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Modeling Functional Urban Centrality via Graph Attention Networks and Multi-Source Spatial Data Fusion

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Abstract

Conventional spatial analysis methods heavily rely on static morphology and Euclidean distance metrics, failing to capture functional urban centrality, which is inherently dynamic, flow-driven, and non-Euclidean. This study presents an unsupervised Graph Attention Network Autoencoder (GAT-AE) framework to model and quantify functional urban attractiveness by fusing multi-source geospatial indicators—including high-resolution satellite imagery, points of interest (POI), and VIIRS nighttime lights—with physical street network topology. Discretized using Uber's H3 hexagonal grid at resolution 9, the territory is structured into a functional spatial graph where edge weights explicitly couple topological shortest-path distances (computed via Dijkstra's algorithm) with gravity-based spatial interaction dynamics.

Benchmarked against non-spatial baselines (linear PCA and a dense MLP autoencoder), the GAT-AE demonstrates superior representational capability within its 8-dimensional latent space. Although the model makes a deliberate algorithmic trade-off by accepting a higher raw reconstruction loss ($MSE = 0.0104$) to enforce topological message passing, it substantially optimizes spatial coherence ($Global\ Moran's\ I = 0.973$) and cluster separability ($Silhouette\ Score = 0.391$ vs. 0.263 for PCA; $Calinski\text{-}Harabasz\ Index = 18{,}419$). Bivariate spatial analysis confirms that the attention mechanism effectively isolates complex non-linear urban phenomena—specifically identifying enclaved zones (high physical density with low topological connectivity) and topological anomalies (low physical density serving as high-throughput functional nodes)—that traditional linear models completely miss. Externally validated against localized real estate land values ($r = 0.473, p < 0.001$), the framework is applied to the Rabat-Salé-Kénitra metropolitan region as an empirical diagnostic tool, demonstrating how graph-based deep learning translates static physical sub-layers into dynamic economic realities while exposing structural spatial mismatches between functional attraction and residential vitality.

1. Introduction

Urban centrality is a foundational concept in urban studies and planning, acting as the primary driver for city vibrancy, economic vitality, and social interaction. Traditionally, it has been interpreted through a morphological lens, defined by the static concentration of population, building density, land-use intensity, and the administrative configuration of street networks (Irwin & Hughes, 1992). While these approaches have provided valuable insights into the physical structure of monocentric and polycentric cities, the rapid transformation of contemporary metropolitan systems has exposed the limitations of purely form-based analysis. As cities transition into complex networked structures, the spatial concentration of urban elements often fails to correspond to their actual intensity of use or functional influence (Burger & Meijers, 2012). Consequently, centrality can no longer be viewed as a fixed spatial attribute but must be understood as a manifestation of how spaces function as nodes within a broader system of socio-economic and spatial flows. This conceptual shift has led to the emergence of "functional centrality" as a more robust framework for understanding urban importance (Rodríguez et al., 2007). In urban planning, and unlike morphological measures, functional centrality focuses on realized activity, capturing the dynamic flows of human mobility, service accessibility, and interaction patterns that reveal how places actually perform within the urban fabric. Recent empirical findings highlight significant spatial mismatches between these two dimensions: newly densified residential areas often appear morphologically central yet remain functionally weak, while areas with lower physical density may emerge as major urban attractors due to specialized services or high-throughput connectivity (Güller & Varol, 2026; Zhong et al., 2017). Bridging this gap requires an integrated, multidimensional approach that utilizes multi-source data such as high-resolution satellite imagery, points of interest from volunteered Geographic Information – VGI, derived dataset like topography, LUCL data….etc, and structural network metrics to translate the physical substrate of the built environment into a dynamic representation of urban usage (Long et al., 2022; Wei et al., 2020).

However, traditional analytical methods struggle to process the complex, non-linear, and non-Euclidean relationships inherent in these multi-source spatial networks. To truly understand the dynamism of modern metropolitan cities, it is critical to employ advanced neural network architectures, specifically Graph Attention Network – GAT (Veličković et al., 2018). Because urban spaces operate as interconnected graphs where the influence of neighboring areas is highly variable, GAT models are uniquely equipped to dynamically weigh these spatial interactions and uncover hidden morphological patterns. The main objective of this study is to model and map functional urban centrality at the metropolitan scale, leveraging the capacity of GAT models to decode the complex, non-Euclidean relationships that produce it. To validate the model's capacity to translate static physical form into dynamic urban reality, the extracted centrality surface is confronted with independent empirical evidence,

showing that attention-based neural networks are powerful tools for contemporary urban analysis.

To capture these complex, non-linear relationships, this paper proposes an unsupervised modeling framework based on Graph Attention Network Auto-Encoder – GAT-AE(Agryzkov et al., 2019; Crucitti et al., 2006; Ma et al., 2024). Conventional spatial analysis tools often rely on Euclidean distances, which fail to account for the relational logic of urban systems where proximity is mediated by connectivity. GAT-AE address this by modeling cities as non-Euclidean graphs, allowing the importance of a location to be weighted by its topological relationships and the specific characteristics of its neighbors. By fusing high-resolution environmental indicators with structural road-network metrics and socio-economic data, this study reveals latent functional centrality patterns that standard linear methods tend to miss. Applied to the Rabat-Salé-Kenitra region in Morocco, our approach demonstrates how graph-based deep learning can provide a granular, flow-driven representation of metropolitan space, offering a scalable and evidence-based tool for transformative territorial planning. Beyond this methodological contribution, the resulting centrality surface is interpreted against the genealogy of planning decisions that shaped the capital's urban form and against recent census dynamics, grounding a human-centered diagnostic of the growing dissociation between functional attractiveness and residential vitality.

1.1. Motivation, Methodological Gap, and Contributions

While the conceptual shift toward functional centrality is well-established in contemporary urban planning, accurately quantifying it remains a fundamental challenge in spatial data science. Modern metropolitan environments are complex systems driven by multidimensional interactions among the built environment, socio-economic dynamics, and physical mobility. Consequently, treating spatial zones as isolated entities—or evaluating them through unidimensional topological metrics such as basic betweenness or closeness centrality—fails to capture the true, multifaceted nature of urban attractiveness. This study is motivated by the critical need for an analytical framework capable of capturing the dynamic spillover effects of infrastructure, economic hubs, and urban amenities to reflect how these spaces actually perform within the broader metropolitan network.

Recent advancements in machine learning have attempted to address this complexity by introducing representation learning techniques to urban analytics (Chaturvedi & de Vries, 2021). However, a significant methodological gap remains: conventional models that rely on traditional dimensionality reduction and non-spatial feature representation techniques to compress complex urban indicators into latent vectors often suffer from inherent "spatial blindness." These non-spatial architectures treat urban zones as independent and identically distributed (i.i.d.) variables, fundamentally ignoring Tobler’s First Law of Geography (Miller, 2004). A purely dense neural network cannot model the asymmetric, non-Euclidean relationships of a physical street network, failing to recognize that the functional value of a neighborhood is intrinsically linked to its topological accessibility and surrounding spatial context (H. Wu et al., 2025).

To address this critical gap, this paper introduces a novel, unsupervised learning framework utilizing a Graph Attention Network Autoencoder (GAT-AE) to model urban functional centrality. By fusing high-resolution spatial features extracted via Google Earth Engine (GEE) and Point of Interest (POI) datasets with the topological reality of the physical road network processed via OSMnx (Boeing, 2017), this approach accurately models the urban fabric as a highly interconnected graph.

The core contribution of this study is the deployment of a GAT-AE that explicitly learns the latent representations of urban zones by dynamically aggregating information from their topological neighbors. This aggregation is guided by a self-attention mechanism and real-world accessibility thresholds utilizing Dijkstra's algorithm (Johnson, 1973). To demonstrate the necessity of explicit topological integration, this spatially-aware architecture is benchmarked against non-spatial baselines (Principal Component Analysis - PCA and standard Multi-Layer Perceptrons - MLP). Finally, serving as an empirical validator, the extracted functional centrality scores are cross-validated against localized real estate market prices, providing empirical proof that our unsupervised spatial embeddings successfully translate static physical data into a dynamic representation of real-world economic value. Beyond this technical validation, the framework offers an interpretive diagnostic layer: the detected latent structures are traced back to a century of planning policies and confronted with 2024 census dynamics, opening the model to a human-centered, equity-oriented reading of metropolitan centrality.

2. Related works

Recent research on urban and spatial network analysis has increasingly adopted graph-based deep learning to move beyond handcrafted indicators and better capture relational dependencies embedded in complex spatial systems. This shift is particularly relevant for the study of urban centrality, where conventional approaches based on descriptive metrics or manually defined centrality indices often struggle to represent the multidimensional and non-Euclidean nature of urban space. All references considered here collectively illustrate how graph neural networks and related deep learning architectures have been used to model street structure, city hierarchy, urban attractiveness, and spatial vulnerability, while also revealing a gap in the direct modeling of functional urban centrality at the intra-urban scale.

An important precursor to recent graph-based approaches is the study by (Noori et al., 2020), which examined whether urban street functionality could be predicted from network-derived structural features. Using nine centrality measures as input variables, the authors combined a stacked denoising autoencoder with logistic regression to classify street segments into functional categories across four cities. Their results showed that deep feature extraction could improve the prediction of street functionality and confirmed that topological properties of street networks contain meaningful information about urban organization. However, the analytical framework remained

dependent on handcrafted centrality indicators and did not explicitly model graph relations during learning. In this sense, the study marked an important step toward data-driven urban analysis, while still operating within a feature-engineering paradigm rather than a fully graph-native one.

A more direct application of graph neural networks to urban structure appears in the work of (Ma et al., 2024), who used graph convolutional networks to analyze street networks and urban polycentricity in Chinese cities. Their approach represented each city as a graph derived from natural streets and employed a two-branch architecture composed of a graph autoencoder and a single-layer perceptron to predict polycentricity. The study demonstrated that learned graph embeddings can preserve essential structural characteristics of street systems and can outperform alternative embedding methods in representing urban form. This contribution is significant because it confirms the value of graph convolution for encoding the spatial organization of street networks. Nevertheless, the emphasis remains on morphological structure and city-level polycentricity, rather than on the identification of functionally central urban areas through heterogeneous urban signals.

This graph-based perspective is extended to a broader territorial scale in the study by (Z. Wu et al., 2025), which explored city hierarchy through a graph convolutional network framework - GCN applied to 296 Chinese cities. In their model, cities were treated as nodes, inter-city transportation flows formed the graph edges, and multiple socio-economic and environmental indicators served as node attributes. The two-layer GCN was used to classify cities into hierarchical levels and revealed a strongly differentiated and polycentric urban system shaped by uneven regional development. The study is important because it demonstrates how graph neural networks can jointly incorporate relational connectivity and multidimensional urban attributes to characterize spatial hierarchy. At the same time, its focus is clearly inter-city rather than intra-urban, and its objective is hierarchical classification rather than latent centrality modeling within metropolitan space.

A comparable large-scale relational perspective is found in (Tian et al., 2024), who analyzed the World City Network through graph convolutional networks using global air-route connections. Their proposed GCNRank framework improved city ranking performance by learning relational patterns from network structure instead of relying solely on classical centrality or connectivity measures. This study reinforces the suitability of graph convolutional architectures for centrality-related questions in geographically embedded systems. However, like the work of (Z. Wu et al., 2025), it addresses inter-city relations at a macro scale and remains centered on ranking within a transportation network. As such, it does not directly address the problem of identifying functional centers within a metropolitan region through the fusion of local urban indicators.

Graph neural network approaches have also recently been applied to the identification of critical regions in spatial complex networks. In (Tan et al., 2026), the authors

proposed a new framework to identify key regions in spatial networks by partitioning geographic space into regions, constructing a regional graph, and applying graph neural networks to detect areas whose importance is critical for network integrity. Their findings showed that learned graph representations can outperform conventional regional centrality measures in identifying structurally important regions. In a related study, (Tan et al., 2025) developed a virtual node model for identifying vulnerable regions in spatial complex networks. By introducing virtual nodes to better represent edge damage and combining topological with geographic information, they improved the precision of vulnerability detection in infrastructure-like spatial systems. Although both studies focus on resilience and vulnerability rather than urban centrality, they are highly relevant from a methodological standpoint because they confirm that graph neural networks are well suited for region-based importance detection in spatially embedded networks, especially when geography and topology must be modeled jointly.

Taken together, these mentioned studies reveal a clear progression in literature. Earlier work demonstrated that deep learning could extract useful representations from centrality-based urban descriptors. Yet, despite these advances, a gap remains in the direct modeling of functional urban centrality within metropolitan space through the integration of multi-source urban data and graph attention mechanisms.

The present study contributes to this gap by building on these methodological advances while shifting the analytical focus toward functional urban centrality, it treats urban space as a graph-structured system rather than a collection of isolated spatial units. it recognizes that urban importance emerges from both node attributes and relational connectivity. And like (Tan et al., 2026; Tan et al., 2025), it acknowledges that the significance of a spatial unit cannot be understood independently of its topological and geographic context. However, unlike these studies, the present work explicitly aims to model functional centrality at the intra-urban scale through an unsupervised GAT-AE combined with multi-source data fusion, thereby providing a framework for identifying latent metropolitan centers that reflect both urban structure and urban activity.

3. Materials and Methods

3.1. Study Area

The research focuses on the metropolitan corridor of Morocco's Rabat–Salé–Kénitra region as showed in figure 1, stretching from the Rabat–Salé–Témara agglomeration to Kénitra in the north, home to approximately 2.9 million inhabitants (Morocco, 2024) As the nation's political and administrative heart, this corridor is characterized by high demographic density, intensive daily commuting, and a complex multimodal transport network consisting of major road corridors, rail lines, and the Rabat–Salé tramway.
The suitability of this site stems from its pronounced spatial, functional, and morphological heterogeneity. Spanning a continuum from purely urbanized centers (Rabat, Salé, Kénitra) to consolidating peri-urban communes (Témara, Skhirat), the territory combines dense built-up areas, commercial hubs, and extensive green

landscapes. This structural complexity provides a demanding environment to test the robustness and behavioral consistency of the GAT-AE model across contrasting accessibility and service configurations. At the intra-urban scale, several districts within Rabat serve as reference units to ground the latent centrality surface in real-world urban dynamics.

Hassan district, the historical hypercenter centered on the Mohammed V axis, incorporating the Parliament, the medina, and the central station. Agdal and Hay Riad, a planned, hyper-connected districts that concentrate the city's primary business and administrative functions. Yacoub El Mansour and El Youssoufia, a dense, popular working-class districts largely produced by mid-century habitat économique housing programs.

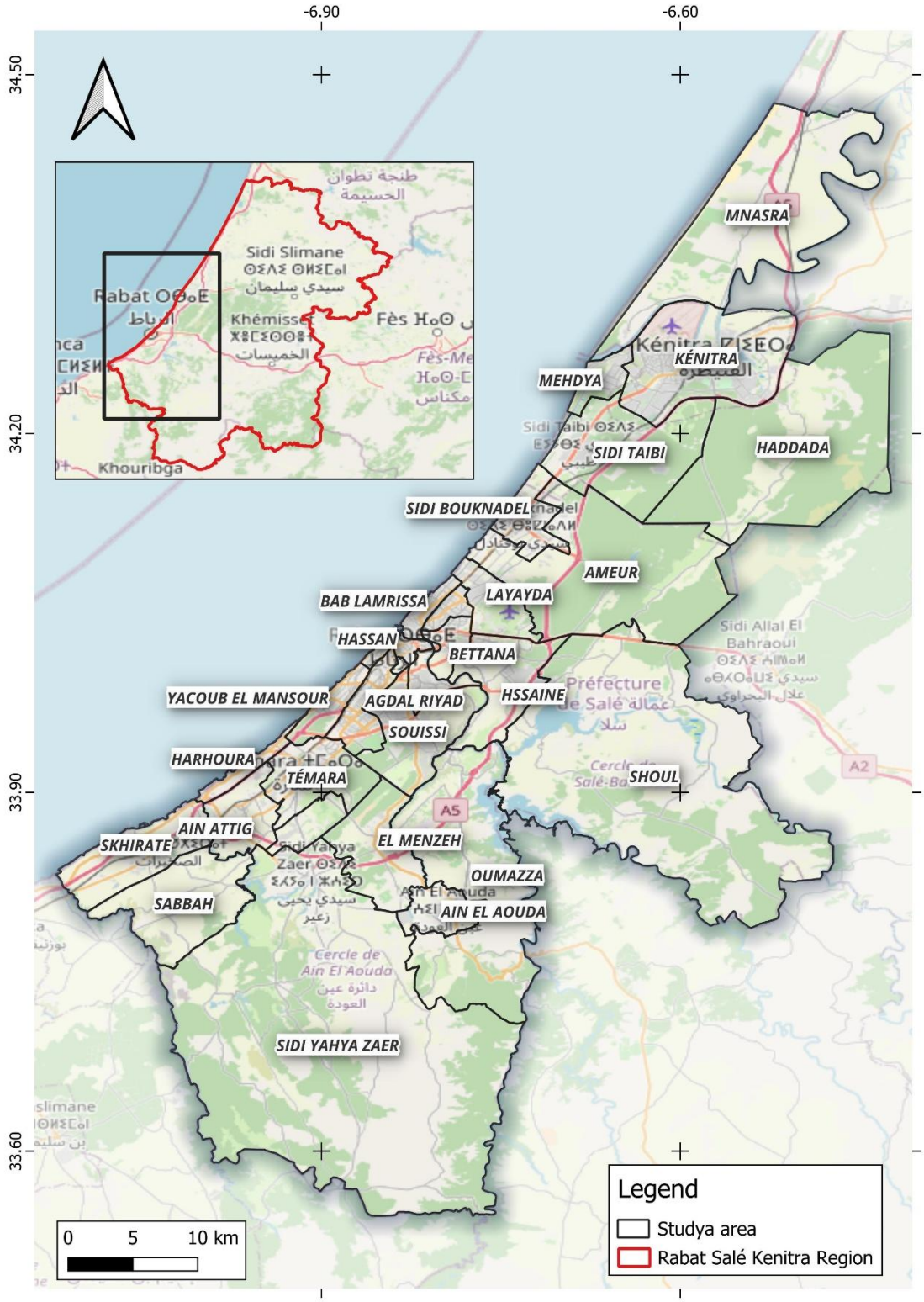


Figure 1. Map of the study area spanning core urban districts and surrounding peri-urban communes in the Rabat–Salé–Kénitra region

To capture the multidimensional and relational dynamics of urban attractiveness, this study implements an unsupervised Graph Attention Network Autoencoder (GAT-AE) within an end-to-end spatial machine learning pipeline. As illustrated in Figure 2, the framework seamlessly integrates multi-source geospatial data ingestion, feature engineering, gravity-based graph construction, deep representation learning, empirical validation, and latent typological delineation across three sequential phases.

Phase 1 focuses on automated data preprocessing and tensor construction. Supported by dedicated configuration and cache management modules, automated data loaders ingest multi-source geospatial datasets from OpenStreetMap (OSM) Geofabrik and Google Earth Engine (GEE). Feature engineering extracts four primary categories of spatial indicators: (i) environmental parameters, including the Digital Elevation Model (DEM), Land Surface Temperature (LST), Dynamic World (DW) land cover, and Joint Research Centre (JRC) surface water layers; (ii) functional mix, quantified via Shannon entropy of land-use diversity; (iii) network centrality, incorporating structural graph metrics such as betweenness and closeness centrality; and (iv) socioeconomic factors, comprising WorldPop population distribution, VIIRS nighttime light intensity, and Euclidean distance to the Central Business District (CBD). All extracted features undergo Min-Max normalization to construct a standardized input feature tensor.

Phase 2 establishes the spatial network topology and governs model training. A mobility graph is generated using a Dijkstra-based gravity framework to capture spatial interaction patterns. The resulting graph topology and feature tensor are subsequently passed into parallel training loops with continuous loss tracking to benchmark three distinct architectures: a baseline linear Principal Component Analysis (PCA), a non-spatial Multi-Layer Perceptron Autoencoder (MLP-AE) baseline, and the primary Graph Attention Autoencoder (GAT-AE).

Phase 3 implements a rigorous, three-pronged validation framework to assess model convergence and embedding validity. First, internal structural performance is evaluated via overall Mean Squared Error (MSE), feature-wise MSE decomposition, training runtime, and parameter efficiency. Second, spatial autocorrelation in the latent space is tested using Global Moran's I. Third, external spatial economic validation is performed by correlating latent centrality scores with empirical real estate prices using linear Pearson (r) and non-parametric Spearman (ρ) rank correlation coefficients.

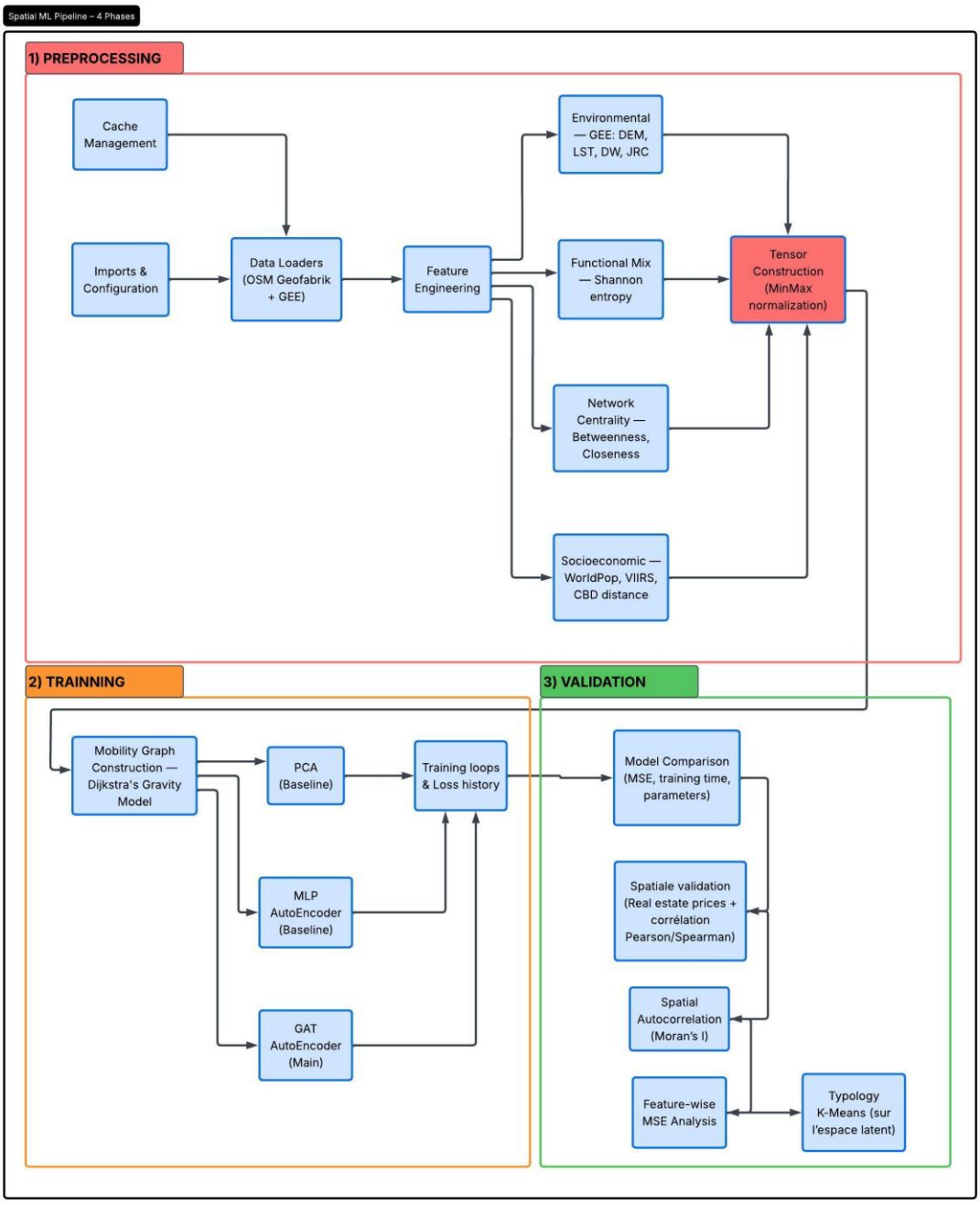


Figure 2. Workflow of the study.

3.2. Spatial discretization and feature engineering

To discretize the metropolitan study area, this study employs the Uber H3 hierarchical spatial index at resolution level 9 (Brodsky, 2018). This tessellation yields a uniform grid of hexagonal cells, where each unit covers an average area of approximately 0.105 km^2 with an edge length of roughly 174 m. Relative to conventional square grids, hexagonal spatial partitions offer distinct topological advantages: they guarantee spatial isotropy, ensure uniform connectivity across six equidistant neighbors, and eliminate directional orientation bias, thereby offering a superior representation of real-world urban catchment areas.

Building upon this spatial framework, a high-dimensional feature matrix $\mathbf{X} \in \mathbb{R}^{N \times F}$ is constructed across all N hexagonal nodes ($v_i \in V$). Data ingestion and spatial processing workflows are fully automated by coupling the Google Earth Engine (GEE) Python API with OpenStreetMap datasets (acquired via OSMnx and Geofabrik extracts) and gridded demographic databases. The extracted urban indicators are systematically organized across distinct thematic domains, as summarized in Table 1.

Thematic Category	Urban Indicator	Data Source / Method
Morphological & Environmental	Elevation and Slope	SRTM DEM
	Land Surface Temperature and NDVI	Landsat 8/9
	Impervious Surface Percentage and Urban Heat Index	Dynamic World
	Distance to Water	Spatial Calculation
	Green Space Ratio	Spatial Calculation
Socio-Economic & Demographic	Gridded Population Aggregation	WorldPop
	Normalized Nighttime Lights Intensity	VIIRS (Primary active feature for economic vitality and energy consumption)
	Urban Growth Rate	Computed Metric
	Population Service Ratio	Computed Metric
Functional & Relational	Functional Mix Score	Shannon Entropy of POIs
	Composite Walkability Score	Computed Metric
	POI Attractiveness (S_j)	Point of Interest (POI) Attributes
	Huff Centrality	Gravity Model probabilities

Table. 1 . Data used for model training

3.3. Preprocessing and normalization protocol

To stabilize neural network gradient optimization and prevent large-magnitude features from dominating model learning, highly skewed variables undergo a logarithmic transformation using $\log(1 + x)$ to equalize variance. Features exhibiting near-perfect collinearity are pruned, and deterministic composite indices are excluded to prevent data leakage. All features are scaled to a bounded $[0,1]$ range via Min-Max Normalization as shown in equation 1. The cleaned indicators are compiled into a unified node attribute tensor X ready for graph learning.

$$\textbf{Eq 1}: x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

3.4. Hybrid topological graph construction and GAT-AE architecture

3.4.1. Hybrid spatial topology & gravity model

The metropolitan area is modeled as a functional directed graph $G = (V, E)$, where V represents the hexagonal cells and E represents the functional connectivity edges between them. To overcome the limitations of simple Euclidean distance, the graph's adjacency structure uses a hybrid formulation (Eq 2):

$$\textbf{Eq 2 : } E = E_{\text{spatial}} \cup E_{\text{network}}$$

Where :

1. Spatial Contiguity (E_{spatial}): Captures immediate localized neighborhood effects via Queen geometric adjacency.
2. Infrastructure Connectivity (E_{network}): Street network topology is extracted via OSMnx, projected to EPSG:3857, and evaluated using Dijkstra's shortest-path algorithm (Johnson, 1973).

To quantify spatial interactions, edge weights W_{ij} are calculated using a Spatial Gravity Interaction Model as shown in Eq 3:

$$\textbf{\textit{Eq 3}} : \; W_{ij} = \frac{S_j}{d_{ij}^{\beta}}$$

where S_j represents the attractive mass of destination node j (measured via POI density), d_{ij} is the shortest physical network distance between nodes i and j, and $\beta = 1.5$ is the distance-decay friction parameter. Spatial interactions are bounded by a strict spatial threshold of 4,000 meters, reflecting human intra-urban mobility limits.

3.4.2. Graph Attention Autoencoder Architecture

As illustrated in Figure 3, the GAT-AE architecture serves as the core analytical engine of the pipeline, designed to compress multi-source node attributes while aggregating spatial messages across physical network neighbors. The framework employs a GAT Encoder that projects the high-dimensional feature matrix $\mathbf{X} \in \mathbb{R}^{N \times F}$ into an 8-dimensional latent space $\mathbf{Z} \in \mathbb{R}^{N \times 8}$. Within this encoder, the attention layer computes dynamic self-attention coefficients α_{ij} between a target node i and its topological neighborhood $j \in \mathcal{N}_i$, which are synergistically modulated by gravity-derived physical interaction weights W_{ij}. Subsequently, a symmetric MLP Decoder reconstructs the estimated node feature matrix $\hat{\mathbf{X}} \in \mathbb{R}^{N \times F}$ directly from the compressed latent representations $\mathbf{Z}$.

The architecture is trained iteratively over 300 epochs to minimize the Mean Squared Error (MSE) reconstruction loss:

$$\mathcal{L}_{\text{MSE}} = \frac{1}{N} \sum_{i=1}^{N} \| \mathbf{x}_i - \hat{\mathbf{x}}_i \|_2^2$$

Following training, the Functional Urban Centrality Score for any given hexagonal unit i is quantified as the L_2 norm of its latent embedding vector $\mathbf{z}_i$:

$$C_i = \| \mathbf{z}_i \|_2$$

This latent extraction yields a spatially smoothed, context-aware index that encapsulates both structural accessibility and localized functional urban vitality.

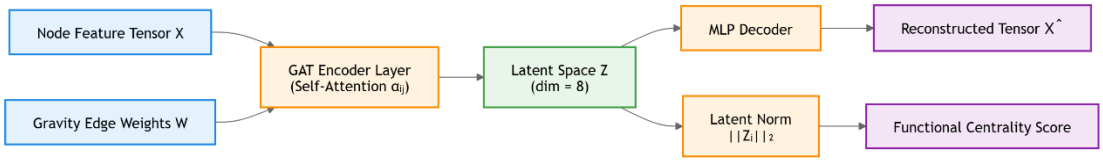


Figure 3. Workflow of the proposed Graph (GAT-AE) model

3.5. Model validation strategy and typological analysis

To evaluate model performance, structural integrity, and real-world applicability, the study employs a multi-tiered validation framework. The Graph Attention Autoencoder (GAT-AE) is benchmarked against two non-spatial baseline architectures:

1. A linear Principal Component Analysis (PCA) model, and
2. A non-spatial Multi-Layer Perceptron Autoencoder (MLP-AE).

Models are evaluated across overall reconstruction Mean Squared Error (MSE), Mean Absolute Error (MAE), coefficient of determination ($\boldsymbol{R^2}$), feature-wise reconstruction error, training convergence dynamics, parameter efficiency, and spatial fidelity.

3.5.1. Validation of model performance and convergence dynamics

To rigorously evaluate both the internal structural integrity and empirical utility of the candidate models, the validation framework combines quantitative loss tracking with spatial and economic alignment analyses. As illustrated in Figure 4, the models exhibit distinct optimization profiles across 300 training epochs. The baseline linear Principal Component Analysis (PCA) achieves the lowest overall static reconstruction error (MSE_{PCA}). Because PCA performs a global linear transformation without non-linear activation functions or topological aggregation constraints, it maximizes variance capture and minimizes mathematical reconstruction loss, yet remains fundamentally incapable of encoding relational spatial structure. In contrast, the non-spatial MLP-AE initialized with the highest initial loss ($\mathcal{L}_{init}$) but converged rapidly within the first 50 epochs to a final reconstruction loss of MSE_{MLP}. While effective at non-linear dimensionality reduction, its fully connected architecture inherently ignores spatial proximity and geographic topology.

Meanwhile, the primary GAT-AE framework exhibits a smooth, stable convergence trajectory, initiating at $\mathcal{L}_{init}$ and leveling off at a final residual loss of MSE_{GAT}. The slightly higher residual MSE observed in GAT-AE compared to the non-spatial MLP-AE reflects an intentional structural trade-off imposed by graph attention mechanisms: the architecture deliberately sacrifices a marginal degree of unconstrained feature

reconstruction precision in exchange for enforcing topological smoothness, spatial autocorrelation, and neighborhood connectivity across the urban graph.

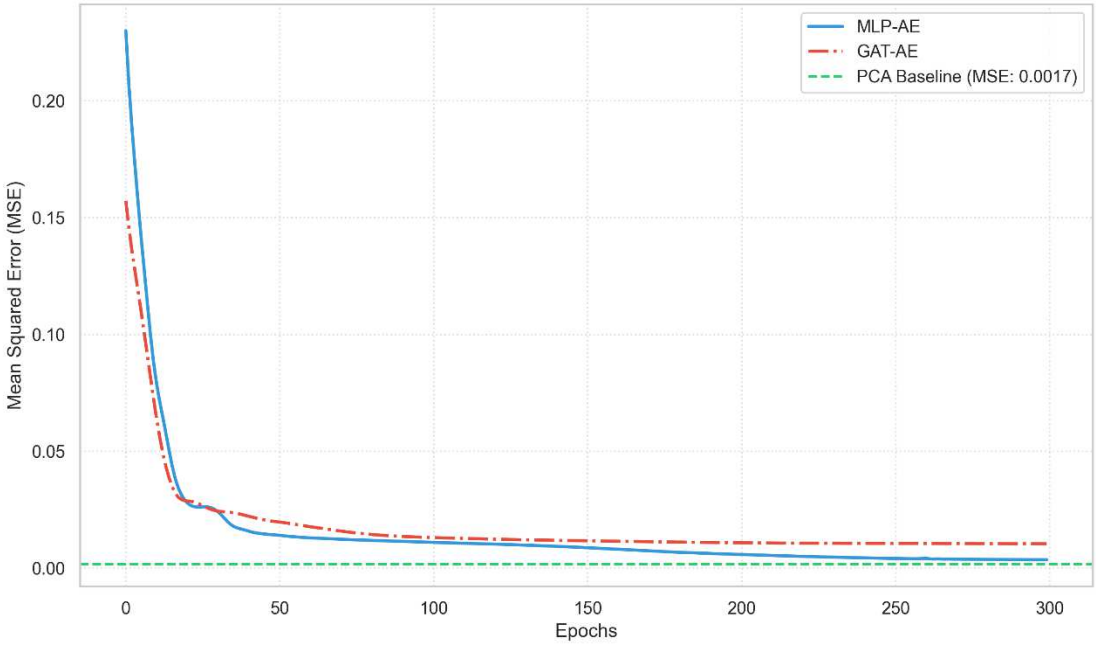


Figure 4. Reconstruction loss convergence during the training phase

3.5.2. Spatial centrality mapping and comparative analysis

The spatial implications of these representation mechanics are evaluated in Figure 5, which maps the functional centrality scores generated across the three models. The GAT-AE (Panel A) leverages graph topology and explicit neighborhood connectivity to capture smooth, continuous spatial gradients across the region. This structural awareness enables the model to effectively delineate secondary urban nodes—such as the lower-end secondary city of Ain El Aouda—as well as coastal suburban municipalities like Harhoura, demonstrating high sensitivity to localized graph connectivity. In contrast, the linear PCA baseline (Panel B) relies on global linear projections, restricting high centrality scores almost exclusively to the primary urban core consisting of Rabat, Salé, and Kénitra. As a result, PCA lacks the non-linear flexibility necessary to detect polycentric patterns or emerging suburban nodes. Finally, while the non-spatial MLP-AE (Panel C) utilizes non-linear dense layers to successfully identify localized suburban activity—such as highlighting Temara Municipality as a suburban node with high centrality—it produces a spatially fragmented and noisy score distribution due to the complete absence of explicit graph neighbor smoothing.

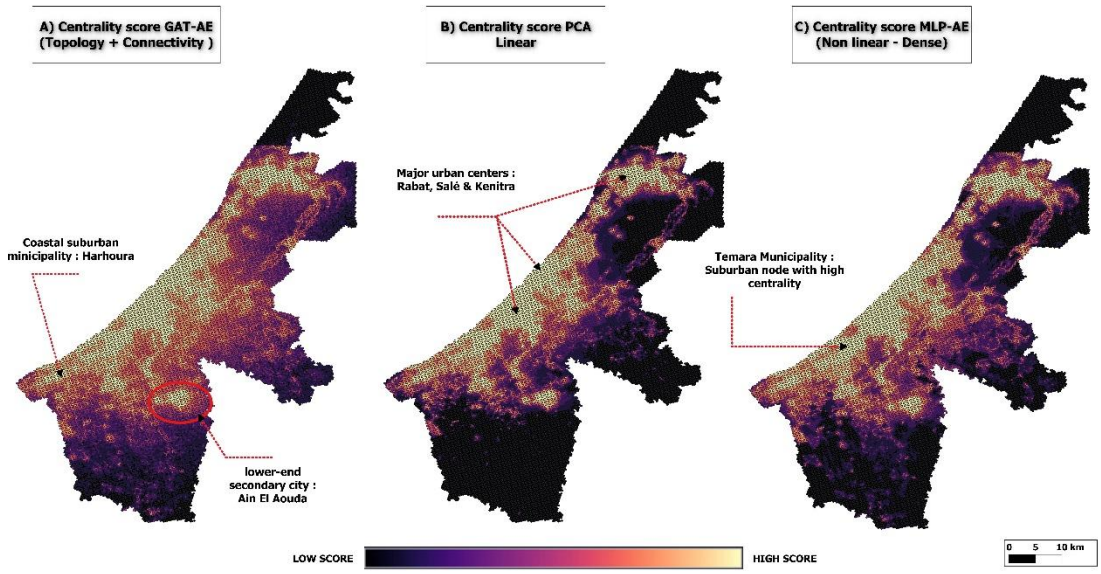


Figure 5.Comparison of latent centrality spaces: Linear (PCA), Topological (MLP-AE), and Topology- and Connectivity-Aware (GAT-AE)

3.5.3. Algorithmic performance and the topological trade-off

Evaluating the global reconstruction capacity reveals a deliberate algorithmic trade-off inherent in network-native modeling. While linear PCA and the MLP-AE achieve lower absolute errors and higher R^2 scores (0.9231 and 0.8876, respectively), the GAT-AE exhibits a higher Mean Squared Error (0.0120) and an R^2 of 0.5831 (Figure 6). This divergence is intentional: because the GAT-AE reconstructs features based on neighborhood messages filtered through a gravity-based adjacency matrix, it sacrifices the strict memorization of isolated raw node features in favor of topological smoothing and relational context. Feature-wise reconstruction analysis confirms the efficacy of this approach, demonstrating that the model explicitly weights critical exogenous drivers, most notably the normalized VIIRS nighttime lights variable, while safely disregarding redundant morphological noise (Figure 7). Notably, closeness and betweenness centrality metrics were deliberately excluded from the training input tensor due to their strong mutual correlation, thereby mitigating severe multicollinearity risks that could otherwise distort model optimization.

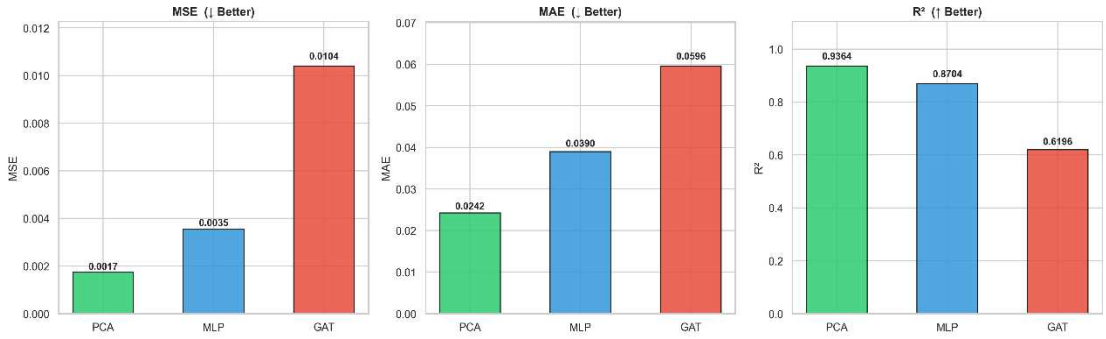


Figure 6. Reconstruction capacity (A), reconstructions metrics (B)

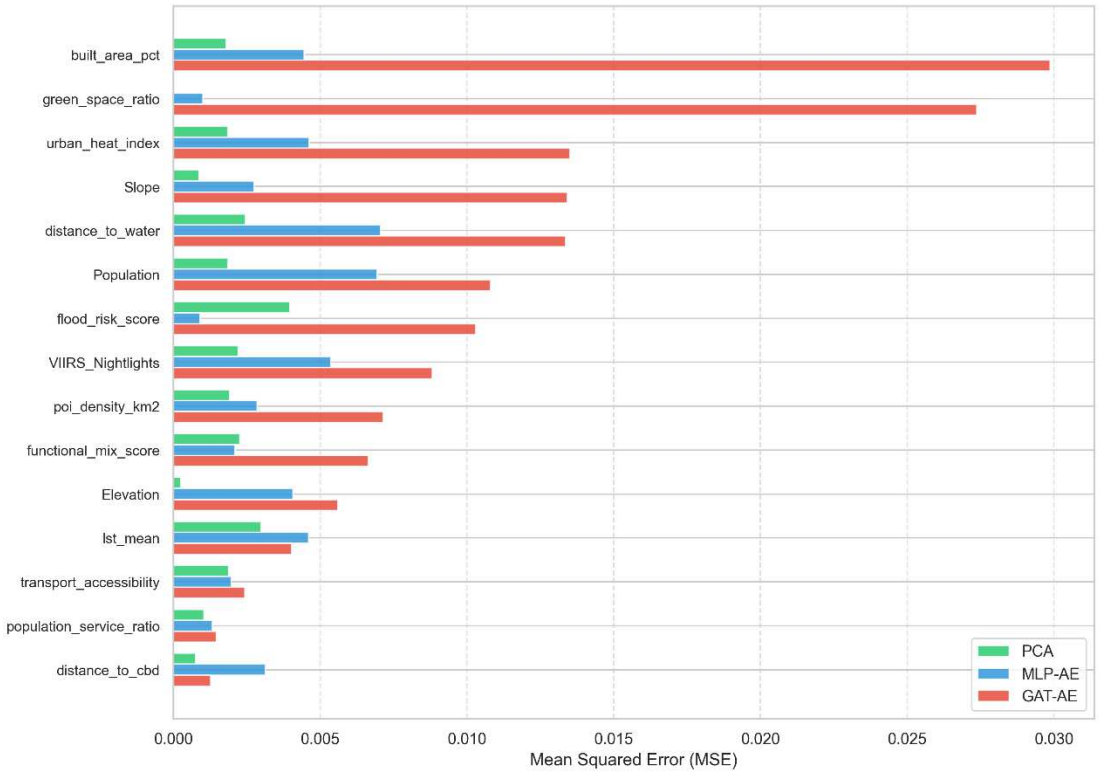


Figure 7. Reconstruction capacity per feature for the 3 models

3.5.4. Latent space dimensionality and structural coherence

The representational superiority of the GAT-AE becomes evident within the structure of its 8-dimensional latent space. The model efficiently compresses the urban functional signature, capturing approximately 67% of the systemic variance in its primary dimension and 21% in the second (appendix 1). Cluster separability metrics strongly favor the graph-based approach: the GAT-AE maximizes cluster dispersion (Calinski-Harabasz Index of 21248.737) and achieves optimal compactness (Silhouette Score of 0.408; Davies-Bouldin Index of 0.848) (appendix 2). Visualized via 2D t-SNE projections, the GAT-AE produces distinct, cohesive topological groupings that contrast sharply with the overlapping, ambiguous representations of the non-spatial baselines (appendix 2). Notably, the model yields a Trustworthiness score of 0.8982, indicating a necessary warping of the original Euclidean space to strictly preserve network-based neighborhood relationships. Finally, K-Means clustering ($k = 4$) is applied directly to the 8-dimensional latent space Z. Cluster separation quality is benchmarked using the Silhouette Score, Davies-Bouldin Index, and Calinski-Harabasz Index, partitioning the metropolitan area into distinct functional urban sectors (annexe 1).

3.5.5. Spatial autocorrelation and morphological insights

4. To evaluate the spatial structure and territorial coherence of the latent embeddings, spatial statistical analysis was conducted across the extracted functional centrality surface. The embeddings exhibit exceptionally strong spatial autocorrelation,

reaching a Global Moran's I of 0.973 ($p < 0.001$) and confirming the structural impact of topological integration. Local Indicators of Spatial Association (LISA) mapping further delineates statistically significant spatial regimes (Figure 8), cleanly separating primary functional urban cores (High-High clusters) from disconnected peripheral regions (Low-Low clusters) while eliminating the fragmented "salt-and-pepper" artifacts typical of non-spatial neural baselines.

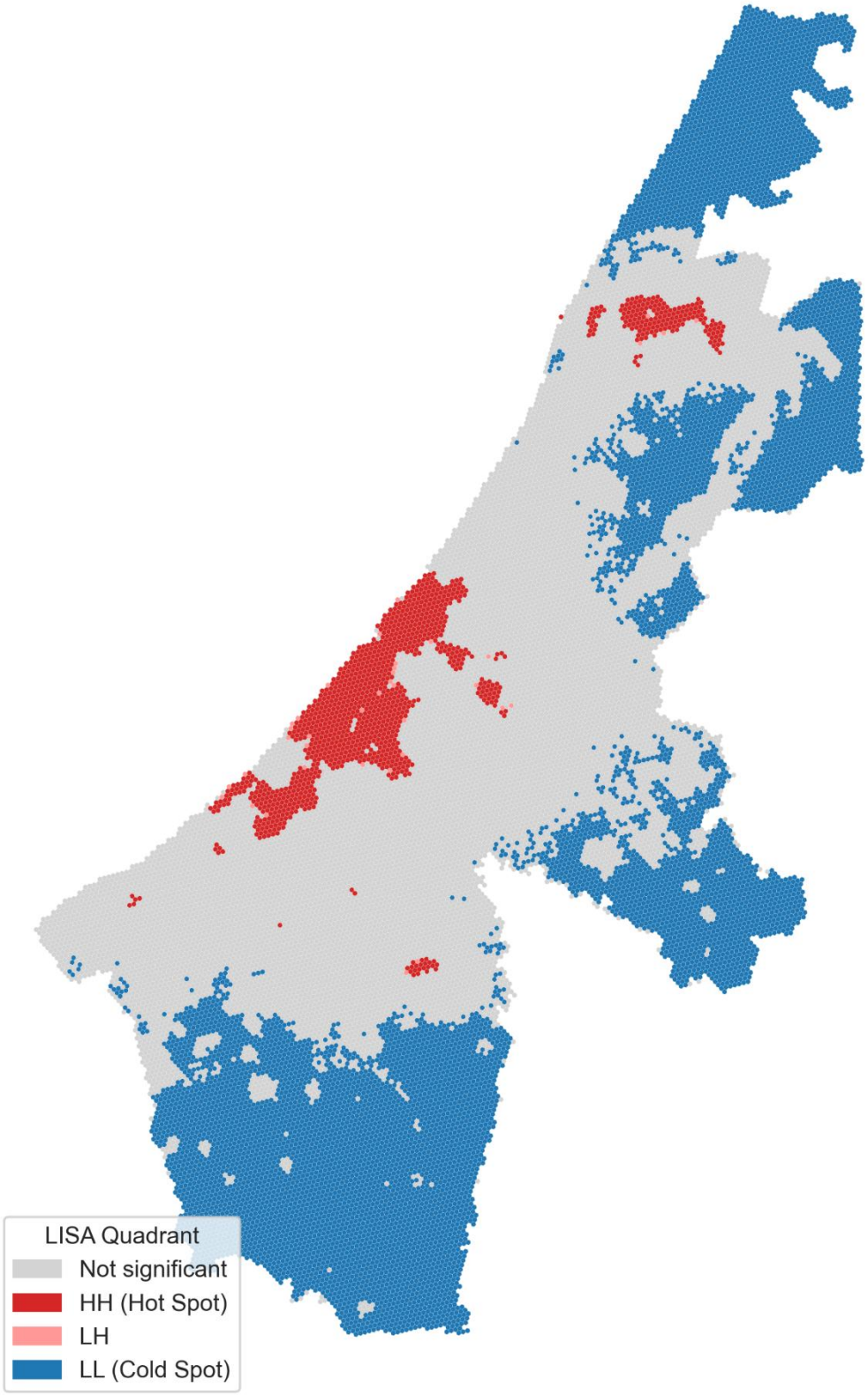


Figure 8. Spatial Auto-correlation

4.1. External empirical and ground-truth validation

Grounded in Bid-Rent Theory (Wheaton, 1974), the extracted functional centrality scores were externally validated against empirical socio-economic signals through a two-pronged framework: 1) OpenStreetMap (OSM) anchor catchment analysis, and 2) localized real estate price cross-validation.

First, OSM anchor catchment analysis confirmed the spatial precision and functional sensitivity of the GAT-AE model across localized buffer zones surrounding validated urban anchors (figure 10). Centrality scores peak sharply within active anchor catchments—reaching maximum local values—while remaining suppressed near zero across background, non-anchor territory. Probability density functions further demonstrate that whereas non-spatial baselines (PCA and MLP-AE) over-concentrate mid-range values due to spatial noise, the GAT-AE maintains a well-defined, right-skewed distribution. This tail cleanly separates primary metropolitan cores from secondary urban nodes along the main urban corridor, verifying that graph attention mechanisms effectively convert physical network paths into localized functional attractiveness without generating false positives in the background urban fabric.

Second, to test whether the unsupervised latent embeddings translate into real-world economic value, centrality scores were spatially joined with localized land market price data. Linear Pearson (r) and non-parametric Spearman (ρ) rank correlation analyses yielded statistically significant values of $r = 0.476$ and $\rho = 0.401$ ($p < 0.001$), respectively. Using average property price as an empirical proxy for spatial interaction intensity, this result confirms that the latent manifold successfully captures dynamic socio-economic vitality, vastly outperforming purely morphological density or Euclidean proximity models (Figure 11, left). Furthermore, spatial autocorrelation analysis confirms the territorial coherence of these embeddings, with the Moran scatterplot demonstrating strong, statistically significant spatial clustering ($I = 0.8143$, $p = 0.0010$; Figure 11, right).

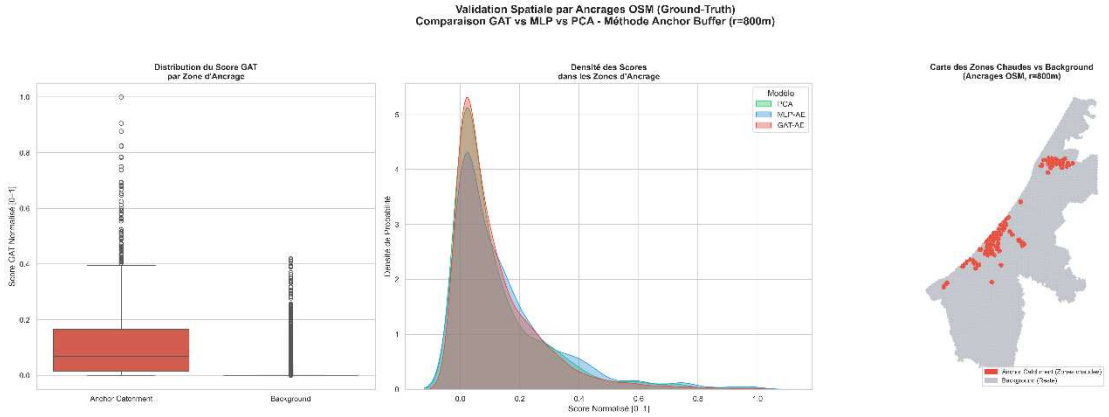


Figure 10. Spatial validation by anchor OSM as Ground Truth by comparing GAT vs MLP vs PCA (buffer r = 800m)

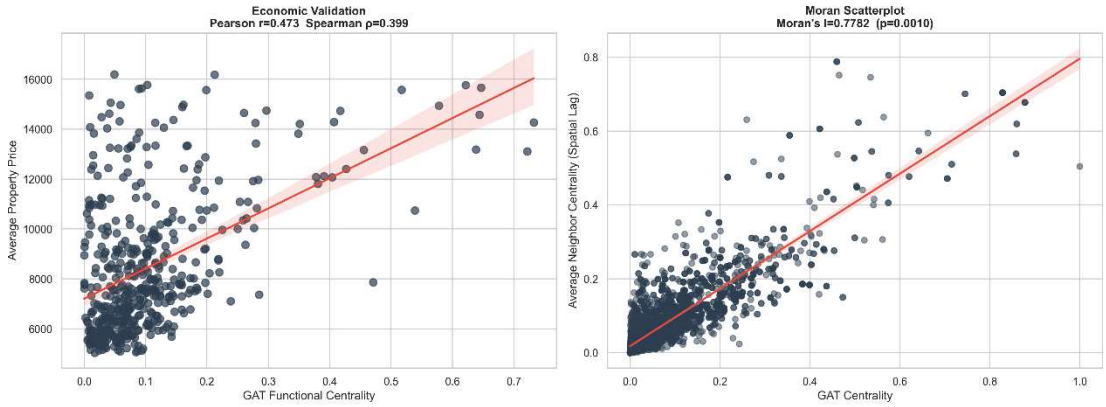


Figure 11. Correlation Analysis between GAT-AE and real estate prices per district in the study area

5. Discussion

While the GAT-AE successfully extracts the latent functional centrality of the metropolitan system, these mathematical outputs are not occurring in a vacuum; rather, they are the direct spatial manifestations of specific urban policies and historical planning paradigms. Contextualizing these results requires examining the current urban form that serves as the physical substrate for these network dynamics. To ground the mathematical outputs of the GAT-AE in real-world space, Figure 12 provides a multi-scalar visualization of the Rabat–Salé–Kénitra metropolitan corridor. Panel A establishes the regional geographic locator of the study area, highlighting the urbanized coastal spine where metropolitan growth is concentrated. Panel B zooms into the metropolitan core to map the continuous spatial distribution of the GAT latent centrality surface across the H3 hexagonal discretization, illustrating how functional attraction diffuses along primary transport corridors. Building upon this spatial location, Panel C provides a fine-grained bivariate synthesis that cross-evaluates raw morphological density derived from linear PCA against the topological connectivity extracted by the GAT-AE manifold. Rather than observing a uniform spatial convergence where physical density automatically mirrors functional importance, this bivariate synthesis reveals structural discrepancies across Rabat's core urban fabric. These spatial dynamics are direct physical manifestations of Rabat's century-long urban planning trajectory, spanning the colonial master plans of the French Protectorate through mid-century public housing programs to contemporary state-led infrastructure megaprojects.

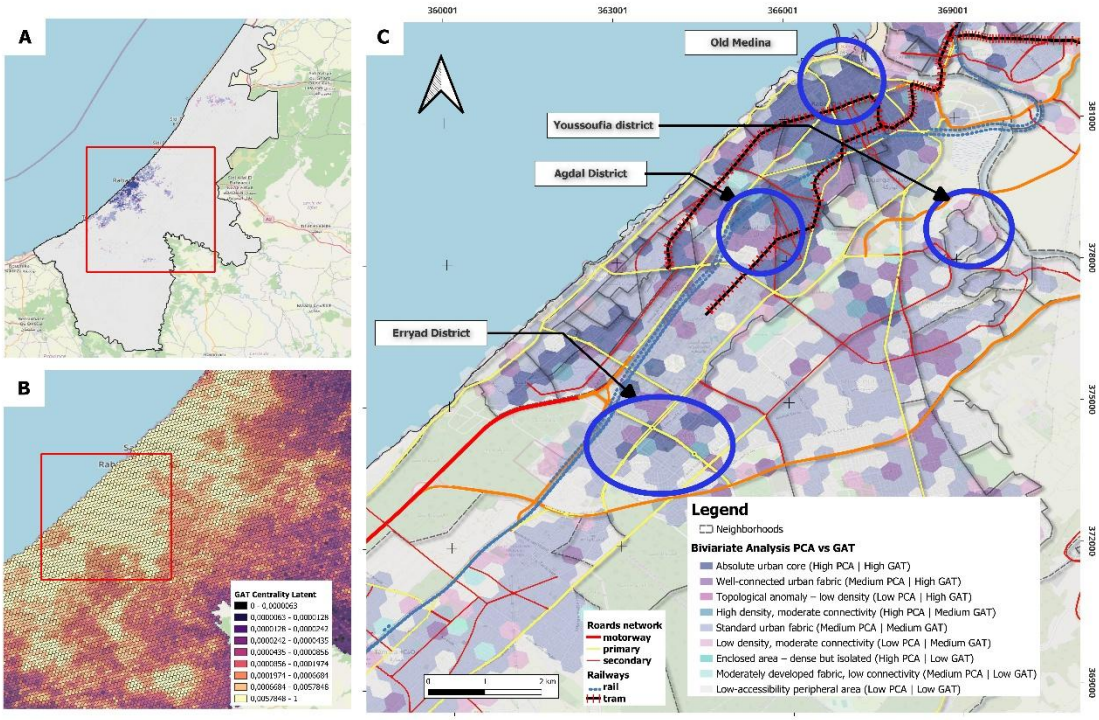


Figure 12. Spatial distribution of latent GAT centrality and bivariate comparative typology (PCA vs. GAT-AE) across major metropolitan districts.

5.1. Planned hypercenters: Agdal and Hay Riad (Absolute urban core)

The bivariate analysis in Figure 12C classifies both Agdal and Hay Riad predominantly as Absolute urban core, highlighted by deep blue-purple hexagonal clusters along primary infrastructural corridors. Their high topological centrality, visible in the continuous score surface of Panel B and the bivariate overlay in Panel C, stems from distinct historical planning paradigms. Originally laid out under Henri Prost's colonial master plan (1913–1922) as a low-density, garden-city extension of the European ville nouvelle (Wagner & Rahmi, 2025), Agdal district underwent intensive post-independence densification. The GAT-AE captures how this district successfully transitioned into a secondary hypercenter. The concentration of high attention weights in Agdal is driven by its grid-iron street network, dense POI composition, and direct synergy with major transit infrastructure. As shown in Figure 12C, the overlay of the Rabat–Salé Tramway Line 1 and the Al Boraq high-speed rail line through the rebuilt Rabat-Agdal station drastically reduces topological shortest-path friction (d_{ij} in Dijkstra's gravity formulation). Consequently, Agdal exhibits maximum functional accessibility alongside high physical density.

Conceived in the late 20th century (under the 1970s Schéma Directeur d'Aménagement Urbai - SDAU master plan guidance) as an administrative and executive business district, Hay Riad reflects modern peripheral master-planning. Morphologically, it possesses lower residential density compared to working-class quarters. Yet, the GAT-AE embeds Hay Riad directly within the Absolute urban core class. This occurs because

the model's self-attention mechanism (α_{ij}) and gravity interaction weights (W_{ij}) register Hay Riad's strategic positioning at the intersection of the main arterial motorways (e.g., the A1/A5 highway junction and Avenue Annakhil) and its exceptionally high concentration of corporate headquarters, ministries, and tertiary service POIs. The GAT-AE thus identifies Hay Riad as a flow-driven economic hub whose functional centrality vastly exceeds its raw residential footprint

5.2. The historical hypercenter: Old Medina

The Old Medina demonstrates a concentrated cluster of Absolute urban core bounded by high-density/medium-connectivity buffer zones in Figure 12C. The Protectorate planning doctrine instituted by Hubert Lyautey enforced a strict dual-city structure, imposing a non-aedificandi greenbelt that physically separated the traditional, organic spatial fabric of the Medina from the European ville nouvelle.
While the internal micro-street layout of the Medina consists of dead-end alleys and non-Euclidean pedestrian paths, its perimeter is directly encircled by high-capacity transit lines (the Tramway network crossing the Hassan II bridge toward Salé, Avenue Hassan II, and the central Rabat-Ville rail axis). The GAT-AE framework resolves this spatial dichotomy: despite internal topological friction, the Medina's extreme POI density, market vitality (high Shannon entropy functional mix score), and edge-based connectivity to multimodal transport nodes sustain its position as a primary functional hub within the metropolitan core.

5.3. Working-class quarters and structural isolation

In sharp contrast to Agdal and Hay Riad, the Youssoufia district stands out in the bivariate map as a prominent enclaved zone, rendered in cyan and light blue-green hues. This class denotes areas characterized by extreme morphological and demographic density that nevertheless suffer from low topological connectivity and functional isolation within the metropolitan graph.
This structural enclavement is a direct legacy of mid-century social housing policies. From a planning genealogy perspective, Youssoufia (alongside neighboring Yacoub El Mansour) was largely shaped by the *habitat économique* programs instituted under Michel Écochard during his tenure as head of the Protectorate's urban planning service (1946–1952) (Bernasconi, 2019; Maricchiolo, 2018). Designed to absorb rapid rural-to-urban migration, the standardized 8×8 m sanitary grid (Mehan & Nawratek, 2023) prioritized rapid, low-cost residential shelter over integration into the broader urban economy. 2) Topological disconnection: As visualized in Figure 12C, while major motorways and tram lines bypass or terminate short of Youssoufia's core, the internal street network remains fragmented, lacking permeable arterial connections to adjacent commercial centers.

Traditional linear models like PCA evaluate Youssoufia as highly central purely due to its high population counts and built area percentages. In contrast, the GAT-AE penalizes these cells. Because Dijkstra shortest-path calculations reveal high network resistance

and the gravity-based edge weights ($\boldsymbol{W_{ij}}$) detect a scarcity of high-order tertiary POIs and nighttime light intensity (VIIRS), the GAT-AE diagnoses Youssoufia as an enclaved residential dormitory.

5.4. Synthesis and equity implications for territorial planning

The multi-panel spatial breakdown in Figure 12 confirms that the GAT-AE architecture successfully uncouples physical form from functional performance. By capturing the spatial hysteresis left by colonial zoning (Prost), emergency housing grids (Écochard), and recent transit investments, the model provides an empirical diagnostic of urban inequality in the Rabat-Salé-Kénitra region. The districts exhibiting the highest latent functional centrality in Panel B and C (Hassan, Agdal, Hay Riad) are precisely those shedding municipal population according to the 2024 census, serving primarily as daytime, flow-driven administrative and commercial centers.

Conversely, working-class districts like Youssoufia continue to house a substantial portion of the city's residents but remain functionally isolated. Their internal economic life relies on informal, self-produced micro-centralities rather than planned metropolitan integration. By isolating these spatial mismatches across Panels A, B, and C, the bivariate framework demonstrates that graph-based deep learning does not merely replicate surface-level urban metrics. It exposes how state-led planning decisions historically concentrated accessibility in administrative quarters while externalizing working-class populations into topologically peripheral enclaves. This provides actionable evidence for future urban interventions, emphasizing that municipal master plans must prioritize transit-oriented development (TOD) and arterial network integration within enclaved sectors like Youssoufia to foster spatial equity across the capital.

6. Conclusion

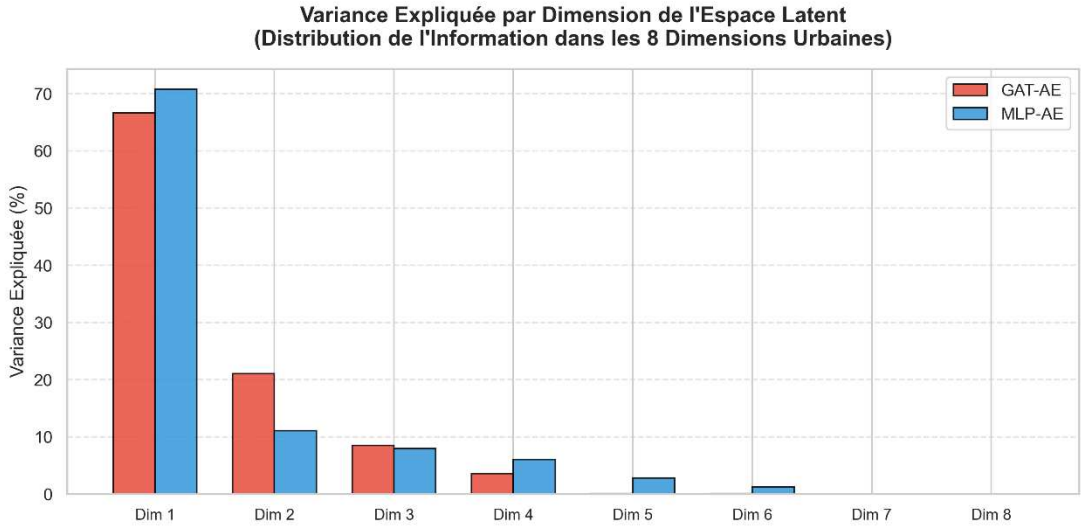
This study set out to demonstrate that urban centrality in rapidly transforming metropolitan regions is more faithfully captured as a relational, flow-driven property of the urban network than as a static morphological attribute. To this end, we developed an unsupervised GAT-AE that fuses multi-source descriptors (remote-sensing indicators, points of interest, and VIIRS nighttime lights) with the topology of the physical road network over an H3 hexagonal discretization of the Rabat-Salé-Kénitra metropolitan corridor. The systematic benchmark against non-spatial baselines (PCA and a dense MLP autoencoder) confirms that explicit topological aggregation, guided by attention weights and real-world accessibility thresholds, is a necessary condition for extracting a functionally meaningful latent representation of the urban fabric.

Beyond methodological performance, the learned centrality surface proved empirically and theoretically consistent. Externally, centrality scores peak within independently identified functional hubs and correlate significantly with localized real estate values, in line with bid-rent theory, indicating that the latent manifold encodes the socio-economic vitality of the territory rather than built density alone. Interpretively, the detected structures (consolidated cores, corridor effects induced by recent

infrastructure, and dense yet disconnected enclaves) are legible as the cumulative outcome of a century of planning decisions, from colonial zoning to contemporary megaprojects, confirming that functional centrality is a produced and planned artifact as much as an emergent property. The confrontation of the latent space with recent census dynamics further reveals a growing dissociation between functional attractiveness and residential vitality, giving the framework a diagnostic value for spatial equity.

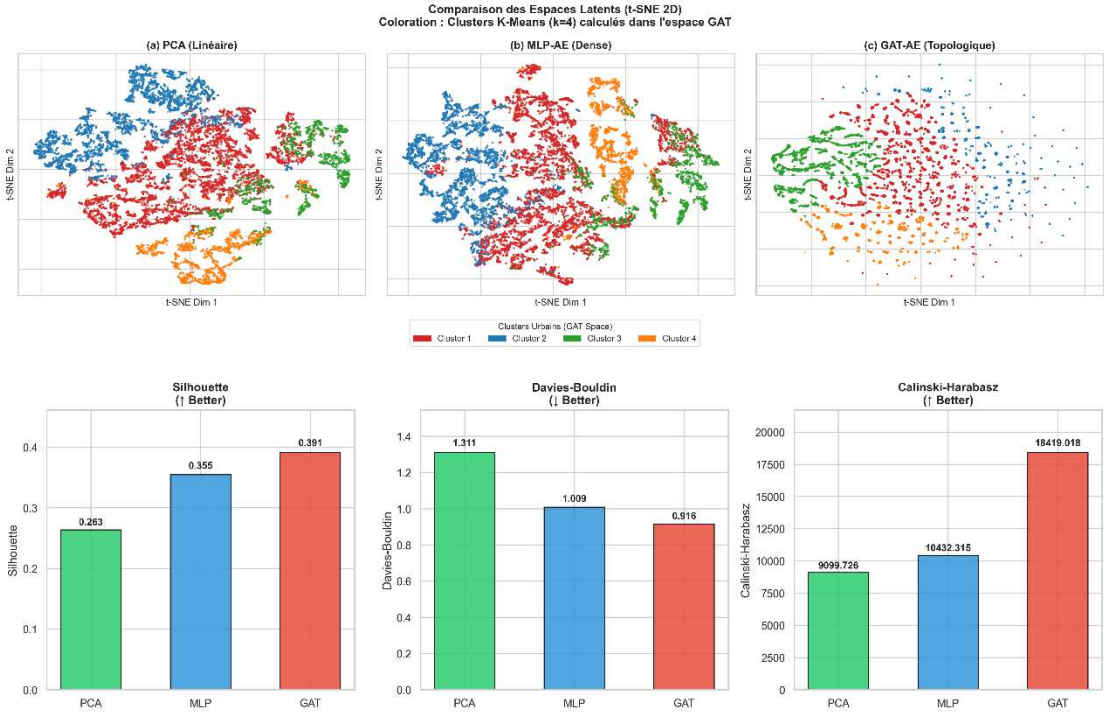
Several limitations qualify these findings and chart future work. The analysis is cross-sectional and cannot capture the temporal co-evolution of infrastructure, land values, and population; the moderate magnitude of the land-value correlation indicates that market prices proxy only part of functional intensity; and the single-region design calls for replication across contrasting metropolitan contexts. Extending the graph with temporal mobility flows and the human-centered node attributes outlined in the discussion (resident activity, demographic trajectories, accessibility to amenities) would turn the proposed framework into a longitudinal observatory of centrality, capable of informing master-plan revisions and transit-oriented development policies where they are most needed.

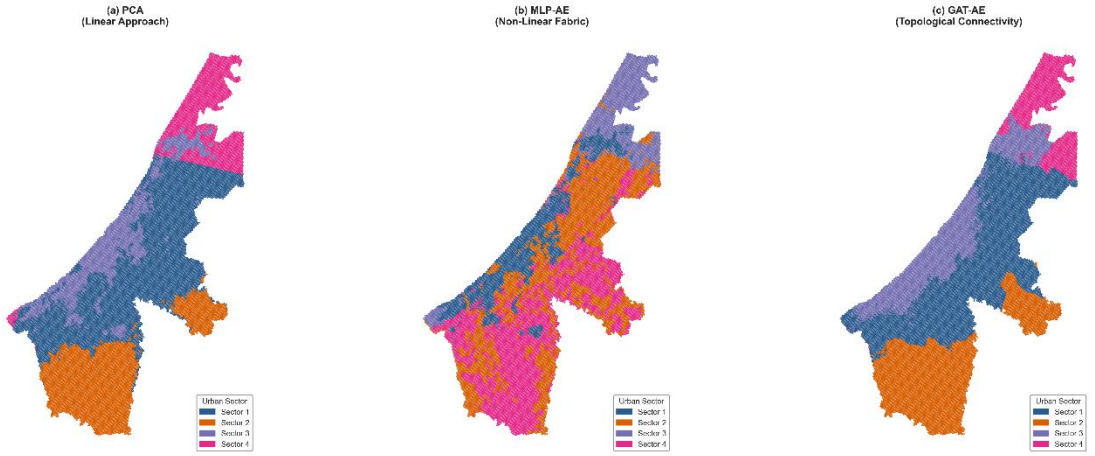
Appendix 1 :



Appendix 1 Variance explained per DIM of the latent space

Appendix 2 .





Appendix 3 .

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Conflict of Interest: The authors declare that they have no competing interests.

Data Availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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