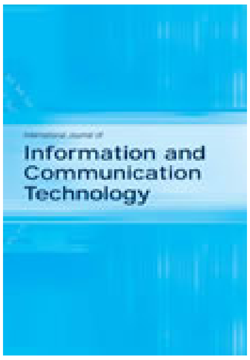

International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

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Article History:

Received:	10 February 2025
Last revised:	19 February 2025
Accepted:	19 February 2025
Published online:	16 April 2025

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Sensitivity analysis of urban planning using random forests and transformers: a case study of residential area renovation

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Abstract: Currently, residential area renovation in urban planning is facing many problems. Traditional sensitivity analysis methods are often difficult to handle. Therefore, this article proposes a comprehensive method that combines random forest and transformer models. Firstly, the random forest algorithm is used to evaluate the feature importance of multidimensional influencing factors in residential area renovation and identify key influencing factors; subsequently, leveraging the advantages of the transformer model, the complex nonlinear relationships and spatiotemporal dependencies between key factors were processed, improving the accuracy and interpretability of sensitivity analysis. Through empirical analysis, the effectiveness and superiority of this method in sensitivity analysis of residential area renovation have been verified, providing more scientific and accurate decision support for urban planning. Research has shown that the combination of random forest and transformer can provide a new approach for sensitivity analysis in complex planning tasks.

Keywords: random forest; transformer; city planning; sensitivity analysis.

Reference to this paper should be made as follows: Deng, Z., Pi, L., Li, J. and Wang, C. (2025) 'Sensitivity analysis of urban planning using random forests and transformers: a case study of residential area renovation', *Int. J. Information and Communication Technology*, Vol. 26, No. 8, pp.35–48.

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1 Introduction

With the acceleration of global urbanisation, residential area renovation has become one of the crucial tasks in urban planning. In this process, how to scientifically evaluate the impact of various factors on the transformation effect to optimise planning decisions has become an important issue in current urban planning research. Traditional sensitivity analysis methods, such as local sensitivity analysis (Frey and Patil, 2002) and single factor sensitivity analysis (Morris, 1992), although providing a preliminary understanding of system output to some extent, often overlook the complex nonlinear relationships and interactions between factors. Therefore, how to handle sensitivity analysis of multidimensional factors has become a hot topic of concern in the academic community. In sensitivity analysis, machine learning-based approaches have shown great promise recently. In particular, RF, as a non-parametric ensemble learning algorithm, is widely used in environmental modelling, economic forecasting, and urban planning due to its ability to effectively process large-scale, high-dimensional data and identify the importance of key factors (Breiman, 2001; Zhang et al., 2024a). For example, Parvin et al. (2022) conducted sensitivity analysis on multiple social, economic, and environmental factors in urban renovation projects using random forests, and achieved relatively accurate evaluation results. However, although random forests perform well in feature selection and variable importance assessment, their performance still has certain limitations when dealing with factors with complex spatiotemporal dependencies.

Deep learning methods, particularly transformer models, have shown remarkable capacity in processing spatiotemporal sequence data in order to solve this challenge recently (Zhang et al., 2024b). Transformer cannot only capture long-term dependencies, but also efficiently process large-scale data, especially suitable for urban planning problems containing time series and spatial features. For example, Fan et al. (2022) used the transformer model to model urban spatial data and analysed the renovation needs and effect predictions in different regions. The successful application of the transformer model shows that deep learning can effectively capture the complex nonlinear relationships and spatiotemporal changes in residential area renovation.

Furthermore, to raise the comprehensiveness and precision of sensitivity analysis even more, more and more studies have begun to use the method of multi model fusion to make up for the shortcomings of a single model. Chen et al. (2020) proposed a method that combines random forests with deep neural networks (DNNs) to conduct sensitivity analysis of urban regional development, utilising the advantages of both, and obtaining more accurate results. Similarly, Sheykhmousa et al. (2020) proposed a framework that combines random forests with SVM and successfully applied it to multi factor evaluation of urban construction projects. In addition, XGBoost, as another common ensemble learning method, is also widely used in the field of urban planning. Sun et al. (2024) conducted an in-depth analysis of multiple influencing factors in residential area renovation by combining XGBoost and random forest algorithm, and proposed a new decision support system. This method optimises the accuracy of sensitivity analysis by integrating multiple machine learning techniques.

With the increasing demand for multidimensional and multi factor analysis in the field of urban planning, some scholars have begun to explore more refined model fusion methods. For example, Chen et al. (2021) proposed a multi-level model that combines random forests with neural networks to improve the processing efficiency and sensitivity analysis accuracy of large-scale urban planning data. Similarly, Parvin et al. (2022) proposed a framework based on deep learning and multi factor analysis, combining convolutional neural networks and LSTM networks to model environmental, social, and economic factors in urban renovation projects, achieving good predictive results.

Furthermore, Song et al. (2014) suggested a sensitivity assessment approach based on spatial data analysis to investigate spatial aspects in house renovation. The spatial regression method was used to model the regional characteristics in urban planning, providing planners with more accurate spatial analysis results. Li et al. (2023) proposed a deep learning-based urban spatial sensitivity analysis framework that can effectively handle high-dimensional and nonlinear relationships in spatial data by combining different types of data, such as remote sensing images, GIS data, etc.

Although significant progress has been made in existing research to some extent, there are still several issues: firstly, most methods fail to fully consider the complex interaction effects and nonlinear relationships between factors; secondly, the handling of spatiotemporal dependencies is still not precise enough; finally, current multi model fusion methods often face issues such as high computational complexity and large data requirements. Therefore, this article proposes a sensitivity analysis framework for urban planning that combines random forests and transformer models, aiming to comprehensively consider the nonlinear relationships and spatiotemporal dependencies of multiple factors, and provide more accurate and scientific decision support for residential area renovation.

The main innovations and contributions of this work include:

1. Innovatively combining the variable importance assessment capability of random forests with the advantages of transformer models in spatiotemporal data processing provides a new technical framework for sensitivity analysis in urban planning. This method can simultaneously capture nonlinear relationships and complex spatiotemporal dependencies.
2. For the first time in the field of sensitivity analysis, the collaborative application of random forest and transformer has been explored, providing new ideas for solving complex factor analysis problems in similar fields.
3. In response to the complexity of residential area renovation, a systematic analysis process has been designed, including data preprocessing, model construction, feature importance ranking, and result visualisation, providing a reusable solution for urban planning research in similar scenarios.

2 Relevant technologies

2.1 Random forest

Based on ensemble learning, random forest is a non-parametric machine learning technique that combines the prediction results of several decision trees so enhancing the generalising capacity and resilience of the model. It is a powerful tool commonly used for classification and regression tasks (Hu and Szymczak, 2023). The core idea of random forest is to use bagging and random feature selection to construct multiple decision trees with differences, and fuse the final results through majority voting or average.

First, random forest creates several subdatas by sampling the main dataset with replacement, and every subdatas is utilised to train a decision tree. This process is called bootstrap sampling, which has the advantage of increasing model diversity and reducing the risk of overfitting (Bai et al., 2022). Secondly, in the construction process of each decision tree, the random forest introduces a strategy of feature subset random selection, which randomly selects a subset from all features at each split node, and then selects the optimal feature for splitting. This mechanism further reduces the correlation between models and improves the integration effect.

For the classification task, assuming that B decision trees $\{T_1(x), T_2(x), \ldots, T_B(x)\}$ are constructed, for the input sample x, the classification result of the random forest is the category with majority voting:

$$\hat{y} = argmax_k \sum_{b=1}^{B} I\left(T_b(x) = k\right) \tag{1}$$

where $I(\cdot)$is the indicator function, with a value of 1 when $T_b(x) = k$, and 0 otherwise.

For regression tasks, the predicted value of the random forest is the average output of all decision trees:

$$\hat{y} = \frac{1}{B} \sum_{b=1}^{B} T_b(x) \tag{2}$$

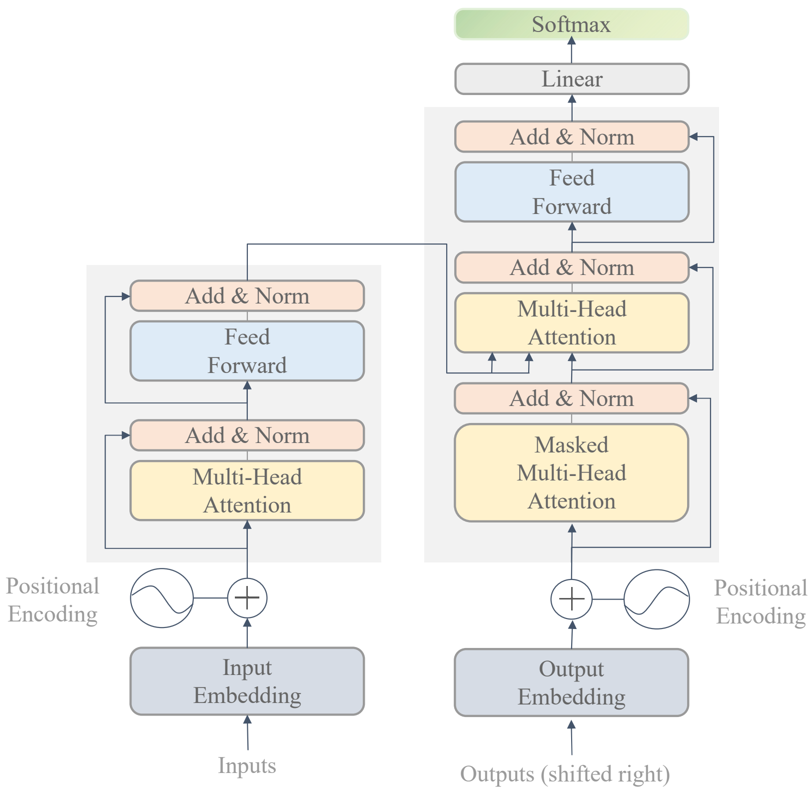
Another significant advantage of random forests is that model performance can be evaluated through out of bag (OOB) errors. OOB error utilises samples that have not been selected for training a decision tree to test the tree, effectively avoiding additional cross validation steps. Furthermore, by use of feature importance analysis, random forests can measure the influence of every feature to the prediction outcomes. For example, by calculating the contribution of feature splitting based on Gini index or mean square error, a global ranking of feature importance can be obtained, which is of great value in applications such as sensitivity analysis. Due their strong nonlinear modelling capacity, noise resilience, and interpretability, random forests have been extensively applied in tasks like classification, regression, feature selection, and anomaly detection.

2.2 Transformer

Based on an attention mechanism, transformer is a deep learning model that has grown to be fundamental architecture for natural language processing and other sequence modelling challenges (Khan et al., 2022). The transformer model diagram is shown in

Figure 1. Transformer efficiently models long-range dependencies between elements in a sequence by completely abandoning RNNs and CNNs, based on self attention mechanism, while significantly improving parallel computing capabilities (Si et al., 2022).

Figure 1 Structure of transformer (see online version for colours)



Transformer's fundamental components consist in multi-head self-attention technique and encoder decoder architecture. Whereas the decoder finishes prediction depending on the features produced by the encoder, the encoder is mostly in charge of feature extraction of the input sequence. Multiple identical sub layers stacked together make up each encoder and decoder; each sub layer features a feedforward neural network (FFN) and a multi-head self-attention mechanism.

In the self attention mechanism, the input sequence is represented as a set of vectors $\{x_1, x_2, \ldots, x_n\}$, and each vector x_i is mapped to a query vector q_i, a key vector k_i, and a value vector v_i through three weight matrices W^Q, W^K and W^V. For any position i in the input sequence, attention weights are calculated for other positions j.

In order to enhance the expressive power of the model, transformer introduces a multi head attention mechanism. Multi head attention generates h sets of attention matrices by applying different linear transformations to Q, K and V, and concatenates the results of these matrices before performing linear transformations. The equation is:

$$Multihead(Q, K, V) = Concat\left(head_1, head_2, \ldots, head_h\right)W^O \tag{3}$$

The calculation for each head is:

$$head_i = Attention\left(QW_i^Q, KW_i^K, VW_i^V\right) \tag{4}$$

In addition, transformer enhances the stability and convergence speed of training through residual connections and layer normalisation.

Transformer lacks the implicit sequence information in RNN, so positional encoding is introduced to enable the model to perceive sequence order by adding position related information to the input embedding. The common position encoding equation is:

$$PE_{(pos,2i)} = \sin\left(\frac{pos}{1{,}000^{2i/d_{model}}}\right) \tag{5}$$

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{1{,}000^{2i/d_{model}}}\right) \tag{6}$$

where pos is the sequence position, i is the index of the vector dimension, and d_{model} is the embedding dimension.

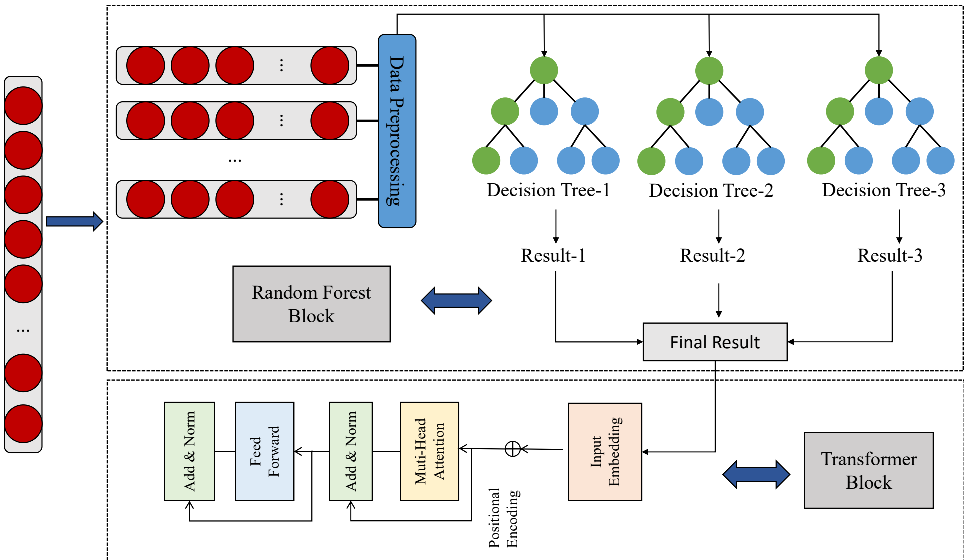
The lack of sequence dependencies, high parallelism, and powerful modelling capabilities of transformers have enabled them to perform outstandingly in tasks such as machine translation, text generation, and image processing, laying the foundation for modern deep learning models.

3 Sensitivity analysis method for urban planning using random forest and transformer

This paper proposes a hybrid method combining random forest (RF) and transformer models for sensitivity analysis of complex multidimensional data analysis in residential area renovation projects. The model framework of this method is shown in Figure 2. The decision to renovate residential areas is usually influenced by multiple factors, such as land use, traffic flow, population density, environmental quality, etc. The relationship between these factors is often nonlinear and has spatiotemporal dependence. Traditional sensitivity analysis methods are often difficult to capture these complex correlations, while our method uses random forest for feature screening, combined with the powerful temporal modelling ability of transformer models, effectively solves these challenges and improves the accuracy and interpretability of analysis.

Usually with residential area renovation, the influencing elements have great scope and are complicated and entwined with one other. This work initially screens and evaluates the relevance of influencing elements using the random forest technique to avoid the effect of repeated characteristics on model performance. By building several decision trees and aggregating their outcomes, random forest can efficiently assess the influence of features to target variables (such as remodelling effect, resident happiness, etc.).

Figure 2 Method framework diagram (see online version for colours)



Specifically, let the input dataset be $D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)\}$, where $x_i \in R^d$ is the feature vector of each sample and y_i is the corresponding target variable. For each tree, the random forest selects an optimal feature at each node for splitting, and the optimisation criteria are usually measured by Gini index or information gain to reduce impurity.

For feature x_j, its importance $I(x_j)$ can be calculated using the following equation:

$$I(x_j) = \frac{1}{B} \sum_{b=1}^{B} \Delta Impurity_{j,b} \tag{7}$$

where B is the number of trees in the forest, and $\Delta Impurity_{j,b}$ represents the reduction of impurity caused by feature x_j in the b^{th} tree. Finally, by calculating the average importance of all features, the most critical features for residential area renovation are selected.

After selecting the most important features through random forest in the first stage, this paper further uses the transformer model for sensitivity analysis to capture the complex nonlinear relationships and spatiotemporal dependencies between these features. The transformer model's capacity to manage long-range relationships and exceptional performance in tasks like natural language processing have progressively attracted it into many disciplines from its conception. This approach increases the sensitivity analysis capacity of the transformer model by using its self attention mechanism to manage the correlation among several features.

Input the feature matrix $X \in R^{N \times k}$ (where N is the number of samples and k is the selected number of features) selected through random forest screening into the transformer model. Firstly, the feature matrix is mapped through the embedding layer and transformed into a higher dimensional representation:

$$E = XW_e + P \tag{8}$$

where $W_e \in R^{k \times d_{model}}$ is the embedding matrix and $P \in R^{N \times d_{model}}$ is the positional encoding, ensuring that the model can understand the sequential relationship of features.

Adopting a multi head self attention mechanism to process input features. In each header, input features are mapped to queries, keys, and values:

$$Q = EW_Q \tag{9}$$

$$K = EW_K \tag{10}$$

$$V = EW_V \tag{11}$$

where W_Q, W_K and W_V are the learned parameter matrices. The self attention mechanism calculates the dependency relationship between features and combines them with weighted attention weights:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{12}$$

where Q, K and V represent the matrix forms of query, key, and value, respectively. d_k is the dimension of the key vector used for scaling to avoid the unstable impact of large values on the attention distribution. Through the multi head mechanism, transformer can parallelly compute multiple different feature interactions, obtain richer information representations, and extract complex dependency relationships between key features.

The features output by the self attention layer are normalised by layers and input into a feedforward neural network (FFN) for nonlinear transformation. Each encoder and decoder layer contains a two-layer feedforward neural network, and its equation is:

$$FFN(x) = ReLU\left(xW_1 + b_1\right)W_2 + b_2 \tag{13}$$

where W_1 and W_2 are the weights of the fully connected layer, and b_1 and b_2 are the bias terms. This step can capture higher-order nonlinear relationships between features, providing a deeper understanding for sensitivity analysis.

After the model training is completed, the sensitivity of each feature is calculated based on its impact on the prediction results. Specifically, the sensitivity is evaluated by solving the gradient of output $\hat{y}$ relative to input feature x_j:

$$S_j = \left|\frac{\partial \hat{y}}{\partial x_j}\right| \tag{14}$$

These sensitivity values S_j represent the magnitude of the impact of feature x_j on residential area renovation decisions, providing quantitative decision-making basis for policy makers.

This method combines the advantages of random forest and transformer to compensate for the shortcomings of traditional sensitivity analysis methods. Firstly, random forests can effectively perform feature selection, avoiding the interference of redundant features on the analysis results. Secondly, the self attention mechanism of transformer can capture the complex relationships and spatiotemporal dependencies between features, making sensitivity analysis results more accurate and profound. This method not only improves the analysis accuracy of residential area renovation projects, but also provides more interpretable model outputs, which can provide strong support for the optimisation of renovation plans and policymaking.

4 Experiment

This work performed several experiments using publicly available datasets related to residential area renovation, evaluated the performance of this method compared to other common methods, and conducted loss function convergence analysis and ablation experiments to confirm the effectiveness of the sensitivity analysis approach combining random forest and transformer models. We investigated the benefits and drawbacks of every model by means of comparison of the experimental data.

4.1 Dataset

The experiment used the City Planning Dataset, which was sourced from publicly available datasets and preprocessed. The dataset contains multidimensional features of residential area renovation projects, such as geographical environment, socio-economic factors, transportation conditions, etc. The target variable is the satisfaction score of residents after renovation. With 20 feature dimensions including economic elements, infrastructure development, environmental quality, traffic flow, etc. The dataset comprises 3,000 samples. The dataset consists of a training set and a testing set; the training set makes up for 80% and the testing set for 20%.

4.2 Evaluation

We have chosen the following evaluation indices to fully assess the effectiveness of the model in sensitivity analysis of residential area renovation:

- Shannon entropy: this indicator measures the uncertainty of the model towards the target variable. The lower the entropy value, the more certain the model's prediction of the target is, and the more suitable it is for efficient decision support.

$$H(Y) = -\sum_{i=1}^{k} p(y_i) \log p(y_i) \tag{15}$$

where y_i is the category of the target variable, and $p(y_i)$ is the probability of that category.

- Mean squared error (MSE): applied to compare the actual value of a model with its expected value, the smaller the number the better the prediction performance.

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{16}$$

where y_i is the true value, $\hat{y}_i$ is the predicted value, and N is the number of samples.

- Feature importance consistency: used to measure the consistency of a model's recognition of feature importance under different experimental settings, with higher values indicating that the model can more stably identify key features.

4.3 Experimental results and analysis

We developed four experimental models for comparison to confirm the success of merging transformer models with random forest:

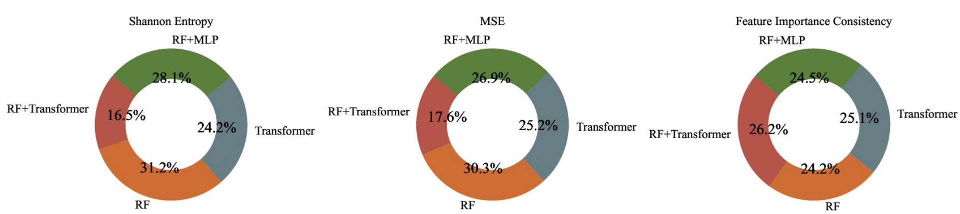
- this article's model combines random forest and transformer for sensitivity analysis
- RF model: use only random forests for feature selection and sensitivity analysis as the baseline model
- transformer model: only use the transformer model for analysis, remove the random forest part, and verify the performance of the transformer in this task.
- RF + MLP model: replace transformer with MLP for nonlinear modelling and test the effectiveness of non-self-attention models.

Table 1 and Figure 3 feature the experimental results:

Table 1 Model comparison experiment results

Method	*Shannon entropy*	*MSE*	*Feature importance consistency*
RF + transformer	0.38	0.21	0.95
RF	0.72	0.36	0.88
Transformer	0.56	0.30	0.91
RF + MLP	0.65	0.32	0.89

Figure 3 Model comparison experiment results (see online version for colours)

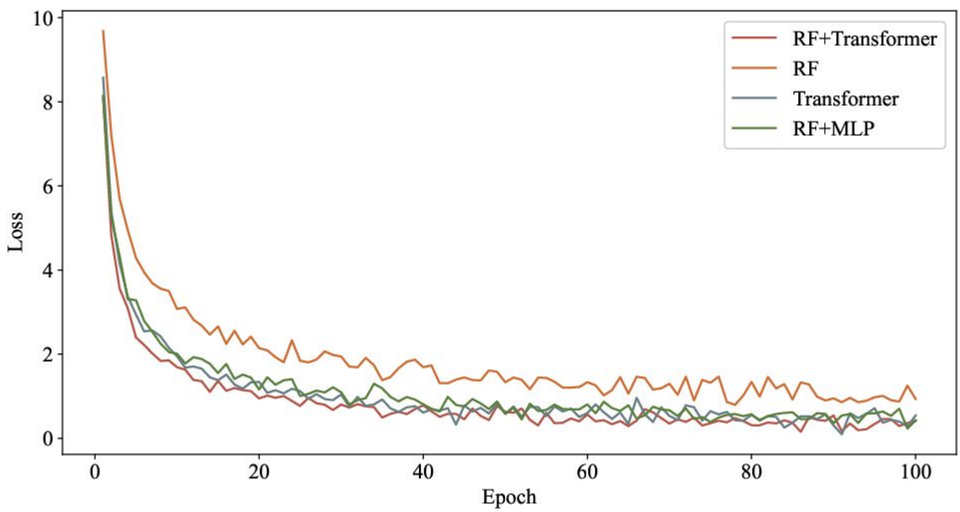


From the results in Figure 3, it can be seen that the RF + transformer model performs the best in all evaluation metrics, especially in Shannon entropy and MSE, which are significantly better than other models, indicating that this method can more accurately predict the target variable and reduce uncertainty. In terms of consistency in feature importance, the RF + transformer model also has the highest value, indicating that this method outperforms other models in terms of stability in feature selection. Through comparative analysis, it is found that the RF and transformer models alone lack the ability to handle complex nonlinear relationships and feature interactions, especially in terms of consistency in feature importance, and perform worse than models combined with transformer. The combination of random forest and transformer models significantly improves the accuracy of sensitivity analysis and effectively identifies key features.

Compared to traditional single methods, combining models can better handle the multidimensional features and complex nonlinear relationships in residential area renovation. This result indicates that this method has high applicability and advantages in urban planning decision making.

In order to analyse the training stability and convergence speed of the model, we conducted convergence experiments on the loss function. We choose mean squared error loss and record the loss value of the model for each epoch during the training process to observe the convergence of the model during the training process. The experimental results are shown in Figure 4.

Figure 4 Experimental chart illustrating convergence of the loss function (see online version for colours)



The RF + transformer model exhibits a fast convergence speed during the training process. As the epoch increases, the loss value rapidly decreases and tends to stabilise, indicating that the model can learn key features in the data well and the training process is relatively stable. In contrast, only the RF model has a slower convergence speed and a higher final loss value, indicating that a single random forest method has weaker performance in handling complex data. Faster convergence speed of the RF + transformer model and lower loss value indicate that this approach has greater learning impact than conventional RF solo techniques.

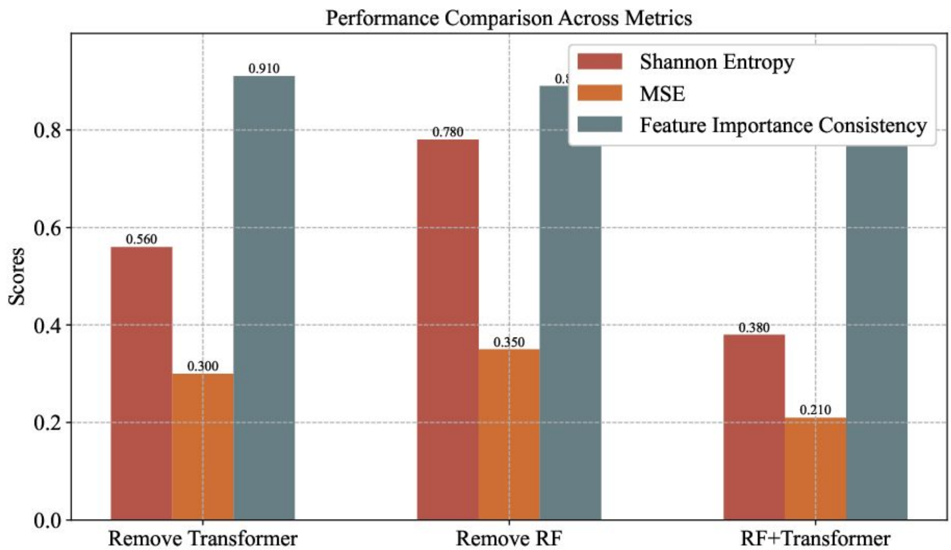
In order to further analyse the roles of each part in the model, we designed two ablation experiments to remove different parts of the model and verify their impact on model performance.

Table 2 Results of ablation experiment

Method	*Shannon entropy*	*MSE*	*Feature importance consistency*
Remove transformer	0.56	0.30	0.91
Remove RF	0.78	0.35	0.89
RF + transformer	0.38	0.21	0.95

As Table 2 and Figure 5 demonstrate, in this experiment we eliminated both the transformer and random forest components.

Figure 5 Results of ablation experiment (see online version for colours)



The experimental results clearly show that the model devoid of random forest has enhanced Shannon entropy and MSE indicators, indicating that relying solely on transformer cannot effectively perform feature selection as when combined with random forest. Transformers can capture nonlinear relationships between features, but lack the feature selection ability of random forests, resulting in lower prediction performance compared to combined models. Therefore, the random forest part plays an important role in improving model performance in this task. The model after removing transformer shows a significant decrease in performance, especially in Shannon entropy and feature importance consistency, indicating that transformer is crucial for capturing nonlinear relationships and inter feature dependencies. Using just random forests causes the model to fail in handling the intricate interactions between features, therefore lowering the prediction accuracy. The transformer component is capable of capturing complex spatiotemporal dependencies, making its role indispensable in this task.

5 Conclusions

This article proposes a comprehensive method combining random forest and transformer models for sensitivity analysis of residential area renovation in urban planning. By utilising random forests for feature importance assessment of multidimensional influencing factors, key influencing factors in residential area renovation were successfully identified; meanwhile, leveraging the advantages of the transformer model, the complex nonlinear relationships and spatiotemporal dependencies between these factors have been addressed, significantly improving the accuracy and interpretability of sensitivity analysis.

Using publicly accessible datasets, we validated the efficiency and superiority of the proposed method in the experimental part by means of comparison studies including four models – including genuine models and ablation experiments. Specifically, the experimental results show that the model combined with transformer can converge faster and more stably compared to the model using only random forest, and achieve significant improvement in prediction accuracy. Through the convergence experiment of the loss function, we further confirmed the role of the transformer module in accelerating the convergence process. In addition, the ablation experiment findings show that addressing nonlinear interactions and enhancing the modelling capabilities of spatiotemporal dependencies depend much on the transformer model.

This study provides a more scientific and accurate decision support method for sensitivity analysis of residential area renovation, which has strong practical significance and broad application prospects. Future research can further explore the combination of transformer with other machine learning methods to enhance the ability to analyse multiple tasks in urban planning. At the same time, research can be conducted on how to further validate the feasibility and scalability of this method in larger scale urban data.

Declarations

All authors declare that they have no conflicts of interest.

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