economic development and enhance quality of life, aligned with the intelligent management of natural resources through participatory governance.

Smart Cities must strengthen conventional infrastructure—such as transportation, housing, and access to healthcare—while simultaneously investing in modern technological structures to enhance quality of life and promote sustainable economic development, alongside investments in social and human capital (Caragliu *et al.*, 2011). According to Andrade and Galvão (2016), the use of technology enables modernization processes that benefit individuals and serve as a key instrument in addressing challenges related to urban mobility, governance, and other urban domains.

A growing number of Smart Cities projects have been implemented worldwide. A number of European cities, such as Amsterdam, Bath, Barcelona, Berlin, Edinburgh, and Manchester, have made significant investments in Smart Cities initiatives (Lee *et al.*, 2014). In Asia, Busan, Singapore, Hong Kong, Seoul, and Songdo are at the forefront of implementing Smart Cities strategies (Lee *et al.*, 2014). Countries in South America, the Middle East, and Africa have also undertaken similar initiatives, albeit on a smaller scale (Lee *et al.*, 2014). In Brazil, cities such as Mossoró (Rio Grande do Norte), Búzios (Rio de Janeiro), Curitiba (Paraná), Porto Alegre (Rio Grande do Sul), São Paulo (capital), Belo Horizonte (Minas Gerais), Rio de Janeiro (capital), and Florianópolis (Santa Catarina) are frequently cited in the literature (Pinheiro Junior, 2019).

To assess and classify a city as Smart, multiple factors and dimensions are considered in determining its level of "intelligence." Guimarães (2018) argues that distinct configurations of dimensions and factors may or may not collectively define a city as Smart. It is worth noting that, depending on local priorities, a city may prioritize one dimension over others. Studies conducted internationally (Giffinger *et al.*, 2007; Anthopoulos *et al.*, 2015; Ahvenniemi *et al.*, 2017; Mokarrari; Torabi, 2021) as well as in Brazil (Guimarães, 2018; Connected Smart Cities, 2022) have sought to define the dimensions and indicators used in the classification of Smart Cities; however, no standardized model has yet been established.

Classification models produce Smart City rankings; however, such instruments present methodological and conceptual limitations, as they depend on the selection of indicators, data availability, and the weighting criteria adopted (Leyva, 2013). Urban analyses must account for the historical, institutional, and socioeconomic specificities of each location, in addition to the methodological framework underlying the ranking process (Giffinger; Gudrun, 2010; Leyva, 2013).

Numerous methodological approaches and analytical frameworks have been employed to classify Smart Cities. Such approaches include benchmarking (Anthopoulos *et al.*, 2015), Multiple Attribute Decision Making (MADM) (Escolar *et al.*, 2019; Mokarrari; Torabi, 2021), Principal Component Analysis (PCA) (Akande *et al.*, 2019), hierarchical clustering (Akande *et al.*, 2019), as well as multivariate and other statistical analyses (Ahvenniemi *et al.*, 2017; Akande *et al.*, 2019).

Within the Brazilian context, recent scholarship has critically examined the consolidation of the Smart Cities agenda, highlighting tensions among stakeholders, territorial asymmetries, and the need for context-sensitive evaluation frameworks tailored to local specificities (Reia; Cruz, 2023). Furthermore, recent studies identify conceptual and operational challenges related to the implementation and measurement of Smart Cities initiatives in the country, underscoring the importance of contextualized methodologies that account for territorial heterogeneities and the administrative capacity of Brazilian municipalities (Maciel *et al.*, 2024).

METHODOLOGY

This study conducted a cluster analysis of Smart Cities in Minas Gerais, building upon the ranking developed by Mokarrari and Torabi (2021), which comprises 28 variables structured into six dimensions. The study sample comprised municipalities in Minas Gerais with more than 100,000 inhabitants, a selection informed by the 2022 Census (IBGE, 2022), which revealed that approximately 64% of the state's population is concentrated in cities of this size. The municipalities included in the analysis are presented in Table 1, with populations ranging from 102,217 to 2,315,560 inhabitants.

The municipalities analyzed are listed in Table 1, with populations ranging from 102,217 to 2,315,560 inhabitants.

Table 1 | Municipalities in Minas Gerais Included in the Analysis and Estimated Population According to IBGE

Cities	Population 2022- IBGE	Cities	Population 2022- IBGE
Belo Horizonte	2,315,560	Teófilo Otoni	137,418
Uberlândia	713,232	Varginha	136,467
Contagem	621,865	Conselheiro Lafaiete	131,621
Juiz de Fora	540,756	Sabará	129,372
Montes Claros	414,240	Vespasiano	129,246
Betim	411,859	Barbacena	125,317
SubstituirUberaba	337,846	Araguari	117,808
Ribeirão das Neves	329,794	Itabira	113,343
Governador Valadares	257,172	Passos	111,939
Divinópolis	231,091	Nova Lima	111,697
Ipatinga	227,731	Araxá	111,691
Sete Lagoas	227,360	Nova Serrana	105,552
Santa Luzia	218,805	Lavras	104,761
Ibirité	170.387	Coronel Fabriciano	104.736
Poços de Caldas	163.742	Muriaé	104.108
Patos de Minas	159.235	Ubá	103.365
Pouso Alegre	152.212	Ituiutaba	102.217

Fonte: Elaborated by the authors.

At the outset of the study, the variables underlying the Mokarrari and Torabi (2021) ranking were examined to determine whether adaptation was required within the Brazilian context. For this purpose, data were obtained from official databases, including the Brazilian Institute of Geography and Statistics (IBGE, 2019, 2022, 2023), the Connected Smart Cities Ranking (2022), and relevant academic literature, in order to identify indicators aligned with the proposed dimensions. Data were collected between July 2021 and January 2023, initially encompassing the 853 municipalities in Minas Gerais and subsequently restricted to 34 cities with more than 100,000 inhabitants.

The initial dataset comprised 71 variables. Nevertheless, limited availability of local data for certain indicators necessitated the inclusion of national and regional data and, in certain cases, the exclusion of variables initially proposed in the ranking developed by Mokarrari and Torabi (2021). According to Yi *et al.* (2021), when robust data for specific indicators are unavailable, their exclusion may be methodologically warranted. Accordingly, the following variables were excluded: "E4 – Urban green areas"; "E5 – Air quality monitoring systems"; "E7 – Energy consumption"; "L4 – Degree of diversity and social cohesion"; "Ec2 – Ease of online service provision for new businesses"; "Ec5 – E-commerce companies"; and "P3 – ICT skills."

Missing data constitute a recurrent limitation in public databases and may arise from data entry errors, incomplete records, or the absence of specific indicators. Little and Rubin (2002) emphasize that high proportions of missing data may undermine the statistical stability of analyses, particularly in unsupervised clustering techniques such as K-Means. In the present study, several variables exhibited substantial levels of missing data, including Hydroelectric Power (85.3%), Air Quality Index (88.2%), Percentage of Recovered Plastic Waste (79.4%), and Biomass Energy (76.5%), thereby justifying their exclusion to preserve the integrity of cluster formation.

Exclusion was adopted instead of estimating missing values, given the high proportion of missing data observed in certain environmental variables. Although this decision may have limited the analytical scope of specific dimensions, it ensures methodological consistency; future research may explore alternative techniques for handling missing data or expanding data sources to mitigate potential distortions in the results. The variables included in the ranking developed by Mokarrari and Torabi (2021), as well as those selected for this study, are summarized in Table 2.

Table 2 | Relationship Between the Variables of the Mokarrari and Torabi (2021) Ranking and the Variables Analyzed in This Study

Mokarrari and Torabi (2021) Ranking Variables		Variables Considered in This Study
	Environment	
E1[1]	Quality of Basic Sanitation	% of urban water supply; % of urban sewage service; % coverage of solid waste collection; % coverage of household waste collection.
E2	Air Quality	Air Quality Index.
E3	Recyclables	Recovery rate of recyclable materials; plastic waste recovered (tons/year).
E4	Urban Green Area	Excluded from the study due to the absence of reliable data in the database.
E5	Availability and Quality of Air Pollution Monitoring Applications	Excluded from the study due to the absence of reliable data in the database.
E6	Renewable Energy Production	Hydroelectric energy; biomass energy.
E7	Energy Consumption	Excluded from the study due to the absence of reliable data in the database.

1 The abbreviation was created to identify the variables throughout the analysis and discussion of the results.

	Quality of Life	
L1	Medical Services for Health	Hospital beds per inhabitant (WHO).
L2	Public Safety	Operations Control Center; Municipal Public Security Council; Civil Police Station; Homicide Police Station; Police Station for the Protection of the Elderly; Police Station for the Protection of Children and Adolescents (DPCA); Police Station for the Protection of Children and Adolescents – specialized units; Environmental Protection Police Station; Specialized Police Station for Assistance to Women; Specialized Police Station for Missing Persons; Cybercrime Police Station; Forensic Medical Institute; Courthouse; Fire Department Unit; Civil Defense; Municipal Guard.
L3	Quality of Cultural Activities	Public libraries; Museums; Theaters or performance venues; Cultural center; Public archive and/or documentation center; Stadiums or sports facilities; Craft market; Cinema; Video rental store; Shopping center; Record, CD, tape, and DVD stores; Bookstores; Art gallery; Higher education institution; Cultural club and recreational association; Lan house; Fixed circus; Acoustic shell.
L4	Level of Diversity and Social Cohesion	Excluded from the study due to the absence of reliable data in the database.
L5	Internet Access	% of residents covered by 4G in the municipality.
L6	Quality of Life	Quality of Life Index.

Table 3 | Relationship Between the Variables of the Mokarrari and Torabi (2021) Ranking and the Variables Analyzed in This Study (continued)

	Mokarrari and Torabi (2021) Ranking Variables	Variables Considered in This Study
	Smart Mobility	
M1	Traffic Conditions	Operations Control Center; Smart traffic lights.
M2	Quality of Public Transportation	Bus fleet adapted for people with disabilities or reduced mobility; Electronic ticketing system for public transportation.
M3	Quality of Transport Infrastructure	Municipal buses with GPS; Bicycle lanes in the municipality; Public bicycle-sharing system.
M4	Availability and Quality of Applications (ride-hailing, bike rental, parking, among others)	App-based services.

Smart Economy		
Ec1	Job Search Availability	Growth of formal employment.
Ec2	Ease of Online Services for New Businesses	Excluded from the study due to the absence of reliable data in the database.
Ec3	Innovation and Entrepreneurship	Growth of creative economy enterprises; Growth of individual microenterprises; Growth of technology companies.
Ec4	Employment	Employed individuals aged 16 to 60 years.
Ec5	E-commerce Companies	Excluded from the study due to the absence of reliable data in the database.

Table 4 | Relationship Between the Variables of the Mokarrari and Torabi (2021) Ranking and the Variables Analyzed in This Study (continued)

Variáveis Ranking Mokarrari e Torabi (2021)		Variáveis para a pesquisa
People		
P1	Access to Adequate Education and Educational Materials	IDEB.
P2	Higher Education	% of formal employment requiring higher education.
P3	ICT Skills	Excluded from the study due to the absence of reliable data in the database.
Governance		
G1	Accessible Open Data on Local Government Decisions	“Portal da Transparência”; e “Portal de dados abertos”.
G2	Contribution and Participation of Residents in Local Government Decision-Making	“Online public consultation so that citizens can send contributions to laws, budgets and plans”; “Discussion groups, such as forums or communities on the internet”; “Online poll on matters of interest to the City Hall”; “Online voting to guide decision-making on public policies, budget, etc.”
G3	Public Online Access to Municipal Financial Information	Provision of information on budget and financial execution (in compliance with Complementary Law 131/2009).

Fonte: Adapted from Rahmani Mokarrari and Torabi (2021).

Following consolidation, the dataset underwent preprocessing procedures, including data cleaning, preparation, and normalization, in accordance with the guidelines proposed by Tan *et al.* (2009). The analysis was conducted in a Python environment using appropriate libraries for data manipulation, visualization, and clustering (NumPy, Pandas, Matplotlib, SciPy, Seaborn, Scikit-learn, and Yellowbrick). Categorical variables were processed through binarization and normalization, and variables with high proportions of missing data were excluded, resulting in a final dataset comprising 61 variables and 34 observations.

After data cleaning and preprocessing in alignment with the research objectives, separate datasets were generated for each dimension to perform the clustering analysis. This step was carried out by filtering the attributes corresponding to each dimension. For the clustering procedure, the unsupervised learning algorithm K-Means was selected for this study. The algorithm partitions the data into a predefined number of centroids (k), specified by the user during execution, thereby directly influencing the clustering results (Almeida, 2021).

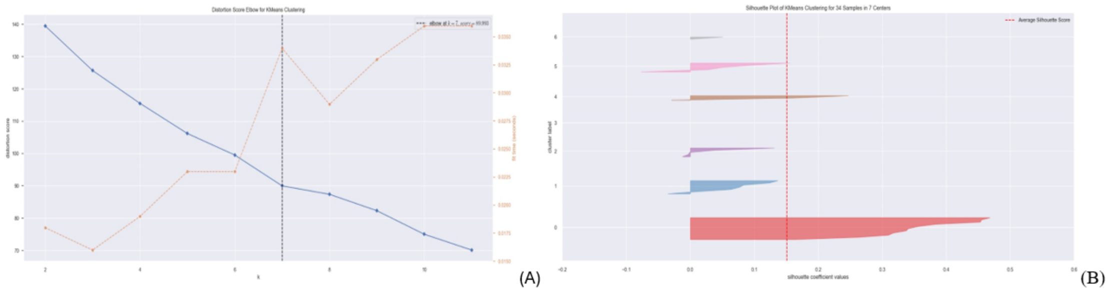
Although K-Means is widely employed due to its simplicity and efficiency, the literature highlights relevant limitations, including sensitivity to outliers, dependence on centroid initialization, and greater suitability for approximately spherical structures, which may reduce its performance when applied to complex and heterogeneous datasets (Li *et al.*, 2022; Khan *et al.*, 2024). In urban contexts, territorial heterogeneity may hinder the clear separation of clusters, requiring careful interpretation of the results and encouraging future comparisons with alternative methodological approaches (Yu *et al.*, 2023).

The optimal number of clusters was determined using the Elbow Method, based on the analysis of inertia and the distances between data points and centroids (Almeida, 2021). Cluster validation was carried out using the Silhouette Score, which assesses the quality of separation among clusters—values close to 1 indicate stronger segmentation, whereas values near zero suggest overlap. The analysis was conducted within a Python environment.

ANALYSIS AND DISCUSSION

The Quality of Life Dimension encompasses not only technological advancement but also social well-being, incorporating areas such as culture, sports, and recreation. The application of the Elbow Method indicated the formation of seven clusters (k = 7), as illustrated in Figure 1(A).

Figure 1 | Elbow (A) and Silhouette (B) Plots for the Quality of Life Dimension

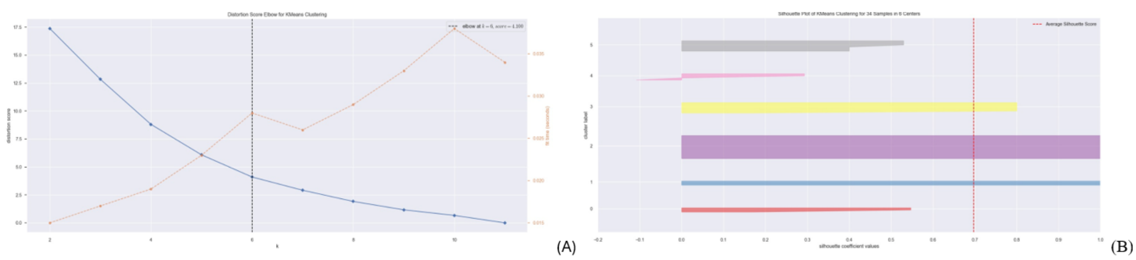


Fonte: Elaborated by the authors.

The Quality of Life Dimension comprised 35 variables, corresponding to 55.5% of the total analyzed. The Silhouette Index was 0.154, indicating overlap among clusters. Municipalities such as Belo Horizonte, Juiz de Fora, and Uberlândia exhibited stronger performance, although they were distributed across partially similar clusters. In contrast, cities such as Vespasiano, Ibirité, Coronel Fabriciano, and Sabará recorded the lowest scores.

The Governance dimension refers to technology- and data-driven urban management aimed at improving public services (Anthopoulos *et al.*, 2015). The Elbow Method indicated the formation of six clusters (k = 6), as illustrated in Figure 2(A). All 34 municipalities analyzed maintained a Transparency Portal providing budgetary and financial information.

Figure 2 | Elbow (A) and Silhouette plots (B) for the Smart Governance Dimension



Fonte: Elaborated by the authors.

The selection of k = 6 using the Elbow Method indicated a balance between intra-cluster cohesion and inter-cluster separation. The Silhouette Index (0.747) confirmed the robustness of the segmentation, consistent with the findings of Figueiredo *et al.* (2019). Coronel Fabriciano and Ituiutaba stood out for meeting all analyzed indicators, except for the Open Data Portal.

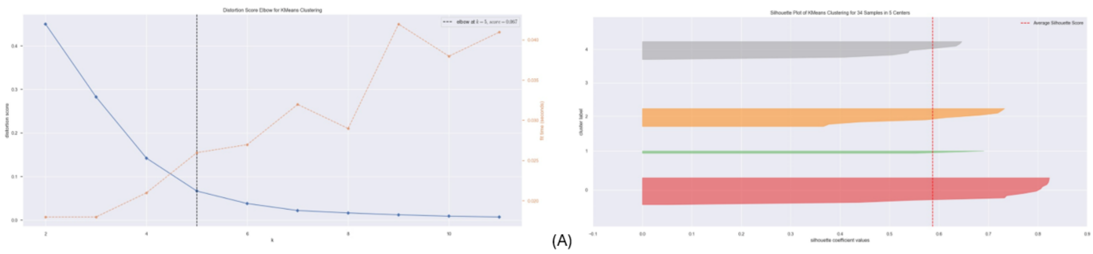
At the time of data collection, according to MUNIC (IBGE, 2019), these municipalities did not maintain an Open Data Portal. Nevertheless, the transparency requirements established by Law No. 12,527/2011 (Brazil, 2011), known as the Access to Information Law, have reinforced the expansion of such mechanisms within municipal administrations.

The stronger performance observed in the Governance dimension may be associated with regulatory and institutional standardization in the country, particularly regarding public transparency and the provision of digital services. Unlike dimensions that depend on structural investments, such as Mobility and Environment, its indicators derive from mandatory legal requirements, which tend to reduce disparities among municipalities. Consequently, institutional advancements may occur more uniformly when driven by national regulatory frameworks, even if inequalities persist in areas more closely tied to financial capacity and urban infrastructure.

The People Dimension encompasses professional skills, social support networks, education, health, and public safety (Abreu, 2022). The Elbow Method indicated the formation of five clusters (k = 5), as illustrated in Figure 3(A).

Overall, clustering was primarily influenced by similarities in the percentage of jobs requiring higher education. The Silhouette Index was 0.587, indicating adequate separation among clusters, consistent with the parameters discussed by Figueiredo *et al.* (2019).

Figure 3 | Elbow (A) and Silhouette (B) Plots for the People Dimension



(A) (B)

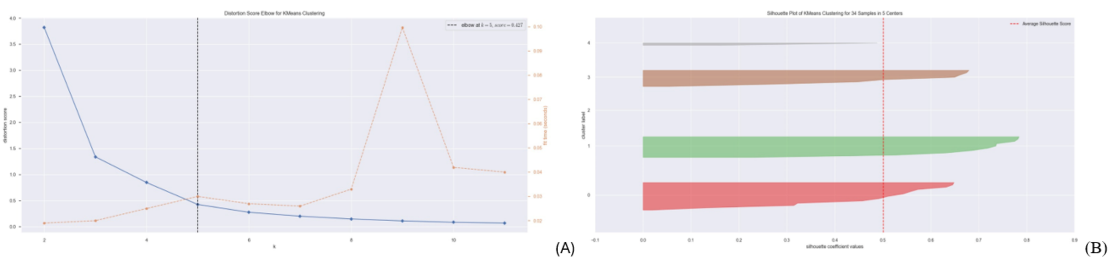
Fonte: Elaborated by the authors.

Recent data indicate a substantial increase in enrollments in distance learning undergraduate programs, surpassing the historic threshold of three million new students in 2022. In contrast, enrollment in on-campus programs has shown a downward trend since 2014, reaching its lowest level in 2021 over the past decade. However, in 2022, this trend was partially reversed, with a renewed increase in the number of students enrolling in on-campus programs (Brazil, 2022).

The Smart Economy dimension examines the economic resources that play a central role in enhancing competitiveness and productivity (Abreu, 2022). It allows for the assessment of key drivers of economic growth, structured around the subdimensions of entrepreneurship and productivity (Giffinger; Gudrun, 2010), which collectively contribute to the economic development of a given territory.

The Elbow plot indicated an optimal value of k = 5. In this case, the Silhouette Index (0.518095), calculated after applying the Elbow Method with k = 5 (Figure 4A), suggests moderate separation among clusters. The selection of k = 5 (Figure 4B) was based on the Elbow Method. A positive Silhouette value indicates reasonable intra-cluster cohesion and inter-cluster separation (Almeida, 2021).

Figure 4 | Elbow (A) and Silhouette (B) Plots for the Smart Economy Dimension



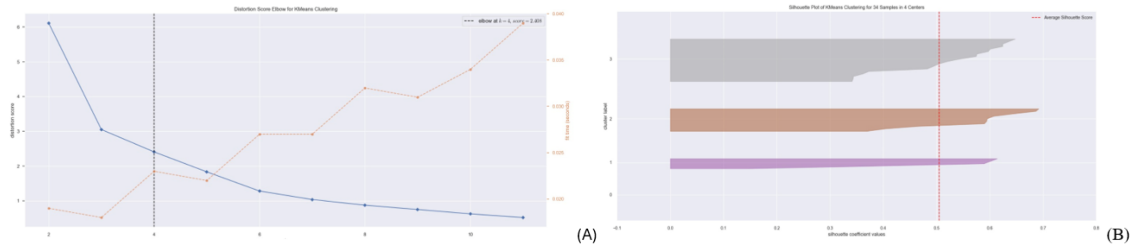
Fonte: Elaborated by the authors.

Minas Gerais has a diversified economy, which influences the composition of clusters within the Smart Economy dimension. The mining sector, particularly iron ore extraction, plays a pivotal role in the state's economy, contributing significantly to revenue generation and employment (FJP, 2020).

The agricultural sector also represents a substantial share of the state's economy, with coffee, sugarcane, corn, and beans among its primary crops. Family farming is characteristic of several regions, including Muriaé, Montes Claros, Sete Lagoas, and Lavras (FJP, 2020). In the industrial sector, steel, metallurgy, automotive manufacturing, and beverage production are particularly prominent, further driving the state's economic performance. Cities such as Belo Horizonte, Contagem, Betim, Ipatinga, and Divinópolis stand out within this industrial landscape (FJP, 2020).

Regarding the Environment dimension, sustainable practices and the integration of advanced technologies are promoted to enhance quality of life, optimize resource use, and reduce environmental impacts in smart cities. This dimension includes basic sanitation indicators, as established by Law No. 14,026 of July 15, 2020 (Brazil, 2020), which guarantees this right to all Brazilian citizens. The Elbow analysis indicated k = 4 clusters (Figure 5A). The corresponding Silhouette Index (0.504914), calculated for k = 4 (Figure 5B), suggests moderate separation among clusters.

Figure 5 | Elbow (A) and Silhouette (B) Plots for the Smart Environment Dimension



Fonte: Elaborated by the authors.

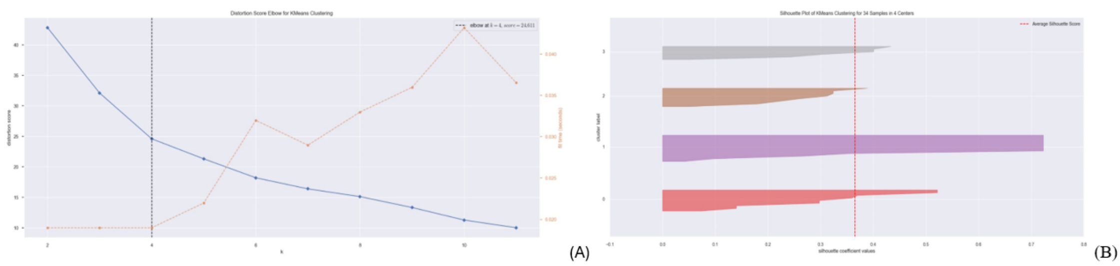
Data from the National Water Agency (ANA, 2023) indicate that, as of 2021, Minas Gerais had 82.4% coverage of the water supply network and 74.1% coverage of the sewage network, of which 44.1% was treated. Additionally, 96.8% of the population had water meters, 24.2% had access to selective waste collection, 2.6% of municipalities maintained rainwater reservoirs, and 25.5% of cities had hydrological data monitoring systems.

Despite these advances, a portion of the population still lacked access to essential basic services, which are guaranteed under the Federal Constitution (Brazil, 1988). It is also important to note that several Brazilian municipalities do not maintain updated data on basic sanitation, which directly affected the scope of this research.

The Smart Mobility Dimension contributes to the reduction and optimization of public space use, while promoting the creation of safer and more accessible urban environments. Giffinger *et al.* (2007) emphasize the relevance of Smart Mobility in addressing accessibility challenges, particularly through contemporary and sustainable transportation systems, as well as the availability of resources enabled by information and communication technologies.

The Elbow analysis indicated k = 4 (Figure 6A). The corresponding Silhouette Index (Figure 6B) yielded a value of 0.370372, suggesting moderate cluster separation.

Figure 6 | Elbow (A) and Silhouette (B) Plots for the Smart Mobility Dimension



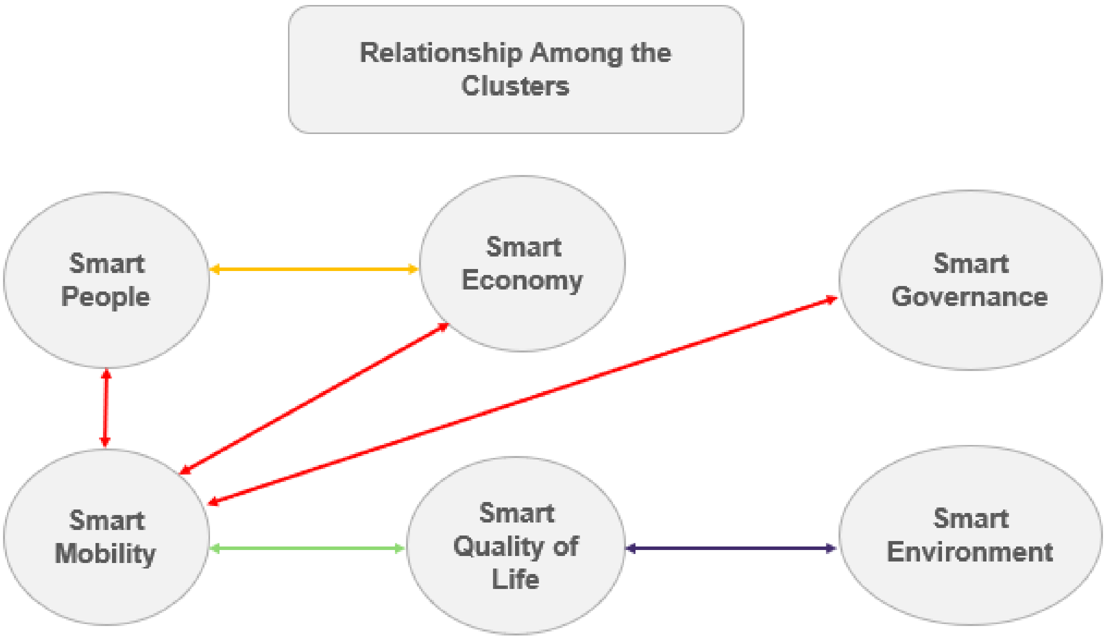
Fonte: Elaborated by the authors.

Only Belo Horizonte and Sabará stood out in this requirement, whereas Coronel Fabriciano did not achieve the minimum score. It is therefore essential to explore the advantages of these cities—such as their capacity for innovation and creativity—which may foster the development of new urban planning strategies.

When analyzing the Silhouette Index values across the six dimensions, only the Governance Dimension achieved a score closer to 1, indicating more consistent cluster separation. In the remaining dimensions, greater intra-cluster similarity and overlap were observed. Since clustering was based on variables comprising each respective dimension, it is evident that, although a value closer to 1 was not attained, as noted by Almeida (2021), the clusters within each dimension demonstrated proximity among the grouped municipalities.

The variables analyzed are interdependent, making the dimensions mutually influential in the process of classifying Smart Cities. As noted by Ozkaya and Erdin (2020), this interdependence occurs both internally—among variables within the same dimension—and externally—across variables belonging to different dimensions—thereby reinforcing the integrated nature of the evaluation model (Figure 7).

Figure 7 | Relationship Among the Clusters



Fonte: Elaborated by the authors.

Figure 7 synthesizes the interrelationships among the six dimensions, taking into account both the theoretical framework and the empirical behavior of the clusters. These relationships were identified through a comparative analysis of clustering patterns within each dimension, particularly by examining the recurrence of municipalities in clusters exhibiting similar performance levels.

The findings indicate that Urban Intelligence cannot be evaluated based on a single dimension, underscoring the interdependence among institutional, socioeconomic, and structural variables. The Governance and People dimensions demonstrated convergence among the highest-performing municipalities, whereas the Environment and Mobility dimensions exhibited similar clustering patterns. Overall, the relationships among dimensions derive from both the theoretical foundation and the empirical distribution of clusters, reinforcing the integrated nature of urban development.

The dimension-by-dimension analysis enabled a clearer understanding of cluster behavior among municipalities in Minas Gerais with more than 100,000 inhabitants. Although the clusters exhibited distinct characteristics, partial similarities were also observed. The Silhouette Index indicated overlap in four of the six dimensions, suggesting that segmentation may not have been optimal in these cases. Only the Governance Dimension demonstrated stronger performance, with an index closer to 1 and greater separation among clusters.

The relationships among clusters identified through the Mokarrari and Torabi (2021) ranking highlight relevant implications for urban development in Minas Gerais. Municipalities that performed better in the Environment, Quality of Life, and Mobility dimensions tended to demonstrate greater efficiency in delivering urban services, reflecting improved living conditions and enhanced economic attractiveness. Although certain environmental variables were not analyzed due to data unavailability, the findings reinforce the importance of sustainability-oriented policies for urban development.

The findings contribute to the literature on regional management and development by demonstrating that Urban Intelligence is unevenly distributed among municipalities within the same state. The analysis of interrelationships among dimensions indicates that institutional, structural, and socioeconomic factors operate in combination, suggesting that isolated interventions are likely to produce limited effects. These results underscore the need for integrated regional planning and greater coordination among sectoral public policies aimed at reducing intermunicipal inequalities.

In some dimensions, the Silhouette Index values were close to zero, indicating potential overlap among clusters, in line with the methodological rationale of the technique (Almeida, 2021). This finding suggests that the characteristics of the municipalities were not clearly segmented, reflecting the structural heterogeneity of the state. Such a pattern constitutes a limitation associated with the complexity of the urban data analyzed. Future research may expand data sources and explore complementary methodological approaches to enhance classification accuracy.

CONCLUSIONS

The primary objective of this study was to analyze the relationships among clusters generated from the six dimensions included in a classification ranking designed for developing countries, as proposed by Mokarrari and Torabi (2021), applied to municipalities in Minas Gerais with populations exceeding 100,000 inhabitants. The data analysis enabled the identification of patterns and relationships among cities, grouped according to the variables within each dimension. The resulting clusters revealed structural differences among municipalities, highlighting both strengths and weaknesses, in alignment with the framework proposed by Mokarrari and Torabi (2021). The observed heterogeneity underscores the need for context-specific policies and strategies tailored to each municipality, particularly given that rankings present inherent limitations and do not fully capture local particularities (Leyva, 2013).

Belo Horizonte, Betim, Uberaba, Juiz de Fora, Uberlândia, and Montes Claros demonstrated superior performance across the analyzed dimensions and in the overall ranking, with some of these municipalities also being listed among the 100 Smartest Cities in the country (Connected Smart Cities, 2022). The findings indicate that the assessment of a Smart City cannot rely on a single dimension; rather, it requires an integrated analysis encompassing multiple variables and dimensions.

From both theoretical and applied perspectives, this study contributes to the literature on regional management and development by proposing a methodological approach tailored to the context of a Brazilian state, highlighting how Urban Intelligence manifests unevenly among municipalities with differing institutional and structural capacities. By examining the interdependencies among strategic dimensions, the research advances the understanding of territorial planning and provides support for the formulation of public policies aimed at promoting sustainable regional development.

However, certain limitations of the study should be acknowledged, particularly those related to the reliance on secondary data available in public databases and constraints concerning the availability and updating of the information used. The exclusion of variables with high proportions of missing data may have reduced the explanatory capacity of specific dimensions, although it was necessary to ensure greater statistical consistency in cluster formation.

Moreover, the sample comprised only municipalities in Minas Gerais with more than 100,000 inhabitants, limiting the generalizability of the findings to smaller cities or to other state contexts. Future research may expand the territorial scope of the analysis, incorporate different population thresholds, and explore complementary methodological approaches—including multicriteria techniques such as MADM—to further refine the classification of Urban Intelligence levels within the Brazilian context.

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