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# Appropriate rental price prediction for condominiums in Pattaya, Thailand, applying artificial neural network approach

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## ABSTRACT

There is a high demand for condominiums in Pattaya, Thailand, a popular tourist destination and business hub. It is an economic and strategic location within the Eastern Economic Corridor (EEC). Accurate rental price estimation is crucial for investors, tenants, real estate developers, and policymakers. Traditional methods, such as regression analysis, have limitations in terms of requiring linear relationships and capturing complex data. This study applied Artificial Neural Network (ANN) to predict condominium rental prices in Pattaya by using factors such as distance to the beach, property size, building age, number of bedrooms and bathrooms, floor level, room type, and sea view. The dataset comprised 983 rental listings used to train the ANN model, validate its performance, and optimize its predictive accuracy. A comparison between the predictions from the ANN model and results obtained from stepwise multiple regression was also conducted. The findings confirm that ANNs provide a higher level of accuracy than multiple regression analysis. This study affirms the effectiveness of ANN in condominium rental price prediction and highlights the importance of combining ANN with traditional methods to enhance prediction accuracy and performance in the Thai real estate market.

**Contribution/Originality:** This study applied Artificial Neural Network (ANN) to estimate the rental prices of condominiums in Pattaya, Thailand. The paper's primary contribution is demonstrating the outperformance of ANNs compared to traditional regression methods in terms of predictive accuracy. The study benefits stakeholders in the real estate market, including real estate investors, developers, and policymakers.

## 1. INTRODUCTION

Pattaya, Thailand, is one of the most popular destinations for many people. Its economy depends on both tourism and business. Its beautiful beaches, temples, museums, botanical gardens, and nightlife activities attract Thai and foreign tourists to visit repeatedly. Pattaya is part of the Eastern Economic Corridor (EEC), a significant economic development zone in Thailand. The EEC is expected to bring foreign investment and create several jobs. Accordingly, Pattaya's economy is bustling, and the demand for accommodation is high.

Renting a condominium in Pattaya has become a compelling option for various groups. On the demand side, tourists visiting the city for a short period, workers receiving company accommodation allowances, or individuals who have not decided to settle down permanently, should prefer renting condominiums. On the supply side, many investors find that investing in real property in Pattaya is attractive, as they can rent the property and wait for gains from price appreciation. Real Estate Information Center (REIC) (2024) reports that in the first quarter of

2024, 36,471 condominiums in Pattaya were sold, and 4,493 new condominiums were offered. Pattaya's total supply of condominiums from 2011 to the first quarter of 2024 totals 112,671 units.

Knowing appropriate rental prices is crucial for investors, tenants, developers, and policymakers. For instance, investors can avoid losses by setting rental prices that are too low. Tenants would not have to pay a price that is too high. Developers are able to use the price data to set the selling price and analyze the feasibility of the condominium project. Policymakers can use the appropriate price in setting a fair tax rate or optimizing land use via zoning.

Traditional valuation methods, such as regression-based pricing models, have limitations in capturing the complex and nonlinear relationships of data in real estate markets (Benjamin, Guttery, & Sirmans, 2004; Robey, McKnight, Price, & Coleman, 2019). These limitations have prompted the adoption of advanced machine learning techniques, such as Artificial Neural Networks (ANNs). ANNs can manage complex interactions among multiple variables and also provide more accurate price determinants (Mostofi, Toğan, & Başağa, 2022; Núñez Tabales, Caridad y Ocerin, & Rey Carmona, 2013; Tin, Wei, Min, Feng, & Xian, 2024).

Prior studies have applied traditional statistical approaches to estimate rental prices; there is a research gap in applying the ANN model to regional real estate markets in Thailand. Few studies have used an ANN model to estimate condominium rental pricing in economic and tourism-driven cities like Pattaya, particularly those incorporating variables such as distance to the beach, room size, building age, and presence of a sea view.

This research fills the gap by applying the ANN model to predict condominium rental prices in Pattaya, Chonburi province, Thailand, and also compares its output with the traditional regression model. The study's objectives are 1) to identify the key determinants of condominium rental prices, including distance to the beach, property size, building age, number of bedrooms, number of bathrooms, floor level, duplex or ordinary condominium, and sea view; 2) to apply the ANN model to capture the complex and nonlinear relationships among these factors; 3) to compare the results from the ANN with the regression model to highlight the advantages of ANN in analyzing complex relationships in real estate pricing. Understanding these factors and their interactions will provide valuable insights into the Thai condominium market, enabling more accurate price predictions and offering practical contributions to market participants, including investors, tenants, developers, and policymakers.

In conclusion, condominium rental pricing in Pattaya is shaped by a complex network of interrelated variables. This study demonstrates that the ANN approach offers a more effective means of modeling such complexities compared to traditional regression techniques. The findings support the use of advanced machine learning methods to better reflect the realities of Pattaya's real estate market and fill important gaps in existing research.

The next section provides a review of relevant literature on rental price prediction, an outline of the study's methodology, a presentation of the ANN model results, and a discussion of their implications for the Pattaya real estate sector.

## 2. LITERATURE REVIEWS

This part includes a comprehensive review of related theories of real estate price prediction. The previous research studies on the factors influencing real estate prices and rental prices using traditional approaches and machine learning methods, such as ANNs, are included.

### *2.1. Related Theories*

There are different analytical approaches to forecasting real estate prices and rental prices. One of the main theories is the Hedonic Pricing Theory initiated by Rosen (1974), which states that a property's value is influenced by various individual attributes of the property. These attributes include floor level, building's age, and public transport accessibility, which tend to have a significant impact on real estate value. This study applies this theory by exploring the impact of condominium attributes such as size, floor level, building age and type, number of bedrooms and bathrooms, and sea view on the rental price of condominiums.

Another essential theory relevant to this study is the Bid-Rent Theory by Alonso (1964). The theory states that property values decrease as the distance from central significant economic areas increases. For Pattaya, the study applies the distance to the beach as a central factor in rental value and considers it a critical location-based determinant of rental price.

### *2.2. Determinants of Property and Rental Prices*

Different empirical studies have explored the various determinants of rental prices for different regions of the world and have revealed different outcomes depending on the particular market conditions of the region. In China's Guangzhou region, the administrative area, rental category, size of the house, and even the floor of the house have been shown to affect rental prices (Mao, 2024). In Spain's Madrid, the size of the apartments and their capacity significantly affect short-term rental prices (De Jaureguizar Cervera, Pérez-Bustamante Yábar, & De Esteban Curiel, 2022).

The studies in Turkey's Istanbul indicate that renters value green spaces, scenic views, access to facilities, the condition of the neighborhood, and proximity to stores (Dökmeci, Under, & Yavas, 2003). Sirmans and Benjamin (1991) conclude that property age, amenities, available services, physical attributes, and location are the key drivers of rental prices.

In Japan, rental prices appear to have a negative relationship with the age of the property, suggesting depreciation of older properties over time (Yoshida & Sugiura, 2015). In Pune, India, the larger floor space and number of rooms significantly increase rental prices. In contrast, properties near employment hubs, schools, and public transport networks tend to have lower prices due to heavy congestion and noise levels (Singla & Bendigiri, 2019).

A study in Ghana's Accra Metropolitan Area has shown that the rental price is primarily influenced by location, the availability of amenities and services, and the number of beds in the house. In conclusion, the studies confirm that the combination of property attributes, location, and accessibility to amenities affects the rental price. However, the degree of influence of each factor varies across the markets.

### *2.3. Traditional and Machine Learning Models for Rental Price Prediction*

#### *2.3.1. Traditional Approaches*

##### *2.3.1.1. Time Series or Autoregressive Integrated Moving Average (ARIMA)*

The ARIMA model, initiated by Box and Jenkins (1970), applies historical time series data to predict rental prices. The model identifies trends and seasonal fluctuations (Box, 2013).

##### *2.3.1.2. Multiple Linear Regression (MLR)*

MLR analyzes the connection between two or more independent variables and a dependent variable. This technique is appreciated for its clarity and ease in measuring the impact of each variable (Montgomery, Peck, & Vining, 2012).

#### *2.3.2. Machine Learning Approaches*

Recently, machine learning algorithms have been used more frequently in real estate appraisal because they can identify nonlinear connections and manage complex, high-dimensional data.

##### *2.3.2.1. Support Vector Machines (SVMs)*

SVMs, presented by Cortes and Vapnik (1995), serve for classification and regression purposes. They operate by converting input data into higher-dimensional spaces through kernel functions such as polynomial and radial basis functions, which enable the identification of nonlinear patterns. Nonetheless, SVMs can require significant computation and are frequently noted for their restricted interpretability.

#### *2.3.2.2. Gradient Boosting Machines (GBMs)*

GBMs presented by Friedman (2001) are a machine learning approach that employs a combination of weak learners typically decision trees to gradually minimize prediction errors. Although GBMs provide excellent accuracy, this method demands substantial computational resources and meticulous hyperparameter tuning to minimize overfitting (Natekin & Knoll, 2013).

While these machine learning methods usually have advantages over traditional statistical models in prediction ability, their effectiveness strongly relies on data quality, suitable characteristic choice, and adequate computational resources. These restrictions have led to more reliance on more resilient and adaptable models, for instance, Artificial Neural Networks.

### *2.4. Artificial Neural Networks (ANNs)*

ANNs are computer models of the natural system found in animal brains when we discovered the biological neural networks (Bi-Nets) and simulated them. It's the piece that gets imitated in humans when we learn to recognize patterns and other features in data. ANNs are highly flexible for modeling complex relationships from input to output. The latter are applied in a wide range of problems such as natural language processing, image recognition, and predictive modeling, and therefore, it follows that they should be heavily used (Rumelhart, Hinton, & Williams, 1986; Xu, Wang, Jiang, & Gong, 2024).

ANNs are modeled based on the neural structure of the human brain, which consists of groups of neurons interconnected in layer-by-layer patterns, for analyzing input data and generating very accurate predictions (Heaton, 2018). ANNs have gained interest in predictive modeling due to their capacity to capture complex, nonlinear relationships and learn from extensive datasets.

Artificial Neural Networks (ANNs) are computational models, made up of interconnected processing units, neurons or nodes, which process inputs and provide useful interpretations of that input. These neurons are the basic building blocks of the network: each of them receives input, performs computations, and sends output to other units. The architecture of the classical ANNs comprises an input layer for raw data input, possibly multiple hidden layers for intermediate processing and pattern recognition, and an output layer for final prediction-making.

ANNs have a learning process through learnable parameters, including weights and biases, which minimize the prediction errors during training. The model employs activation functions to introduce nonlinear transformations, enabling the network to model complex relationships and learn patterns in the data. These elements make ANNs effective and powerful tools in various tasks, including predictive modeling, image recognition, and natural language processing (Heaton, 2018; LeCun, Bengio, & Hinton, 2015; Nielsen, 2015).

#### *2.4.1. Advantages of ANNs*

The primary benefit of ANNs is their capability to model complex, nonlinear relationships between independent variables and the dependent variable (LeCun et al., 2015). Unlike the traditional linear regression model, which requires the linearity of data, ANNs do not need predefined relationships, allowing them to learn the pattern of data automatically.

Moreover, ANNs can also handle multiple types of data (Chao, 2023; Chaudhuri & Ghosh, 2016; Chen, Farag, Butt, & Al-Khateeb, 2024). This makes them suitable for predicting rental prices in dynamic markets such as Pattaya, where multiple factors interact unpredictably.

#### *2.4.2. Challenges of ANNs*

ANNs have benefits over traditional statistical methods, but they also have several challenges. The main drawback is their "black box" characteristic, which causes difficulty in understanding and interpreting how the model generates its predictions. Moreover, ANNs require large amounts of data with high quality for computational power, which can be a limitation in some markets where high-quality data is not available or insufficient (Fan, Xiong, Li, & Wang, 2021; Kumar Mally, 2023; Neves, de Castro Neto, & Aparicio, 2020).

### *2.5. Applications of ANNs in Real Estate Price and Rental Prediction*

Different empirical studies have applied ANN in real estate price prediction with various determinants. Borst (1991) was one of the earliest researchers who explored that ANNs are a reliable method in predicting property values. McGreal, Adair, McBurney, and Patterson (1998) found the superior predictive accuracy of ANNs compared to traditional valuation techniques in predicting property sales data. ANNs outperform multiple regression analysis in housing price prediction, especially in capturing nonlinear relationships among variables (Chaudhuri & Ghosh, 2016; Neves et al., 2020).

In Istanbul, Turkey, Selim (2009) showed that the ANN models outperformed traditional regression models in the accuracy of housing price prediction. Similarly, Lin and Chen (2011) affirmed the robustness and promising results of ANN models in real estate prices in the Taiwanese market. In both real estate markets, the ANNs' ability to capture nonlinear patterns in the data was a key factor in their outperformance.

A study conducted in Johor Bahru, Malaysia, by Raman, Tan, and Lee (2019) further obtained the strength of ANNs in terms of high predictive accuracy for property valuation. The results are consistent with the prior study of Núñez Tabales et al. (2013), which explored that ANN has a superior prediction performance, especially with the large datasets.

The application of neural networks to predict condominium prices in Australia showed that size and location are the most important determinants (Peterson & Flanagan, 2009). In Hong Kong, the three most important factors, including interest rate, unemployment, and household size, affect property value. This study affirms the superior performance of ANNs over SVM and ARIMA (Xu & Zhang, 2022). Lim, Wang, Wang, and Chang (2016) investigated the performance of ANN and ARIMA models for Singapore condominium price forecasting, and confirmed the ability of ANN to capture the nonlinear trends of housing price indices.

ANNs are also studied to predict the real estate rental prices. Nguyen and Cripps (2001) used characteristics such as location, building age, and proximity to transport facilities to forecast the real estate rental price in Australia. In Taipei, Taiwan's housing market, floor level, floor area, pet-friendliness, and restaurant availability influence the rental price (Yang, Dai, Chao, Wei, & Yang, 2023). In Cape Town, Oshodi, Olanrewaju, and Akinmoladun (2019) found that balcony access and floor space as the most important determinants of rental price using an ANN model with 78.95% predictive accuracy. Additional evidence from Malaysia by Mohd, Masrom, and Johari (2019) demonstrated that ANNs can handle heterogeneous property data. Seya and Shiroi (2019) confirmed that Deep Neural Networks perform better than Kriging methods in forecasting property rental prices in Japan.

Researchers also studied an ANN model in short-term rental prediction, such as Airbnb. The study by Liu (2021) used independent variables including user ratings, number of reviews, location, size, and seasonal demand trends. The results indicated the ability of ANNs to capture fluctuations in rental demand and incorporate them with non-traditional variables such as customers' reviews. Past studies have identified various models and factors influencing rental prices. However, there is a significant gap in adopting the ANN model to predict condominium rental prices in tourist areas such as Pattaya using local characteristics, for instance, distance to the beach, sea view, building age, or building type. This study addresses this gap by applying both ANN and regression models to estimate and compare the prediction performance of condominium rental prices in Pattaya.

Figure 1 presents a conceptual framework of regression analysis indicating the influence of a condominium's age, size, number of bathrooms, number of bedrooms, floor level, distance from the beach, duplex feature, and sea view on the rental price.

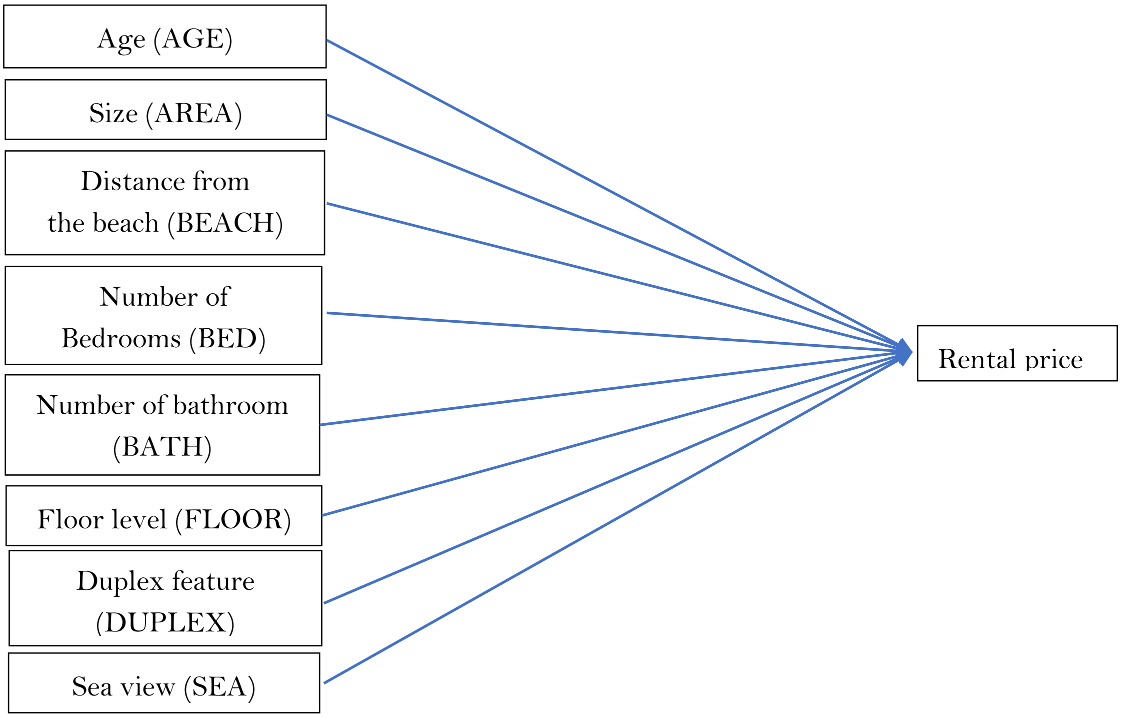


**Figure 1.** Conceptual framework for regression analysis.

## 3. METHODOLOGY

### *3.1. Data Collection*

This study's population consists of condominiums for rent in Pattaya. A sample of the condominiums was randomly selected from FazWaz's website, one of Thailand's leading platforms that serves as a marketplace for real estate and is ranked among Thailand's top five real estate agents (Top 5 Real Estate Agents in Thailand, 2023). The snapshot data on 1,050 condominiums available for rent were used in the study. The incomplete data set was removed, and 983 condominium data points remained for the study. The use of snapshot data in this research has some drawbacks; however, the predicted results reflect the current state of the relationship between the rental price and its independent variables. If the study focuses on long-term relationships between rental prices and their determinants, artificial neural networks (ANNs) must utilize longitudinal data for learning. If trends of temporal dynamics exist, longitudinal data will provide better predictions. Nonetheless, the benefits of using snapshot data include ease of data collection, no need for long-term data, and lower computational costs. The predicted results are appropriate if time-based patterns are not significant. Those interested in predicting the appropriate rental price based on the current relationship should use updated snapshot data for the prediction.

### *3.2. Variables*

The dependent variable for the study is the rental price per square meter (RENT). The key independent variables are applied from previous studies, including age of building (De Jaureguizar Cervera et al., 2022; Mao, 2024), number of bedrooms and bathrooms (Dökmeci et al., 2003), distance from the beach (Singla & Bendigiri, 2019), floor level (Mao, 2024; Yoshida & Sugiura, 2015), type of room (Mao, 2024; Yoshida & Sugiura, 2015), and sea view (Dökmeci et al., 2003). The list of independent variables is shown in Table 1.

**Table 1.** Independent variables for the study.

| Independent variables | Description |
|---|---|
| AGE | Age of the condominium building in years |
| AREA | Size of condominium in square meters |
| BATH | Number of bathrooms |
| BEACH | Distance from the beach in kilometers |
| BED | Number of bedrooms |
| FLOOR | Condominium's floor level |
| DUPLEX | Duplex condominium = 1, otherwise = 0 |
| SEA | Sea view condominium = 1, otherwise = 0 |

The study compared the effectiveness of forecasting using an artificial neural network (ANN) with forecasting using multiple regression analysis. The results will determine whether ANNs should be recommended as a tool to predict the appropriate rental price for condominiums in Pattaya.

The descriptive statistics are calculated to provide information on the distribution of the data studied before the examinations of multiple regression and ANN are conducted.

### *3.3. Model Approach and Validation*

This study employs two models Multiple Regression Analysis (MRA) and Artificial Neural Networks (ANN) to estimate condominium rental prices in Pattaya. Comparing these approaches enables an examination of their respective benefits and limitations in capturing the dynamics of the local real estate market.

As discussed in the introduction and literature review, the choice of ANN is applied because there may be complex and nonlinear relationships among the factors, such as proximity to the beach, presence of sea view, floor level, and room size data.

For the model specification and diagnostic test in MRA, the Durbin-Watson statistic is used to detect autocorrelation in the residuals of the data in the model. The Sum of Squared Residuals (SSR) measures the total variation in the dependent variable that the regression model does not explain. The model fit is assessed by the adjusted R-squared value.

The ANN dataset is divided into a training set and a testing set. The sum of squared errors (SSE) is used as a loss function during ANN training. Root mean squared error (RMSE) is applied after training to evaluate the model's prediction accuracy.

### *3.4. Multiple Regression Analysis*

Multiple regression is used as the traditional technique for prediction accuracy comparison with artificial neural networks. Additionally, the analysis allows the study to determine the impact of predictors that ANNs do not exhibit. This study applies the stepwise technique to the multiple regression analysis since this method can select only statistically significant independent variables into the model. This technique also reduces multicollinearity and the model's overfitting problem, as redundant variables with no unique information will not be included. The influence of the independent variables on the rental price can be described as follows:

$$RENT = \beta_0 + \beta_1 AGE + \beta_2 AREA + \beta_3 BATH + \beta_4 BEACH + \beta_5 BED + \beta_6 FLOOR + \beta_7 DUPLEX + \beta_8 SEA + e \quad (1)$$

Where, $\beta_0$ is the constant in the equation.

$\beta_1$ to $\beta_8$ are beta coefficients showing the impact of each independent variable, and

e is the error term.

However, only statistically significant factors will remain after selection using the Stepwise technique.

### 3.5. Artificial Neural Network Analysis

This research uses Neural Designer software to discover the appropriate rental prices for condominiums. The reasons for using Neural Designer Software in this study are its outstanding advantages. It employs efficient machine learning techniques and simplifies the results. Additionally, users do not need to write code to perform the analysis. The software provides a neural network for function approximation with multiple layers, including scaling, perceptron, unscaling, and bounding layers. These layers are organized in a network architecture as presented in Figure 2.

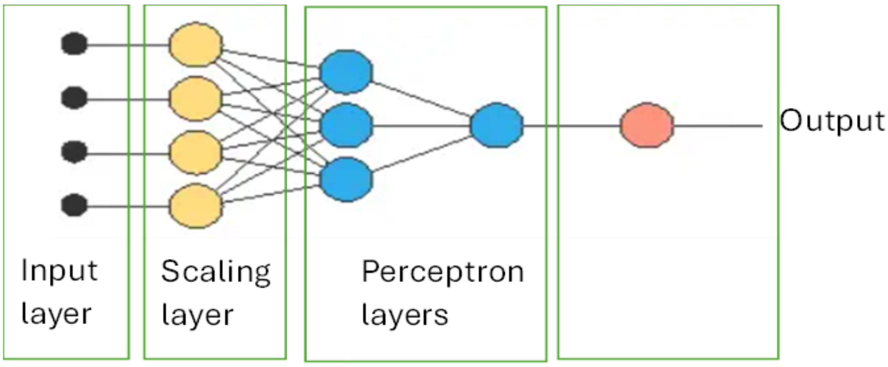


**Figure 2.** ANNs' architecture.

The data of the independent variables are fed into the input layer and undergo transformation at different layers. The scaling layer is used to make the independent variables' values, which have different scales, comparable before moving into perceptron layers for training. The calculated output will be unscaled back to the original units at the unscaling layer.

The Neural Design software would discover the optimal network architecture for the model with the training strategy's algorithm that allows for the minimum error.

To find the model by the ANNs, the input variables' data, Xi, from each node will be weighted by the weights, Wi, and added by the bias, b, to create a weighted sum as follows:

$$\mathrm{S} = \mathrm{b} + \sum_{i=1}^{n}(\mathrm{W_i X_i}) \quad (2)$$

Then, the weighted sum will be transformed through the activation function in hidden layers as follows:

$$\mathrm{Y} = \mathrm{f(S)} \quad (3)$$

$$\mathrm{Y} = f\left(\sum_{i=1}^{n}(\mathrm{W_i X_i})\right) \quad (4)$$

The weights and biases will be adjusted to generate the predicted values with minimum errors. Hyperbolic tangent activation, Rectified Linear Unit (ReLU) activation, Linear activation, and Logistic activation are the most used activation functions in the software. The Quasi-Newton method, an optimization algorithm, trains neural networks to improve the model's accuracy. This study divides the data into three sets with the average of the proportion range as suggested by Buhl (2023): 80% for the training set, 10% for the selection set, and 10% for the testing datasets. The high proportion of training data helps capture the data's variability. The training set is used to construct several models during the model design process. The selection dataset is used to validate and improve the model to ensure that the model created for the training dataset is practical for new data. The testing dataset is then used to evaluate the model's effectiveness on unseen data.

## 4. RESULT

### 4.1. Descriptive Analysis

The descriptive statistics of all variables from the sample set of 983 condominiums in Pattaya, Thailand, are summarized in Table 2. The correlation coefficients between 8 independent variables and rental price are exhibited in Figure 3. Half of them are positively correlated with the price (FLOOR at 0.499, SEA at 0.407, BED at 0.0584, BATH at 0.0247). The other half are negatively correlated with the price (AGE at -0.563, BEACH at -0.222, AREA at -0.089, DUPLEX at -0.046). The high coefficient values indicate a higher likelihood that the independent variables significantly affect the dependent variable.

**Table 2.** Descriptive statistics.

| | AGE | AREA | BATH | BEACH | BED | DUPLEX | FLOOR | SEA | RENT |
|---|---|---|---|---|---|---|---|---|---|
| Mean | 10.86 | 59.01 | 1.31 | 1.31 | 1.36 | 0.02 | 12.86 | 0.48 | 472.11 |
| Median | 9.00 | 46.00 | 1.00 | 1.23 | 1.00 | 0.00 | 9.00 | 0.00 | 429.00 |
| Maximum | 41.00 | 334.00 | 5.00 | 4.97 | 4.00 | 1.00 | 57.00 | 1.00 | 1,570.00 |
| Minimum | 1.00 | 22.00 | 1.00 | 0.07 | 1.00 | 0.00 | 1.00 | 0.00 | 125.00 |
| Std. Dev. | 7.44 | 36.91 | 0.54 | 0.78 | 0.58 | 0.14 | 10.92 | 0.50 | 197.92 |
| Observations | 983 | 983 | 983 | 983 | 983 | 983 | 983 | 983 | 983 |

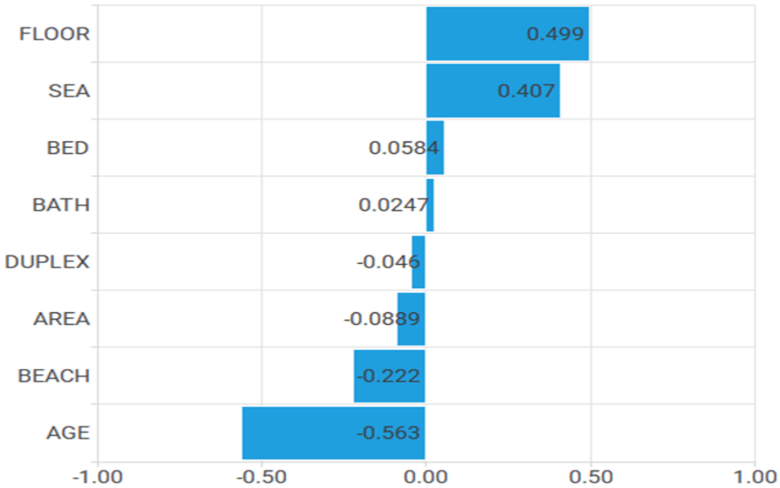

**Figure 3.** Pearson correlation between 8 independent variables and rental price.

### *4.2. Multiple Regression Analysis*

Table 3 reports that five determinants statistically significantly impact the rental price. The condominium's age (AGE) and distance from the beach (BEACH) have a negative effect on the rental price, while the number of bedrooms (BED), floor level (FLOOR), and sea view (SEA) have a positive impact. The explanatory variables could explain 43.44% of the rental price. Durbin-Watson statistics reported no serial correlation (1.5 < DW < 2.5).

**Table 3.** Regression results.

| Value | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 500.38 | 19.49 | 25.670 | 0.000* |
| AGE | -11.239 | 0.664 | -16.923 | 0.000* |
| BEACH | -33.394 | 6.383 | -5.231 | 0.000* |
| BED | 22.202 | 8.517 | 2.607 | 0.010* |
| FLOOR | 5.664 | 0.539 | 10.510 | 0.000* |
| SEA | 63.787 | 11.738 | 5.434 | 0.000* |
| R-Squared | 0.437 | | | |
| Adjusted R-Squared | 0.434 | | | |
| Durbin-Watson Stat | 2.016 | | | |
| Sum squared residuals | 21642960 | | | |

**Note:** * Significance at 1% level.

### *4.3. ANN Analysis*

To find the optimal model, the ANNs perform neuron and input selection and generate an optimal architecture, as shown in Figure 4, and the ANN model can be found in Appendix A. The selected independent variables for rental price (RENT) prediction include five variables: the area of the condominium (AREA), the condominium's floor level (FLOOR), the distance from the condominium to the beach (BEACH), the age of the condominium's building (AGE), and the sea view (SEA). Most of these independent variables are statistically significant in regression analysis, except for AREA, which is added, and BED, which is removed. The differences between the independent variables in the regression model and the ANN model arise because the regression assumes a linear relationship in designating variables; nevertheless, the ANNs apply an algorithm that allows for learning and adjustment until only meaningful variables are left for the optimal model. Accordingly, the AREA variable is added as its nonlinear relation with the rental price is found, and the BED variable is removed as its existence does not assist in lowering the prediction error.

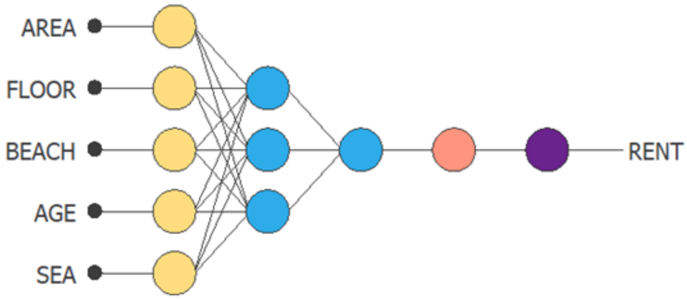


**Figure 4.** ANN's architecture.

Figure 5 shows the precision of the predicted rental price. At the 45-degree line, the predicted and the actual rental prices are the same. The value determination indicates that the ANN's algorithm improved the explanatory power. 63.93% of the variation in the rental price can be explained by the ANN model, which is better than the traditional multiple regression model, whose 43.32% of the variation in the rental price can be explained. However, the ANN's prediction for the rental price might not be effective, as the ordered pairs are widely dispersed from the line.


**Figure 5.** The graph shows the precision of the predicted rental price.

The errors of the ANN model for training, selection, and testing sets are measured in sum squared error or sum squared residuals to compare with the multiple regression model. The results in Table 4 show that the ANN model's total sum squared errors and root mean squared error (RMSE) are much less than those of the multiple regression model.

**Table 4.** Comparison between the sum of squared errors of the ANN model and multiple regression.

| | Sum of squared errors (SSE) | Root mean squared error (RMSE) |
|---|---|---|
| ANN | | |
| Training set | 3589.55 | 2.39 |
| Selection set | 1405.51 | 2.58 |
| Testing set | 1265.70 | 2.46 |
| Total | 6260.76 | 2.44 |
| Multiple Regression | 21626753.00 | 143.52 |

## 5. DISCUSSION

This study applies multiple regression analysis and ANN to determine the condominium rental price in Pattaya, Thailand, by incorporating different independent variables, including distance to the beach, property size, building age, number of bedrooms, number of bathrooms, floor level, duplex or ordinary condominium, and sea view. The determinants are applied from different previous studies.

The results of multiple regression analysis identify that condominium age and distance from the beach have a negative correlation with rental price, confirming previous studies in Japan (Amenyah & Fletcher, 2013) and India (Singla & Bendigiri, 2019). The positive impact of the number of bedrooms, floor level, and sea view matches the study in Madrid (Sirmans & Benjamin, 1991), Istanbul (Yoshida & Sugiura, 2015), and Australia (Nguyen & Cripps, 2001), which identified the enhancement of spaciousness, elevation, and scenic views on the rental price. The multiple regression model has an adjusted R-squared of 43.44 percent, indicating moderate explanatory power.

In contrast, the ANN model provides an accurate and adaptive estimation of condominium rental prices in Pattaya, Thailand, with a coefficient of determination ($R^2$) of 63.93 percent, which confirms the accuracy of ANN predictions of housing and rental prices in the studies of McGreal et al. (1998); Selim (2009) and Peterson and Flanagan (2009).

The study also identifies the predictive capability of ANN and its outperformance relative to traditional regression analysis. The model has lower Sum of Squared Errors (SSE) and Root Mean Squared Error (RMSE) values than the traditional model, which confirms the better ability of ANN to minimize errors, consistent with past studies (Mohd et al., 2019; Seya & Shiroi, 2019). The study also identifies the prediction capacity of ANNs and their outperformance in regression analysis. ANNs can handle the nonlinear relationships between variables used in the analysis, such as room view. These findings affirm the capacity and accuracy of ANNs in rental price prediction, which conform to other studies (Abidoye, Chan, Abidoye, & Oshodi, 2019; Goodfellow, Bengio, & Courville, 2016; LeCun et al., 2015; Mohd et al., 2019; Nielsen, 2015; Yang et al., 2023).

The regression model provides a better understanding of the influence and weight of dependent variables on the rental price. ANNs are more utilized in terms of the precision of prediction. Thus, combining these methods benefits stakeholders with better estimation accuracy and application in market dynamics (Xu & Zhang, 2022). However, the reasoning regarding the independent variable is still essential to avoid overfitting the model to untrue relationships.

## 6. CONCLUSION

### *6.1. Theoretical Implications*

For theoretical implications, ANN models encode publicly announced variables, employing high-level algorithm analysis without linearity limitations and demonstrating superior prediction ability over multiple regression models, although they cannot explain the influences of variables on the rental price. However, the ANN investigation supports Hedonic Pricing Theory (Rosen, 1974) as the ANN model demonstrates the linkage between the condominiums' characteristics, including area, floor level, age, sea view, and rental price. Additionally, the ANN model also supports the Bid-Rent Theory (Alonso, 1964) as distance to the beach was discovered to be a predictor of the rental price. Despite the contributions of this study, some limitations should be acknowledged.

### *6.2. Practical Implications*

The results of this study apply to different stakeholders. Real estate investors can use ANNs to receive appropriate and market-competitive rental prices to optimize returns and minimize the risk of overpricing or underpricing.

Real estate developers can understand the drivers of rental prices, such as distance to the beach, room area, and view from the ANN model; thus, they can add value to their projects and design property projects to meet consumer preferences. Furthermore, typical condominium owners can use it as an alternative benchmark for market-based rental prices.

For managerial implications, the developers can use the ANNs' rental price to project the condominium's cash flow for their feasibility studies of new projects, effectively target buyers, and prioritize land development in areas with high predicted rental prices. Condominium owners can incorporate these factors to set appropriate rental prices and avoid underpricing their properties.

### *6.3. Policy Implications*

The accuracy estimation also supports policymakers in monitoring dynamics in the real estate sector, establishing benchmarks for condominium rental prices, and protecting people from overpricing. Policymakers can allocate resources and infrastructure to property areas with potentially high prices.

In conclusion, the ANN model applies to stakeholders transitioning from intuition-based to data-driven decision-making. This promotes market transparency and efficiency in real estate markets. ANNs are well-established methods for setting rental prices that consider the recently disclosed condominium properties, especially in fast-growing and dynamic real estate markets like Pattaya. As a result, the ANNs' rental price provides beneficial information for real estate market participants. Policymakers can protect consumers from overpricing condominiums by providing the ANNs' rental price as a guideline, planning for fair tax rates regarding the potential income creation of condominiums, and using the ANN's rental price to estimate potential rental income tax revenues.

## 7. LIMITATIONS AND FUTURE RESEARCH

A key limitation of this study is its omission of macroeconomic variables, such as inflation rates, economic growth, interest rates, and unemployment rates. The results are also constrained by the limited data scope, as it draws only from the Pattaya area. The dataset used in the study is a snapshot in time without considering temporal changes in market conditions. The rapid change in relationship structure, for example, the drop in tourist numbers during the pandemic crisis, could make the model created from old data outdated and inappropriate for use. Those who would like to use ANN for rental prediction should keep updating the data and rerun it to find the updated model for accurate prediction. Additionally, ANN users must be able to acquire a large sample size to result in an effectively generalized model and to avoid model overfitting. Future research should be conducted in different major areas in Thailand, such as Bangkok and Chiang Mai. Smart city data, including pollution levels, traffic situations, or public transport, may be incorporated into the study.

Additionally, data is still the key to the success of ANNs' prediction because ANNs use data for training and learning relationships. Small data or old data might not represent the correct pattern of relationships. The rapid change in relationship structure, for example, the drop in tourist numbers during the pandemic crisis, could make the model created from old data outdated and inappropriate for use. Those who would like to use ANNs for rental prediction should keep updating the data and rerun it to find the updated model for accurate prediction. Also, the application of ANNs to the short-stay rental market, such as Airbnb, should be conducted in future studies to explore the overall rental price structure in tourism areas. The model can also be applied to housing for employees in tourism destinations, which face challenges in terms of affordability and accessibility.

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## Supplementary material

ANNs' Model
The ANNs discovered the model for the rental price prediction as follows:
scaled_AREA = (AREA-59.01279831)/36.9076004
scaled_FLOOR = (FLOOR-12.85960007)/10.91930008
scaled_BEACH = (BEACH-1.305299997)/0.784035027
scaled_AGE = (AGE-10.85659981)/7.441609859
scaled_SEA = SEA*(1+1)/(1-(0))-0*(1+1)/(1-0)-1
perceptron_layer_1_output_0 = tanh( 2.88003 + (scaled_AREA*0.30624) + (scaled_FLOOR*-0.165295) + (scaled_BEACH*0.694656) + (scaled_AGE*2.50522) + (scaled_SEA*-0.165819) )
perceptron_layer_1_output_1 = tanh( -1.65673 + (scaled_AREA*0.716831) + (scaled_FLOOR*-0.199917) + (scaled_BEACH*0.515554) + (scaled_AGE*0.0497823) + (scaled_SEA*-0.243526) )
perceptron_layer_1_output_2 = tanh( 0.475768 + (scaled_AREA*-0.43637) + (scaled_FLOOR*-0.311676) + (scaled_BEACH*-0.190266) + (scaled_AGE*0.478451) + (scaled_SEA*-0.159676) )
perceptron_layer_2_output_0 = ( 0.518451 + (perceptron_layer_1_output_0*-0.92347) + (perceptron_layer_1_output_1*-0.620771) + (perceptron_layer_1_output_2*-0.890531) )
unscaling_layer_output_0=perceptron_layer_2_output_0*197.9170074+472.1080017