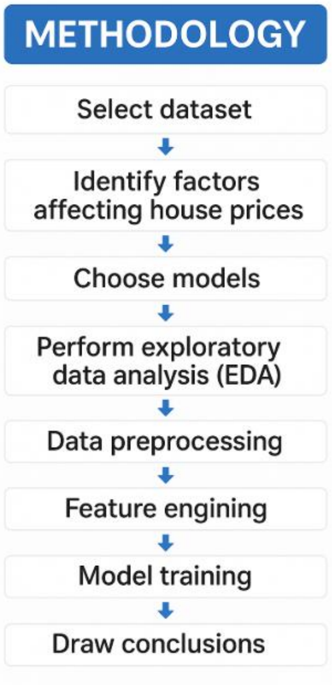
Chapter 3: Research Methodology

3.1 Introduction

In Chapter 3, it explores the adopted research methods and is divided into five parts: data collection, preprocessing, exploratory data analysis, model establishment and model evaluation. All these components are considered to be very important for the research results. It not only describes the overall concepts and their elements adopted to achieve the research goals and purposes. Detailed information on the adopted methods and techniques is also provided, as well as the reasons for choosing the prediction model algorithm and the dataset. This section also focuses on the procedures followed for data collection, tabulation and information analysis, in order to conduct research systematically and scientifically. Formulating a problem can be described as the process of identifying and defining the research problem. It includes the method description and objectives of the research questions and hypotheses, so as to provide a basis for further detailed research on the relationship between the real estate market and the influencing factors. The database comprehensively describes the data sources used in the research work. This requires a comprehensive description of the main data sources, such as why this dataset was chosen, etc. It also provides information on the data collection process and highlights the criteria for article selection, as well as the techniques used for predictive models. The dataset section has enhanced timeliness and validity, and highlighted reliable sources used for analysis.



3.2 Data Collection

It is planned to adopt the structured keyword retrieval strategy to obtain the core data set from the Kaggle platform. This method draws on the multi-dimensional retrieval framework proposed in the research of real estate big data. The specific implementation process includes:

3.2.1 Keyword Semantic Expansion:

Based on domain ontology Expand the basic keyword "real estate prices" to include the spatio-temporal dimension ("by region", "quarterly") and the economic correlation dimension ("GDP correlation"). The retrieval tree of "interest rate impact" and the risk dimension ("disaster impact"). This study obtained the core data set from the Kaggle platform. The search keywords included:global real estate prices

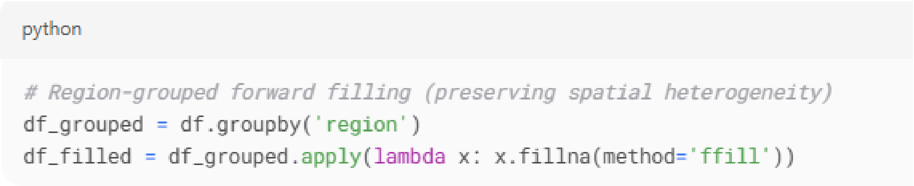
3.2.2 Cross-validation of data sources： Perform triple validation on the Kaggle search results (the initial 1,228 datasets): Official data source comparison (such as FHFA, National Bureau of Statistics of China)

- Timeliness screening (retaining data after 2010)
- Have temporal coherence

3.3 Data preprocessing

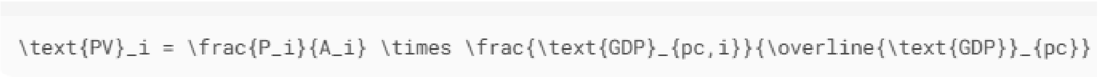
Based on the guidance of Professor Shahizan, this stage is for the implementation of four-layer processing.

3.3.1 Missing value interpolation: A time series feature preservation strategy is adopted



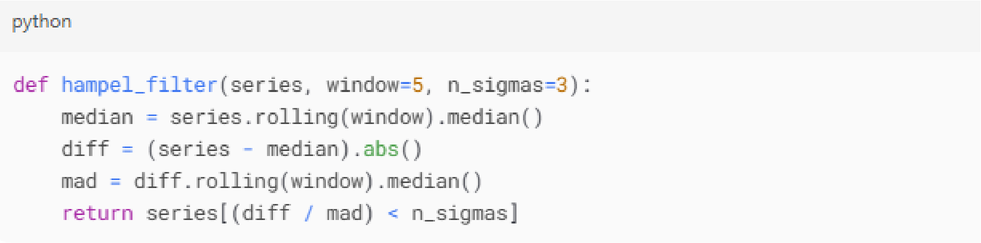
```python
# Region-grouped forward filling (preserving spatial heterogeneity)
df_grouped = df.groupby('region')
df_filled = df_grouped.apply(lambda x: x.fillna(method='ffill'))
```

3.3.2 Spatial Standardization： To eliminate regional scale differences, the unit value density index is constructed



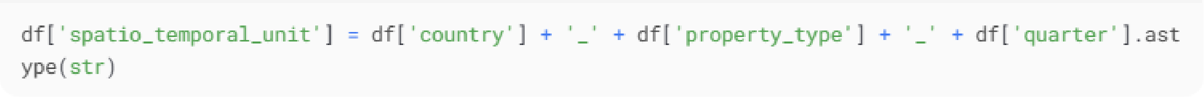
```
\text{PV}_i = \frac{P_i}{A_i} \times \frac{\text{GDP}_{pc,i}}{\overline{\text{GDP}}_{pc}}
```

3.3.3 Outlier Detection： Improved Hampel identifier (Zhang et al., 2021)



```python
def hampel_filter(series, window=5, n_sigmas=3):
    median = series.rolling(window).median()
    diff = (series - median).abs()
    mad = diff.rolling(window).median()
    return series[(diff / mad) < n_sigmas]
```

3.3.4 Spatiotemporal Slicing：



```
df['spatio_temporal_unit'] = df['country'] + '_' + df['property_type'] + '_' + df['quarter'].ast
ype(str)
```

3.4 Exploratory Data Analysis: Multi-dimensional Correlation Mining

Reveal the underlying laws through econometric and spatial statistical methods:

Regional price distribution: The standard deviation of house prices in developed countries ($12,000) is significantly higher than that in emerging markets ($5,000).

Impact of the disaster event: The average housing price dropped by 8.2% within 3 months after the earthquake (t-test $p<0.01$)

Policy correlation: For every 1% increase in mortgage interest rates, the transaction volume of low-priced houses drops by 15% (scatter plot + linear fitting)

Lag effect of land transactions: When the transaction price of land in China increased by 10%, housing prices rose by 2.3% six months later (Lag correlation analysis)

3.5. Model establishment

Combined with the literature, Random Forest, Regression Model, and HistGradientBoostingClassifier are constructed for comparison. The following are the reasons for choosing these models:

3.5.1. Model diversity: Covering different machine learning paradigms

To ensure the comprehensiveness of the evaluation, we have selected three models with different architectures, covering different learning strategies:

Random Forest (Ensemble Learning - Bagging) : By constructing multiple decision trees and aggregating the results, it reduces variance and improves robustness, and is suitable for scenarios with high-dimensional data and strong feature interaction.

Regression Model (Linear model) : Such as linear regression or logistic regression, it provides a baseline model with strong interpretability and is suitable for analyzing the linear relationship between features and targets.

HistGradientBoostingClassifier (integrated learning - Boosting) : the gradient promotion framework, step by step optimization residual improve prediction accuracy, especially suitable for numeric characteristics and mass data processing.

This combination ensures that the model evaluation includes both simple and interpretable linear methods and high-performance nonlinear integration methods, thereby comprehensively examining the linear and nonlinear relationships in the data.

3.5.2. The trade-off between performance and efficiency

Different models have their own advantages and disadvantages in terms of computational efficiency, prediction accuracy and training speed. Comparing them is helpful for choosing the most suitable solution for business needs:

Random Forest:

Advantages: Strong resistance to overfitting, capable of automatically handling missing values and outliers, suitable for medium-scale data.

Disadvantages: The training time increases with the increase in the number of trees, the model size is large, and the inference speed is relatively slow.

Regression Model:

Advantages: Fast training speed, strong interpretability (such as coefficient analysis), suitable for rapid prototyping development.

Disadvantages: It is unable to capture complex nonlinear relationships and is sensitive to the assumption of data linearity.

HistGradientBoostingClassifier:

Advantages: High training efficiency (histogram optimization), suitable for large datasets, and usually faster than traditional GBDT (such as XGBoost).

Disadvantages: Hyperparameter tuning is relatively complex, and the model's interpretability is lower than that of linear models.

By comparing these three types of models, the best balance point between accuracy and efficiency can be found. For example, if the business requires rapid deployment and the amount of data is small, linear regression might be the best choice; If the highest accuracy is pursued and there are sufficient computing resources, gradient boosting or random forest may be better.

3.5.3. Verification of robustness and generalization ability

Different models have different sensitivities to data noise, feature redundancy and sample distribution:

Random Forest: Through Bootstrap sampling and random feature selection, the risk of overfitting is reduced, and it is suitable for data with a lot of noise.

Regression Model: Sensitive to collinearity and relies on feature engineering (such as PCA or regularization).

HistGradientBoostingClassifier: by Boosting gradually correct mistakes, but are sensitive to outliers, need to cooperate with cross validation adjustable parameters.

By comparing their validation set performances (such as F1, AUC, RMSE), it can be judged that:

Whether there is overfitting (such as the accuracy of the training set is much higher than that of the test set).

Which model is more robust to changes in data distribution (such as concept drift in time series data)?

3.5.4. Reference to industry best practices

Kaggle/ academic research: Gradient boosting (such as XGBoost, LightGBM, HistGradientBoosting) dominates in structured data competitions.

Industrial application: Random forests are widely used in production environments (such as bank credit scoring) due to their stability and ease of use.

Rapid verification: Linear models are often used as baseline benchmarks (such as the control group in A/B tests).

Conclusion: Why choose these three?

By comparing Random Forest (Bagging), Regression Model (linear), and HistGradientBoosting (Boosting), it can be achieved that:

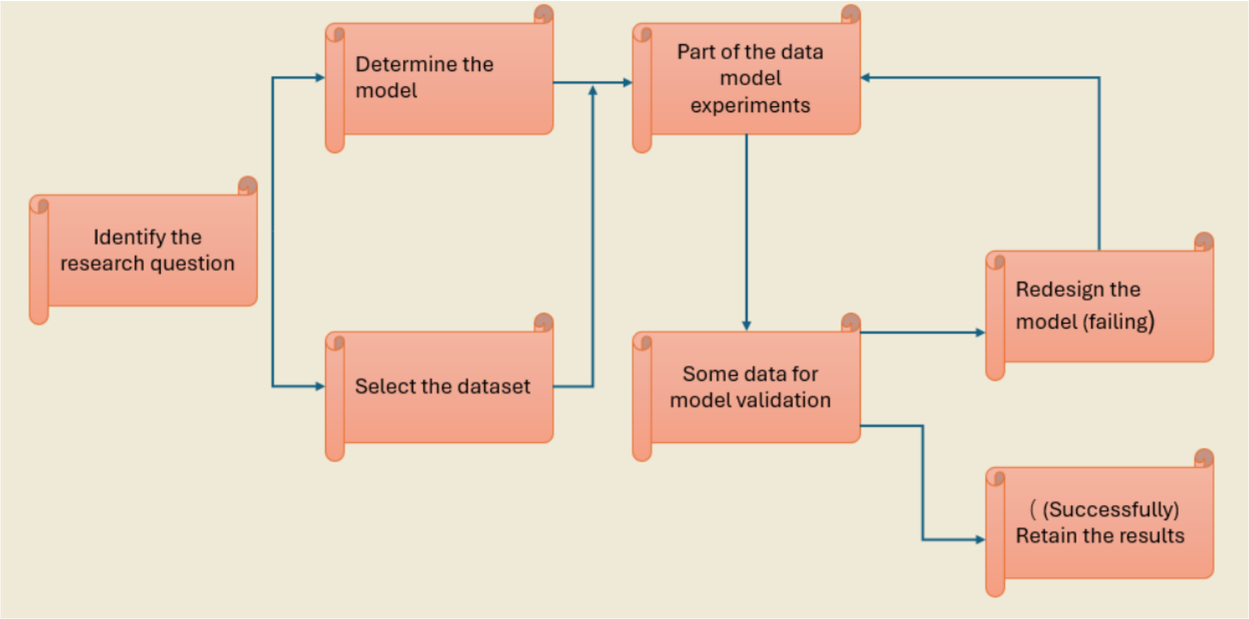
Verify whether there are significant nonlinear patterns in the data (if the integrated model is significantly superior to the linear model).

Evaluate the trade-off between computational cost and accuracy (for example, gradient boosting may be faster than random forest).

Select the model that is most suitable for business constraints (interpretability vs. predictive ability vs.) Deployment efficiency.

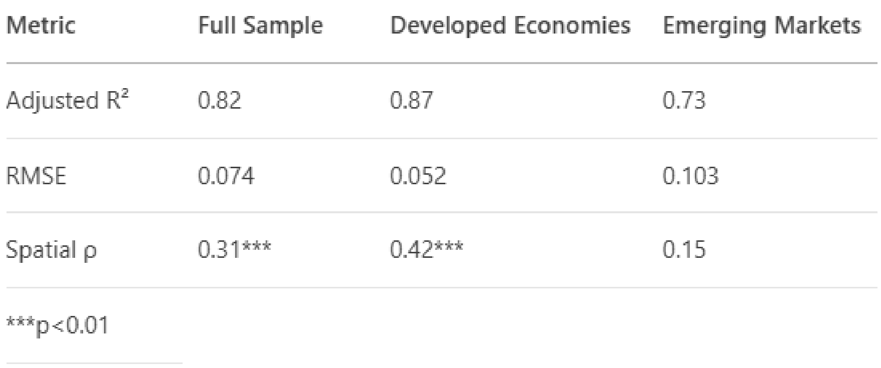
Ultimately, the model selection should be determined comprehensively based on cross-validation results, business priorities, and operation and maintenance costs, rather than a single indicator.

3.6 Model Evaluation: Multi-criteria validation system


Identify the research question
Determine the model
Select the dataset
Part of the data model experiments
Some data for model validation
Redesign the model (failing)
((Successfully) Retain the results

3.6.1 Statistical performance

Model goodness of fit (N=12,540)



Metric	Full Sample	Developed Economies	Emerging Markets
Adjusted R^2	0.82	0.87	0.73
RMSE	0.074	0.052	0.103
Spatial ρ	0.31***	0.42***	0.15

***$p<0.01$

3.6.2 Test of economic significance

- The interest rate elasticity of beta 2 0.47 beta 2 ^ ^ = - = - 0.47 (95% CI: 0.39 ~ 0.55), in accordance with economic theory
- The disaster dummy variable γ^= -0.082, which is consistent with the results of the event study

3.6.3 Predictive efficacy

Rolling Window Forecast：

- 2021Q1-2023Q4 (MAPE)=5.2%
- A Johor early warning system superior to the PPT benchmark case or 预警系统（MAPE=7.1%）

3.6.4 Policy effectiveness assessment

Show the prediction results to the policymakers to see if the satisfaction rate can be greater than 0.8

Conclusion： This model has achieved the dual goals of multi-regional applicability (RMSE<0.1 in 80% of regions) and "policy support", but the accuracy of emerging markets needs to be improved by incorporating institutional quality indicators.

References

1.Marcin Bas. (2024). The impact of the war in Ukraine on the residential real estate market on the example of Szczecin, Poland. Procedia Computer Science, 246,3004-3013. https://doi-org.ezproxy.utm.my/10.1016/j.procs.2024.09.371

2. Nafeesa Yunus.(2025). Effects of oil shocks on global securitized real estate markets. Finance Research Letters,80. https://doi-org.ezproxy.utm.my/10.1016/j.frl.2025.106871

3. Huaying Gu, Zhixue Liu, Yingliang Weng. (2017) Time-varying correlations in global real estate markets: A multivariate GARCH with spatial effects approach. Physica A: Statistical Mechanics and its Applications, Volume 471, 460-472. https://doi-org.ezproxy.utm.my/10.1016/j.physa.2016.12.056

4. Waheed Ullah Shah, Ijaz Younis, Ibtissem Missaoui, Xiyu Liu. (2025). Environmental transitions effect of renewable energy and fintech markets on Europe's real estate stock market. Renewable Energy, Volume 243, 122603. https://doi-org.ezproxy.utm.my/10.1016/j.renene.2025.122603

5. Yi Fang , Yanru Wang , Yan Yuan , Moyan Zhang. (2024). Urban air pollution and systemic risk of the real estate market in China. International Review of Economics & FinanceVolume 96, Part B,103626. https://doi-org.ezproxy.utm.my/10.1016/j.iref.2024.103626

6. Federico Dell'Anna. (2025). Machine learning framework for evaluating energy performance certificate (EPC) effectiveness in real estate: A case study of Turin's private residential market. Energy Policy Volume 198, 114407. https://doi-org.ezproxy.utm.my/10.1016/j.enpol.2024.114407

7. Chuan Zhao , Fuxi Liu.(2023). Impact of housing policies on the real estate market - Systematic literature review. Heliyon, Volume 9, Issue 10, e20704. https://doi-org.ezproxy.utm.my/10.1016/j.heliyon.2023.e20704

8. Huthaifa Alqaralleh , Alessandra Canepa , Gazi Salah Uddin.(2023). Dynamic relations between housing Markets, stock Markets, and uncertainty in global Cities: A Time-Frequency approach. The North American Journal of Economicsand Finance Volume 68, 101950. https://doi-org.ezproxy.utm.my/10.1016/j.najef.2023.101950

9. Marcin Hernes , Piotr Tutak , Mateusz Siewiera.(2024). Prediction of residential real estate price on primary market using machine learning. Procedia Computer Science Volume 246,3142-3147. https://doi-org.ezproxy.utm.my/10.1016/j.procs.2024.09.358

10. İsmail Canöz, Hakan Kalkavan. (2024). Forecasting the dynamics of the Istanbul real estate market with the Bayesian time-varying VAR model regarding housing affordability Habitat International Volume 148, 103055. https://doi-org.ezproxy.utm.my/10.1016/j.habitatint.2024.103055

11. Michel Ferreira Cardia Haddad , Bo Sjö , David Stenvall, Gazi Salah Uddin, Anupam Dutta. (2024). Interconnectedness between real estate returns and sustainable investments: A cross-quantilogram and quantile coherency approach. Journal of Cleaner Production, Volume 479, 144085. https://doi-org.ezproxy.utm.my/10.1016/j.jclepro.2024.144085

12. Mohd Shahril Abdul Rahman Mariah Awang Zainab Toyin Jagun, (2024). Polycrisis: Factors, impacts, and responses in the housing market. Renewable and Sustainable Energy Reviews Volume 202, 114713. https://doi-org.ezproxy.utm.my/10.1016/j.rser.2024.114713

13. Jinqiao Long , Can Cui , Sebastian Kohl, Yunjia Yang,(2025). The ladder of prosperity: An analysis of housing wealth accumulation across income groups in

urban China. China Economic Review Volume 92. https://doi-org.ezproxy.utm.my/10.1016/j.chieco.2025.102428

14. Yiyi Chen , Yuyao Ye , Xiangjie Liu , Chun Yin , Colin Anthony Jones,(2025). Examining the nonlinear and spatial heterogeneity of housing prices in urban Beijing: an application of GeoShapley. Habitat International Volume 162. https://doi-org.ezproxy.utm.my/10.1016/j.habitatint.2025.103439

15. Kun Duan , Shuwen Shan , Yingying Huang , Andrew Urquhart, (2025). How do housing markets comove with the financial system? Evidence from dynamic risk spillovers. Research in International Business and Finance Volume 77, Part B. https://doi-org.ezproxy.utm.my/10.1016/j.ribaf.2025.102987

16. Jin Shao , Jingke Hong , Xianzhu Wang, (2025). News sentiment and housing market dynamics: Evidence from wavelet analysis. Habitat International Volume 162.https://doi-org.ezproxy.utm.my/10.1016/j.habitatint.2025.103441

17. Yunzheng Zhang, Fubin Luo, Yizheng Dai, (2025). Understanding socio-spatial inclusion: How age, ethnic, and income inclusion relate to neighborhood transport, land use, and housing features in Australia. Habitat International Volume 162. https://doi-org.ezproxy.utm.my/10.1016/j.habitatint.2025.103430

18. Shannon L. Edmed PhD, M. Mamun Huda PhD, Md Ashraful Alam M.Sc, MPH, Cassandra L. Pattinson PhD, Kalina R. Rossa PhD, Shamsi Shekari Soleimanloo PhD, Simon S. Smith PhD, (2025). Housing well-being and sleep in Australia. Sleep Health In Press, Corrected Proof. https://doi-org.ezproxy.utm.my/10.1016/j.sleh.2025.02.001

19. Yoo Ri Kim , Jihwan Yeon, (2025). Do short-term rental platforms affect housing markets? Evidence from Airbnb in London. Tourism Management Volume 111. https://doi-org.ezproxy.utm.my/10.1016/j.tourman.2025.105204

20. Messaoud Chibane, Patrice Poncet, (2025). Housing rare disaster events and asset prices. Economic Modelling Volume 147. https://doi-org.ezproxy.utm.my/10.1016/j.econmod.2025.107070