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SOCIO-DEMOGRAPHIC TYPOLOGIES OF TAMIL NADU'S URBAN AGGLOMERATIONS

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Abstract
Addressing the challenges of urbanization is the key for sustainable development in India. Tamil Nadu holds distinct place urban landscape with substantial share in India's urban population. The objective of the study is to identify the multidimensional clusters based on socio-demographic and economic characteristics. The study atempts to establish the structural baseline typology of Urban Agglomerations in Tamil Nadu. The study was performed on 15 selected Urban agglomerations using a comprehensive set of ten variables covering population structure, labour force dynamics, and migration patterns derived from the Census of India 2011 and United Nations World Urbanization Prospects 2018. Hierarchical Agglomerative Clustering using Ward's method was performed to identify the possible number of clusters and K-Means clustering was performed to optimize the groupings.The three-cluster solution was identified and evaluated with the silhouette analysis for clustering quality.The findings endorse the importance of differentiated urban planning, especially for Chennai. The Highly dynamic economic centres need strategic prioritization with a dedicated focus on other stable regional hubs. The study adds evidence-based insight for the stakeholders involved in urban governance for balanced regional growth. Future studies should revalidate these 2011 structural typologies by integrating the contemporary data upon its availability.
Keywords: Urban Agglomeration, Tamil Nadu, Cluster Analysis, Hierarchical Clustering, K-Means Clustering.

1. INTRODUCTION

Urbanization is a phenomenon that has been witnessed in human society since the beginning of various civilizations across the world. Especially when people started to live together within a particular area for multiple reasons, this led them to concentrated dwelling (Mendieta, 2019). Despite the dynamic changes in the magnitude of urbanization in different regions with their constantly changing definitions, urbanization is one of the four demographic mega-trends in the world. It determines the spatial distribution of the world's population. It is projected that 68% of the World's Population will live in urban areas, a significant shift from 55% in 2018 (World Urbanization Prospects, 2019). Sustainable development, the primary agenda or goal of several world organizations, demands the integration of strategic planning in the governance of urban cities and systems worldwide. In contrast to the emergence of well-planned urbanization considering its economic benefits, there are many uncontrollable environmental degradation challenges due to unplanned and undifferentiated urbanization. Because of that, people residing in certain areas are experiencing health issues and face higher living costs, which signifies a complex socioeconomic and demographic process. Several countries are trying to bring out the best governance to meet the demands of urban residents by mitigating the adverse effects of demographic change.

India, one of the world's most populated countries (Mahambare et al., 2025), significantly contributed to global urbanization. India has five megacities out of 33 worldwide and is projected to add two more by 2030. A significant decline of 12.4% of the India's rural population was projected between 2018 and 2050 (World Urbanization Prospects, 2019). Rapid urbanization creates an alarming need to refocus governance to ensure future with sustainable cities with consistent and accelerated economic growth. As of the 2011 census, Tamil Nadu's urban areas had 48.45% of its total population, the highest share of urban population among the Indian states. As a result, Tamil Nadu faces unique challenges in terms of urban governance. Understanding the urban typologies is critical in managing the existing and upcoming urban centres, for better planning and implementation towards sustainable development. Consequently, the welfare and needs of the residents will be addressed in the best possible way by mitigating the current challenges. An Urban Agglomeration (UA) is key to effectively analyzing and working on urbanization (Fang & Yu, 2017). It integrates cities, economic cooperation, and spatial development, making regional planning and sustainable development essential. The UA concept has been practised in the Census of India since 1971 to understand urbanization patterns better. According to the Census of India 2011, UA is a continuous urban spread constituting a town and its adjoining outgrowths, or two or more physically contiguous towns together with or without outgrowths of such towns. Given the prolonged delay of the 2021 Census, this study serves to establish a critical, multidimensional baseline typology of UAs based on their last fully-enumerated structural characteristics (2011).

With this structural baseline context, this study aims to identify the multidimensional clusters based on socio-demographic and economic characteristics to establish the structural baseline typology of Urban Agglomerations in Tamil Nadu. The study addresses the research question, 'What stable, multidimensional typologies of UAs can be empirically identified using 2011 Census data to inform differentiated and evidence-based urban governance in Tamil Nadu?" This study will utilize a Hierarchical agglomerative clustering method, using Ward's method to identify distinct clusters based on a comprehensive set of ten indicators covering the population structure, labour force dynamics, and migration patterns drawn from the Census of India 2011 and United Nations World Urbanization Prospects (UN WUP) 2018 projections. Various studies have performed quantitative approaches, particularly cluster analysis, to bring out valuable findings in the identification of distinct groupings of urban areas based on various demographic and socioeconomic indicators (Abhishek et al., 2017; Iungman et al., 2024; Santos et al., 2023). Urbanization trends in India have been examined by several studies using various statistical methods (Chettry, 2024; Gopiraj & Sundaram, 2023; Zagyi et al., 2021). However, the studies about specific applications of cluster analysis in finding the multidimensional UA clusters in Tamil Nadu are limited. In order to address this research gap, this study aims to establish the structural baseline typology of Urban Agglomerations in Tamil Nadu using cluster analysis. This approach will identify distinct multidimensional functional clusters and provide evidence-based insights into the hierarchical structure of UAs in Tamil Nadu to help researchers, policymakers, and urban planners. The following sections will present the literature review and reveal the materials and methods employed. Subsequently, the result section presents the cluster analysis performed, followed by the discussion, and concludes with a summary and potential future research directions.

2. LITERATURE REVIEW

Recent developments have seen accelerated urbanization in the Global South (Camatti et al., 2024), contrasting with historical growth (Mulligan, 2013). Despite of its economic and social benefits (Cobb & Braithwaite, 2021; Nautiyal et al., 2021; Sasana et al., 2019), urbanization has harmful effects on the environment (Mitra & Shepherd, 2015), biodiversity (Menon, 2025) that affects natural climate (Seto & Shepherd, 2009). In order to overcome these effects, the importance of integrated urban and environmental planning has been repeatedly mentioned in the literature (Manasi & Jamwal, 2016; Shadiya, 2024). Traditional urban classification models offer a deep insight but it has been criticized for its economic focus that fails to capture the dynamic nature of urban growth (Mironowicz, 2025; Cahnman et al., 2017). Also, the modern forces like globalization and technological advancements makes a great impact on urban demographics. Multivariate clustering and regression have played an important role in spatio-temporal assessment (Govender & Sivakumar, 2020) and the division of urban forms (Dibble et al., 2019). Cluster-based analysis offers a structured approach to understanding and contributes to more effective policy and planning outcomes (Grubesic et al., 2014). Identification of meaningful clusters informs better resource distribution (Kumari & Thakur, 2025). Recent studies on multivariate analysis have started exploring the urban patterns based on data centric typologies such as Deep learning and clustering (Bobkova et al., 2021; Debray et al., 2025) and, Neural Networks and Big Data (Nice et al., 2020).

To overcome the limitations and move beyond the limits, Urban Agglomeration as distinct concept in urban studies, recognized by its social and economic ties (Tan & Huang, 2022) and spatial integration (Priyashani et al., 2023). It has the strong theoretical support for its multiscale structure (Fang et al., 2018), thereby it presents the more nuanced outputs than other classifications. The concept of Urban Agglomeration played a significant role India's urban development since 1971 (Lonavath et al., 2020). Literature reveals that India's urban growth is uneven with cities increasing in discrete manner supported by the evidence like urban footprint increase (Gaurav et al., 2018), peripheral expansion (Kumar & Sehgal, 2025), Urban Population Surge (Bhat et al., 2017) in various places. Unlike in Kerala (Krishna et al., 2024), dispersed urbanization was observed due to complex topography and socio-economic factors in many places. In the past decades, Tamil Nadu has experienced important demographic change shaped by rapid urbanization, results in informal settlement expansion, infrastructural inadequacies (Madhivadhani, 2021), population growth (Rajakumar & Sashikkumar, 2020). Compared to other regions, the western region of Tamil Nadu has emerged of urban expansion (Sudalayandi et al., 2021) and Chennai has been observed to move outward, indicating dispersed development (Sridhar & Sathyanathan, 2022). The studies focused on dividing the urban typologies of Tamil Nadu based on socio-demographic and economic variables are very limited. Population dynamics (Lai et al., 2025; Qiang et al., 2024; Simelane et al., 2013), Labour Force Dynamics (Goto, 2024; Wu & Wang, 2021) and Migration patterns (Gowri Shankar et al., 2025; Han et al., 2025) plays a significant role in understanding the urban typologies. Therefore, this study attempts to address the research gap in establishing the structural baseline typologies of urban agglomeration in Tamil Nadu using socio-demographic and economic variables with the multivariate approach for capturing exhaustive urban patterns.

3. MATERIALS AND METHODS

This study was performed using the data extracted from the Census of India 2011 and UN WUP 2018. Using the UA concept as a primary guiding principle, study variables were selected to ensure international comparability. Since, the UA aligns with the standard classification adopted by the UN WUP 2018. This study uses ten variables for the analysis. Nine variables were derived and computed from the latest available data from the government, the Census of India 2011, based on the definitions of UA. These nine focus on three key aspects, such as population structure (Literacy rate and Population Density per sq.km), labour force dynamics (Average HH size, Work participation rate and Main worker share) and migration patterns (Migration rate, Work/employment Migration share, Marriage Migration share and Household Migration share). The last variable percentage change in population 2011-2025 was computed using the estimates and projections from UN WUP 2018 to account for temporal change. Since the UN bases its data on national sources and follows definitions set by those authorities, the data extracted from the

Theoretical and Empirical Researches in Urban Management
Volume 20 Issue 4 / November 2025

Census of India and the UN WUP adhere to the same definitions and concepts. As a result, the study ensured consistency in the definition of UA.

The study analyzed 15 UAs in Tamil Nadu, based on 25 UAs identified by the Census of India 2011. This selection focused the analysis on the largest urban entities and allowed for comparison with international urbanization patterns. The UAs were chosen using a population threshold established by the UN WUP 2018, with an annual population of 300,000 inhabitants or more in 2018. The choice of UN WUP 2018 estimates helped incorporate the temporal change between the 2011 Census data collection and the later UN projections. Before the analysis, the dataset was examined for missing values and no missing data points for the variable were identified.

This study employs a cluster analysis approach to determine the unique clusters of Tamil Nadu based on the variables considered to establish the structural baseline typology. The Statistical Package for Social Sciences software was used for the analysis. The dataset was standardized using z-scores. Agglomerative hierarchical clustering was performed using Ward's method with Squared Euclidean distance, making it computationally simpler to determine the proximity between clusters (Lee & Willcox, 2014). The choice of Ward's method was taken to create highly dense and accurate cluster with small data (Mongi et al., 2019). Combining the hierarchical clustering to determine the number of clusters and the K-Means clustering to optimize the cluster memberships helps to bring out better clustering outcomes (Ruswanti et al., 2024). Based on the two possibilities identified from the hierarchical clustering (K=2 or K=3), K-Means clustering was subsequently employed to determine the most appropriate number of clusters. The variables that extend the statistical significance in cluster separation were identified based on the ANOVA results. The silhouette statistics were calculated for both K-Means cluster outputs to assess the resulting clusters' quality and validate the cluster solutions. The number of clusters that yielded the highest average silhouette score in the K-Means analysis was selected as the optimal number of distinct UA clusters of this study. Therefore, combining the visual and hierarchical information from the dendrogram with the quantitative evaluation of cluster quality from the silhouette score in K-Means provides an extensive approach to establish the structural baseline typology of Tamil Nadu's UAs.

4. RESULTS

Table 1 represents the agglomeration schedule for the hierarchical clustering performed using the Ward linkage method, based on the Rescaled Absolute Squared Euclidean Distance. The increasing dissimilarity coefficients show the clear cluster formation pattern at 14 stages. The clustering begins with the more similar pairs, such as Ranipet and Vellore, which merge near 0.000. Then Thanjavur and Tiruchirappalli merge at the next stage, with the coefficient 0.004, followed by Thoothukkudi and

Tirunelveli during stage 3. After that, the other UA started merging with the already paired clusters, where consolidation with the similar cluster happened with increasing coefficients during the following stages. In particular, Erode and Karur during stage 5 and Madurai and Salem during stage 7 show their distinctiveness as they got paired with larger coefficients during the later stages. The UAs with more dissimilarities have merged during the last few stages, 10-14, with increasingly significant coefficients. During stage 11, Hosur joined the established cluster with a high coefficient of 0.703. Chennai, with a high coefficient of 1.469 during stage 13, shows its dissimilarity with other UAs. Based on the agglomeration schedule, the decision on the optimal number of clusters is guided by the significant difference in the coefficients during the stages of clustering. The maximum difference was observed during stage 14 (0.787), followed by the second largest difference during stage 13 (0.544). Therefore, the agglomeration schedule strongly suggests the dataset is best partitioned into 2 or 3 distinct clusters.

TABLE 1 - AGGLOMERATION SCHEDULE

Stage	Cluster Combined		Coefficients	Stage Cluster First Appears		Next Stage
	Cluster 1	Cluster 2		Cluster 1	Cluster 2	
1	8	15	0.000	0	0	10
2	10	12	0.004	0	0	6
3	11	13	0.009	0	0	4
4	3	11	0.025	0	3	6
5	4	6	0.051	0	0	7
6	3	10	0.094	4	2	10
7	2	4	0.146	0	5	9
8	7	9	0.231	0	0	12
9	2	14	0.321	7	0	11
10	3	8	0.485	6	1	12
11	2	5	0.703	9	0	14
12	3	7	0.925	10	8	13
13	1	3	1.469	0	12	14
14	1	2	2.256	13	11	0

Figure 1 represents the dendrogram of the hierarchical clustering process of selected UAs in Tamil Nadu. The horizontal lines denote the rescaled distance at which clusters merge. The visual interpretation of the clusters formed at short distances reveals the highly similar UA. The clusters that formed with a zero distance include Ranipet and Vellore (Northern Pair), Thanjavur and Tiruchirappalli (Delta Group), Thoothukkudi and Tirunelveli (South Group) and Erode and Karur (Western Group). Conversely, the cluster merge at a considerable distance denotes the dissimilarity in cluster groups. Notably, Chennai has the most significant distance before merging into the other clusters, showing its distinct nature among the UAs in Tamil Nadu. The final merge at a distance of 25 suggests the K=2 solution, and the vertical line cut at 17 strongly suggests the K=3 solution. These two solutions were considered the dataset's most appropriate and defensible partitions.

Theoretical and Empirical Researches in Urban Management
Volume 20 Issue 4 / November 2025

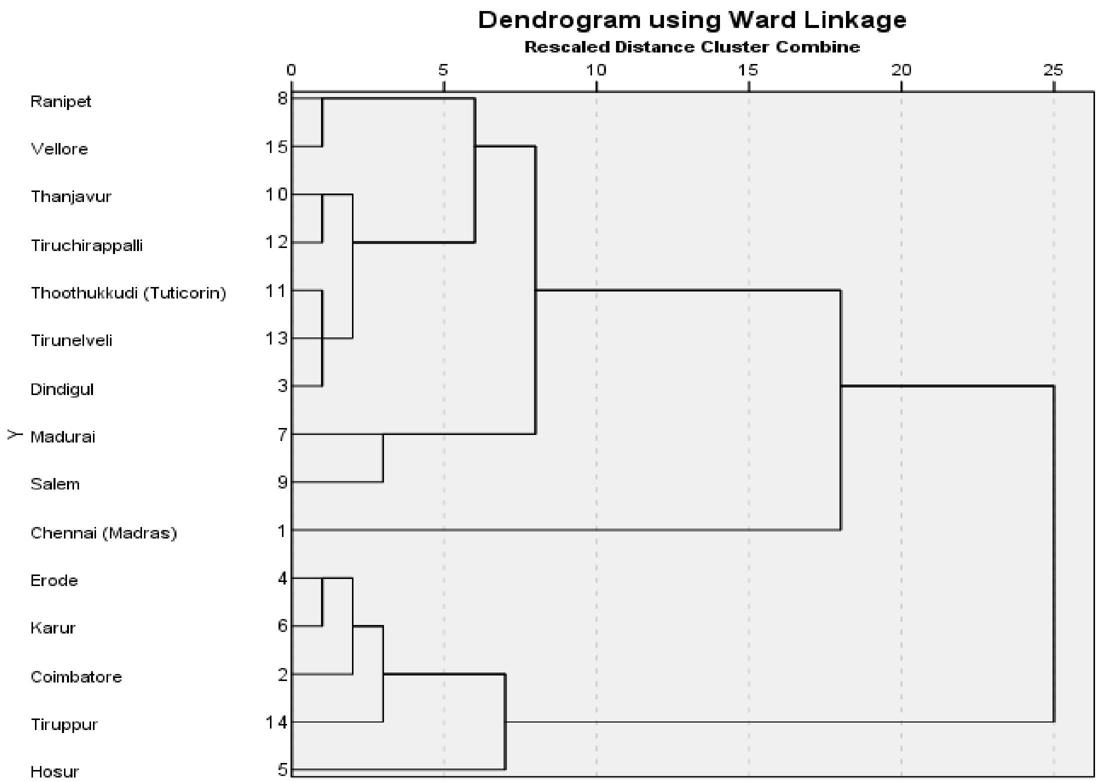

FIGURE 1 - DENDROGRAM USING WARD LINKAGE

Based on the hierarchical agglomerative clustering results, K-Means clustering was performed for K=2 and K=3 for robust analysis to find the optimum number of clusters. Before performing the K-Means clustering, the dataset was standardized using z-scores. Table 2 shows K-Means clustering results for each UA, such as cluster membership and the distance to the cluster centre.

TABLE 2 - CLUSTER MEMBERSHIP WITH THE DISTANCE TO CLUSTER CENTRE

S. No.	Urban Agglomeration	K=2		K=3	
		Cluster	Distance to cluster center	Cluster	Distance to cluster center
1	Chennai (Madras)	1	2.667	1	0.000
2	Coimbatore	2	2.014	3	2.036
3	Dindigul	2	1.418	2	0.919
4	Erode	2	2.829	3	1.997
5	Hosur	2	4.037	3	3.269
6	Karur	2	2.475	3	1.274
7	Madurai	1	2.667	2	2.511
8	Ranipet	2	2.784	2	2.294
9	Salem	2	3.140	2	3.124
10	Thanjavur	2	2.603	2	1.829
11	Thoothukkudi (Tuticorin)	2	1.715	2	1.425
12	Tiruchirappalli	2	2.239	2	1.437
13	Tirunelveli	2	1.508	2	1.045
14	Tiruppur	2	4.155	3	2.031
15	Vellore	2	2.943	2	2.164

Table 3 shows the Z-scores of final cluster centres and p-value for the ten clustering variables used in the study. Based on the results of K-Means clustering for K=2, the variables that show a statistically significant difference at the ≤ 0.05 level are Population density (p-value < 0.001), Marriage Migration share (p-value = 0.003) and Household Migration Share (p-value = 0.005). For K=3, the variables that show a statistically significant difference at ≤ 0.05 level are Work Participation Rate (p-value = 0.004), Average HH Size (p-value = 0.017), Main Worker share (p-value = 0.013), Migration Rate (p-value < 0.001), Work/employment Migration Share (p-value = 0.003), Marriage Migration Share (p-value < 0.001) and Household Migration Share (p-value < 0.001).

TABLE 3 - NFINAL CLUSTER CENTERS AND P-VALUE

	K=2			K=3			
Variables	**1**	**2**	**p-Value**	**1**	**2**	**3**	**p-Value**
Literacy Rate	0.74	-0.11	0.279	0.61	0.28	-0.63	0.228
Work Participation Rate	-0.16	0.02	0.820	-0.15	-0.57	1.05	0.004*
Population Density	2.16	-0.33	<0.001*	2.07	0.01	-0.43	0.062
Average HH Size	0.13	-0.02	0.855	0.44	0.48	-0.96	0.017*
Main Worker Share	-0.96	0.15	0.153	-1.91	-0.22	0.78	0.013*
Percentage Change in population 2011-2025	-0.41	0.06	0.552	-0.26	-0.41	0.80	0.082
Migration Rate	-0.30	0.05	0.664	0.02	-0.64	1.14	<0.001*
Work/employment Migration Share	-0.35	0.05	0.615	-0.19	-0.57	1.06	0.003*
Marriage Migration Share	1.76	-0.27	0.003*	3.41	-0.31	-0.12	<0.001*
Household Migration Share	1.68	-0.26	0.005*	3.47	-0.35	-0.07	<0.001*
Significant at the 0.05 level							

Table 4 shows the distance between the final cluster centres, quantifying the separation of urban cluster profiles in multivariate space. For K=2, the distance of 4.072 between clusters 1 and 2 represents the distinctiveness of the two cluster profiles. For K=3, Clusters 1 and 3 have the most considerable distance of 6.879, showing their significant distinction, and the substantial difference of 6.031 shows that clusters 1 and 2 are well-separated. In contrast, Clusters 2 and 3 also exhibit better distinction with a distance of 3.762.

TABLE 4 - DISTANCES BETWEEN FINAL CLUSTER CENTERS

K=2			K=3			
Cluster	**1**	**2**	**Cluster**	**1**	**2**	**3**
1		4.072	1		6.031	6.879
2	4.072		2	6.031		3.762
			3	6.879	3.762	

Table 5 shows the silhouette value computed using the Euclidean dissimilarity measure for cluster members identified using K-Means clustering. The cluster members of the k=2 solution exhibit weak clustering quality, where most cases have a silhouette value less than 0.5. For the K=3 solution, more than half of the cases have the silhouette value more than 0.5, and Chennai has the silhouette value of 1, showing its distinctiveness as an outlier city.

TABLE 5 - SILHOUETTE VALUE

S. No.	Urban Agglomeration	K=2		K=3	
		Cluster	Silhouette Value	Cluster	Silhouette Value
1	Chennai (Madras)	1	0.604	1	1
2	Coimbatore	2	0.324	3	0.273
3	Dindigul	2	0.391	2	0.509
4	Erode	2	0.395	3	0.428
5	Hosur	2	0.324	3	0.352
6	Karur	2	0.396	3	0.475
7	Madurai	1	0.321	2	0.391
8	Ranipet	2	0.365	2	0.471
9	Salem	2	0.232	2	0.261
10	Thanjavur	2	0.348	2	0.535
11	Thoothukkudi (Tuticorin)	2	0.397	2	0.479
12	Tiruchirappalli	2	0.257	2	0.542
13	Tirunelveli	2	0.410	2	0.517
14	Tiruppur	2	0.320	3	0.546
15	Vellore	2	0.333	2	0.518

TABLE 6 - SILHOUETTE STATISTICS

K Value	Cluster	Case Count	Mean	Minimum	Maximum
K=2	1	2	0.462	0.321	0.604
	2	13	0.346	0.232	0.410
	Total	15	0.361	0.232	0.604
K=3	1	1	1.000	1.000	1.000
	2	9	0.469	0.261	0.542
	3	5	0.415	0.273	0.546
	Total	15	0.486	0.261	1.000

Table 6 shows the overall and cluster-wise silhouette statistics for the K-Means clustering performed. For K=2, cluster 1 (0.462) has a higher mean silhouette value than cluster 2 (0.346). For K=3, Cluster 1 shows the strong and perfect cohesion with the silhouette value of 1, whereas cluster 2 (0.469) has the second-best mean silhouette value, followed by cluster 3 (0.415).

5. DISCUSSIONS

This study attempted to identify the multidimensional clusters based on socio-demographic and economic characteristics to establish the structural baseline typology of UAs in Tamil Nadu. The cluster analysis was performed using agglomerative hierarchical clustering (ward's method) and K-Means clustering to identify optimal clustering of UAs. The hierarchical clustering suggested that K=2 or K=3 is the most appropriate k-value for the K-Means clustering process. Subsequently, the silhouette score played a critical role in selecting the final solution by validating K-Means clustering results. The overall mean silhouette score (0.486) for K=3 is better than K=2 (0.361), despite the silhouette scores suggesting the clusters are moderately separated. Therefore, the three-cluster solution (K=3) is identified as the better solution. Further, it was supported by the statistical significance of clustering variables, including work participation rate, average HH size, main worker share, migration rate, work/employment migration share, marriage migration share, and household migration share. In contrast, the two-cluster model (K=2) showed statistical significance only among Population density, Marriage Migration share and Household Migration Share. Thus, the three-cluster model provides significant and distinct profiles of UA based on the demographic and labour force metrics. Therefore, Table 7 shows the members of the three-cluster solution (K=3). The cluster profiles include cluster 1 - The outlier megacity (Chennai), cluster 2 - Established regional and transitional hubs (Madurai, Dindigul, Ranipet, Salem, Thanjavur, Thoothukkudi, Tiruchirappalli, Tirunelveli, Vellore) and cluster 3 - Dynamic economic engine (Coimbatore, Erode, Hosur, Karur, Tiruppur).

TABLE 7 - CLUSTER PROFILE AND THEMATIC CHARACTERIZATION

Cluster Number	Cluster Name	Cluster Members
Cluster 1	The Outlier Megacity	Chennai (Madras)
Cluster 2	Established Regional and Transitional Hubs	Madurai, Dindigul, Ranipet, Salem, Thanjavur, Thoothukkudi (Tuticorin), Tiruchirappalli, Tirunelveli, Vellore
Cluster 3	Dynamic Economic Engine	Coimbatore, Erode, Hosur, Karur, Tiruppur

As a single member, Chennai forms cluster 1, which is unique. The distinct nature of Chennai is associated with the non-economic migration associated with it, which is evident with high z-scores for Marriage migration share (+3.41) and household migration share (+3.47) and supported by the population density with a high z-score (2.07). Furthermore, Chennai is observed as a clear outlier with its perfect silhouette score of 1 and the last individual member to join the cluster during stage 13 with a high coefficient (1.469). The findings show the uniqueness of Chennai in the urban context, which is favoured by its economic diversification and it is identified as one of the world's megacities as per UN WUP 2018.

Cluster 2 comprises of nine UAs including Madurai, Dindigul, Ranipet, Salem, Thanjavur, Thoothukkudi, Tiruchirappalli, Tirunelveli and Vellore. It can be termed as the Established regional hubs based on its old and established nature. The cluster group negatively associates with Work participation rate (–0.57) and Work/employment migration share (–0.57), showing the lack of employment-driven migration as its economic activities are less dependent on the migrated population. The cluster's z-scores for other key variables show less impact, characterized by their negative or near-zero z-scores. Relatively more stable demographic structure than other clusters emphasis its nature as administrative, cultural, and educational centres.

Coimbatore, Erode, Hosur, Karur, and Tiruppur forms cluster 3. The cluster's nature is highly associated with its dynamic industrial and economic profile. The key labour and migration variables like Work

Theoretical and Empirical Researches in Urban Management
Volume 20 Issue 4 / November 2025

participation rate, Main worker share, Migration rate, and Work/employment migration share exhibit high positive z-scores. Thus, work/ employment is a significant pull factor for these UAs. The high concentration of employment-seeking migrants with a negative Z-score for Average household size shows that the smaller household size is likely tied to single or temporary migrant living arrangements. The significant difference between final cluster center of 1 and 3 highlights its recent industrial growth with a distinct urban demographic and economic profile.

Thus, Chennai's urban governance demands unique approaches to its opportunities and challenges. Various studies agree with Chennai's distinctiveness in India's urban setting (Suresh et al., 2022; Tripathi, 2025). The members of cluster 3 deserves more strategic interventions on industries and labour management. The UAs in cluster 2 could be considered to promote the regional development initiatives to foster balanced and sustainable urbanization in Tamil Nadu. The heterogeneity in cluster groupings of UAs in Tamil Nadu highlights the challenges in framing a uniform urban policy and initiatives. The limitation of this study is its data reliance based on the census of India 2011, although it is India's latest available official data. For this reason, the study attempted to establish the structural baseline typology of UAs in Tamil Nadu. In order to overcome these limitations, future studies could incorporate the Census of India 2027 data upon its availability to understand the post-2011 shifts and validate the urban profile with the upcoming datasets. Furthermore, the internal heterogeneity within clusters 2 and 3 can be explored using recent advanced techniques with environmental data and geospatial big data, such as nighttime light imagery.

6. CONCLUSIONS

This study used cluster analysis to identify multidimensional clusters based on socio-demographic and economic characteristics and establish the structural baseline typology of UAs in Tamil Nadu. The study was performed based on data from the Census of India 2011 and the UN WUP 2018, intending to understand and determine urban profiles using population structure, labour force dynamics, and migration patterns. The cluster members were determined using the K-Means clustering process, based on the number of clusters identified using the hierarchical clustering process. The optimal cluster solution was identified and validated using silhouette scores. The three-cluster solution was identified as statistically significant solution with Chennai as separate cluster. Cluster 3 is identified with five UAs representing the dynamic economic engines and the remaining nine UAs formed cluster 2, representing the established regional and transitional hubs. Thus, the structural baseline typology of UAs in Tamil Nadu was identified. This study recognises, strengthens, and supports the need for differentiated urban governance in the context of Tamil Nadu for balanced regional growth. In essence, this study added evidence-based insights on urbanization patterns of Tamil Nadu.

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Theoretical and Empirical Researches in Urban Management
Volume 20 Issue 4 / November 2025

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