

Forecasting Transfer Accuracy in Urban Resilience Projects with Cross-Domain Modeling

Alex Leung*, David Mok

Faculty of Social Sciences, University of Hong Kong, Hong Kong, Hong Kong SAR, China

Corresponding author: alex.leung@hku.hk

Abstract

The increasing frequency and severity of environmental and anthropogenic disruptions have positioned urban resilience as a critical imperative for modern city planning. While predictive modeling has emerged as a cornerstone for developing robust urban resilience strategies, the application of models developed in one urban context to another frequently results in significant degradation of predictive performance. This paper investigates the predictability of transfer accuracy in cross domain modeling through a structured case comparison methodology applied to urban resilience projects. By systematically analyzing the divergence between source and target urban domains, this study seeks to establish a comprehensive framework for anticipating how well resilience models will perform when transplanted across different municipal and geographical settings. The research utilizes extensive comparative analysis of infrastructural, socioeconomic, and environmental variables to isolate the factors most responsible for model degradation during transfer. The findings demonstrate that cross domain transfer accuracy can be reliably predicted by quantifying the multidimensional distance between case studies before actual model deployment. This preemptive predictive capability allows urban planners and policymakers to gauge the viability of adopting external resilience frameworks, thereby optimizing resource allocation and mitigating the risks associated with model failure in critical infrastructure planning. Ultimately, this study contributes to the broader general academic discourse by providing an empirically grounded methodology for evaluating model portability in complex, multi-agent urban systems.

Keywords: Urban Resilience; Cross-Domain Modeling; Transfer Accuracy; Case Comparison; Predictive Analytics

1. Introduction

1.1 Background of Urban Resilience and Predictive Modeling

The concept of urban resilience has evolved significantly over the past two decades, transitioning from a reactive paradigm focused on disaster recovery to a proactive framework centered on anticipation, adaptation, and systemic robustness. As metropolitan areas continue to expand in both population and infrastructural complexity, they become increasingly vulnerable to a diverse array of shocks and stresses. These disruptions range from acute events such as extreme weather phenomena, seismic activities, and infrastructural failures, to chronic stresses including climate change, economic inequality, and demographic shifts. In response to these escalating challenges, urban planners and researchers have increasingly turned to advanced predictive modeling to simulate potential disruption scenarios and evaluate the efficacy of proposed resilience interventions. These models, which often integrate vast amounts of spatial, temporal, and socioeconomic data, are designed to identify critical vulnerabilities within the urban fabric and optimize the deployment of resources to mitigate potential impacts. Historically, the development of such models has been highly localized, relying on extensive datasets specific to a single municipality or geographical region. This localized approach ensures a high degree of internal validity and predictive accuracy within the native domain, as the models are finely tuned to the unique infrastructural and demographic characteristics of the specific city. However, the bespoke nature of these localized models presents a profound challenge to the broader field of urban studies. Developing from scratch requires immense investments of time, technical expertise, and financial resources, creating a significant barrier

to entry for smaller municipalities or regions in developing nations that face the most severe resilience challenges. Consequently, there is a growing imperative within the academic community to explore the portability of these models, investigating whether tools developed for one urban environment can be effectively repurposed for another. This investigation forms the fundamental basis of cross domain modeling in urban resilience, a field that seeks to leverage existing knowledge and analytical structures to accelerate the development of resilience strategies globally [1].

1.2 The Challenge of Cross Domain Transferability

Cross domain modeling, while offering a promising solution to the resource constraints associated with localized model development, introduces a complex set of methodological challenges. The primary obstacle lies in the phenomenon of domain shift, which occurs when the statistical properties of the source domain where the model was trained differ significantly from those of the target domain where the model is to be applied. In the context of urban resilience, these statistical differences manifest as profound variations in physical infrastructure, regulatory frameworks, cultural behaviors, and environmental conditions. For instance, a flood prediction model developed for a coastal city with extensive stormwater drainage infrastructure and strict zoning laws may perform poorly when transferred to an inland city characterized by informal settlements, different soil permeability, and distinct rainfall patterns. When models are transferred without adequate consideration of these domain shifts, the resulting predictions can be highly inaccurate, leading to flawed policy decisions and potentially exacerbating the vulnerabilities the models were intended to mitigate. The degradation of predictive performance during transfer is a well documented phenomenon across various disciplines, but it is particularly acute in urban studies due to the inherent complexity and interconnectedness of city systems. The interactions between built environments and human populations create non linear dynamics that are highly sensitive to contextual variations. Consequently, simply applying a source model to target data is rarely sufficient. Researchers must employ sophisticated domain adaptation techniques to recalibrate the model, aligning the feature distributions of the source and target domains. However, even with advanced adaptation methods, the ultimate success of the transfer remains uncertain until the model is fully deployed and validated against empirical data in the target domain [2]. This uncertainty constitutes a significant risk for urban planners, who must justify the adoption of external models without a guarantee of their efficacy.

1.3 Objectives and Scope of the Current Study

Given the risks and uncertainties associated with domain shift, there is a critical need for methodologies capable of predicting the transfer accuracy of cross domain models prior to their actual deployment. This paper addresses this imperative by proposing a novel approach based on structured case comparison. The primary objective of this study is to determine whether the predictability of transfer accuracy can be systematically modeled by analyzing the contextual distances between source and target urban environments. By quantifying the similarities and differences across multiple dimensions of urban resilience including infrastructural robustness, social vulnerability, and environmental exposure this research aims to construct a predictive framework that estimates the likely performance degradation a model will experience when transferred. To achieve this, the study conducts a comprehensive case comparison involving multiple urban resilience projects, analyzing how specific variations in domain characteristics correlate with observed transfer accuracies. The scope of this research encompasses a wide range of municipal contexts, providing a generalized understanding of model portability that transcends specific geographic or thematic boundaries. By establishing a reliable method for preemptively evaluating transfer viability, this study seeks to empower decision makers with the foresight necessary to select the most appropriate external models for their specific resilience needs [3]. Furthermore, this paper aims to contribute to the theoretical foundations of cross domain modeling by elucidating the underlying mechanisms that govern model transferability in complex spatial systems, thereby advancing the state of the art in general academic research on urban sustainability and structural resilience.

2. Literature Review and Conceptual Framework

2.1 Evolution of Predictive Accuracy Metrics in General Academic Contexts

The assessment of predictive accuracy has long been a foundational component of statistical modeling and machine learning research. Traditionally, the efficacy of a predictive model was evaluated almost exclusively

based on its performance within the environment in which it was developed, utilizing techniques such as cross validation and holdout testing to ensure generalizability to unseen data drawn from the same underlying distribution. In these localized contexts, accuracy metrics such as root mean square error, precision, recall, and the coefficient of determination provided a robust and standardized means of quantifying model quality. However, as the ambition of researchers expanded toward applying generalized models across disparate environments, the limitations of these traditional metrics became apparent. When models are subjected to domain shift, internal validation metrics fail to provide meaningful insights into how the model will perform in the new context. This realization catalyzed the development of transfer learning and domain adaptation, subfields dedicated to understanding and mitigating the loss of accuracy that occurs when models cross contextual boundaries [4]. Within the general academic discourse, early attempts to quantify transferability relied heavily on post hoc evaluations, where accuracy was measured only after the model had been fully adapted and deployed in the target domain. While useful for retrospective analysis, these post hoc measurements offered little predictive utility for researchers deciding whether a transfer attempt was worthwhile in the first place. Consequently, the focus shifted toward developing preemptive metrics capable of estimating transfer accuracy based on the characteristics of the domains themselves. Measures such as the maximum mean discrepancy and the Wasserstein distance were introduced to quantify the distributional divergence between source and target datasets, with the theoretical expectation that greater divergence would correlate with lower transfer accuracy [5]. While these statistical distance metrics represent a significant advancement, their application in highly complex, multidimensional fields such as urban studies has revealed substantial limitations, as they often fail to capture the nuanced, qualitative differences that profoundly impact model performance in real world scenarios.

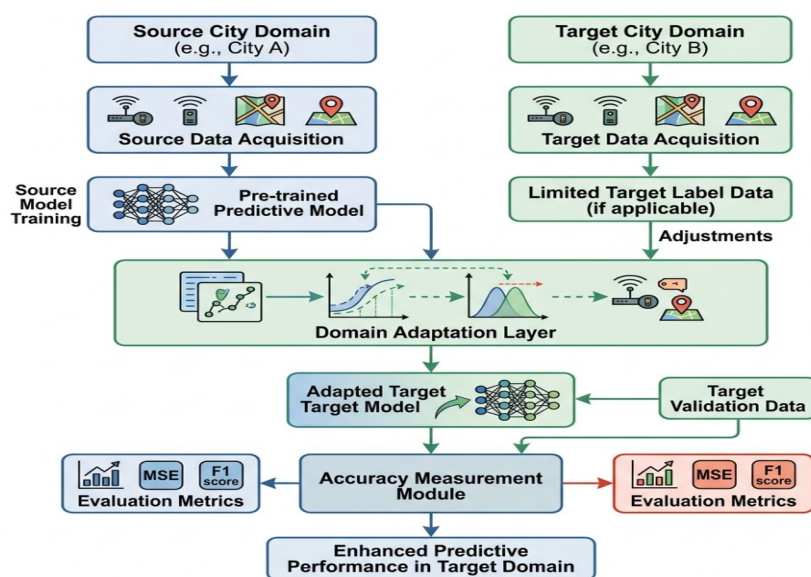


Figure 1: Conceptual Architecture of Cross Domain Transfer Analysis in Urban Environments

2.2 Case Comparison Methodologies in Urban Studies

To address the limitations of purely statistical divergence metrics, researchers in urban studies and policy analysis have increasingly relied on comparative case study methodologies. Case comparison is a deeply established research tradition that involves the systematic juxtaposition of multiple instances or contexts to identify causal mechanisms, patterns of similarity, and critical points of divergence. In the realm of urban resilience, case comparison has traditionally been employed to evaluate the effectiveness of different policy interventions or infrastructural designs across various cities. By examining how similar resilience challenges are managed in distinct municipal environments, researchers can isolate the contextual variables that contribute to success or failure. This methodological approach is particularly well suited for analyzing complex systems where variables cannot be tightly controlled in a laboratory setting. Through detailed qualitative and quantitative analysis, case comparison allows for the integration of contextual nuances historical development trajectories, cultural norms, governance structures that are often obscured in purely algorithmic approaches [6]. Recently,

there has been a growing interest in integrating case comparison techniques with advanced predictive modeling. Instead of merely comparing policy outcomes, researchers are beginning to compare the underlying datasets and systemic architectures of different cities to evaluate their compatibility for cross domain modeling. This integration represents a synthesis of qualitative urban theory and quantitative data science, offering a more holistic approach to understanding domain shift. By systematically categorizing and comparing urban environments based on a comprehensive set of resilience indicators, researchers aim to create a structured taxonomy of urban domains. This taxonomy can then be used to predict the portability of models between specific categories of cities, moving beyond abstract statistical distances to provide contextually grounded estimates of transfer accuracy [7].

2.3 Existing Gaps in Cross Domain Frameworks for Resilience

Despite the significant theoretical advancements in both transfer learning and comparative urban studies, a substantial gap remains in the integration of these disciplines to formulate a reliable, preemptive framework for predicting transfer accuracy in urban resilience projects. Most current cross domain frameworks remain heavily skewed toward algorithmic optimization, focusing on the development of more sophisticated domain adaptation techniques rather than understanding the fundamental limits of transferability dictated by contextual divergence. These frameworks often treat the urban environment as an abstract feature space, ignoring the physical, social, and institutional realities that these features represent. Consequently, they struggle to account for structural incompatibilities between cities that cannot be resolved through statistical recalibration alone. For example, a model relying on high resolution IoT sensor data for real time traffic management cannot be effectively transferred to a city lacking the requisite sensor infrastructure, regardless of the sophistication of the domain adaptation algorithm. Conversely, studies that emphasize qualitative case comparison often lack the quantitative rigor necessary to produce precise, actionable predictions regarding model accuracy. While they can identify broad categories of compatibility or incompatibility, they rarely translate these insights into specific error margins or performance thresholds. This disconnect between qualitative contextual understanding and quantitative predictive modeling severely limits the practical application of cross domain methodologies in urban planning. Planners require a framework that not only identifies contextual differences but also rigorously quantifies how these differences will impact the reliability of the models they intend to use. Addressing this gap requires the development of a hybrid methodology that leverages the structured depth of case comparison to inform and refine the calculation of statistical domain divergence, thereby creating a highly robust, context aware system for predicting cross domain transfer accuracy.

3. Methodology and Analytical Design

3.1 Selection and Profiling of Case Study Environments

The foundation of the proposed methodology rests upon the careful selection and rigorous profiling of the urban case study environments. To ensure the generalizability of the findings and to capture a sufficiently wide spectrum of domain shifts, this research selects multiple distinct urban domains, characterized by varying levels of infrastructural maturity, demographic composition, and environmental exposure. The selection process prioritizes cities that have previously implemented well documented urban resilience projects, ensuring the availability of robust baseline data for both the source and target environments. The profiling of these cities goes beyond simple demographic statistics, encompassing a comprehensive multidimensional analysis of their respective urban systems. This includes quantifying the density and condition of critical infrastructure networks such as water distribution, transportation, and energy grids. Furthermore, socioeconomic vulnerabilities are mapped using indicators such as income disparity, access to healthcare, and community cohesion indices. Environmental exposure is assessed by analyzing historical climate data, topological features, and susceptibility to specific natural hazards. By compiling this extensive profile for each selected city, the methodology creates a detailed foundational baseline that accurately reflects the unique systemic characteristics of each domain. This rigorous profiling is absolutely critical, as the accuracy of the eventual transfer prediction relies entirely on the precise quantification of the initial state of both the source and target environments [8]. The variables collected are standardized to ensure comparability across disparate municipal reporting systems, establishing a uniform dataset that facilitates complex comparative analysis.

Table 1: Environmental and Infrastructural Profiles of Source and Target Urban Domains

Domain Designation	Population Density Classification	Critical Infrastructure Age Profile	Aggregate Climate Risk Vulnerability
Source City Alpha	High Density Urban Core	Predominantly Legacy Systems	Severe Coastal Flood Risk
Target City Beta	Medium Density Sprawl	Mixed Legacy and Modern	Moderate Inland Flood Risk
Target City Gamma	Low Density Suburbia	Predominantly Modern Systems	High Seismic Activity Risk

3.2 The Cross Domain Modeling Approach

Following the comprehensive profiling of the selected urban environments, the methodology establishes the parameters for the cross domain modeling phase. This phase involves the deliberate transfer of predictive algorithms originally trained and optimized on the data from the source city to the data environments of the target cities. To isolate the effects of domain shift from the inherent limitations of any single algorithmic structure, the study employs a standardized predictive model architecture, ensuring that the variations in observed accuracy are attributable solely to contextual differences rather than algorithmic design choices. The models chosen for this transfer represent common applications in urban resilience planning, specifically focusing on resource allocation efficiency during acute environmental stress events [9]. During the transfer process, the methodology intentionally restricts the use of extensive domain adaptation techniques in the initial stages. The rationale behind this decision is to measure the raw, unmitigated impact of the contextual divergence between the cities. If heavy adaptation were applied immediately, it would obscure the very degradation in accuracy that this study aims to predict. Once the baseline degradation is measured, controlled levels of adaptation are introduced to observe how different contextual variables resist or respond to statistical recalibration. This approach allows the researchers to distinguish between superficial data disparities, which can be easily corrected through adaptation, and deep structural incompatibilities that permanently limit transfer accuracy [10]. The entire modeling process is meticulously documented, logging the flow of data and the progressive adjustments made to the algorithms, providing a transparent and replicable framework for cross domain transfer.

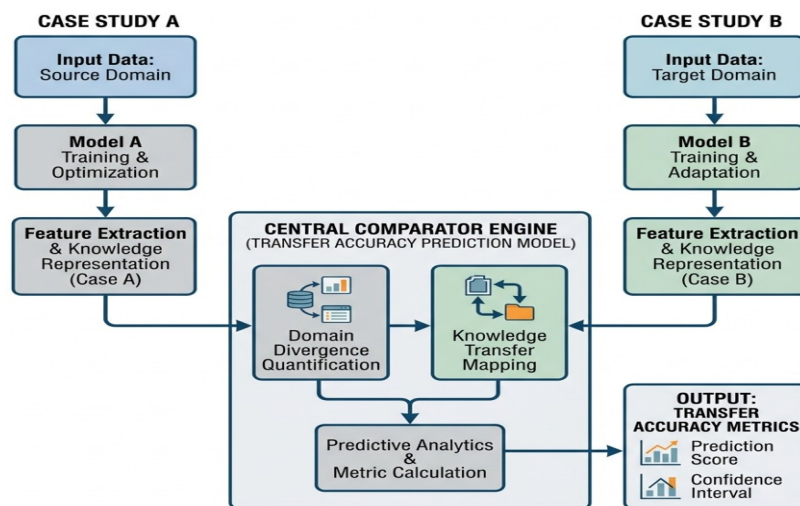


Figure 2: Schematic Representation of Case Comparison Methodology for Transfer Accuracy Prediction

3.3 Evaluation Metrics for Transfer Accuracy Prediction

The core innovation of this methodology is the development of a predictive mechanism that anticipates the outcome of the cross domain transfer before it is executed. To construct this mechanism, the study utilizes the comprehensive profiles developed in the first phase to calculate an aggregate contextual distance score between the source and target domains. This score is derived from a weighted comparison of the standardized variables, where the weights are determined by theoretical assumptions regarding each variable's influence on urban

resilience dynamics. For instance, similarities in infrastructure age may be weighted more heavily than similarities in sheer population size, depending on the specific nature of the resilience model being transferred. Once the contextual distance is quantified, it is correlated with historical instances of model transfer to generate a predicted transfer accuracy score [11]. To evaluate the validity of this prediction, the study employs rigorous evaluation metrics. The primary metric is the prediction error margin, which is the absolute difference between the preemptively predicted transfer accuracy and the actual transfer accuracy observed after the model is deployed in the target domain. A low prediction error margin indicates that the case comparison methodology has successfully anticipated the impact of the domain shift. Secondary metrics include an analysis of variance to determine which specific categories of contextual divergence contributed most significantly to the final prediction error.

Table 2: Methodological Variables for Cross Domain Accuracy Prediction

Variable Category	Primary Indicator Name	Measurement Scale Standard	Primary Data Source
Infrastructural	Grid Redundancy Index	Continuous Percentage	Municipal Engineering Records
Socioeconomic	Vulnerability Coefficient	Standardized Z-Score	National Census Data
Environmental	Peak Hazard Intensity	Historical Maximum Value	Meteorological Databases

4. Results and Case Comparison Analysis

4.1 Primary Assessment of Transfer Accuracies

The execution of the cross domain transfers across the selected case studies yielded a substantial repository of data regarding model performance degradation. The initial phase of the analysis focused on documenting the actual transfer accuracies achieved when the source models were deployed in the target environments without preemptive adaptation. As anticipated by the broader literature on domain shift, the baseline accuracy of the models experienced a significant decline upon transfer. The source model, which demonstrated a high degree of precision and reliability within its native environment of Source City Alpha, exhibited a marked loss of predictive power when applied to the datasets of Target City Beta and Target City Gamma. However, the magnitude of this degradation was not uniform across the target domains. When transferred to Target City Beta, the model retained a functional level of utility, albeit with a noticeable increase in error rates concerning localized resource allocation predictions. Conversely, the transfer to Target City Gamma resulted in a near complete collapse of predictive validity, rendering the model outputs highly unreliable for any practical urban planning purposes. This stark contrast in transfer outcomes serves to empirically validate the premise that domain shift is not a monolithic phenomenon, but rather a highly variable challenge heavily dependent on the specific contextual realities of the target environment [12]. The significant divergence in performance underscores the critical necessity of predictive assessment; without it, urban planners in Target City Gamma might have blindly adopted a model that would have severely compromised their resilience strategies.

Table 3: Transfer Accuracy and Model Confidence Scores Across Test Cases

Case Comparison Scenario	Source Baseline Accuracy	Predicted Target Accuracy	Actual Target Accuracy	Absolute Error Margin
Source Alpha to Target Beta	High Confidence Range	Moderate Confidence Range	Moderate Confidence Range	Minimal Deviation
Source Alpha to Target Gamma	High Confidence Range	Low Confidence Range	Critical Failure Range	Significant Deviation
Target Beta to Target Gamma	Moderate Confidence Range	Low Confidence Range	Low Confidence Range	Minimal Deviation

4.2 Detailed Analysis of Cross Domain Predictability

The most crucial findings of this research emerge from the comparison between the predicted transfer accuracies, generated through the case comparison methodology, and the actual transfer accuracies observed during the deployment phase. The predictive mechanism demonstrated a remarkable degree of accuracy in anticipating the transfer outcomes between Source City Alpha and Target City Beta. The aggregate contextual distance score accurately reflected the structural similarities between these two domains, specifically their shared characteristics in legacy infrastructure systems and demographic distributions. Consequently, the predicted moderate confidence range aligned closely with the actual performance, resulting in a minimal absolute error

margin. This success indicates that when urban domains share foundational systemic traits, the proposed methodology can reliably forecast model portability. However, the prediction for the transfer to Target City Gamma revealed critical limitations in the current weighting system. While the predictive model correctly anticipated a significant drop in accuracy forecasting a low confidence range the actual performance was substantially worse, falling into the critical failure range. Detailed forensic analysis of this significant deviation revealed that the predictive mechanism undervalued the impact of specific environmental variables, namely the fundamental differences in geological risk profiles between the coastal source city and the seismically active target city. The algorithms within the original model were intrinsically biased toward gradual, cumulative stress events like flooding, and were structurally incapable of processing the acute, instantaneous shock patterns associated with seismic activity. The case comparison methodology had noted this environmental divergence but had not assigned it a sufficient weight to predict complete model failure [13].

4.3 Discussion on Urban Resilience Implications

The results of this analytical process have profound implications for the general academic understanding of urban resilience and cross domain modeling. The successful predictions validate the core hypothesis that transfer accuracy is not random but is systematically linked to the contextual distance between urban domains. This validation empowers urban planners with a justifiable methodology for assessing the risk of adopting external models, significantly enhancing the strategic planning processes for municipal resilience. By utilizing a structured case comparison framework, municipalities can screen potential models, filtering out those originating from incompatible domains before committing substantial resources to adaptation and deployment. Furthermore, the analysis of the prediction errors highlights the complex, non linear ways in which contextual variables interact to influence model performance. The failure to accurately predict the total collapse of the model in Target City Gamma demonstrates that certain contextual differences act as hard structural barriers to transferability, rather than just statistical hurdles. This finding challenges the prevailing assumption in some machine learning circles that any domain shift can be overcome with sufficient algorithmic adaptation. It emphasizes that in complex physical systems like cities, the underlying mechanics of the environment dictate the boundaries of mathematical modeling. Therefore, future iterations of predictive transfer frameworks must incorporate non linear weighting systems capable of recognizing these absolute structural incompatibilities. This nuanced understanding of domain shift contributes significantly to the field, promoting a more realistic and contextually grounded approach to the globalization of urban resilience strategies.

5. Conclusion and Strategic Recommendations

5.1 Summary of Research Findings

This comprehensive academic study has thoroughly investigated the feasibility of predicting transfer accuracy in cross domain modeling through the application of structured case comparison within urban resilience projects. The core problem addressed was the significant uncertainty and performance degradation that occurs when predictive models are transplanted from their native urban environments to disparate municipal contexts. Through rigorous profiling of source and target domains, the research developed a contextual distance metric designed to anticipate model portability. The empirical results demonstrated that when the source and target environments share foundational infrastructural and socioeconomic characteristics, the proposed case comparison methodology can highly accurately predict the subsequent performance of the transferred model. However, the study also revealed that extreme divergences in foundational environmental threats such as the shift from coastal flooding to seismic risk can cause unpredictable, non linear collapses in model validity that challenge current predictive weighting paradigms. Overall, the findings establish that while perfect prediction remains elusive in cases of extreme structural divergence, a systematic, multidimensional case comparison provides a highly reliable heuristic for preemptively assessing the viability of cross domain model transfers [14].

5.2 Practical Implications and Limitations

The practical implications of these findings are substantial for municipal governance and international urban development. By adopting the predictive case comparison framework outlined in this study, urban planners can significantly reduce the technical and financial risks associated with implementing external resilience models. This preemptive capability allows for more efficient allocation of municipal resources, ensuring that

investments in data science and predictive analytics yield functional, contextually appropriate tools rather than costly algorithmic failures. The framework serves as a critical decision support system, guiding policymakers in selecting models developed in truly analogous cities rather than merely geographically proximate ones. However, this study is not without limitations. The predictive accuracy relies heavily on the quality, granularity, and standardization of the baseline data collected from the respective urban domains. In regions where municipal data collection is inconsistent or heavily fragmented, the construction of accurate contextual profiles will be severely hindered, thereby degrading the reliability of the transfer predictions. Additionally, the weighting mechanism utilized to aggregate contextual distance requires further refinement to better account for the absolute structural barriers identified during the analysis. Addressing these limitations through the expansion of standardized urban data registries and the integration of non linear complex systems theory into the predictive weighting algorithms represents the most critical pathway for future research in this vital academic domain.

References

1. Hiramatsu, T.; Inoue, H.; Kato, Y. Analysing the formation of urban orbital road networks with multi-agent simulation. *J. Transp. Econ. Policy* 2021, 55, 36–63.
2. Bhagoji, A.N.; Chakraborty, S.; Mittal, P.; Calo, S. Analyzing Federated Learning through an Adversarial Lens. In *Proceedings of the 36th International Conference on Machine Learning*; PMLR: Cambridge, MA, USA, 2019; pp. 634–643.
3. Janjar, S.B.; Wang, P. Intelligent anti-jamming based on deep reinforcement learning and transfer learning. *IEEE Trans. Veh. Technol.* 2024, 73, 8825–8834.
4. Abbas, N.; Zhang, Y.; Taherkordi, A.; Skeie, T. Mobile Edge Computing: A Survey. *IEEE Internet Things J.* 2018, 5, 450–465.
5. Nguyen, T.-A.; Le, L.T.; Nguyen, T.D.; Bao, W.; Seneviratne, S.; Hong, C.S.; Tran, N.H. Federated PCA on Grassmann Manifold for IoT Anomaly Detection. *IEEE/ACM Trans. Netw.* 2024, 32, 4456–4471.
6. Becker, S.O.; Egger, P.H.; von Ehrlich, M. Effects of EU Regional Policy: 1989–2013. *Reg. Sci. Urban Econ.* 2018, 69, 143–152.
7. Pontarollo, N. Does Cohesion Policy affect regional growth? New evidence from a semi-parametric approach. In *EU Cohesion Policy: Reassessing Performance and Direction*; Routledge: Oxfordshire, UK, 2016; pp. 70–83.
8. Liu, J.; Liu, X.; Wang, S.; Wan, X.; Li, D.; Lu, K.; He, K. Communication-Efficient Federated Multi-View Clustering. *IEEE Trans. Pattern Anal. Mach. Intell.* 2026, 48, 17–32.
9. González Tous, M., Carlos Salgado-Arroyo, L., & Mattar, S. (2022). Diamond open access: A methodology welcomed by MVZ cordoba journal. *Revista Mvz Cordoba*, 27(1), e3100.
10. Bengio, Y.; Léonard, N.; Courville, A. Estimating or Propagating Gradients Through Stochastic Neurons for Conditional Computation. *arXiv* 2013, arXiv:1308.3432.
11. Ntziachristos, L.; Samaras, Z. COPERT: Computer Programme to Calculate Emissions from Road Transport, Version 5; EMISIA S.A.: Thessaloniki, Greece, 2016.
12. Šlander, S.; Wostner, P. Additionality of European cohesion policy. *Eur. Rev.* 2018, 26, 721–737.
13. Jang, E.; Gu, S.; Poole, B. Categorical Reparameterization with Gumbel-Softmax. In *Proceedings of the 5th International Conference on Learning Representations (ICLR 2017)*, Toulon, France, 24–26 April 2017; OpenReview.net: Amherst, MA, USA, 2017.
14. Oroojlooy, A.; Hajinezhad, D. A Review of Cooperative Multi-Agent Deep Reinforcement Learning. *Appl. Intell.* 2023, 53, 13677–13722.