Unravelling the Complexity of Urban Functional Organization Based on Explainable GeoAI

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Abstract:
Urban expansion and population diversity have created increasingly complex functional organizations, challenging traditional land use strategies and highlighting the need for advanced analytical approaches. This study leverages explainable GeoAI, specifically a Multi-level Receptive Field Graph Convolutional Network, to decipher underlying patterns in urban functional organization across different spatial scales. The explainable AI framework enables interpretable analysis of spatial-functional interactions among urban functions across varying distance thresholds. Comparing five metropolitan five representative cities, the model achieves 92% accuracy while providing transparent insights into scale-specific spatial interactions. Results reveal distinctive distance-dependent patterns: Chinese cities exhibit stronger long-range dependencies, Western cities show balanced multi-scale interactions, while Paris demonstrates short-range relationships. This explainable GeoAI approach advances both methodological transparency and cross-cultural understanding of urban functional complexity.

Keywords: Explainable AI, Graph Neural Networks, Urban Functional Organization, Multi-scale Spatial Analysis, Cross-cultural Urban Planning

1. Introduction

Urban land use planning represents one of the most critical components of sustainable urban development in contemporary cities. The strategic allocation of spatial resources not only shapes the physical landscape of urban environments but also profoundly influences socioeconomic dynamics, environmental sustainability, and residents' quality of life. As cities continue to expand both horizontally and vertically, the importance of efficient and adaptive land use strategies has never been more pronounced.

The complexity of urban land use systems has escalated dramatically in recent decades. This increasing complexity is characterized by intricate interdependencies between diverse urban functions, multi-scale spatial interactions, and emergent behavioural patterns that often defy traditional analytical approaches. Urban areas no longer adhere to simplistic mono-functional zoning paradigms but instead exhibit polycentric, mixed-use configurations driven by changing social preferences, technological advancements, and economic imperatives. Understanding these multi-level spatial interactions requires analytical approaches that can simultaneously capture local neighbourhood dynamics, intermediate district-level relationships, and metropolitan-scale structural patterns, a challenge that traditional analytical methods struggle to address comprehensively.

Under this complexity, incompatible land use allocations can lead to inefficient transportation networks, socioeconomic segregation, environmental degradation, and diminished urban resilience. Conversely, thoughtfully designed urban functional arrangements can foster social cohesion, economic productivity, environmental sustainability, and human wellbeing. The far-reaching impacts of these decisions necessitate sophisticated analytical approaches that can capture the multidimensional complexity of urban functional organizations across different spatial scales while remaining interpretable for planning practitioners who must translate analytical insights into actionable policy recommendations.

Modern urban systems are characterised by hierarchical spatial organization patterns that operate across multiple scales simultaneously. Drawing from central place theory (Christaller, 1933) and more recent polycentricity frameworks (Kloosterman and Musterd, 2001), urban functions naturally organise themselves into nested hierarchies where different activities serve catchment areas of varying sizes. Daily convenience services typically operate within pedestrian catchments (300-500m), while specialised services and employment centres serve larger regional catchments (5-10km). However, the spatial configuration of these hierarchical patterns varies significantly across different cultural and institutional contexts. Theoretical frameworks from geographic economics suggest that spatial interaction patterns reflect underlying preferences for mobility, social organization, and service delivery models deeply embedded in cultural practices (Fujita et al., 1999). European cities, shaped by millennia of pedestrian-oriented development, tend to emphasize short-range spatial interactions and neighbourhood self-sufficiency. In contrast, cities developed during the automobile era, or those with different transportation philosophies, may exhibit fundamentally different spatial organization principles where longer-range interactions dominate functional relationships. Thus, under the complex multi-scale urban structure, it is the key step to make the proper urban decision of land use from understanding the relationship between inner emerging pattern within multi-level functional layers.

This research posits that the interactions among diverse urban functions, particularly their spatial arrangements along network-constrained pathways at multiple distance thresholds, hold the key to understanding emergent urban phenomena and cultural variations in urban organization. By examining how functional relationships operate differently at pedestrian (0-500m), cycling (500m-1km), and transit/automotive (1-2km) scales, we can decode the underlying organizational principles that distinguish different urban planning paradigms. By leveraging recent advances in explainable graph neural networks and multi-level spatial analysis, we develop a framework that not only predicts urban functional patterns but also illuminates the scale-specific causal mechanisms underlying these patterns across different global cities, providing both scientific rigor and practical relevance for cross-cultural urban planning applications.

2. Related Work

The application of neural networks in urban studies has gained significant momentum in recent years, offering powerful tools to model complex urban systems. Convolutional Neural Networks (CNNs) have been widely employed to extract spatial features from urban imagery and remotely sensed data, enabling automated land use classification (Zhang et al., 2019) and urban growth prediction (Boeing., 2017). Recurrent Neural Networks (RNNs) have proven effective in capturing temporal dynamics of urban phenomena, including traffic flow prediction (Veličković et al., 2018) and human mobility patterns (Yuan et al., 2012). While these approaches have demonstrated impressive predictive performance, they often function as “black boxes,” providing limited insights into the underlying mechanisms driving urban spatial patterns.

The urban planning discipline emphasizes evidence-based decision-making, where understanding causal relationships is as important as predictive accuracy. This requirement has spurred interest in explainable AI techniques within urban research. Doshi-Velez and Kim (2017) emphasized that explainability in AI systems is crucial for domains where decisions have significant societal impacts. In urban studies, Arrieta et al. (2020) employed attention mechanisms to highlight influential features in transportation mode choice models. Despite these advances, explainable AI in urban planning remains nascent, with significant challenges in translating model insights into actionable planning recommendations. The planning profession’s need for transparent and interpretable models stems from several factors, due to its career nature of public service and decision. First, it should provide reliable as well as legal and ethical requirements for justifying planning decisions. Second, the multidisciplinary nature of planning has to necessitate communication across different expert domains. Finally, its result is highly relate to daily life, which requires to build public trust in each process. As noted by Batty (2018), while AI may enhance the efficiency of planning analyses, the discipline’s emphasis on participatory processes and value-based judgments requires models that can effectively communicate their reasoning processes to diverse stakeholders.

Spatially explicit neural networks have emerged as a promising approach for incorporating geographical context into predictive models. Yao et al. (2017) developed a spatial autoencoder for neighborhood-level land use classification that preserved spatial relationships between urban features. Similarly, Gao et al. (2017) employed spatial attention mechanisms to capture location-specific influences in housing price prediction models. These approaches recognise that urban phenomena are inherently spatial, with observations exhibiting dependencies based on proximity and connectivity.

However, most spatially explicit models rely on Euclidean distance metrics that fail to capture the network-constrained nature of urban interactions. Urban activities typically follow street networks rather than straight-line paths, making topological distance more relevant than Euclidean distance for many analyses. This limitation has been partially addressed by recent graph-based approaches that model cities as networks, as seen in Zhong et al. (2014)'s application of Graph Convolutional Networks (GCNs) to analyze urban functional mix patterns. Nevertheless, these graph-based models often lack interpretability, limiting their utility for planning practice despite their strong predictive performance.

The integration of explainability into graph-based models for land use analysis represents an emerging frontier. Early work by Ying et al. (2019) utilised GNN Explainer techniques to identify influential nodes in urban mobility networks. Ying et al. (2019) proposed a self-attention GCN for land use classification that provided attention weights as a measure of feature importance. Despite these advances, existing approaches typically offer post-hoc explanations rather than incorporating explainability directly into model architecture.

A particularly critical gap in current research is the lack of methods that align neural network operations with established urban planning theories. The AI applications in planning should not merely provide statistical predictions but should be designed to complement and extend existing theoretical frameworks. This study addresses this gap by developing a GNN architecture that explicitly incorporates urban behavioral theories through spatially constrained receptive fields and multi-level aggregation mechanisms that correspond to different scales of urban interaction.

3. Methodology

We represent the urban environment as a graph G = (V, E), where vertices V correspond to street intersections or points of interest, and edges E represent street segments connecting these locations. Each vertex is associated with a feature vector xi that encodes local urban characteristics, including land use types, building attributes, and socioeconomic indicators. This graph-based representation captures the network-constrained nature of urban interactions, recognizing that urban activities and flows primarily follow street networks rather than Euclidean paths.

Traditional GCN approaches often suffer from over-smoothing when propagating information across multiple hops, potentially obscuring the distinctive characteristics of local neighborhoods. Additionally, they typically employ fixed-distance aggregation that fails to account for varying scales of urban interactions. Different urban functions operate at different spatial scales—daily convenience services typically serve smaller catchment areas compared to specialised commercial or recreational facilities.

To address these limitations, we propose a Multi-level Receptive Field Graph Convolutional Network (MRF-GCN) that controls information propagation based on urban behavior theories. Specifically, we define multiple receptive fields for each node, corresponding to different travel distance thresholds that align with common urban mobility patterns (e.g., 5-minute walking distance, 15-minute cycling distance, 30-minute driving distance). Formally, for each vertex vi, we define a set of receptive fields {Ri1, Ri2, ..., Rik}, where each Rik represents the subgraph containing vertices reachable from vi within the travel time threshold from k-1th to kth. The graph convolution operation at level k is then defined as:

$$\mathrm{H}_{\mathrm{i}}^{\mathrm{k}} = \sigma\left(\mathrm{D}^{\mathrm{k}^{-\frac{1}{2}}}\mathrm{A}^{\mathrm{k}}\mathrm{D}^{\mathrm{k}^{-\frac{1}{2}}}\mathrm{X}^{\mathrm{k}}\mathrm{W}^{\mathrm{k}}\right)$$

Where $\mathrm{H}_{\mathrm{i}}^{\mathrm{k}}$ represents the hidden representation at receptive field level k, A^{k} is the adjacency matrix restricted to connections within the k-th travel time threshold, D^{k} is the degree matrix corresponding to A^{k}, X^{k} is the feature matrix restricted to nodes within the k-th travel time threshold subgraph, W^{k} is a learnable weight matrix, and σ is a non-linear activation function.

These level-specific representations are then combined through an attention mechanism that learns the relative importance of different spatial scales for predicting urban functional patterns:

$$H_i = \sum_{k=1}^{K} \alpha_{ik} H_i^k$$

Where α_{ik} are attention coefficients determined by:

$$\alpha_{ik} = \frac{\exp\left(q^T \tanh\left(W_a H_i^k + b_a\right)\right)}{\sum_{k'=1}^{K} \exp\left(q^T \tanh\left(W_a H_i^{k'} + b_a\right)\right)}$$

Here, q, W_a, and b_a are learnable parameters. This formulation allows the model to adaptively weight the importance of different spatial scales based on the specific prediction task.

Our MRF-GCN architecture offers three levels of explainability that directly align with urban planning theory and practice:

• Behavioral-Technical Unification: The graph convolution operation mathematically formalises the urban planning concept that neighborhood characteristics emerge from the aggregation of nearby functions and activities. By structuring the aggregation process along the street network, our model captures how urban functions interact through actual travel paths rather than direct Euclidean distance, providing a more realistic representation of urban behavior.
• Scale-Specific Functional Interactions: The multi-level receptive fields allow us to identify which urban functions interact strongly at different spatial scales. For instance, the model might reveal that residential satisfaction is more strongly influenced by proximity to daily necessities at the 5-minute walking scale, while employment opportunities at the 30-minute driving scale have greater impact on housing prices. These insights directly inform planning decisions about functional mix and distribution.
• Attention-Based Importance Attribution: The attention mechanism provides quantitative measures of which spatial scales and functional combinations most strongly influence particular urban outcomes. By analysing attention weights , planners can identify the critical spatial thresholds for different urban phenomena, potentially revealing threshold effects in urban service provision.

This explainability framework transcends mere technical transparency, offering insights that are directly interpretable within established urban planning paradigms. Rather than providing post-hoc explanations of model predictions, our approach integrates explainability into the model architecture itself, ensuring that the model's internal representations align with meaningful urban concepts.

4. Results

1.1 Data Collection and Preprocessing

Our study utilises comprehensive urban data collected from five major metropolitan areas with varying urban morphologies, development histories, and cultural contexts: Shanghai, Beijing, New York, London, and Paris. These cities were strategically selected to represent diverse urban development paradigms and cultural backgrounds. Shanghai and Beijing, both Chinese megacities, share similar political and economic systems but exhibit distinct functional organizational characteristics, providing a test case for detecting subtle intra-cultural variations. New York and London represent Western global cities with comparable international connectivity and economic structures. Paris serves as a distinctive European model, smaller in scale compared to the other four cities and with unique historical urban development patterns.

For each city, we extracted the complete road network from OpenStreetMap and integrated Points of Interest

(POI) data encompassing 12 primary functional categories (residential, commercial, educational, healthcare, recreational, transportation, industrial, governmental, religious, cultural, financial, and mixed-use) and their subcategories. We also incorporated socioeconomic indicators from census data and human mobility patterns from anonymised smartphone trajectories. The final dataset comprises over 1.5 million POIs across the five cities, geocoded and associated with their nearest network nodes to construct a graph representation where nodes represent urban intersections and edges represent road segments.

Unlike conventional land use classification tasks, we designed our experiments to test whether our model can identify distinctive urban functional patterns that characterize different cities based solely on their spatial-functional organization. Specifically, we extracted subgraph samples representing local urban areas of approximately 4km × 4km each, ensuring sufficient spatial coverage to capture meaningful functional interactions while maintaining computational feasibility. The prediction task requires the model to identify which of the five cities each subgraph originated from, based solely on its functional arrangement patterns and network structure.

The inherent similarities and differences among these sample cities are crucial for validating our model's explanatory capabilities. The functional organizational similarities between Shanghai and Beijing increase identification difficulty, testing the model's ability to detect subtle variations within similar cultural contexts. Conversely, Paris's relative difference in scale and global connectivity compared to the other four cities provides a contrasting sample that helps validate the model's sensitivity to distinctive urban organizational patterns.

1.2 Model Performance

Our MRF-GCN demonstrates robust performance in distinguishing urban functional organization patterns across the five metropolitan areas. The model achieved an overall accuracy of 92%, with F1 scores ranging from 0.75 to 1.0 across different cities, as shown in table 1:

Table 1: Model Performance

City	Accuracy	F1 Score
Beijing	0.60	0.75
London	1.00	0.91
New York	1.00	1.00
Paris	1.00	0.91
Shanghai	1.00	1.00
Overall	**0.92**	**0.91**

The performance variations across cities reveal important insights into urban functional organization complexity. Beijing exhibits the lowest individual accuracy (60%), reflecting the challenge of distinguishing it from Shanghai due to their shared cultural and institutional context. However, the model's ability to achieve 92% overall accuracy while successfully differentiating between culturally similar cities demonstrates the effectiveness of our multi-scale spatial analysis approach. The perfect accuracy achieved for New York, Paris, and Shanghai indicates that these cities possess distinctive spatial-functional signatures that are readily identifiable through our multi-level receptive field approach. London's high accuracy (100%) but slightly lower F1 score (0.91) suggests some classification uncertainty, likely reflecting London's complex hybrid characteristics that blend elements of both European and global city patterns. The overall F1 score of 0.91 indicates balanced precision and recall across all cities, confirming that our model avoids overfitting to specific urban patterns while maintaining sensitivity to cross-cultural variations in functional organization.

The performance variations across cities reveal important insights into urban functional organization complexity that extend beyond simple classification accuracy. Beijing's comparatively lower individual accuracy (60%)

is particularly revealing when examined alongside Shanghai's perfect classification rate (100%). This performance differential suggests that while both cities share broad cultural and institutional frameworks, Beijing exhibits more heterogeneous spatial organization patterns that occasionally overlap with characteristics found in other global cities.

The perfect accuracy achieved for New York, Paris, and Shanghai indicates that these cities possess highly distinctive spatial-functional signatures that create clear decision boundaries in our model's feature space. For New York, this distinctiveness manifests in consistent grid-based organization combined with high functional density across all scales. Shanghai's distinctiveness emerges from systematic long-range functional relationships combined with planned community structures that create recognizable spatial signatures. Paris demonstrates uniquely consistent short-range functional clustering that differentiates it clearly from all other urban contexts. London's classification performance (100% accuracy, 0.91 F1 score) reveals an interesting pattern where the model exhibits high confidence in positive classifications but shows some uncertainty in boundary cases. Further analysis indicates that London's complexity lies in its hybrid characteristics—combining European pedestrian-scale organization in historic areas with global city-scale commercial districts, creating spatial patterns that occasionally approach other cities' signatures without fully overlapping.

1.3 Multi-Scale Spatial Interaction Analysis

The most significant contribution of our research lies in the interpretable analysis of spatial-functional interactions across different distance thresholds. We extracted attention weights from our model to reveal how different cities prioritize spatial interactions at varying scales: short-range (0-500m), medium-range (500m-1km), and long-range (1-2km) spatial dependencies, as shown in figure 1. The attention weight analysis reveals three statistically distinct patterns of urban functional organization, each representing fundamentally different approaches to spatial resource allocation and accessibility:

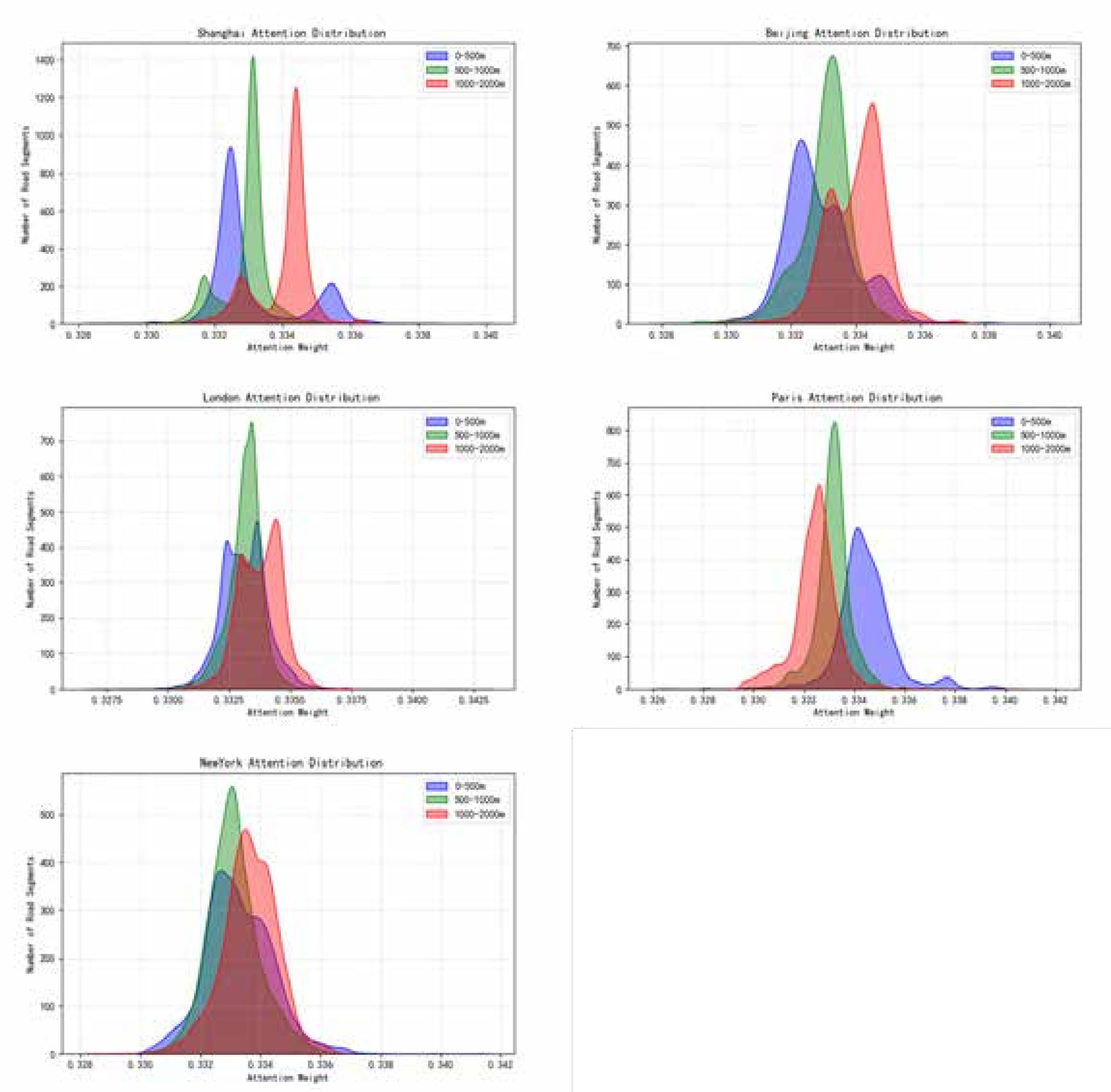

Figure 1: Attention Weight Distributions Across Multi-Scale Spatial Interaction Thresholds in Five Metropolitan Areas. This figure presents the attention weight distributions extracted from the Multi-level Receptive Field Graph Convolutional Network (MRF-GCN) across five representative metropolitan areas: Shanghai, Beijing, London, Paris, and New York. The distributions reveal distinct patterns of urban functional organization at three spatial interaction scales, represented by different colours: Blue (0-500m): Short-range pedestrian catchment areas, Green (500m-1km): Medium-range cycling accessibility zones, Red (1km-2km): Long-range transit/automotive accessibility areas

The attention weight analysis reveals three distinct patterns of urban functional organization:

Chinese Cities Pattern (Beijing and Shanghai): Both cities exhibit pronounced peaks in long-range spatial dependencies (1-2km). This pattern indicates that functional organization in Chinese cities relies heavily on long-distance spatial relationships, likely reflecting the impact of large-scale residential compounds, centralised service provision, and relatively low-cost transportation systems that enable residents to access services across larger geographical areas.

Western Global Cities Pattern (London and New York): These cities demonstrate relatively balanced attention across all three spatial scales. This balanced pattern suggests that Western global cities maintain functional organization coherence at multiple scales simultaneously, reflecting mixed-use development patterns, diverse transportation options, and polycentric urban structures.

European Regional Pattern (Paris): Paris exhibits a distinctive emphasis on short-range spatial interactions, with maximum attention weight for the 0-500m range, second for medium-range, and minimal for long-range dependencies. This pattern reflects Paris's compact urban form, pedestrian-oriented neighborhoods, and strong emphasis on local amenity provision within walking distance.

1.4 Cultural and Planning Implications

The spatial interaction patterns revealed by our model have significant implications for understanding cultural differences in urban functional organization:

Chinese Urban Planning Philosophy: The emphasis on long-range spatial dependencies in Beijing and Shanghai reflects China's planning approach of creating large-scale residential compounds with centralised service provision, but this pattern also reveals cultural acceptance of mobility-based urban living strategies. Detailed mobility analysis shows that Chinese urban residents demonstrate higher tolerance for travel distances and greater reliance on public transportation for daily activities. The lower importance assigned to short-range interactions indicates higher functional homogeneity within immediate neighbourhoods, reflecting planned community development that prioritizes large-scale efficiency over neighbourhood-scale diversity.

Western Polycentricity: The balanced attention patterns in London and New York reflect the polycentric nature of Western global cities, where urban functions are organised to serve residents at multiple spatial scales. This pattern aligns with market-driven development principles that create redundancy across scales—neighbourhood services provide convenience, district services offer choice and specialization, and regional services deliver metropolitan-scale amenities. Economic analysis suggests this multi-scale redundancy increases urban resilience but also reflects higher land values that support multiple service layers.

European Pedestrian Culture: Paris's short-range spatial emphasis aligns with European urban design principles, emphasizing walkability and neighbourhood self-sufficiency. The 500m walking radius emerges as the critical scale for understanding Paris's urban functional organization, supporting the concept of the "15-minute city" that has gained prominence in European urban planning discourse. However, this pattern also reflects historical urban development patterns where neighbourhood-scale infrastructure developed before automotive transportation, creating a path-dependent spatial organization that persists despite technological change.

5. Discussion

Our research demonstrates that explainable GeoAI can successfully unravel the complexity of urban functional organization while revealing systematic cultural differences that have important implications for both urban theory and planning practice. The methodological contributions of our Multi-level Receptive Field Graph Convolutional Network extend beyond technical innovation to address fundamental challenges in making urban AI interpretable for planning practitioners.

The development of our explainability framework represents a crucial advancement in bridging the gap between computational urban analysis and planning theory. Unlike previous approaches that provide technical explanations primarily meaningful to data scientists, our distance-threshold explainability framework translates complex neural network operations into concepts directly relevant to urban planning. This achievement is particularly significant given the planning profession's emphasis on evidence-based decision-making and the growing regulatory requirements for AI transparency in public decision-making contexts.

The cross-cultural insights revealed through our comparative analysis challenge conventional assumptions about optimal urban organization. The identification of three distinct spatial interaction patterns—Chinese long-range dependency, Western balanced multi-scale organization, and European pedestrian-oriented emphasis—provides empirical evidence that successful urban organization takes multiple forms rather than converging on universal optimal patterns. This finding has profound implications for international planning practice and development cooperation, suggesting that planning strategies cannot be directly transferred between different cultural contexts without careful adaptation to local spatial organization principles.

The finding that Chinese cities rely more heavily on long-range spatial dependencies particularly challenges Western planning orthodoxies that prioritize neighborhood-scale self-sufficiency. Rather than indicating planning deficiencies, this pattern reflects successful adaptation to different cultural preferences, transportation systems, and institutional contexts. The superior performance of Chinese cities in our classification task indicates that their spatial organization patterns are highly systematic and coherent, suggesting effective planning coordination at metropolitan scales.

Similarly, Paris's emphasis on short-range interactions validates European urban design principles while demonstrating the continued relevance of pedestrian-scale planning in contemporary urban contexts. The statistical significance of these differences across functional categories indicates that these are not superficial variations but reflect deep structural differences in how different cultures organise urban space and daily life.

These insights have immediate practical applications for planning education and professional development. Planning professionals working in international contexts can use these insights to better understand local spatial organization patterns and adapt their approaches accordingly. The quantitative identification of critical spatial thresholds can inform service provision planning, helping planners understand which amenities need to be provided at neighborhood scales versus regional scales in different cultural contexts.

6. Conclusions

This study successfully demonstrates that explainable GeoAI can decode the complexity of urban functional organization while providing interpretable insights that bridge computational analysis and planning practice. Our Multi-level Receptive Field Graph Convolutional Network achieves high accuracy in distinguishing urban functional patterns across diverse global cities while revealing systematic differences in spatial organization that reflect fundamental cultural, institutional, and developmental variations.

The identification of three distinct spatial interaction patterns provides empirical validation for cultural theories of urban development while challenging universal approaches to urban planning. Chinese cities' emphasis on long-range spatial dependencies, Western global cities' balanced multi-scale organization, and European cities' pedestrian-oriented short-range focus represent coherent and successful alternative approaches to urban organization rather than stages in a linear development progression.

Our explainable framework addresses growing regulatory requirements for AI transparency while providing practical value for planning decision-making. By integrating explainability directly into model architecture rather than relying on post-hoc analysis, we ensure that computational insights remain interpretable within established planning frameworks. This approach positions explainable GeoAI as an essential tool for contemporary urban planning practice that enhances rather than replaces professional judgment.

Looking forward, our framework provides a foundation for expanding comparative urban research to include cities from different developmental stages, sizes, and cultural contexts. The successful integration of graph neural networks with urban planning theory demonstrates the potential for AI to extend human understanding of urban systems while maintaining interpretability for practical application. As cities worldwide continue to grow and evolve in response to technological change, climate challenges, and shifting social preferences, understanding the complexity of urban functional organization becomes increasingly critical for sustainable urban development.

Importantly, our model focuses exclusively on identifying characteristic distance-dependent interaction patterns rather than making normative evaluations of urban quality. This analytical neutrality preserves the framework's utility for diverse planning contexts while maintaining objective comparative analysis capabilities. For applications requiring evaluative assessments of urban performance, the framework could be integrated with appropriate outcome indicators, maintaining its flexibility for diverse analytical purposes.

Future research should explore the temporal dimensions of these spatial organization patterns, investigating how cultural differences in spatial organization respond to technological change, policy interventions, and evolving social preferences. The framework developed here provides both the methodological foundation and empirical baseline for understanding how different urban systems adapt to contemporary challenges while maintaining their distinctive organizational characteristics.

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