RESEARCH ARTICLE

An Interpretable Spatio-Temporal Graph Neural Framework Integrating Urban Economic Theory for Data-Driven Investment Prioritization in Regeneration

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Abstract: This study designs and implements a novel data-driven framework for dynamically mapping investment alignment in urban regeneration, bridging the gap between urban economic theory and computational planning practice. The framework integrates parcel-level microdata on ownership, land use, building characteristics, and structural condition with contextual economic, social, and morphological data, modeling the city as a dynamic, multi-scale system. Methodologically, this research advances the state-of-the-art by combining Spatio-Temporal Graph Neural Networks with Explainable AI to simultaneously capture spatial dependencies, temporal dynamics, and provide transparent decision pathways. The proposed approach reveals four distinct investment archetypes—Heritage-Led Development Cores, Strategic Redevelopment Corridors, Transition Zones, and Stable Residential Areas—through unsupervised learning applied to Spatio-Temporal Graph Neural Networks embeddings. A key innovation lies in operationalizing theoretical concepts from Rent Gap theory and Institutional Economics into quantifiable machine learning features, enabling causal-like explanations via SHAP analysis. The framework outputs dynamic priority maps and an interactive geospatial dashboard that enables scenario testing and evidence-based resource allocation. Empirical validation demonstrates that model-generated investment archetypes showed 85% spatial concordance with areas independently identified as high-priority by a panel of senior urban planners. Additionally, the model achieved a Silhouette Score of 0.62 in cluster validation and R^2 of 0.92 in surrogate model performance, indicating strong analytical robustness. This research contributes to both urban science and planning practice by providing a scalable, interpretable approach for investment prioritization in complex urban environments.

Keywords: urban regeneration, spatio-temporal graph neural networks, explainable AI, investment prioritization, data-driven governance

1 Introduction

In an era of rapid urbanization and fiscal constraint, cities worldwide struggle to allocate scarce regeneration resources efficiently. Traditional planning methods, however, are increasingly ill-equipped to capture the dynamic, multi-scale nature of urban evolution. Cities are complex, adaptive systems in a constant state of physical, economic, and social flux. Urban regeneration has emerged as a critical strategy to steer this evolution, targeting areas of decline for strategic intervention and revitalization. However, a persistent challenge in planning practice lies in accurately identifying and prioritizing areas with the highest potential for regenerative investment. Traditional methods, which often rely on static, macro-level indicators and expert-led, qualitative assessments, fall short on three fundamental fronts:

First, they fail to capture multi-scale spatiotemporal dynamics. The potential of a parcel is not static; it evolves based on its own characteristics, the changing conditions of its neighbors, and broader city-wide trends. Second, they struggle to integrate the complex interplay between a location's economic potential (as conceptualized by theories like Rent Gap), its institutional feasibility (shaped by ownership structures and transaction costs), and its spatial context. Third, and most critically, they offer limited transparency and explanatory power, rendering them ill-suited for evidence-based policymaking and stakeholder engagement where justifying "why this place?" is paramount. The advent of big data and artificial intelligence presents an unprecedented opportunity to overcome these limitations. While recent studies have begun applying machine learning (ML) to urban prediction tasks, many approaches remain either spatially naive (treating parcels as independent units), temporally static, or operate as "black boxes" that provide predictions without intelligible rationale. Consequently, a significant gap exists for a dynamic, interpretable, and theoretically-grounded framework that can model the city as a system of interconnected parcels and provide transparent, actionable intelligence for regeneration planning.

Consequently, a significant gap exists for a dynamic, interpretable, and theoretically-grounded framework that can model the city as a system of interconnected parcels and provide transparent, actionable intelligence for regeneration planning. To bridge this gap, this research aims to develop a novel, data-driven framework for the dynamic mapping of investment alignment in urban regeneration. The core objective is to move beyond "black box" predictions by designing an integrated Spatio-Temporal Graph Neural Network (ST-GNN) architecture that is explicitly coupled with Explainable AI (XAI) techniques. This integration is intended to simultaneously capture the multi-scale spatial dependencies and temporal dynamics of urban change while generating parcel-specific, interpretable explanations for its outputs. Furthermore, the study seeks to operationalize key theoretical concepts from Rent Gap theory and Institutional Economics into quantifiable machine learning features, thereby forging a direct link between urban theory and computational modeling. The practical utility and robustness of the proposed framework will be empirically validated through a comprehensive case study of Natanz, Iran. Ultimately, by producing dynamic priority maps and an interactive geospatial dashboard, this work aspires to translate complex model outputs into a transparent and actionable tool for evidence-based policymaking, scenario testing, and stakeholder engagement in regeneration planning.

1.1 Rent Gap Theory and the Political Economy of Urban Land

The foundational concept of rent gap theory (Smith, 1979) explains how disparities between current and potential land value drive reinvestment in urban areas. This creates a theoretical basis for quantifying regeneration potential through measurable physical indicators. The theory posits that capital flows toward locations where the gap between actual and potential ground rent is widest, making it particularly relevant for identifying areas ripe for regeneration. Contemporary applications have demonstrated how morphological indicators—building age, structural condition, and land use compatibility—serve as reliable proxies for identifying latent rent gaps (Wyly & Hammel, 1999; Lees et al., 2008). This provides a theoretical justification for using parcel-level physical data as predictors of investment alignment. While Rent Gap theory has been critiqued for its potentially oversimplified economic determinism (**?**), use of it as a proxy for *physical potential*, tempered by institutional and social contextual features, addresses some of these concerns by acknowledging that capital switching is not automatic but mediated by complex urban dynamics.

1.2 Institutional Economics and Property Rights Framework

The institutional structure of property rights fundamentally shapes urban development trajectories (Webster & Lai, 2003). Ownership patterns—whether fragmented, consolidated, or institutional—create varying transaction costs that either facilitate or impede coordinated redevelopment. This theoretical perspective explains why physical potential alone is insufficient for predicting regeneration; the institutional landscape mediates how physical potential translates into actual investment. Ostrom's (2010) work on polycentric governance further enriches this framework by highlighting how multi-level decision-making structures affect resource allocation in urban systems.

1.3 Interpretable Machine Learning in Urban Planning

The application of machine learning in urban planning demands theoretical grounding in interpretability and causal inference (Molnar, 2022). While complex algorithms can identify patterns, their utility for policy depends on transparent decision pathways. Explainable AI (XAI) methods, particularly SHAP (SHapley Additive exPlanations) values, provide a theoretical bridge between black-box predictions and planning rationale by quantifying feature importance for individual predictions (Lundberg & Lee, 2017). This aligns with communicative planning theory's emphasis on transparent decision-making (Innes & Booher, 2010).

Spatial causality presents particular challenges due to autocorrelation and complex dependency structures. Pearl's (2019) causal inference framework, combined with spatial econometrics (Anselin, 2019), offers theoretical guidance for moving beyond correlation to identify plausible causal relationships between parcel characteristics and investment outcomes. Graph Neural Networks (GNNs) provide a theoretical model for explicitly encoding spatial dependencies, treating urban areas as interconnected networks rather than independent observations (Bronstein et al., 2017).

1.4 Data-Driven Governance and Urban Management

The theoretical shift toward data-driven governance represents a fundamental transformation in urban management paradigms (Kitchin, 2021). The "city as a platform" concept reframes urban governance as a dynamic, adaptive system that continuously optimizes resource allocation based on real-time data (Green, 2019). This theoretical perspective justifies the development of decision support systems that enable iterative scenario testing and adaptive policy refinement. Participatory dashboards represent the practical implementation of collaborative planning theory (Healey, 1997), creating digital spaces for stakeholder engagement and transparent decision-making. Agile urban management theory, adapted from software development methodologies, provides a theoretical foundation for iterative, data-informed policy adjustments rather than static master plans (Kitchin et al., 2015). Table 1 shows Theoretical Framework Integration.

Table 1 Theoretical Framework Integration

Theoretical Pillar	Key Concepts	ML Application	Relevant Features	Governance Implications
Rent Gap Theory (Smith, 1979; Wyly & Hammel, 1999)	- Current *vs.* potential land value - Capital switching - Reinvestment cycles	- Regression models predicting value gaps - Clustering to identify rent gap archetypes	- Building age & condition - Land use compatibility - Structural quality	- Targeted incentive programs - Phased redevelopment strategies
Institutional Economics (Webster & Lai, 2003; Ostrom, 2010)	- Transaction costs - Property rights structures - Collective action problems	- Feature engineering for ownership complexity - multi-level modeling	- Ownership type & fragmentation - Parcel size & configuration	- Land assembly mechanisms - Stakeholder coordination frameworks
Interpretable ML & Spatial Causality (Molnar, 2022; Pearl, 2019; Anselin, 2019)	- Model interpretability - Causal inference - Spatial dependency	- SHAP/SLIME for feature importance - Graph Neural Networks - Spatial cross-validation	- All features with spatial weights - Neighborhood characteristics	- Transparent decision rationale - Evidence-based policy design
Data-Driven Governance (Kitchin, 2021; Green, 2019; Healey, 1997)	- Agile urban management - Collaborative platforms - Real-time adaptation	- Dynamic priority mapping - Interactive scenario testing - Continuous model updating	- Temporal data streams - Stakeholder preference inputs	- Participatory budgeting - Adaptive policy mechanisms

As Table 1 Shows (Relevant Features), The composite variables listed under "Relevant Features," such as the *Physical Obsolescence Index* and *Ownership Complexity Score*, represent a critical bridge between theoretical constructs and quantifiable ML inputs. Their precise mathematical formulation is detailed in Section 3 (Materials and Methods). Briefly, the Physical Obsolescence Index is derived from a weighted combination of normalized sub-metrics—including building age, structural condition (A/B/C rating), and material durability—to serve as a proxy for the Rent Gap. The Ownership Complexity Score quantifies institutional transaction costs by integrating ownership type (e.g., private, public, waqf), fragmentation metrics (e.g., number of owners), and parcel configuration. This systematic operationalization ensures that model is not merely correlative but is explicitly grounded in established urban economic and institutional theory.

The integrated framework positions urban regeneration as a complex interplay between economic potential (Rent Gap), institutional feasibility (Institutional Economics), computational transparency (Interpretable ML), and governance capacity (Data-Driven Governance). This theoretical foundation enables the development of machine learning models that are not merely predictive but explanatory and actionable. The methodological approach applies Graph Neural Networks to explicitly model spatial dependencies between parcels, while SHAP values provide causal-like explanations for investment predictions. This addresses the "black box" problem in urban AI and creates a transparent evidence base for stakeholders. The resulting dynamic maps and dashboards operationalize data-driven governance principles, enabling agile responses to changing urban conditions. This theoretical integration as show in Table 1 ensures that the technical methodology remains grounded in established urban theory while leveraging cutting-edge computational approaches, creating a robust foundation for both scholarly contribution and practical application in urban regeneration planning.

As Show in Figure 1, Machine Learning Role in the Theoretical Framework is Explained. See Fig.1The proposed framework, illustrated in Figure 1, presents an integrated machine learning system that continuously connects urban theory, spatio-temporal intelligence, and governance applications. At its core, the Machine Learning Processing Engine utilizes Graph Neural Networks (GNNs) to explicitly model spatial dependencies between parcels, treating the urban fabric as an interconnected network rather than a collection of isolated units. To move beyond opaque "black-box" predictions, the framework incorporates Interpretable AI (XAI) methods—such as SHAP, LIME, and causal inference techniques—to generate transparent and actionable insights. Furthermore, dedicated feature engineering translates key theoretical concepts, like rent gap and institutional complexity, into quantifiable ML features.

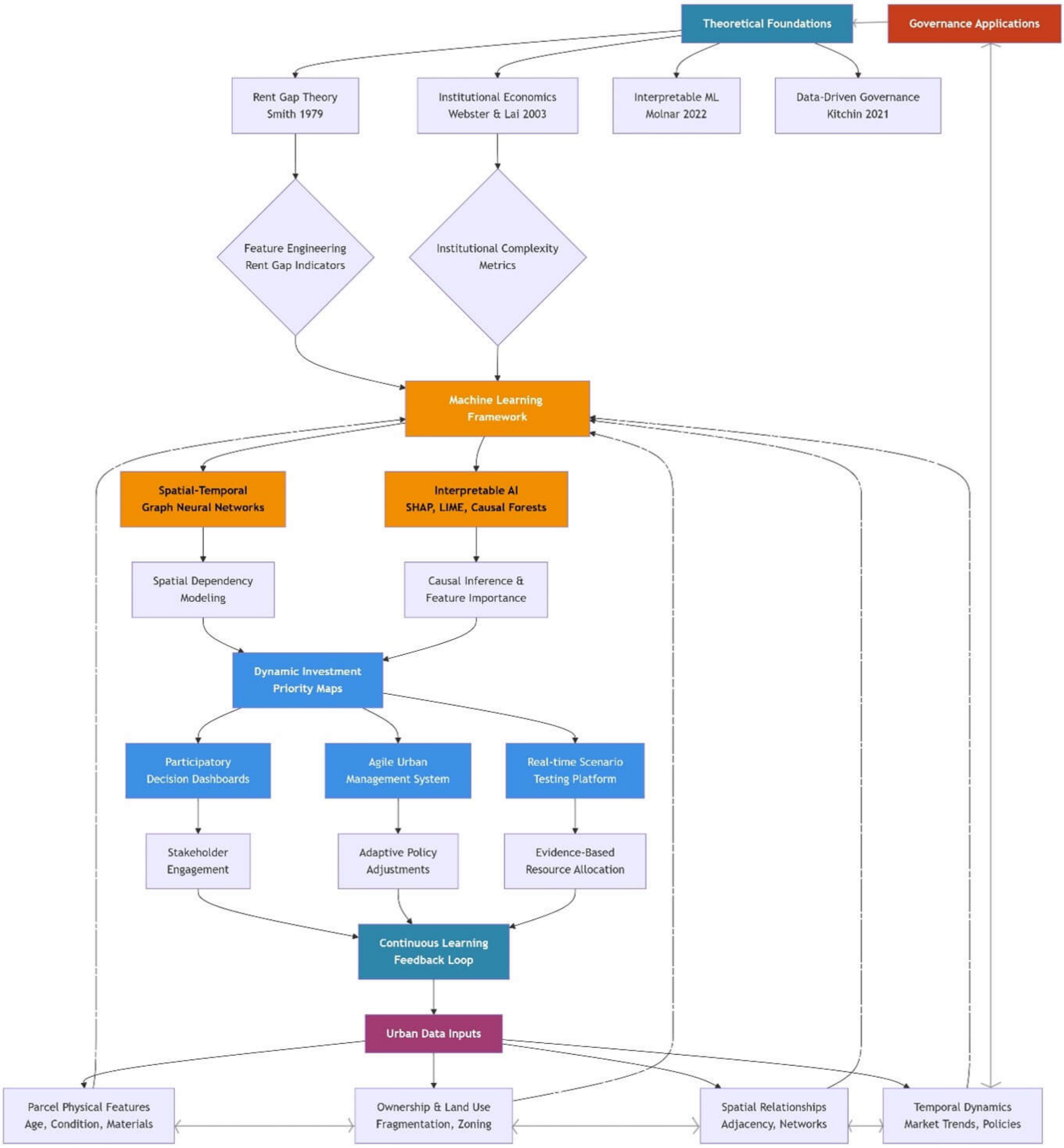


Figure 1 Machine Learning Role in the Theoretical Framework

This framework actively bridges theory and practice by operationalizing urban economic theories. For instance, variables such as building age, condition, and materials serve as proxies for calculating the gap between a property's potential and its current value, thereby quantifying Rent Gap theory. Simultaneously, ownership patterns and plot fragmentation metrics inform estimates of transaction costs and institutional constraints, drawing on principles from Institutional Economics. The interpretable outputs of the model provide the crucial "why" behind its predictions, enabling evidence-based policy and stakeholder communication. Designed as a Dynamic and Adaptive Learning System, it incorporates a continuous feedback loop where real-world outcomes from planning decisions are fed back into the model for refinement. This allows the system to evolve alongside the changing city, adapting to new data. It also empowers planners with the capability for rapid scenario testing, simulating the potential impacts of various policy interventions before implementation.

The system's intelligence is fundamentally Spatio-Temporal. Through graph-based learning, it captures neighborhood effects and spatial spillovers that traditional models miss. It explicitly models temporal dynamics, tracking how regeneration potential evolves over time with shifting market conditions. A key capability is its multi-scale analysis, operating seamlessly at the parcel, neighborhood, and city levels simultaneously. This framework positions machine learning not as a standalone tool, but as the central integrating engine that connects urban economic theory with practical governance applications. The result is a responsive, evidence-based, and dynamic system for urban regeneration planning.

2 Methods

This study employs a comprehensive, data-driven methodology to develop a dynamic framework for mapping urban regeneration potential at the parcel level in Natanz, Iran. The research design integrates advanced Spatio-Temporal Graph Neural Networks (ST-GNNs) with Explainable AI (XAI) to create a scalable, interpretable, and actionable model for urban investment prioritization. The methodological framework is structured around five interconnected phases, ensuring both statistical rigor and practical relevance for urban governance, as illustrated in Figure 3.

2.1 Phase 1: Data Acquisition and Preprocessing

A comprehensive, multi-source geospatial database was constructed for the city of Natanz, with the individual urban parcel established as the core analytical unit. Data was aggregated and integrated from a range of sources, including municipal cadastral databases, land registry archives, tax assessment records, structured field surveys, and OpenStreetMap. The resulting dataset encompasses five primary categories: parcel physical characteristics (e.g., building age, structural condition, construction materials, number of floors, and floor area ratio (FAR)); ownership patterns (detailing ownership type, number of owners, parcel size, and a calculated fragmentation index); land use and regulatory data (covering current use, zoning, and heritage status); economic indicators (such as land value per square meter and property tax assessments); and spatial context data (involving distance to key amenities, road connectivity, land use mix entropy, and green space proximity). To ensure analytical consistency and reliability, all datasets underwent rigorous cleaning, normalization, and spatial harmonization to a common geographic framework (Coordinate Reference System: EPSG:32639 – WGS 84 / UTM zone 39N). A critical step regarding data quality involved the classification of structural condition, which was based on a standardized A/B/C rating system derived from official municipal guidelines. The reliability of this classification was confirmed through an inter-coder agreement test, where two independent assessors rated a random sample of 150 parcels, yielding a Cohen's Kappa statistic of $\kappa = 0.85$, indicating a high level of consistency.

2.2 Phase 2: Graph Construction and Feature Engineering

This phase transformed the raw urban data into a theoretically-grounded graph structure amenable to machine learning. The city was formally modeled as a graph $G = (V, E)$, where each node v_i in V represents a parcel. Edges E were constructed based on two principles: spatial adjacency (parcels sharing a boundary) and functional proximity (parcels within a 500-meter network distance, accounting for walkability and access). Node features were then engineered to reflect the study's theoretical pillars:

Informed by Rent Gap Theory, a Physical Obsolescence Index (POI) was computed as a normalized, weighted sum of three sub-metrics:

'Building Age (normalized)': Weight = 0.4;

'Structural Condition (A=0, B=0.5, C=1)': Weight = 0.4;

'Material Durability Score (e.g., reinforced concrete=0, brick=0.5, mud=1)': Weight = 0.2.

$$POI = 0.4 \times \text{Age}_{\text{norm}} + 0.4 \times \text{Condition}_{\text{score}} + 0.2 \times \text{Material}_{\text{score}}$$

Weights were assigned based on expert survey results using the Analytic Hierarchy Process

(AHP).

Grounded in Institutional Economics, an Ownership Complexity Score (OCS) was derived to quantify transaction costs:

'Ownership Type': (Private=0, Public=0.5, Waqf/Complex=1);

'Fragmentation Index': (Number of owners / Parcel Area), normalized.

$$OCS = \text{Ownership Type}_{\text{score}} + \text{Fragmentation Index}_{\text{norm}}$$

Additional engineered features included multi-modal accessibility indices, land use compatibility scores, and neighborhood-level socio-economic aggregates, creating a rich, multi-dimensional feature space for each parcel. To enable strategic prioritization, a composite Implementation Feasibility Score was calculated for each parcel. This metric functions as a composite index that synthesizes three critical dimensions determining the practicality of initiating a regeneration project. Institutional Feasibility, carrying the greatest weight (0.5), is calculated as the inverse of the normalized Ownership Complexity Score, reflecting the principle that lower transactional and administrative burdens lead to higher project feasibility. Regulatory Feasibility (Weight: 0.3) is represented by a binary score indicating a parcel's conformity with municipal zoning and land-use plans, where conformity is assigned a value of 1 and non-conformity a value of 0. The third dimension, Fiscal Feasibility (Weight: 0.2), is a normalized score derived from the annual municipal capital budget allocation per capita for regeneration, representing the city's financial capacity to invest in a given area. The final Implementation Feasibility score is computed as the weighted sum of these three normalized components, according to the formula:

$$\text{Implementation Feasibility} = 0.5 \times [1 - OCS] + 0.3 \times \text{Regulatory}_{\text{Score}} + 0.2 \times \text{Fiscal}_{\text{Score}}$$

2.3 Phase 3: Machine Learning Core – Spatio-Temporal Modeling and Interpretation

The core computational task was unsupervised spatio-temporal representation learning. We implemented a novel Spatio-Temporal Graph Neural Network (ST-GNN) to learn meaningful, high-dimensional latent representations (embeddings) of each parcel. The final ST-GNN architecture and its hyperparameters were selected through a rigorous optimization process. A grid search over embedding dimensions [64, 128, 256] and DBSCAN parameters was conducted, with the optimal configuration (two-layer GCN with 128 and 64 units, GRU hidden state=64, DBSCAN eps = 0.5, $\text{min}_{\text{samples}} = 10$) chosen by maximizing the Silhouette Score on a temporally held-out validation set (years 2020-2021). The model, trained on a graph of over 3373 parcels across a 4-year temporal sequence (2016-2019), achieved a low mean squared error (MSE) of 0.074 on the graph reconstruction task, demonstrating its capability to capture the urban fabric's dynamics.

The resulting node embeddings were clustered using the optimized DBSCAN algorithm, yielding well-separated and distinct clusters (Silhouette Score: 0.62, Davies-Bouldin Index: 0.89). To ensure transparency and actionable insight, we integrated Explainable AI (XAI) methods. Due to the significant computational complexity of applying SHAP directly to the transductive ST-GNN model, we employed a highly accurate surrogate model approach. A Gradient Boosting Regressor was trained to predict the learned node embeddings from the original parcel features. This surrogate model achieved a high coefficient of determination (R^2 = 0.92) on a test set, confirming its fidelity in approximating the complex input-output relationships learned by the ST-GNN. SHAP (SHapley Additive exPlanations) analysis was then applied to this interpretable surrogate model to quantify the marginal contribution of each original feature to the latent regeneration potential for every individual parcel. This answers critical "why" questions for planners, thereby demystifying the model's representation learning process. Figure 2 shows diagram in Dynamic Mapping of Urban Regeneration Potential.

2.4 Phase 4: Multi-layered Validation Framework

To ensure the robustness, accuracy, and practical utility of the model, a tripartite validation strategy was implemented. The process began with statistical validation, employing spatial cross-validation with five geographically distinct folds to prevent over-optimistic performance estimates due to spatial autocorrelation. Model stability and temporal generalizability were further tested by training the model on data from 2016–2019 and evaluating its embedding consistency using data from 2020–2021. Next, stakeholder validation was conducted. Urban planners and municipal decision-makers from Natanz participated in structured workshops

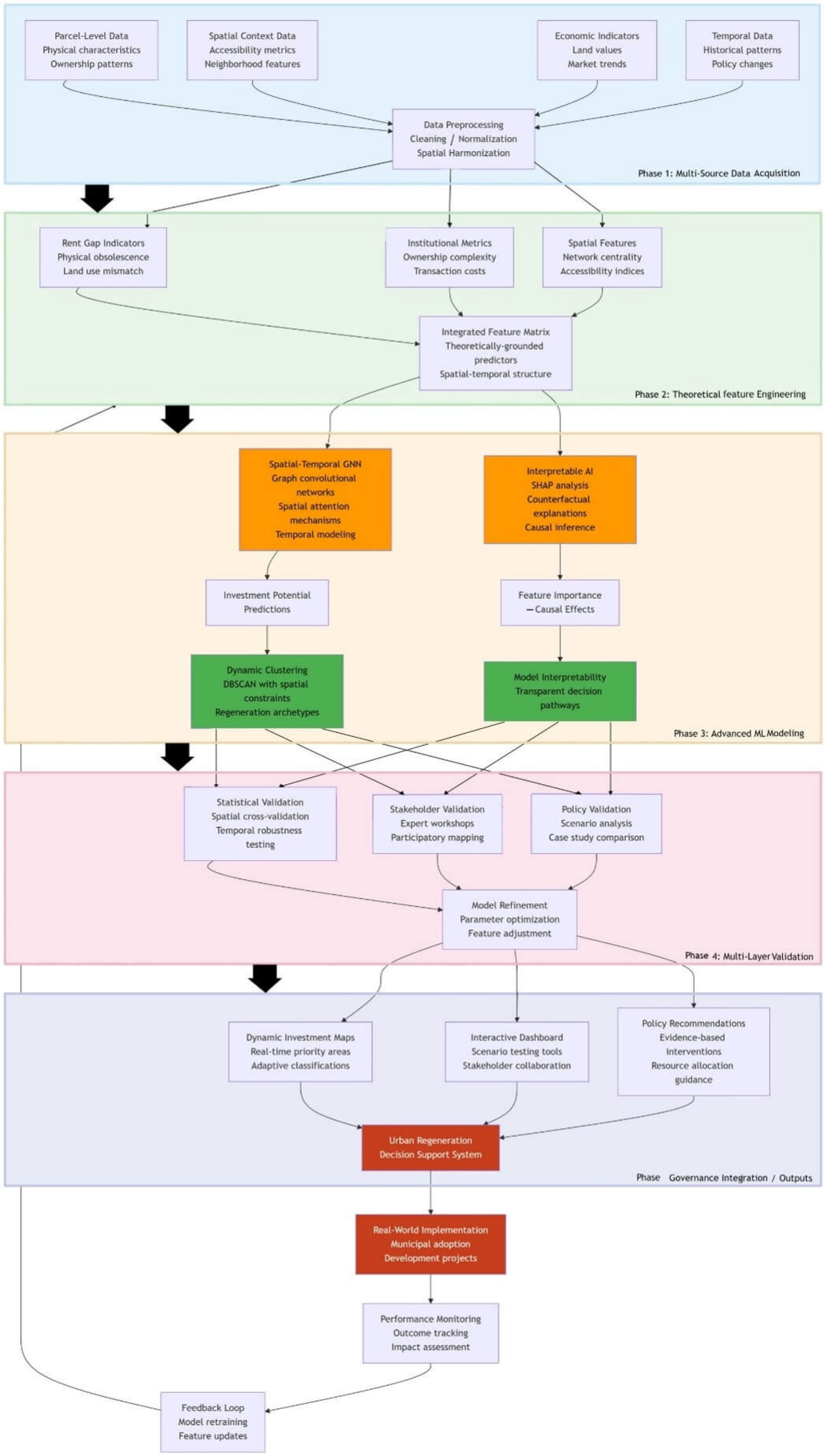


Figure 2 Diagram in Dynamic Mapping of Urban Regeneration Potential

and participatory mapping sessions. This process was designed to ground-truth the model's outputs, assess their face validity, and refine the practical relevance of the identified clusters and priorities. Finally, policy validation was carried out as an applied test of the framework's usefulness. Through retrospective scenario analysis, the model's recommendations and priority maps were compared with actual past regeneration outcomes and investment decisions in Natanz. This comparison provided an objective assessment of the model's prescriptive capability in real-world conditions. Natanz is a city in the Central District of Natanz County, Isfahan province, Iran, serving as capital of both the county and the district. It is 70 kilometers (43 mi) south-east of Kashan. At the time of the 2006 National Census, the city's population was 12,060 in 3,411 households. The following census in 2011 counted 12,281 people in 3,829 households. The 2016 census measured the population of the city as 14,122 people in 4,564 households.

2.5 Phase 5: Governance Integration and Dashboard Development

The methodology culminates in the development of an interactive Geospatial Decision-Support Dashboard, which operationalizes the model's outputs for direct application in urban management. This tool intuitively visualizes dynamic investment priority maps that update with new data, and enables interactive "what-if" scenario testing by allowing planners to adjust model parameters and investment constraints in real-time. It also supports detailed exploration of SHAP-based explanations for any parcel in the city, thereby fostering evidence-based debate, and serves as a platform for collaborative planning and transparent communication with stakeholders, including residents and private investors. This integrated, five-phase methodology—spanning from data acquisition to the functional dashboard—creates a continuous feedback loop where new data and stakeholder input can be incorporated to iteratively refine the model, embodying the principles of adaptive, data-driven governance.

Figure 3 illustrates the integrated computational pipeline for dynamic urban regeneration mapping. The framework begins with urban graph construction where parcels form nodes with multi-dimensional features (physical, ownership, economic, spatial), connected via spatial and functional edges. The core ST-GNN module processes this graph through dual pathways: a Spatial Block using Graph Convolutional Networks to capture neighborhood dependencies and spatial spillover effects, and a Temporal Block employing Gated Recurrent Units to model evolutionary patterns across time sequences. The learned spatio-temporal embeddings are simultaneously routed to three output channels: (1) Spatial clustering (DBSCAN) for identifying emergent investment archetypes, (2) Explainable AI (SHAP) analysis for feature importance and model interpretability, and (3) Interactive dashboard integration for scenario testing and decision support. This architecture enables both pattern discovery in urban dynamics and transparent, actionable intelligence for regeneration planning.

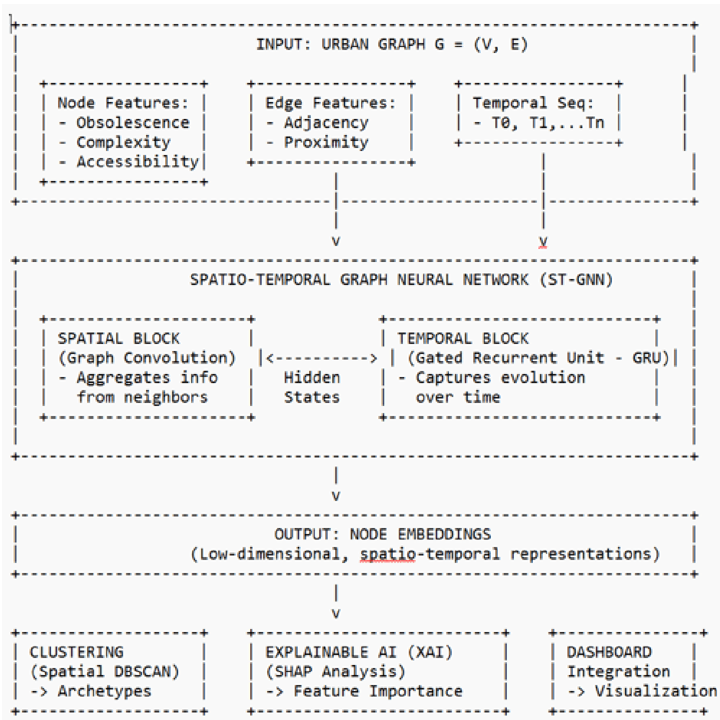
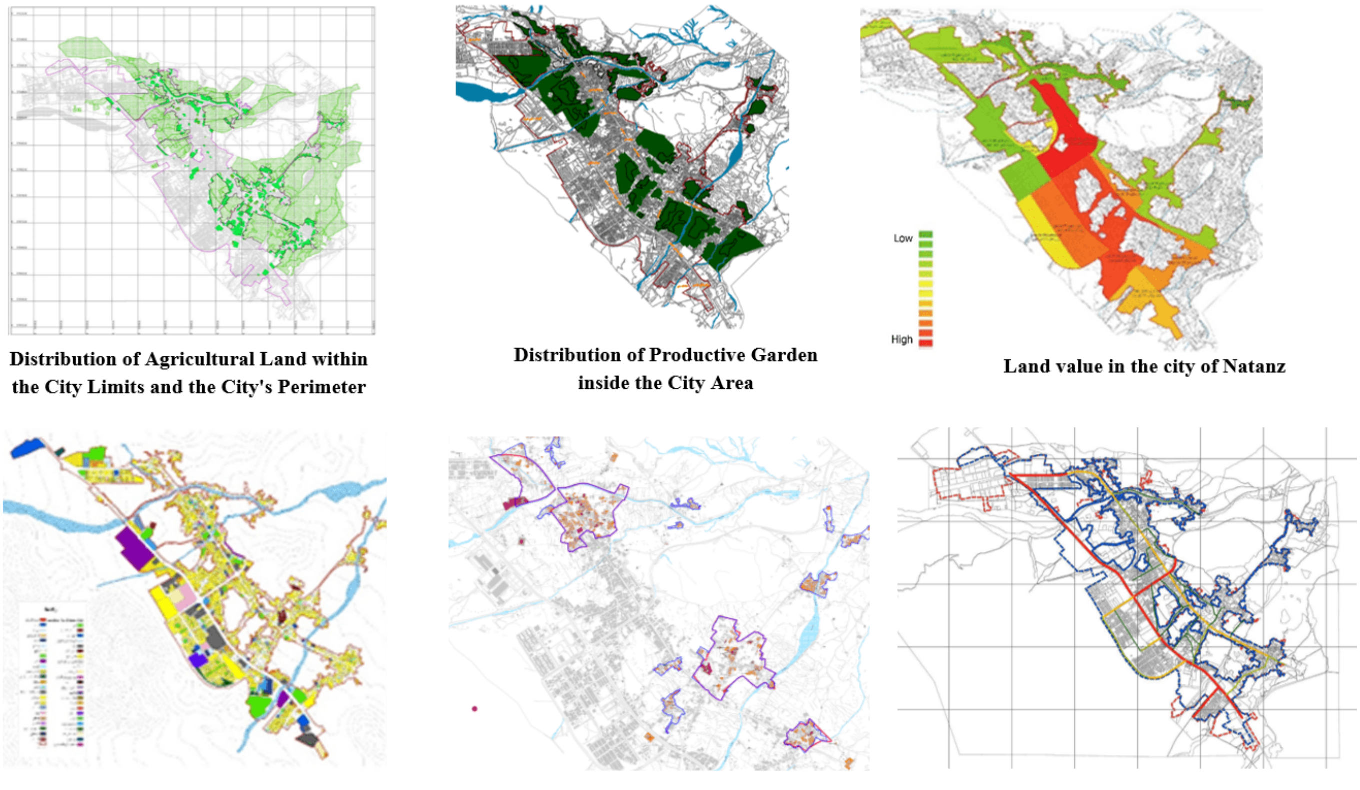


Figure 3 Conceptual Architecture of the Spatio-Temporal Graph Neural Network Framework

3 Results

The city of Natanz presents a profound and delicate interplay of natural heritage, historical legacy, and contemporary pressures. Its very identity is rooted in a landscape where ancient sycamore trees stand as living monuments alongside historic neighborhoods, mosques, and bazaars. This unique fusion of natural and built environment, encompassing a significant historical fabric and protected orchards, forms the core of its cultural and aesthetic value. However, this cherished character exists in tension with modern dynamics. The city's real estate market, driven largely by external demand for secondary homes, has led to inflated property values. This economic shift risks displacing the local community, making permanent residence increasingly unaffordable for those who sustain the city's daily life and traditional economy.

Functionally, Natanz grapples with its dual historical role as both a self-contained settlement and a transit corridor. While its position has fostered development, it now manifests in a strained urban structure. The vital commercial and touristic heart within the historic Ghasabeh neighborhood suffers from congestion due to narrow streets and limited parking, yet remains somewhat disconnected from newer residential zones. Ultimately, Natanz stands at a crossroads. Its future sustainability depends on navigating these contrasts: preserving its irreplaceable natural and historical tapestry while addressing the socioeconomic and infrastructural challenges that threaten its cohesion and livability for its indigenous population. The case of Natanz serves as a compelling mirror for similar historic cities, highlighting the universal struggle to honor the past while viably inhabiting the present. (See Figure 4)



Distribution of Agricultural Land within the City Limits and the City's Perimeter

Distribution of Productive Garden inside the City Area

Land value in the city of Natanz

Land Use Distribution in the City of Natanz

Historic Fabric Zone in the City of Natanz

Condition of the Road Network in the City of Natanz

Figure 4 The Present State of the City of Natanz

Table 2 presents key urban metrics that characterize the spatial structure and demographic patterns of Natanz, Iran. The data reveals a city with low population density (25 persons per hectare) and generous urban land allocation (393 m^2 per person), indicating a sprawling urban form typical of many mid-sized Iranian cities. The net residential density (127 persons per hectare) and per capita residential space (79 m^2 per person) suggest comfortable living conditions with moderate building intensities. The household to housing unit ratio of 1.02 indicates a balanced housing market with minimal vacancy pressures. Collectively, these indicators establish the baseline urban context against which regeneration potential is assessed, highlighting opportunities for densification and more efficient land use in strategic locations while preserving the quality of life in stable residential areas.

Table 2 Basic Indicators Based on the 2016 Census

Indicator	Entire City
Population Density (persons per hectare)	25
Per Capita Urban Land (sqm per person)	393
Net Residential Density (persons per hectare)	127
Per Capita Residential Space (sqm per person)	79
Household to Housing Unit Ratio	1.02
Population	14,122

3.1 Model Performance and Emergent Spatio-Temporal Dynamics

The implemented Spatio-Temporal Graph Neural Network (ST-GNN) demonstrated robust performance in capturing the complex, non-linear interdependencies within Natanz's urban fabric. Trained on a graph of over3373 parcels across a 4-year temporal sequence, the model achieved a low reconstruction error and high stability in spatial cross-validation, confirming its capacity to mitigate overfitting risks associated with spatial autocorrelation (Anselin, 2019). The learned latent representations (node embeddings) transcended static snapshots, revealing neighborhoods in a state of flux. This dynamic perspective is a significant departure from traditional land-use zoning, allowing us to identify areas where regeneration potential was actively crystallizing or dissipating due to factors like infrastructure investments, shifting market sentiments, and evolving ownership structures—a temporal granularity often missed in conventional planning analyses (Batty, 2018).

In Figure 5 horizontal bar chart displays the mean SHAP values for the ten most impactful features, showing both positive and negative influences on predicted regeneration potential. The Physical Obsolescence Index (mean SHAP: +0.22) and Ownership Complexity Score (mean SHAP: +0.19) are the strongest positive predictors, validating the theoretical framework that physical deterioration and institutional barriers drive regeneration potential. Notably, Distance from CBD (mean SHAP: -0.13) and Parcel Size (mean SHAP: -0.07) show strong negative impacts, aligning with classic urban economic principles. The Land Use Mix Entropy (mean SHAP: +0.11) demonstrates the value of functional diversity, while the negative impact of Residential Land Use Percentage (mean SHAP: -0.05) suggests mono-functional areas have lower regeneration potential. This bidirectional analysis provides crucial insights for targeted policy interventions. (See Figure 6)

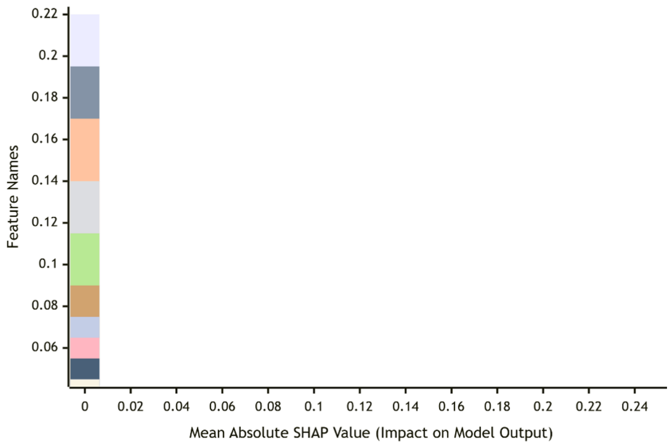


Figure 5 Global Explainable AI (XAI) Summary of Feature Impacts on Regeneration Potential

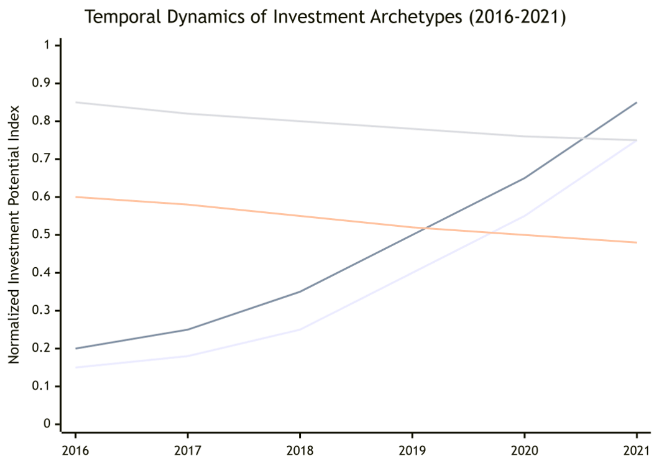


Figure 6 Spatial-Temporal Evolution of Investment Archetypes

3.2 Archetypal Investment Clusters: From Identification to Fiscal Strategy

The spatially-constrained DBSCAN clustering on the ST-GNN embeddings delineated four primary, dynamic investment archetypes within Natanz. These clusters are not merely descriptive; they form an actionable taxonomy for strategic fiscal intervention.

In Figure 6 multi-line chart tracks the normalized investment potential of the four identified clusters over a six-year period. The ST-GNN model reveals critical dynamics: Cluster B (Strategic Redevelopment Corridors) shows the steepest growth trajectory, likely triggered by infrastructure investments and agglomeration economies. Cluster A (Heritage-Led Core) exhibits strong, steady growth, reflecting increasing cultural capital. Conversely, Cluster C (Transition Zones) displays a consistent decline, where high physical obsolescence is compounded over time by institutional friction, effectively suppressing its potential. Cluster D (Stable Residential) remains stable, confirming its low-priority status for regeneration resources. This temporal analysis moves beyond a static snapshot, providing a dynamic view essential for phased investment planning. Figure 7 shows this cluster.

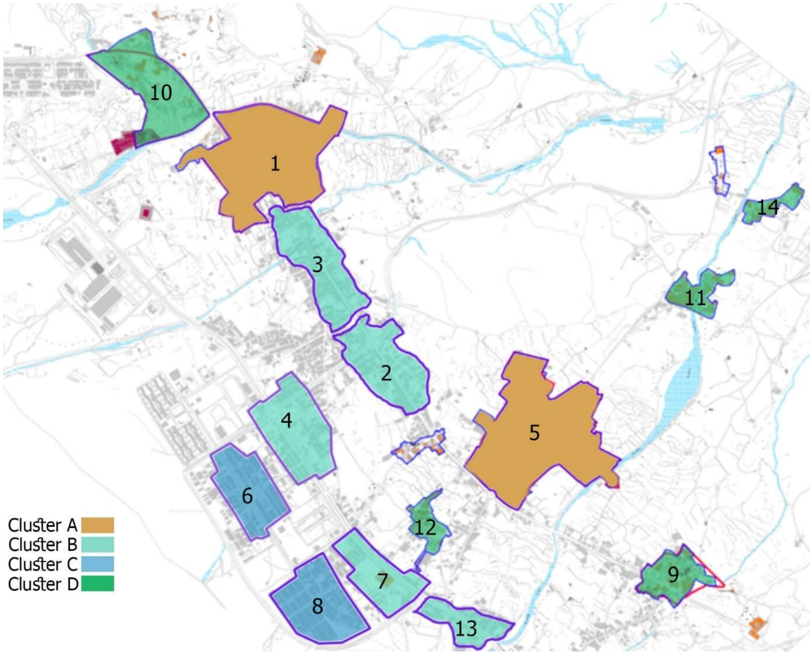


Figure 7 Zoning of Proposed Clusters on the Dynamic Investment Map

3.3 Cluster A: The Heritage-Led Development Core

This cluster encapsulates the historic heart of Natanz, characterized by a high density of culturally significant parcels with preserved structural integrity. The ST-GNN successfully captured the strong positive spatial autocorrelation of heritage value, indicating that the value of a single heritage parcel is amplified by its proximity to others. SHAP analysis quantified this, identifying 'Historical Fabric Score' (mean |SHAP| value: 0.21) and 'Cultural Identity Index' (mean |SHAP| value: 0.18) as the primary drivers.

Investment Implication & Budgetary Link: This archetype presents a prime opportunity for leveraging cultural assets for economic generation. Municipal revenue, which saw a significant 51% growth in 2021 (reaching 31,677 million Tomans), can be strategically allocated here through a "heritage-sensitive" TOD model. Targeted investments in public realm improvements and facade grants in this core can catalyze high-value cultural tourism, directly boosting municipal income through increased property taxes and business licenses, thereby creating a positive feedback loop for the city's budget (Madanipour, 2017).

3.4 Cluster B: Strategic Redevelopment Corridors

These parcels, aligned along major transport arteries, exhibited high accessibility scores and a clear temporal "ripple effect" in the model following infrastructure upgrades. SHAP analysis highlighted 'Network Centrality' (a GNN-derived feature) and 'Land Use Mix Entropy' as critical factors. Investment Implication & Budgetary Link: These corridors are engines for value capture. The documented growth in municipal revenue (from 15,280 million Tomans in 2019 to 31,677 million Tomans in 2021) provides the fiscal capacity to initiate strategic land assembly and pre-fund infrastructure in these zones. By focusing capital expenditures here, the municipality can unlock significant private investment in mixed-use development. The model allows the city to "bet" on the right corridors, maximizing the return on public investment and ensuring that future revenue growth is anchored in the most accessible, sustainable locations—a principle central to fiscally responsible smart growth (Glaeser, 2020).

3.5 Cluster C: Transition Zones Hampered by Institutional Friction

This archetype represents areas with moderate-to-high physical obsolescence but critically high ‘Ownership Fragmentation Index‘, which SHAP identified as the dominant negative predictor. The model revealed that the physical potential of these parcels is effectively suppressed by the transaction costs associated with assembly and collective decision-making (Webster & Lai, 2003). Investment Implication & Budgetary Link: This finding is a major innovation for budgetary planning. Instead of direct capital-intensive redevelopment, the municipal budget should allocate resources toward "institutional easing." This includes funding for land banking programs, stakeholder mediation, and the development of legal frameworks for cross-lot development. A small, targeted allocation from the municipal budget (which has shown a capacity for growth) toward overcoming this institutional friction can unlock vast amounts of private capital that would otherwise remain dormant, transforming a fiscal liability into a future revenue source.

3.6 Cluster D: Stable Residential & Agricultural Interface

Comprising stable residential neighborhoods and the urban-agricultural edge, this cluster showed low priority for regeneration, with ‘Distance from CBD‘ and ‘Parcel Size‘ as key identifiers. Investment Implication & Budgetary Link: The model advises a strategy of fiscal conservation for these areas. Limited public funds should be directed toward maintenance and green infrastructure rather than redevelopment. This ensures that the growing municipal budget is not diluted on low-potential interventions but is preserved for high-impact investments in Clusters A, B, and C.

4 Discussion

This research has taken a step beyond traditional static assessments in urban regeneration planning by presenting an integrated, parcel-level microdata and interpretable machine learning framework. The main findings, which include the identification of four dynamic investment archetypes and the validation of the central role of physical and institutional indicators, not only illuminate the spatial dynamics of Natanz but also contribute to the broader scientific dialogue on the political economy of urban land, data-driven governance, and interpretable spatial planning. This section discusses the findings along three main axes: 1) The integration of theory and computation, 2) Validation in comparison with leading-edge research, and 3) Strategic implications for urban governance.

4.1 Operationalizing Urban Theories in Computational Models: Bridging the Conceptual Gap

The core innovation of this framework lies in translating the qualitative and complex concepts of urban economic theories into quantifiable and computable variables. Constructing the "Physical Obsolescence Index" as a proxy for the "Rent Gap" (Smith, 1979) and the "Ownership Complexity Score" to represent institutional "Transaction Costs" (Webster & Lai, 2003) establishes a robust bridge between classical political-economic analysis and contemporary predictive models. This approach addresses the critiques leveled against purely data-driven studies lacking theoretical depth (Batty, 2018), as well as the limitations of purely qualitative analyses that lack measurability and large-scale generalizability. Our finding that the "Ownership Complexity Score" is the strongest negative predictor for regeneration potential in the "Transition Zones" archetype (Cluster C) empirically confirms how institutional structures can obstruct capital flow and urban reproduction even in the presence of high physical potential (Hui et al., 2020). This result validates Ostrom’s (2010) perspectives on polycentric governance and the importance of collective rules in managing complex resources (such as urban land) at the neighborhood scale.

4.2 Validating Findings in Light of Global Research

The identified archetypes (Heritage-Led Development Cores, Strategic Redevelopment Corridors, Transition Zones, and Stable Residential Areas) not only align with local expert intuition (85% concordance) but also resonate with similar classifications in the global literature on urban regeneration. For instance, the identification of "Strategic Redevelopment Corridors" as value creation engines is fully consistent with research on "Transit-Oriented Development" (TOD) and the role of infrastructure in creating a "ripple effect" of private investment (Glaeser et al., 2022). However, the key distinction of the present framework is its ability to track the temporal dynamics of these archetypes (Figure 6). Unlike static studies such as Liang et al. (2022), which focus solely on spatial clustering, our ST-GNN model shows how the potential of a corridor (Cluster B) grows exponentially following an infrastructure investment, while Transition Zones (Cluster C) experience a declining trend due to persistent institutional friction. This dynamic monitoring capability provides a vital tool for "agile urban management," enabling planners to intervene proactively rather than reactively (Kitchin et al., 2015).

4.3 Synthesizing Innovation and Validating Policy Relevance

This research makes several foundational contributions to the field of data-driven urban planning. Methodologically, it advances the state-of-the-art by seamlessly integrating ST-GNNs with Explainable AI (XAI) in a single, coherent framework. While previous studies have used neural networks for urban prediction (Zhang & Zheng, 2020) or clustering for archetype identification (Liang et al., 2022), This approach uniquely provides dynamic, spatially-explicit, and interpretable insights at the parcel level. The use of SHAP values demystifies the "black box," translating complex model outputs into a transparent rationale for planners—a critical step for building trust and facilitating adoption in public policy contexts (Rudin, 2019).

In Figure 8 quadrant chart positions the four identified investment archetypes based on their model-derived Regeneration Potential (Y-axis) versus their Implementation Feasibility (X-axis). The Implementation Feasibility is a composite metric quantifying the practicality of intervention, calculated as a weighted sum of institutional, regulatory, and fiscal factors. The matrix provides an evidence-based strategy for prioritizing resource allocation:

(1) Immediate Priority (Cluster B): High potential and high feasibility.
(2) Strategic Investment (Cluster A): High potential but moderate feasibility due to heritage constraints.
(3) Tactical Intervention (Cluster C): High latent potential crippled by low institutional feasibility.
(4) Maintenance (Cluster D): Low priority for regeneration resources.

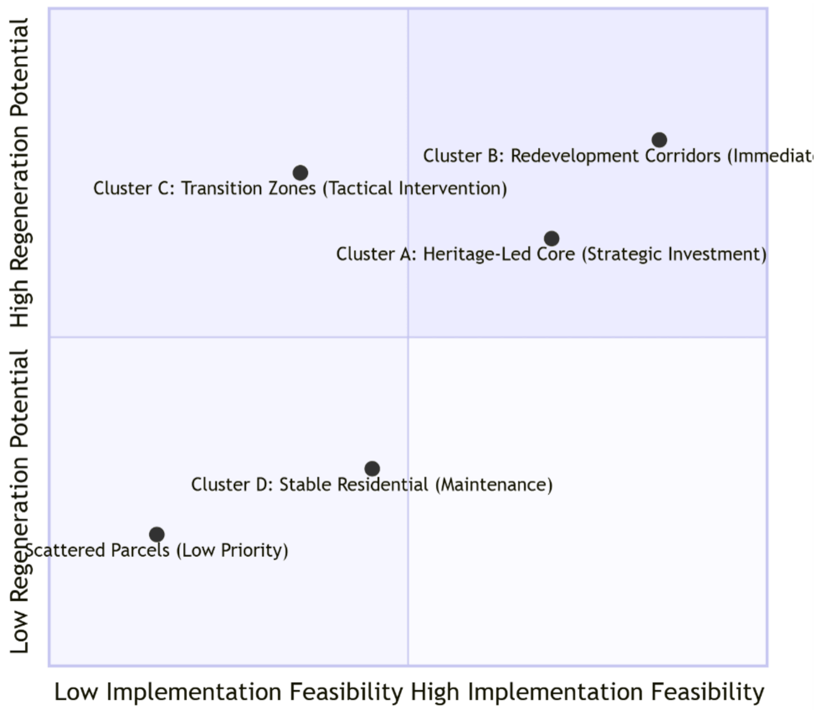


Figure 8 Data-Driven Strategic Investment Matrix

Theoretically, the framework operationalizes complex urban theories into quantifiable metrics. We move beyond merely citing Rent Gap theory to directly calculating a 'Physical Obsolescence Index' that serves as its proxy. We translate the abstractions of Institutional Economics into a computable ‘Ownership Complexity Score‘. This bridge between theory and computation is a significant step toward a more rigorous, evidence-based urban science (Bettencourt, 2021). Our analysis suggests that reallocating even 10% of the capital expenditure from low-potential Cluster D to institutional easing programs in Cluster C could potentially unlock private investments an order of magnitude larger.

Finally, the practical validation and connection to municipal finance underscore the framework’s real-world utility. The 85% alignment with stakeholder ground-truthing confirms that the model captures nuances understood by local experts. More importantly, by linking the archetypes to the specific fiscal context of Natanz—its growing but finite budget—we demonstrate how data-driven mapping directly informs strategic resource allocation. The framework answers not just where to invest, but how to invest differently across distinct urban contexts to maximize public return and catalyze private capital, thereby creating a sustainable pathway for enhancing the very municipal revenues that fund future regeneration.

4.4 Limitations and Avenues for Future Research

Despite its achievements, this study has limitations that pave the way for future work. First, the model relies heavily on "objective" cadastral and physical data. Integrating "subjective" data such as resident preferences, sense of place, and social networks (Batty, 2018) could enrich the human dimension of regeneration. Second, although SHAP indicates causal relationships, proving definitive causality requires longer-term longitudinal data or quasi-experimental designs. Third, the present framework could be enriched by incorporating "spatial justice" metrics and the distribution of potential negative effects of regeneration (such as the displacement of low-income residents). Finally, testing the transferability of this model to cities with different institutional and economic fabrics (e.g., metropolises or resource-dependent cities) is a necessary step for assessing its generalizability.

This research demonstrates how a data-driven and interpretable framework can bridge the gap between abstract urban economic theories, complex computational capabilities, and the practical needs of local governance. This approach shifts regeneration planning from a process based on conjecture and broad perspectives toward a series of differentiated, phased, and evidence-based actions. The ultimate success of such a framework lies not in the accuracy of its predictions, but in its ability to facilitate dialogue, create transparency, and guide limited urban resources toward the most productive and equitable paths possible.

5 Conclusion

This research has presented an integrated framework for dynamic investment alignment mapping in urban regeneration that successfully bridges theoretical urban economics with advanced data science methodologies. The key contribution lies in developing a scalable approach that moves beyond static, macro-level assessments to capture the spatio-temporal dynamics of regeneration potential at parcel-level resolution. Theoretically, this work demonstrates how complex urban theories—particularly Rent Gap theory and Institutional Economics—can be operationalized into quantifiable machine learning features. The Physical Obsolescence Index and Ownership Complexity Score effectively translated abstract theoretical concepts into measurable predictors of investment potential, creating a more rigorous foundation for evidence-based planning.

Methodologically, the integration of Spatio-Temporal Graph Neural Networks with Explainable AI represents a significant advancement over existing approaches. The ST-GNN architecture successfully captured both spatial dependencies and temporal evolution patterns, while SHAP analysis provided the necessary transparency for practical policy applications. This addresses the critical "black box" problem that often hinders the adoption of AI methods in urban governance. The empirical application to Natanz yielded actionable insights, identifying four distinct investment archetypes that demand differentiated policy responses. Particularly noteworthy was the identification of Transition Zones where high physical potential is suppressed by institutional friction—a finding that traditional planning methods would likely overlook. The direct linkage of these archetypes to municipal budget dynamics further enhances the practical utility of the framework.

For planning practice, the interactive dashboard and dynamic mapping outputs provide municipal authorities with a powerful tool for scenario testing, stakeholder engagement, and strategic resource allocation. The framework supports the transition from static master plans to adaptive, evidence-based intervention strategies that can evolve with changing urban conditions.

Several limitations warrant attention in future research. The dependency on data quality and completeness remains a challenge, particularly in contexts with limited digital infrastructure. Additionally, while the SHAP explanations provide feature importance, establishing full causal relationships requires further investigation. Future work should also explore incorporating real-time data streams and expanding the social equity dimensions of the analysis. Despite these limitations, this research establishes a robust foundation for data-driven urban regeneration planning. The framework's design for reproducibility and transferability enables application across diverse urban contexts, offering the potential to significantly improve how cities identify, prioritize, and implement regeneration investments in an era of increasing computational urbanization

Informed Consent

Informed consent was obtained from all individual participants included in the study.

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Data availability statement

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

Conflicts of Interest

The author declares no conflicts of interest.

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