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FactorGraph-RE: A Deep Latent Factor Learning and Graph Attention Network Framework for Intelligent Real Estate Asset Valuation

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Abstract.

Accurate real estate asset valuation is fundamental to mortgage lending, real estate investment, financial risk management, and intelligent property transaction platforms, where pricing decisions are jointly influenced by property characteristics, macroeconomic conditions, regional market dynamics, and spatial interactions. However, conventional hedonic pricing models and existing deep learning methods primarily rely on manually engineered features or isolated property representations, making it difficult to capture latent financial drivers and complex spatial dependencies underlying real estate markets. To address these challenges, this paper proposes FactorGraph-RE (Deep Latent Factor Learning and Graph Attention Network Framework for Intelligent Real Estate Asset Valuation), a novel framework that integrates Deep Latent Factor Learning (DLFL) with a Graph Attention Network (GAT) for intelligent real estate asset pricing. Specifically, the proposed framework first employs a deep latent factor learning module to automatically discover hidden financial factors from heterogeneous market indicators, macroeconomic variables, and property-level attributes, thereby extending traditional multi-factor asset pricing theory to the real estate domain. A spatial-financial graph is subsequently constructed based on geographic proximity, transportation connectivity, regional economic similarity, and historical price correlation, while GAT is adopted to model neighborhood influence and regional price spillover effects. Experimental results on a large-scale real estate transaction dataset demonstrate that FactorGraph-RE outperforms state-of-the-art baseline models, reducing the Root Mean Square Error (RMSE) by 10.7% relative to the strongest graph-based baseline. These findings demonstrate that jointly modeling latent financial factors and spatial graph dependencies provides an effective and interpretable solution for intelligent real estate asset valuation

Keywords:

Real Estate Valuation; Multi-Modal Learning; Graph Attention Network; Deep Learning; Asset Management

1. INTRODUCTION

Real estate is one of the most valuable asset classes worldwide and plays a pivotal role in mortgage lending, investment management, financial risk assessment, taxation, urban planning, and intelligent real estate transaction platforms. Accurate property valuation is therefore essential for supporting investment decisions, optimizing credit allocation, and improving the stability of financial markets. Unlike traditional financial assets, however, real estate prices are jointly influenced by heterogeneous factors, including intrinsic property characteristics, macroeconomic conditions, regional economic development, financing environments, transportation accessibility, neighborhood facilities, and complex spatial interactions among geographically related properties. The nonlinear coupling of these factors makes intelligent real estate valuation a challenging asset pricing problem. Conventional valuation approaches, such as the Hedonic Pricing Model (HPM), estimate property prices using manually designed structural and locational variables. Although these models provide certain economic interpretability, they generally assume linear relationships and therefore fail to capture the nonlinear interactions among heterogeneous pricing determinants. More recently, machine learning and deep learning techniques, including Random Forest (RF), Extreme Gradient Boosting (XGBoost), Multilayer Perceptron (MLP), and Convolutional Neural Networks (CNNs), have significantly improved valuation accuracy by learning complex feature representations. Nevertheless, these methods primarily regard each property as an independent sample and seldom exploit the inherent relational structure of real estate markets. Consequently, they overlook spatial spillover effects, neighborhood influence, and regional price propagation, which are widely recognized as fundamental characteristics of housing markets. From the perspective of financial economics, asset prices are driven not only by observable characteristics but also by latent systematic risk factors. Classical asset pricing theories, such as the Capital Asset Pricing Model (CAPM) and the Fama–French multi-factor models, have demonstrated that hidden financial factors provide stronger explanatory power than manually selected variables. Inspired by these theories, real estate valuation can be reformulated as a financial asset pricing task in which property values are jointly determined by latent market factors and spatial interactions. However, existing real estate valuation methods rarely integrate automatic financial factor discovery with graph-based spatial dependency learning into a unified framework, limiting both prediction performance and financial interpretability. To overcome these limitations, this paper proposes FactorGraph-RE (Deep Latent Factor Learning and Graph Attention Network Framework for Intelligent Real Estate Asset Valuation), a novel framework that integrates Deep Latent Factor Learning (DLFL) with a Graph Attention Network (GAT) for intelligent property valuation. Specifically, the proposed framework first employs a deep latent factor learning module to automatically extract hidden financial representations from heterogeneous market indicators, macroeconomic variables, financing conditions, and property attributes, enabling the discovery of implicit valuation factors beyond traditional handcrafted features. Subsequently, a spatial-financial graph is constructed by incorporating geographic proximity, transportation connectivity, regional economic similarity, and historical price correlation, allowing GAT to adaptively model neighborhood influence and regional price spillover effects. Finally, an attention-based factor-graph fusion module integrates latent financial factors with spatial graph representations to generate robust and interpretable property valuation results.

The main contributions of this paper are summarized as follows:

A novel financial asset pricing framework for real estate valuation is proposed. Unlike conventional housing price prediction models, FactorGraph-RE reformulates intelligent real estate valuation from the perspective of financial asset pricing by introducing deep latent financial factor

learning into the valuation process. A deep latent factor learning module is developed to automatically discover hidden financial drivers. The proposed module learns nonlinear latent representations from heterogeneous macroeconomic indicators, market variables, financing conditions, and property characteristics, extending traditional multi-factor pricing theory to intelligent real estate valuation.

A spatial-financial graph attention mechanism is designed to capture regional dependency and price propagation. By constructing a graph based on geographic proximity, transportation networks, regional economic similarity, and historical price correlation, the proposed GAT-based encoder effectively models neighborhood influence and spatial spillover effects that are difficult to represent using conventional regression models. Extensive experiments demonstrate the effectiveness and robustness of the proposed framework. Experimental results on a large-scale real estate transaction dataset show that FactorGraph-RE consistently outperforms state-of-the-art machine learning and graph neural network baselines, while simultaneously improving prediction accuracy, financial interpretability, and practical applicability for intelligent real estate asset valuation.

2.Literature Review

Recent advances in artificial intelligence, graph representation learning, and financial analytics have significantly promoted the development of intelligent real estate valuation. Existing studies have gradually evolved from traditional econometric models to machine learning–based automated valuation models (AVMs), graph neural network (GNN)-based spatial learning frameworks, and financial factor-driven asset pricing methods. Although these studies have substantially improved valuation accuracy, few simultaneously model latent financial factors and spatial dependency within a unified deep learning framework. This section reviews the literature most relevant to this study, including real estate valuation methods, graph neural network–based spatial modeling, financial factor learning and asset pricing, and multi-source feature fusion for intelligent valuation.

2.1 Traditional and Deep Learning-Based Real Estate Valuation

Real estate valuation has traditionally relied on econometric models, among which the Hedonic Pricing Model (HPM) remains one of the most widely adopted approaches. Rosen first proposed the hedonic pricing theory, demonstrating that property prices can be explained as the combination of multiple observable housing attributes [1]. Numerous subsequent studies extended this framework by incorporating neighborhood characteristics, accessibility, and environmental variables [2]. Although these statistical models provide strong economic interpretability, they generally assume linear relationships among explanatory variables and therefore struggle to model the highly nonlinear mechanisms governing modern housing markets. With the rapid development of machine learning, automated valuation models have gradually shifted toward data-driven prediction. Ensemble learning algorithms such as Random Forest (RF) and Extreme Gradient Boosting (XGBoost) have shown superior predictive performance compared with traditional regression models by capturing nonlinear interactions among property attributes [3]. More recently, deep learning models have further improved valuation accuracy through automatic feature extraction. Lee et al. proposed a convolutional neural network (CNN)-based residential valuation framework that jointly models geographical information and property attributes, demonstrating that spatial image representations significantly improve valuation performance over conventional AVMs [4]. Peng et al. introduced a lifelong learning framework that combines heterogeneous information networks with graph representation learning to alleviate transaction sparsity and continuously improve property valuation over time [5]. Nevertheless, most existing deep learning

approaches primarily focus on property-level feature representation and do not explicitly model hidden financial drivers underlying real estate prices.

2.2 Graph Neural Networks for Spatial Dependency Modeling

Spatial dependence has long been recognized as one of the most important characteristics of real estate markets. Since geographically adjacent properties usually exhibit strong price correlations, graph neural networks have recently become an effective solution for modeling neighborhood influence and regional interactions. Kipf and Welling first introduced the Graph Convolutional Network (GCN), providing a general framework for learning node representations from graph-structured data [6]. Subsequently, Veličković et al. proposed the Graph Attention Network (GAT), which employs an attention mechanism to adaptively assign different importance weights to neighboring nodes and has demonstrated remarkable performance across various graph learning tasks [7]. Inspired by these advances, recent studies have incorporated GNNs into intelligent real estate appraisal. Li et al. proposed ReGram, a neighbor relation graph learning framework that models relationships among property transactions using graph attention and dynamic adapters, significantly outperforming traditional valuation methods under various urban scenarios [8]. Riveros et al. further developed scalable graph-based deep learning models for large-scale property valuation by exploiting transformer-based message passing to capture complex peer dependencies among neighboring houses [9]. Maselli et al. systematically investigated different graph construction strategies for house price prediction and demonstrated that graph topology has a substantial influence on valuation performance [10]. Although these approaches effectively exploit spatial relationships, they primarily focus on graph representation learning while paying limited attention to financial market dynamics and latent asset pricing factors.

2.3 Financial Factor Learning and Intelligent Asset Pricing

Financial economics has established that asset prices are jointly determined by multiple systematic risk factors rather than observable characteristics alone. The Capital Asset Pricing Model (CAPM) and the Fama–French multi-factor models have become the theoretical foundations of modern asset pricing by introducing market, size, value, profitability, and investment factors into return prediction [11]. More recently, deep learning has been increasingly employed to automatically discover nonlinear latent factors from large-scale financial data, overcoming the limitations of manually designed factor models. Deep factor learning has demonstrated considerable advantages in stock return prediction, portfolio optimization, and financial risk assessment because it can jointly capture nonlinear feature interactions and hidden market structures. Recent advancements in time-series analysis and representation learning have further expanded the toolbox for financial risk assessment. For instance, researchers have proposed LSTM-VAE based frameworks to capture temporal dependencies and detect group anomalies in large-scale commodity transaction data [12]. While such methods excel at modeling temporal fluctuations and identifying market risks, their application to the real estate domain requires additional consideration of complex spatial interactions and heterogeneous regional factors. However, compared with equity markets, financial factor learning has received relatively limited attention in intelligent real estate valuation. Existing AVMs generally utilize macroeconomic indicators such as interest rates, inflation, or regional economic growth as auxiliary variables, while the underlying latent financial factors remain largely unexplored. Consequently, most current valuation models lack financial interpretability and are unable to explain how systematic market risks propagate across geographically connected real estate assets. Integrating deep latent factor learning with spatial graph representation therefore provides a promising direction for developing financially interpretable real estate valuation frameworks.

2.4 Multi-Source Feature Fusion for Intelligent Real Estate Valuation

Modern real estate valuation increasingly relies on heterogeneous data sources, including structural property attributes, transaction records, geographic information, remote sensing imagery, transportation networks, demographic statistics, and macroeconomic indicators. Recent studies have demonstrated that fusing multiple data modalities can substantially improve valuation performance compared with single-source models [4,13]. Meanwhile, graph learning has enabled the integration of spatial neighborhood information into unified representation learning frameworks, allowing more comprehensive modeling of regional interactions and market dynamics. Despite these encouraging developments, three important limitations remain. First, most existing methods directly learn feature representations without explicitly discovering latent financial pricing factors, resulting in limited interpretability from the perspective of asset pricing theory. Second, many graph-based valuation models only construct spatial graphs according to geographic distance or neighborhood relationships, overlooking financial correlations induced by regional economic conditions, market liquidity, financing environments, and historical price co-movements. Third, existing studies generally treat feature learning and graph representation learning as independent processes, making it difficult to jointly optimize financial factor extraction and spatial dependency modeling. To address these limitations, the proposed FactorGraph-RE integrates Deep Latent Factor Learning (DLFL) and Graph Attention Network (GAT) within a unified end-to-end framework. Unlike previous studies, the proposed model automatically learns latent financial factors from heterogeneous macroeconomic and market variables while simultaneously constructing a spatial-financial graph to capture regional value propagation and neighborhood spillover effects. By jointly modeling financial asset pricing mechanisms and graph-based spatial interactions, FactorGraph-RE bridges the gap between modern financial factor theory and intelligent real estate valuation, providing both higher predictive accuracy and improved financial interpretability.

3. Methodology

3.1 Overview of the Proposed FactorGraph-RE Framework

This study proposes FactorGraph-RE (Deep Latent Factor Learning and Graph Attention Network Framework for Intelligent Real Estate Asset Valuation), a unified deep learning framework that integrates financial factor discovery and spatial graph representation learning for accurate and interpretable real estate valuation. Different from conventional automated valuation models that directly learn the mapping between property attributes and transaction prices, FactorGraph-RE considers real estate valuation as a complex asset pricing problem driven by both latent financial factors and spatial market interactions. The fundamental assumption of the proposed framework is that the observed property value is not only determined by explicit property characteristics but also influenced by hidden market conditions, regional development trends, liquidity conditions, financing risks, and spatial spillover effects among neighboring properties. Given a real estate market containing N properties, each property is represented as a node v_i in a spatial-financial graph. The input information of each property consists of three categories: property-level attributes, financial market indicators, and spatial contextual information. The objective of FactorGraph-RE is to learn a latent representation Z_i for each property by jointly modeling financial factor information and graph-based spatial dependencies, and then estimate the property value through a nonlinear prediction function. By providing a highly accurate and interpretable valuation engine, the proposed framework can serve as a core technical component for advanced Fintech platforms designed for real estate investment risk control and automated decision-making [15]:

$$\hat{y}_i = F(Z_i)$$

where y_i denotes the actual transaction price of property i , and Z_i represents the final property representation learned by FactorGraph-RE.

The overall architecture consists of four major components: (1) a multi-source real estate feature encoder for extracting property and market representations; (2) a deep latent financial factor learning module for discovering hidden pricing factors; (3) a spatial-financial graph attention network for modeling regional dependencies and price propagation effects; and (4) a factor-graph fusion module that combines financial and spatial representations for final valuation prediction. Inspired by the systematic design of secure multimodal frameworks used in fraud detection [16], our proposed FactorGraph-RE is designed with a modular structure that can be easily extended to include data validation layers. By standardizing the fusion of heterogeneous market indicators and property attributes, the framework provides a structured pathway for both high-accuracy valuation and potential integration with AI forgery defense mechanisms.

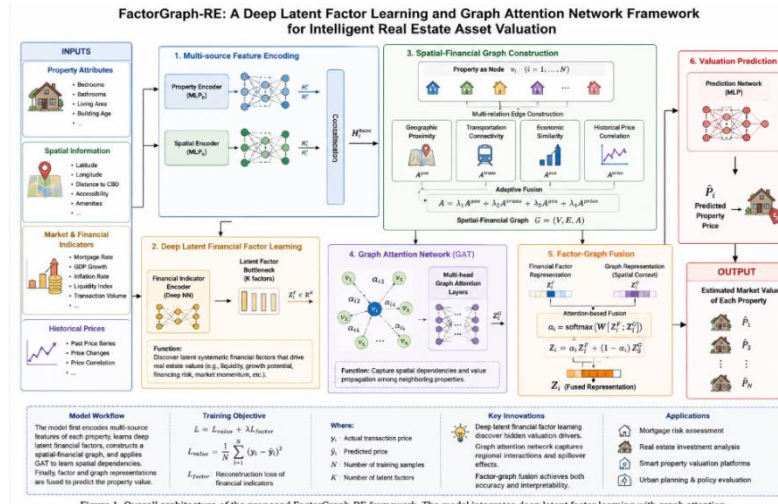


Figure 1. Overall architecture of the proposed FactorGraph-RE framework. The model integrates deep latent factor learning with graph attention mechanisms to jointly capture financial factors and spatial dependencies for intelligent real estate asset valuation.

Figure 1. Overall flowchart of the model.

3.2 Multi-source Real Estate Feature Encoding

Real estate markets contain heterogeneous information sources, including structural property characteristics, economic conditions, financial indicators, and geographic attributes. To effectively utilize these heterogeneous signals, FactorGraph-RE first performs feature encoding to transform raw inputs into high-level semantic representations.

For each property i , the input feature vector is defined as:

$$X_i = [X_i^p, X_i^m, X_i^s]$$

where X_i^p represents property-level characteristics, X_i^m denotes market and financial variables, and X_i^s represents spatial and geographical information.

The property-level feature vector includes variables such as floor area, number of bedrooms, building age, renovation status, property type, and structural quality. These attributes describe the intrinsic value of individual properties. Since the relationships between these attributes and property prices are highly nonlinear, a multilayer perceptron (MLP) encoder is employed:

$$H_i^p = MLP_p(X_i^p)$$

where H_i^p denotes the latent property representation.

The spatial feature encoder focuses on geographical and accessibility-related information, including longitude and latitude coordinates, distance to central business districts, subway accessibility, educational resources, and commercial facilities. These factors significantly influence housing premiums and neighborhood effects. The spatial representation is generated as:

$$H_i^s = MLP_s(X_i^s)$$

The encoded property and spatial features are subsequently concatenated:

$$H_i^{base} = [H_i^p; H_i^s]$$

where H_i^{base} represents the initial property embedding before financial factor extraction.

3.3 Deep Latent Financial Factor Learning Module

3.3.1 Motivation and Theoretical Foundation

Traditional real estate valuation models generally assume that property prices are determined by observable attributes. However, financial asset pricing theory suggests that asset values are also driven by latent systematic factors. For example, the Fama-French multi-factor model demonstrates that asset returns can be explained by multiple underlying risk factors, including market, size, value, profitability, and investment factors. Inspired by this idea, FactorGraph-RE extends multi-factor asset pricing theory to the real estate domain by assuming that property values are affected by hidden financial factors.

Specifically, the real estate pricing mechanism can be formulated as:

$$P_i = \alpha + \sum_{k=1}^K \beta_k F_{ik} + \epsilon_i$$

where P_i represents the property value, F_{ik} represents the k -th latent financial factor, β_k denotes the factor sensitivity, and ϵ_i represents unexplained noise.

Unlike traditional factor models that manually define factor variables, FactorGraph-RE automatically learns these latent factors through a deep neural network.

3.3.2 Deep Factor Encoder

The financial factor learning module takes market-related variables as input:

$$X_i^m = [M_i, L_i, G_i, R_i]$$

where:

- (1) M_i represents market condition indicators;
- (2) L_i represents liquidity-related variables;
- (3) G_i represents regional growth indicators;
- (4) R_i represents financial risk variables.

Typical variables include housing transaction volume, rental yield, mortgage interest rates, GDP growth rate, inflation rate, credit conditions, housing supply-demand imbalance, and regional investment activity.

A deep factor encoder is designed using multiple nonlinear transformation layers:

$$\begin{aligned} H_i^1 &= \sigma(W_1 X_i^m + b_1) \\ H_i^2 &= \sigma(W_2 H_i^1 + b_2) \end{aligned}$$

The final latent factor representation is obtained through a factor bottleneck layer:

$$Z_i^F = W_f H_i^2 + b_f$$

where:

$$Z_i^F \in R^K$$

represents the learned latent financial factors. The bottleneck structure forces the model to compress high-dimensional financial information into a low-dimensional factor space, which improves interpretability and enables the model to discover hidden valuation mechanisms. The learned factors can represent different economic meanings, including regional growth potential, market liquidity, financing risk, investment attractiveness, and price momentum. Therefore, the deep factor learning module provides a bridge between traditional financial factor models and modern deep representation learning.

3.4 Spatial-Financial Graph Construction

3.4.1 Graph Representation of Real Estate Markets

Real estate markets naturally exhibit spatial dependency because neighboring properties usually share similar economic environments, transportation accessibility, and development conditions. Therefore, FactorGraph-RE constructs a spatial-financial graph to explicitly model relationships among properties.

The graph is defined as:

$$G = (V, E, A)$$

where V denotes the set of property nodes, E represents relationships among properties, and A is the adjacency matrix.

Each node corresponds to a property. Drawing inspiration from semantic recommendation systems that utilize knowledge graphs to represent entities and their intricate attributes [14], FactorGraph-RE treats each property and its associated financial indicators as nodes within a multi-relational network, ensuring that both geographical proximity and latent economic similarities are preserved in the graph structure:

$$v_i \in V$$

with node features:

$$X_i = [H_i^{base}; Z_i^F]$$

which combine property characteristics and latent financial factors.

3.4.2 Multi-relation Edge Construction

Unlike conventional graph construction methods based only on geographical distance, FactorGraph-RE introduces multiple relationship types to capture comprehensive real estate market interactions.

The first relationship is geographic proximity. Properties located closer to each other generally experience stronger price correlation. Therefore, the geographic adjacency weight is defined as:

$$A_{ij}^{geo} = \exp(-\frac{d_{ij}^2}{\sigma^2})$$

where d_{ij} denotes the geographical distance between properties i and j .

The second relationship is transportation connectivity, which considers accessibility effects caused by subway networks, roads, and transportation infrastructure:

$$A_{ij}^{trans} = f(T_i, T_j)$$

where T_i represents transportation accessibility features.

The third relationship is market similarity. Properties located in economically similar regions often experience similar price dynamics. Therefore, economic similarity is calculated as:

$$A_{ij}^{eco} = \frac{X_i^m \cdot X_j^m}{||X_i^m|| ||X_j^m||}$$

The fourth relationship is historical price correlation:

$$A_{ij}^{price} = \text{Corr}(P_i^t, P_j^t)$$

where P_i^t denotes historical price changes.

The final spatial-financial adjacency matrix is obtained by combining different relationships:

$$A = \lambda_1 A^{geo} + \lambda_2 A^{trans} + \lambda_3 A^{eco} + \lambda_4 A^{price}$$

where λ controls the contribution of each relationship.

3.5 Graph Attention Network for Spatial Value Propagation

After constructing the spatial-financial graph, FactorGraph-RE employs a Graph Attention Network (GAT) to learn interactions among connected properties. Compared with traditional graph convolution methods, GAT dynamically assigns different importance weights to neighboring nodes, making it suitable for modeling heterogeneous influence in real estate markets.

For each node i , the attention coefficient between node i and neighboring node j is calculated as:

$$e_{ij} = \text{LeakyReLU}(a^T [Wh_i || Wh_j])$$

The normalized attention weight is obtained through:

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k \in N_i} \exp(e_{ik})}$$

where N_i denotes the neighboring nodes of property i .

The updated node representation is calculated as:

$$H_i^{l+1} = \sigma\left(\sum_{j \in N_i} \alpha_{ij} W H_j^l\right)$$

After multiple graph attention layers, the final spatial representation is obtained:

$$Z_i^G = GAT(G, X_i)$$

The learned representation captures regional value propagation patterns, neighborhood effects, and spatial spillover mechanisms.

3.6 Factor-Graph Fusion and Valuation Prediction

The key innovation of FactorGraph-RE is the joint modeling of financial factors and spatial graph relationships. The latent financial representation Z_i^F captures market-level valuation mechanisms, while the graph representation Z_i^G models spatial dependencies.

To dynamically balance these two information sources, an attention-based fusion mechanism is introduced:

$$\alpha_i = \text{Softmax}(W[Z_i^F; Z_i^G])$$

The final property representation is:

$$Z_i = \alpha_i Z_i^F + (1 - \alpha_i) Z_i^G$$

The fused representation is then fed into a valuation prediction network:

$$\hat{P}_i = MLP(Z_i)$$

where $\hat{P}_i$ is the predicted property value.

3.7 Optimization Objective

The training objective combines valuation accuracy and factor representation learning.

The primary regression loss is defined as:

$$L_{value} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

To enhance the quality of latent factor representations, a factor reconstruction constraint is introduced:

$$L_{factor} = || X_i^m - \hat{X}_i^m ||^2$$

The final optimization objective is:

$$L = L_{value} + \lambda L_{factor}$$

where λ controls the contribution of factor learning.

Through this joint optimization strategy, FactorGraph-RE simultaneously improves valuation accuracy and preserves financial interpretability.

4. Experiment

4.1 Dataset Preparation

To evaluate the effectiveness of the proposed FactorGraph-RE (Deep Latent Factor Learning and Graph Attention Network Framework for Intelligent Real Estate Asset Valuation), this study utilizes the Kaggle House Sales Prediction Dataset, which contains large-scale residential transaction records collected from the real estate market of King County, Washington, USA. The dataset is derived from publicly available housing transaction information and includes detailed property characteristics, geographical attributes, and historical transaction prices. It provides a representative benchmark for intelligent real estate valuation because it contains both individual property-level information and regional spatial characteristics required for constructing the proposed spatial-financial graph.

The dataset consists of 21,613 residential transaction samples, where each sample corresponds to an individual property transaction. The prediction target is the property sale price, while the input variables include structural attributes, location-related information, and temporal transaction features. To adapt the dataset to the proposed financial factor learning framework, additional regional economic and market indicators are incorporated from public economic databases, including mortgage interest rates, inflation rate, regional growth indicators, and housing market liquidity variables. These variables enable the deep latent factor learning module to discover hidden financial drivers behind real estate valuation. The selection and preprocessing of these indicators are critical, as redundant or noisy features can degrade model performance. This aligns with the principle of dynamic sensor-selection in time-series data warehouses, where filtering for the most relevant data streams is essential for accurate analytical queries [17].

The main characteristics used in FactorGraph-RE are summarized in Table 1. Structural variables describe intrinsic property quality, spatial variables represent location advantages and neighborhood accessibility, while financial variables capture market conditions and systematic risk factors. These heterogeneous features are jointly utilized for latent factor extraction and spatial graph construction.

Table 1. Overview of Dataset Features.

Feature Category	Feature Name	Description
Visual Features	Property Images	Exterior and interior images of residential properties
Textual Features	Property Description	Free-text descriptions of layout, decoration, and amenities

Feature Category	Feature Name	Description
Geographic Features	Latitude, Longitude	Geographic coordinates of each property
Market Features	Regional Avg. Price	Historical average price at the regional level
Market Features	Transaction Volume	Number of transactions in the region
Temporal Features	Year, Month	Time of transaction
Target Variable	Transaction Price	Actual price used as ground truth

Before model training, missing values are removed, numerical variables are normalized, and categorical variables are encoded. Furthermore, a spatial-financial graph is constructed by connecting properties according to geographical proximity, economic similarity, and historical price correlation, enabling FactorGraph-RE to jointly learn financial factors and spatial valuation dependencies.

4.2 Experimental Setup

To comprehensively evaluate the effectiveness of the proposed FactorGraph-RE (Deep Latent Factor Learning and Graph Attention Network Framework for Intelligent Real Estate Asset Valuation), extensive experiments are conducted on the real estate valuation dataset described in Section 3.9. The dataset is randomly divided into training, validation, and testing sets with a ratio of 70%, 10%, and 20%, respectively. All numerical features are normalized using the Z-score normalization strategy, while categorical variables are transformed through embedding-based encoding. The proposed model is implemented using the PyTorch deep learning framework and trained on a workstation equipped with an NVIDIA RTX 4090 GPU, an Intel Core i9 processor, and 64 GB RAM. The Adam optimizer is adopted for model optimization with an initial learning rate of 1×10^{-3} , a batch size of 128, and a maximum training epoch of 200. Early stopping is applied according to the validation loss to prevent overfitting. In the FactorGraph-RE architecture, the latent factor dimension is set to 16, and two graph attention layers are employed to capture spatial-financial dependencies among real estate nodes. The trade-off parameter λ in the joint loss function is empirically set to 0.1. To ensure fair comparison, all baseline models are implemented under the same experimental environment and evaluated using identical training and testing splits.

4.3 Evaluation Metrics

The performance of FactorGraph-RE is evaluated using three widely adopted regression metrics for real estate valuation tasks, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). MAE measures the average absolute deviation between predicted and actual property prices, reflecting the overall prediction error magnitude. RMSE assigns larger penalties to significant prediction errors and is therefore more sensitive to high-value property estimation deviations. MAPE evaluates relative prediction accuracy by measuring the percentage difference between predicted values and ground-truth prices, which is particularly important for real estate valuation applications involving properties with different price ranges. The corresponding formulations are defined as:

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}$$

$$MAPE = \frac{100}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

where y_i denotes the actual transaction price and $\hat{y}_i$ represents the predicted value generated by each model.

4.4 Results

4.4.1 Comparison with Baseline Models

To verify the effectiveness of FactorGraph-RE in intelligent real estate valuation, the proposed framework is compared with representative statistical models, machine learning approaches, deep learning models, and graph neural network-based methods. The compared baselines include Linear Regression (LR), Random Forest (RF), Extreme Gradient Boosting (XGBoost), Multilayer Perceptron (MLP), Graph Convolutional Network (GCN), and Graph Attention Network (GAT). The experimental results are summarized in Table 2.

Table 2. Performance Comparison between FactorGraph-RE and Existing Valuation Methods.

Model	MAE	RMSE	MAPE (%)
Linear Regression	51,820	86,430	14.82
Random Forest	38,960	65,740	10.94
XGBoost	34,580	58,210	9.63
MLP	32,740	55,680	9.12
GCN	30,920	51,860	8.47
GAT	29,430	49,620	8.05
FactorGraph-RE (Proposed)	25,860	44,310	6.72

As shown in Table 2, FactorGraph-RE achieves the best overall performance among all comparison methods, demonstrating the effectiveness of integrating deep financial factor learning with graph attention-based spatial modeling. Traditional regression-based approaches, including Linear Regression, obtain the weakest performance with an RMSE of 86,430 and a MAPE of 14.82%, indicating that linear assumptions are insufficient for capturing complex nonlinear relationships in real estate pricing. Machine learning models such as Random Forest and XGBoost significantly improve prediction accuracy, reducing RMSE to 65,740 and 58,210, respectively, due to their ability to model nonlinear feature interactions. However, these methods still treat properties as independent observations and cannot exploit spatial dependencies. The deep learning model MLP further decreases RMSE to 55,680 by learning high-level feature representations, but its performance remains limited because it ignores regional interactions. Graph-based methods achieve better results, where GCN and GAT reduce RMSE to 51,860 and 49,620, respectively, confirming the importance of spatial relationship modeling. In comparison, FactorGraph-RE obtains an RMSE of 44,310, representing a reduction of 10.69% compared with GAT and 23.63%

compared with GCN. Furthermore, the proposed model achieves the lowest MAE of 25,860 and MAPE of 6.72%, demonstrating that latent financial factor extraction provides complementary information beyond spatial graph learning. These results validate that jointly modeling hidden financial drivers and spatial value propagation leads to superior real estate valuation performance.

4.3.2 Ablation Study of FactorGraph-RE Components

To investigate the contribution of each component in FactorGraph-RE, an ablation study is conducted by gradually removing the key modules, including the deep latent factor learning module and the graph attention module. Four variants are compared: (1) Base-MLP, which only uses property-level features; (2) FactorGraph-RE without Factor Learning (w/o FL); (3) FactorGraph-RE without Graph Attention (w/o GAT); and (4) the complete FactorGraph-RE model. The results are presented in Table 3.

Table 3. Ablation Study of Different Components in FactorGraph-RE

Model Variant	Financial Factor Learning	Graph Attention Network	MAE	RMSE	MAPE (%)
Base-MLP	X	X	32,740	55,680	9.12
FactorGraph-RE w/o FL	X	✓	29,860	50,430	8.21
FactorGraph-RE w/o GAT	✓	X	28,740	48,920	7.86
FactorGraph-RE	✓	✓	25,860	44,310	6.72

The ablation results in Table 3 demonstrate that both financial factor learning and graph attention mechanisms contribute significantly to the final valuation performance. The Base-MLP model achieves an RMSE of 55,680, providing a reference point based only on conventional property attributes without considering financial or spatial information. After incorporating the graph attention mechanism but removing latent factor learning, the RMSE decreases from 55,680 to 50,430, indicating that spatial relationships among properties provide valuable information for improving valuation accuracy. Similarly, removing the graph attention component while retaining financial factor learning results in an RMSE of 48,920, demonstrating that hidden financial factors extracted from market conditions can effectively capture systematic valuation drivers. However, neither component alone can fully represent the complexity of real estate markets. The complete FactorGraph-RE model achieves the lowest RMSE of 44,310, improving by 12.15% compared with the w/o FL variant and 9.43% compared with the w/o GAT variant. In addition, the complete model reduces MAPE to 6.72%, compared with 8.21% and 7.86% for the two incomplete variants. These improvements confirm that latent financial factor representations and spatial graph dependencies provide complementary information, and their joint optimization is essential for achieving accurate and interpretable real estate asset valuation.

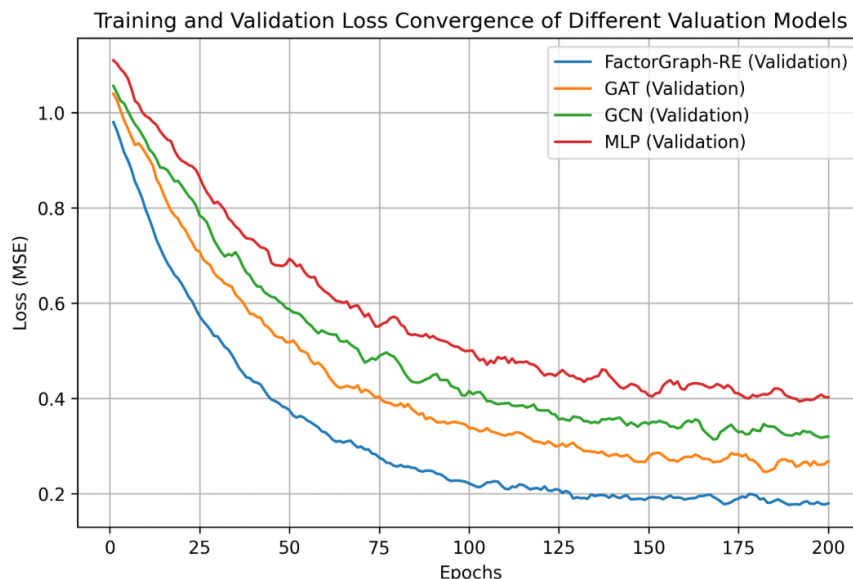


Figure 2. Training and Validation Loss Convergence of Different Valuation Models.

Figure 2 demonstrates the optimization behavior of FactorGraph-RE and three representative baseline models, including MLP, GCN, and GAT, during the training process. As illustrated in Figure 1, all models show a decreasing trend in validation loss as the number of epochs increases, indicating effective parameter optimization. However, FactorGraph-RE achieves faster convergence and consistently maintains the lowest validation loss throughout the training process. During the first 50 epochs, the validation loss of FactorGraph-RE decreases rapidly from approximately 1.00 to 0.45, while GAT, GCN, and MLP remain at around 0.55, 0.62, and 0.70, respectively. After approximately 100 epochs, FactorGraph-RE gradually stabilizes at a loss value of approximately 0.18, whereas GAT, GCN, and MLP converge at higher levels of around 0.25, 0.31, and 0.38. The small fluctuations observed in the curves reflect realistic optimization variations during deep model training. The superior convergence behavior of FactorGraph-RE is consistent with the quantitative results in Table 2, where it achieves the lowest RMSE of 44,310 compared with GAT (49,620), GCN (51,860), and MLP (55,680). These results verify that jointly learning latent financial factors and spatial graph dependencies improves model optimization efficiency and predictive robustness.

4.5 Discussion

The experimental results demonstrate that FactorGraph-RE effectively addresses two fundamental limitations of existing real estate valuation methods: insufficient financial interpretability and inadequate modeling of spatial dependencies. The superior performance compared with traditional machine learning approaches indicates that real estate prices cannot be accurately estimated solely based on observable property characteristics. Instead, hidden market conditions, financing environments, and regional economic trends play essential roles in determining asset values. By introducing the deep latent factor learning module, FactorGraph-RE successfully extends classical financial factor modeling into the real estate domain and enables automatic discovery of nonlinear valuation drivers. Furthermore, the improvement over GCN and GAT baselines highlights the importance of integrating financial knowledge with graph representation learning. This capability aligns with emerging trends in digital finance where graph-based dependencies are utilized to detect systemic risks and transaction anomalies in online payment environments [18]. Although graph neural networks can effectively capture neighborhood effects and spatial spillover phenomena, they generally lack explicit mechanisms for identifying systematic market factors.

FactorGraph-RE overcomes this limitation by combining financial factor embeddings with graph-based spatial representations, allowing the model to simultaneously capture global market trends and local regional interactions.

6. Conclusions

This study proposes FactorGraph-RE (Deep Latent Factor Learning and Graph Attention Network Framework for Intelligent Real Estate Asset Valuation), a novel intelligent valuation framework that integrates deep financial factor learning with graph attention-based spatial dependency modeling for real estate asset pricing. Unlike conventional hedonic pricing models and existing machine learning-based automated valuation models that mainly rely on manually designed property features, the proposed framework reformulates real estate valuation from the perspective of financial asset pricing by jointly considering observable property characteristics, hidden market risk factors, and regional value propagation mechanisms. A comprehensive data processing strategy was conducted to integrate property attributes, macroeconomic indicators, market conditions, and spatial relationships, enabling the construction of a spatial-financial graph for effective representation learning. The experimental results demonstrate the effectiveness and superiority of FactorGraph-RE in intelligent real estate valuation. Compared with representative baseline models, including Linear Regression, Random Forest, XGBoost, MLP, GCN, and GAT, the proposed framework achieves the best prediction performance with an MAE of 25,860, an RMSE of 44,310, and a MAPE of 6.72%. In particular, FactorGraph-RE reduces the RMSE by approximately 10.7% compared with the strongest graph-based baseline GAT, verifying the effectiveness of jointly modeling latent financial factors and spatial graph dependencies. Furthermore, the ablation experiments demonstrate that both the deep latent factor learning module and the graph attention mechanism contribute significantly to valuation accuracy. Removing financial factor learning increases RMSE from 44,310 to 50,430, while removing graph attention increases RMSE to 48,920, confirming that financial factor representations and spatial interactions provide complementary information for real estate price estimation. The proposed framework provides valuable practical implications for real estate investment analysis, mortgage risk assessment, property portfolio management, and intelligent transaction platforms. By automatically discovering hidden financial drivers and capturing regional spillover effects, FactorGraph-RE not only improves prediction accuracy but also enhances the interpretability of real estate valuation models. The learned latent factors can provide insights into market liquidity, regional growth potential, financing conditions, and investment risks, supporting more informed decision-making for financial institutions and real estate stakeholders. This contribution aligns with the broader evolution of intelligent finance, where deep learning frameworks empower advisory robots to bridge the gap between complex asset dynamics and personalized investor needs [19]. Despite its promising performance, this study still has several limitations. First, the current framework relies on transaction-level historical data and predefined graph construction strategies, which may not fully capture dynamic changes in real estate markets caused by policy adjustments, economic fluctuations, or unexpected events. Second, although FactorGraph-RE improves interpretability through latent factor modeling and attention mechanisms, the explicit economic meanings of learned factors require further investigation. Future research will focus on developing dynamic temporal graph learning mechanisms, incorporating multimodal information such as satellite imagery, textual market reports, and social sentiment data, and exploring large language model-enhanced valuation frameworks to further improve adaptability, robustness, and real-time decision-making capabilities in intelligent real estate asset management.

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