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Sales Rate Prediction for Condominiums in the Bangkok Metropolitan Region Using Deep Learning: Identification of Determinants and Model Validation

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ABSTRACT

The sales rate is very important information for condominium design and development processes. However, predicting it accurately requires substantial expertise and experience. This research investigated the use of a Deep Learning model to predict condominium sales rates and explored various determinants that influence sales rates. The research was done by (1) identifying the determinant factors from the literature review, (2) collecting 199 data from market survey reports, (3) creating a Deep Learning model that can predict the sales rate of a condominium by its determinant factors, and (4) verifying the model by checking its coefficient of determination (R^2 value). The research results revealed the three-layered network (34 input nodes, 19 hidden layer nodes and one output node) with R^2 of 0.703 and RMSE of 0.539, showing the model has enough accuracy for planning purposes. The determinant factors comprise both internal and external factors, which can be divided into six groups: (1) Price-related factors, (2) Entrepreneur-related factors, (3) Room-related factors, (4) Project structure-related factors, (5) Common-area-related factors, and (6) Location-related factors. By understanding the influence of this set of data on project sales rate, the project stakeholders can efficiently contribute to the project's success. In addition, the results showed the high accuracy of the Deep Learning model even in the case of a limited amount of data.

Keywords: sales rate prediction, absorption rate, deep learning, condominium development

INTRODUCTION

Currently, the development of residences continues to grow rapidly with a significant increase (Real Estate Information Center, 2022). One of the types of real estate businesses favored by developers is a condominium project. This can be classified based on height, as specified in Thailand's Building Control Act, into low-rise condominiums, which are less than 23 meters in height, and high-rise condominiums, which exceed 23 meters in height, as shown in Figure 1. In conducting this business, real estate developers must be well-versed in the criteria for selecting project attributes that are suitable for the specific type of residential development with precision and accuracy. These pieces of information are crucial for efficient analysis, investment planning, sales, and construction (Tochaiwat, 2020).

However, the criteria for selecting factors suitable for the current residential monthly sales rate, normally called absorption rate by the people in the real estate industry, heavily depend on the knowledge and expertise of professionals, drawing from both experience and skills as the foundation (Real Asset, 2021). Hence, there is a limitation regarding the number of experts available, as it requires a significant amount of time to gain experience and is susceptible to errors due to human factors, erroneous decision-making and other changing marketing environments (Tochaiwat & Seniwong, 2024). In the academic field, efforts have been made to address these issues by developing various models as tools for processing and forecasting project success.

Upon reviewing relevant literature, the researchers found that there is no existing predictive model that uses clustering characteristics to predict the sales rate of condominium projects. This led the researchers to investigate the use of Deep Learning models as a tool for analyzing the characteristics derived from the collection of factors and predicting the sales rates of condominiums, which generally involve non-linear relationships among factors, complex, dynamic and large data. Given that Deep Learning models are effective tools for analyzing complex and multifaceted problems and factors (Big Data Thailand, 2020), this technique is well-suited for predicting the sales rate suitable for the various condominium development projects. It presents significant determinant factors and can identify the sales rates of condominium projects. This model serves as a valuable tool for business feasibility analysis, enhancing competitiveness, and achieving success in future real estate business.

Figure 1

Examples of Condominiums in the Bangkok Metropolitan Region

(a) Low-rise Condominium

(b) High-rise Condominium

Note. (a) From *Siamese Gioia*, by Siamese Asset Plc., 2025, Siamese Asset Plc. (www.siameseasset.co.th/projects). Copyright 2025 by Siamese Asset Plc. (b) From *Life Rama4-Asoke*, by AP(Thailand) Plc., 2025, AP (Thailand) Plc. (www.apthai.com/th/condominium/life-rama-4-asoke). Copyright 2025 by AP(Thailand) Plc.

LITERATURE REVIEW

Residential condominiums represent a form of residential real estate project where developers allocate shared ownership rights to residents within a large, subdivided building. Because this research is aimed at predicting sales rates, an investigation into key factors was conducted, including aspects related to project configuration, feasibility analysis, and physical factors. These factors are elaborated as follows:

Determining the Project Configuration

Since a good residential project must meet the basic needs of the residents, determining the project configuration is a crucial process (Quester et al., 2007). For residential condominium projects, companies or real estate developers must start by acquiring land that meets the customer’s and company's requirements, typically from various land brokers. Subsequently, they analyze and verify whether the acquired land aligns with the customer’s and company's needs before precisely defining the physical characteristics, which can be segmented based on price levels and types of residential buildings, into 7 primary categories (Money Buffalo, 2021) as follows. It should be noted that the prices were converted according to an exchange rate of 35.268 Baht per US Dollar (Bank of Thailand, 2023).

1. Super Economy Class: This category represents residential condominium projects with a price level lower than $1,418 per square meter. Such projects are relatively scarce in the current real estate market due to continuously rising land prices and development costs. Typically, Super Economy Class projects are low-rise residential buildings, typically not more than 8 stories high. In Thailand, the law stipulates that a high-rise building is defined as a building that is taller than 23 meters (Office of the Council of State, 1979). They offer basic amenities and are often located away from public utilities.

2. Economy Class: This category represents residential condominium projects with a price level ranging from $1,418 to $1,985 per square meter. These projects are typically located in urban areas and are often high-rise buildings, exceeding 8 stories. They feature a central common area that meets standard requirements.

3. Main Class: This category encompasses residential condominium projects with a price range of $1,986 to $2,835 per square meter. Main class projects are typically found within the mass transit system's vicinity and exhibit well-designed central common areas and various workspaces. This is the most readily available category with high competition among developers.

4. Upper Class: This category encompasses residential condominium projects with a price range of $2,836 to $4,253 per square meter. Upper class projects are typically located within 500 meters of a mass transit system or within walking distance. In this category, there is greater diversity and beauty in the common areas, such as saunas, movie rooms, or decor that reflects personal tastes. This type is readily available and faces high competition among developers, similar to the main class category.

5. High Class: This category represents residential condominium projects with a price range of $4,254 to $5,671 per square meter. High class projects are typically located in the central business district and near major mass transit routes. This category introduces contemporary material brands and focuses on luxury in design. They have higher and more spacious levels, and there is an increased emphasis on detailed central common areas.

6. Luxury Class: This category comprises residential condominium projects with a price range of $5,672 to $8,506 per square meter. These projects are not only centrally located but also exude luxury in terms of materials and design. Additionally, they introduce various room types and offer a closer resemblance to actual homes, such as multi-level units or limiting the number of units on each floor.

7. Super Luxury Class: This category represents residential condominium projects with a price of $8,506 per square meter and above. These projects go through meticulous construction and state-of-the-art design processes. Furthermore, they often offer highly personalized services, such as hotel-style management, childcare services, private chefs, room cleaning, and transportation services.

Feasibility Study of the Project

In conducting a feasibility study of the project, the approach may vary depending on the project's surrounding environmental factors (Henilane, 2016). Based on the literature review, there are three main components to studying project feasibility, as follows (Tochaiwat, 2020; Singhasakulchaichan, 2015).

1. The study of market feasibility consists of analyzing economic trends, market demand, and competitive analysis to perform market segmentation. This leads to the identification of target customer groups and the positioning of the product. This segmentation is derived from the demographic characteristics of customer groups within each segment, such as age, gender, family characteristics, income, or other relevant factors, depending on the type of residential property being studied.

2. The study of physical project feasibility includes an examination of physical constraints such as land and environmental conditions, as well as relevant legal regulations pertaining to the construction site. This is essential for developing the project layout. Additionally, concepts from marketing segmentation may be applied to explore a clearer understanding of the physical feasibility since physical potential and location are significant factors in project development (Rahman et al., 2019).

3. A financial feasibility study encompasses income estimation, cost analysis, and the proportion of capital investment, borrowing, interest on loans, and the project's cash flow projection. It aims to provide an estimate of the returns the project is expected to yield, ensuring investment confidence in the project's ability to generate a viable income.

Determinants of condominium project's sales rate

Since increasing project sales is of paramount importance, factors that residents consider as having the most significant influence on the project's success can vary and impact residents' purchasing decisions (Gibler & Nelson, 2003; Opoku & Abdul-Muhmin, 2010). Therefore, it is essential to review the various factors related to sales rates and residents' preferences, as detailed below.

1. Demographic factors

In the context of demographic characteristics, in a study by Srikongkaew (2015), it was found that market factors influencing the decision to purchase condominiums in Bangkok vary significantly between different gender groups. Female respondents were found to have a statistically significant higher likelihood of facing more difficulty in deciding to purchase compared to their male counterparts. This aligns with the findings of Chusun (2013) who studied factors influencing the decision to choose condominiums and discovered that sociodemographic characteristics, particularly gender, were associated with purchasing behavior.

Meanwhile, in research by Kasiputra (2011), it was revealed that income disparities among households significantly affected the decision-making process when purchasing residential units. Those with higher household incomes placed more emphasis on their purchasing decisions compared to those with lower household incomes. This is consistent with the findings of Zeng (2013), who emphasized the importance of demographic characteristics in the success of projects.

2. Physical project factors

Given that physical and interior convenience factors within the project are influential in stimulating sales rates (Aryani & Tu, 2017; Wang, 2013), the literature review reveals that in the study by Patangwesa (2013), it was noted that physical project factors significantly influence the decision-making behavior of purchasing condominiums. Consumers prioritize safety as the foremost factor, followed by the aesthetic quality of the condominium units and the quality of materials and equipment used in the units. This aligns with Wangbenmad (2013), who studied factors influencing the decision to purchase condominiums in Hat Yai District, Songkhla Province, and found that the sampled group emphasized the importance of choosing high-quality materials and a one-year construction guarantee.

Similarly, research by Wen et al. (2019) highlighted that the quality of common areas affects the selling price, consistent with Rinchumphu et al. (2013), who stated that well-designed common areas should cater to the residents' needs. This mirrors the research by Nasar and Elmer (2016), which indicated that project characteristics are significant factors contributing to increased sales. Collectively, all these factors align with the main variables that impact sales rate predictions. Moreover, Chia et al. (2016) found that interior decoration can influence the residents' decision-making process, consistent with the findings of Kumar and Khandelwal (2018), stating that interior aspects like size, type, and usability can enhance project sales rates. In conclusion, residential characteristics, particularly those associated with usability, are the foremost influential factors in residents' purchasing decisions (Elsinga & Hoekstra, 2005; Nahmens & Ikuma, 2009). Therefore, these features should be designed to match the project's surroundings, ultimately leading to increased sales rates and project success (Hsu et al., 2012).

Numerous research studies have consistently emphasized the significance of the project's location as a critical physical factor (Li et al., 2020), such as in the work of Mang et al. (2018), which indicates that a poor location can lead to an overall project inefficiency. This is in line with research conducted by Koklic and Vida (2006); Maoludvo and Apriamingsih (2015), suggesting that the distances to various essential amenities and the project's location can impact sales rates. Similarly, research by Khan et al. (2017); Ismail and Shaari (2020) suggests that in the future, residents will prioritize the project's location and its surroundings. This factor often includes proximity to transportation routes and access to public amenities (Laokaewnoo, 2018; Suttiwongpan et al., 2019).

From the literature review, it was found that both demographic factors and physical aspects of the project significantly influence sales rates. However, the data collection process for selecting factors to be used in the analysis focused on those related to the physical project factors. This is because this study aimed to examine the factors influencing the sales rate of projects from the perspective of real estate developers. Moreover, the study focused on factors that developers can initially determine to assess a project's feasibility and design.

Deep Learning

In forecasting sales rates, a literature review concerning the neural network technique has found it to be an effective tool capable of deciphering complex relationships (Abiodun et al., 2018). Moreover, it has been identified as a highly efficient technique (Laszlo & Ghous, 2020; Temür et al., 2019). This technique comprises the following details:

Deep Learning is one of the most popular and widely accepted Artificial Intelligence models, known for its high precision. Its operational mechanism is derived from the study of human brain processes (Matel et al., 2022). Deep Learning consists of three types of layers: the input layer, hidden layers, and the output layer (Boussabaine, 1996; Wu & Feng, 2017). Through the process of connecting the relationships between the input and output layers, it seeks to discover the interrelationships between the two and assign associated weights (Geetha & Nasira, 2014; Panyafong et al., 2020).

In the application of forecasting, a literature review has shown that in several studies, Deep Learning is found to be more efficient than other established techniques (Lim et al., 2016; Rico-Juan & De La Paz, 2021). In the realm of residential real estate, Nguyen and Cripps (2001); Morano et al. (2015) employed Deep Learning models to evaluate property values. Meanwhile, Zainun et al. (2010) used Deep Learning models to predict the housing market demand. Nguyen and Cripps (2001); Nghiep and Al (2001) developed Deep Learning models and compared them with Multiple Regression Analysis (MRA) models. The results indicated that the Deep Learning model performed better in predicting residential values for medium to large-sized data samples, aligning with Afonso et al. (2019), who compared Deep Learning and Random Forest models to predict New Zealand housing prices and found Deep Learning to be the most effective technique. Morano et al. (2015) also concluded that the neural network model is suitable for predicting property values in Italy, even with limited data. Additionally, the research by Matz et al. (2023) has demonstrated the capabilities of Deep Learning in forecasting the relationships of demographic characteristics that impact the area. The research by Hedyehzadeh et al. (2020) has demonstrated a comparison showing that deep learning techniques are more effective than conventional methods. Additionally, Khalafallah (2008) presented the development of a Deep Learning model to support real estate investors and home developers in making informed financial decisions.

The mentioned literature is evident that, although there has been a lack of research demonstrating the forecasting of sales rates in the past due to the difficulty of obtaining sales rate data for training the models, a comprehensive review of the literature indicates the sufficient potential of Deep Learning to be employed in developing sales rate models. This will contribute to creating new knowledge for stakeholders in future endeavors.

METHODOLOGY

This research was conducted to examine the factors that influence sales rates as well as to develop a sales rate prediction model for condominiums located in the Bangkok Metropolitan Region (BMR) area by the Deep Learning technique. Figure 2 shows the boundary of the BMR area, which contains Bangkok and the five adjacent provinces of Nakhon Pathom, Pathum Thani, Nontha Buri, Samut Prakarn, and Samut Sakhon. In the data analysis process using Deep Learning models, the input datasets from 199 residential condominium projects were gathered through a review of market reports and internet sources. This dataset comprised 36 factors, categorized into six groups of factors: (1) Price-related factors (factors concerning the price of units such as price per square meter and selling price), (2) Entrepreneur-related factors (or type of project developers), (3) Room-related factors (factors concerning room area and functions such as number of bedrooms, number of bathrooms and room area), (4) Project Structure-related factors (factors concerning buildings such as the number of floors and number of units), (5) Common-area-related factors (factors concerning the project facilities such as swimming pool, fitness center and security system), and (6) Location-related factors (factors concerning the location zones of projects and the distances from significant places) (Agency for Real Estate Affairs, 2011, 2014, 2017). It should be noted that the number of datasets acquired in this research was limited because the sales rates of condominium projects were always treated by real estate developers as one of the pieces of confidential information because they reveal the competitive potential of the projects and seem to be an important piece of information for performing a feasibility study and marketing strategy formulation for their competitors. To deal with this challenge, the authors used all datasets contained in the marketing reports surveyed by a professional market research company instead.

The mentioned factors were then analyzed using Deep Learning modeling techniques, with the input data being divided into 189 datasets for model development and an additional randomized 10 datasets for validation selected by the Systematic Random Sampling Technique. As to the analysis process, the acquired datasets were then analyzed by RapidMiner, the application that was discussed by Laszlo and Ghous (2020) for its high accuracy and short processing time and was used in several former pieces of research such as Çelik and Basarir (2017); Geetha and Nasira (2014). The input factors were then examined and for some factors with high levels of data duplication that affect certain relationships within the data, the program filtered out irrelevant or redundant factors that may reduce the model's accuracy. This ensured that only relevant and correlated data was retained, ultimately enhancing the accuracy of the resulting model. The remaining data were then used to create a Deep Learning model by finding the optimized structure of the network with the least Root-Mean-Square-Error (RMSE), thereby obtaining a model that is suitable for practical use (Calasan et al., 2020). Each node independently has its own weights, biases, and activation functions.

As for the model testing, the Root-Mean-Square-Error (RMSE) and the R^2 of the acquired model were then checked by inputting the testing datasets into the model to test the model's accuracy. Finally, the research results were then discussed and the conclusion and the recommendations were explained.

RESULTS

To analyze the data using a Deep Learning model, it is necessary to preprocess the datasets of residential building projects to make it suitable as input data for the neural network model. The details of this preprocessing are as follows:

Fundamental Data of Residential Buildings

In order to group and categorize residential building prices, this can be done to provide a comparative view among projects in each price category from a total of 199 projects. This can be visually represented using a pie chart, as shown in Figure 3.

From the pie chart, it is evident that the number of projects in each price level group comprises the following: (1) Economy Class: 56 projects (28.14%), (2) Main Class: 50 projects (25.13%), (3) Upper Class: 45 projects (22.61%), (4) Super Economy Class: 32 projects (16.08%), (5) Luxury Class: 10 projects (5.03%), (6) High Class: 5 projects (2.51), and (7) Super Luxury Class: 1 project (0.50%), respectively. It can be concluded that the majority of the datasets used in this study were from economy class and main class, whose prices per square meter do not exceed $2,835. The price level clearly reflects the preferences and buying powers of residents regarding residential projects.

In comparing price ranges based on the number of residential building projects for analyzing the factors influencing the sales rate of residential building projects, a literature review revealed a total of 36 factors. The categorial factors and dummy factors were encoded. Then, the representative value of each factor was calculated by arithmetic mean and mode for quantitative and qualitative factors respectively, as shown in Table 1.

Figure 2

Boundaries of the Bangkok Metropolitan Region (BMR)

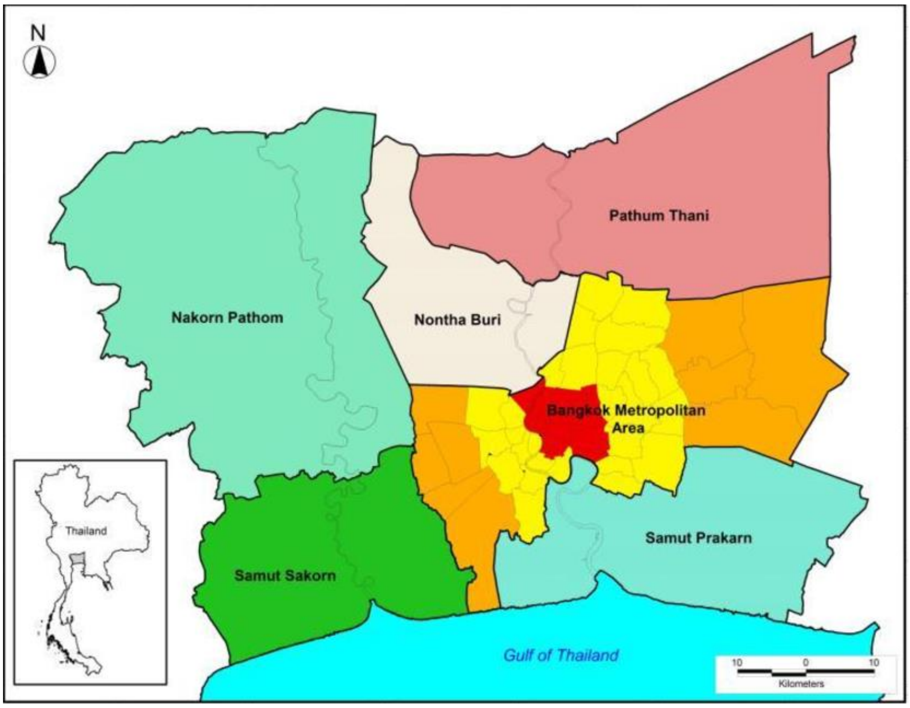


Figure 3

Price Ranges of the Sample Projects

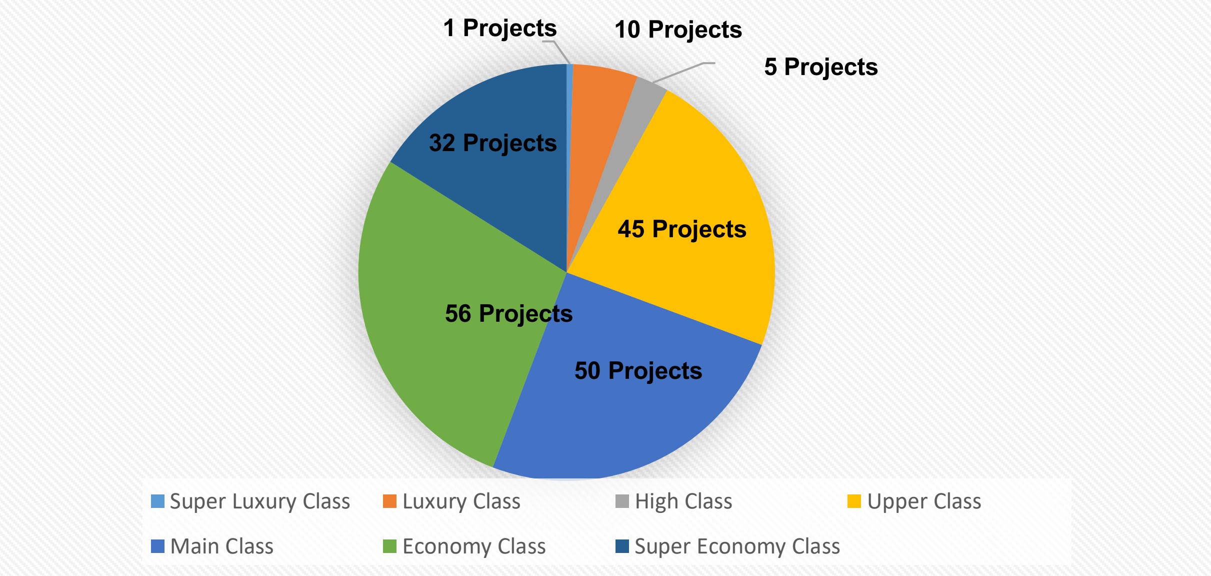


Table 1

The Factors Collected From the Literature Review and Their Representative Values.

Factors Considered for Analysis	Representative Value (Mean for Quantitative Variable / Mode for Qualitative Variable)
1. Price per square meter (US Dollar/ Square Meter)	2,614.02
2. Price (US Dollar)	231,371.21
3. Entrepreneur (0 = Not Listed Company, 1 = Listed Company)	0
4. Number of bedrooms (Rooms)	1
5. Number of bathrooms (Rooms)	1
6. Number of living rooms (Rooms)	1
7. Number of building floors (Floor)	24
8. Parking (Lot)	308.79
9. Room size (Square Meter)	51.36
10. Number of rooms in project (Rooms)	237.05
11. Pool (0 = Not Available, 1 = Available)	1
12. Fitness (0 = Not Available, 1 = Available)	1
13. Multi-purpose room (0 = Not Available, 1 = Available)	1
14. Security system (0 = Not Available, 1 = Available)	1
15. Dining area (0 = Not Available, 1 = Available)	1
16. Working space (0 = Not Available, 1 = Available)	1
17. Garden (0 = Not Available, 1 = Available)	1
18. Sauna (0 = Not Available, 1 = Available)	1

Table 1 (Continied)

Factors Considered for Analysis	Representative Value (Mean for Quantitative Variable / Mode for Qualitative Variable)
19. Playground (0 = Not Available, 1 = Available)	0
20. Cinema (0 = Not Available, 1 = Available)	0
21. Retail (0 = Not Available, 1 = Available)	0
22. Laundry (0 = Not Available, 1 = Available)	0
23. Number of parking spaces/Number of rooms (Ratio)	13.97
24. Location (Zone Number)	4
25. Distance from an expressway (Kilometer)	4.36
26. Distance from a BTS station (Kilometer)	4.20
27. Distance from a shopping mall (Kilometer)	3.50
28. Distance from a park (Kilometer)	3.62
29. Distance from a bus stop (Kilometer)	4.40
30. Distance from a market (Kilometer)	2.64
31. Distance from a hospital (Kilometer)	3.37
32. Distance from a main road (Kilometer)	2.35
33. Distance from a temple (Kilometer)	2.86
34. Distance from a gas station (Kilometer)	2.57
35. Sales rate (Unit / Month)	7.91
36. Number of years from launch (Years)	6

Table 1 shows the representative values for the various factors used as input to find the factors affecting the sales rate. Overall, the determinant factors that lead to the sales rate concern both internal and external factors.

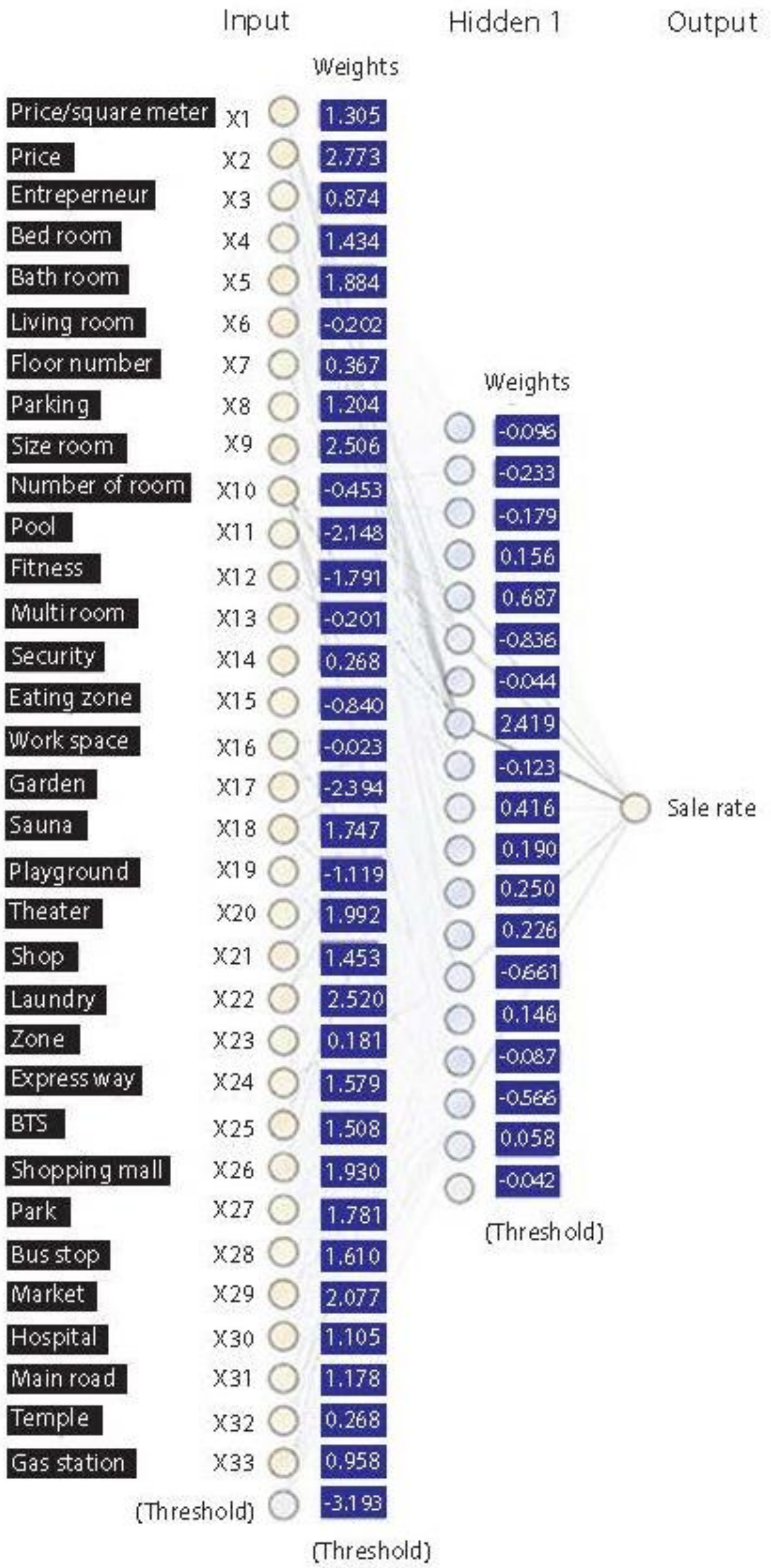
Results Obtained from the Deep Learning Analysis

All 36 determinant factors and one dependent factor were analyzed by RapidMiner software, recommended by Laszlo and Ghous (2020) for their high accuracy. After 200 training cycles with a learning rate of 0.01, the results showed that two determinants, i.e., the ratio of parking spaces per number of units and the number of years from launch, were screened out because of their redundancy and low classification ability. The remaining factors become the nodes of the input layer, as shown in Figure 4.

From this network, the determinants of condominium sales rates can be summarized to provide recommendations for various stakeholders. The process of node partitioning in the program can result from data segmentation and statistical calculations in RapidMiner, which are derived from experiments and considerations of factors that influence the optimal partitioning of nodes. This will be discussed in the section on results analysis and conclusions. The identified factors will be used as foundational elements for further analysis by the relevant stakeholders.

Figure 4

Deep Learning Network With the Factors Influencing the Sales Rate



FINDINGS AND DISCUSSION

The factors that have a significant influence on the sales rate consist of six groups of factors, as follows:

1. **Price-related factors**

This group of factors includes Price per Square Meter (X_1) and Selling Price (X_2). Price per square meter and selling price impact the sales rate. For instance, residents use them as key information for purchasing a condominium. In addition, selling prices exceeding the loan amount approved by banks for condominium buyers is a reason why many buyers have to cancel their presales agreements made with real estate developers.

2. **Entrepreneurial factors**

The type of Entrepreneurs (X_3) influences the sales rate of condominiums. Publicly listed companies in the stock exchange are generally developers with high registered capital and extensive experience in developing multiple projects, are well-known and can encourage condominium buyers to make purchases more readily compared to smaller, non-listed developers.

3. **Room-related factors**

The function of the room, i.e., Number of Bedrooms (X_4), Number of Bathrooms (X_5), Number of Living Rooms (X_6), and the Room Size (X_9) that align with buyers' needs can support and encourage the decision to purchase. This consideration can contribute to an increase in the sales rate of a project.

4. **Project-structure-related factors of the residential building**

The Number of Floors (X_7), Number of Parking Spaces (X_8) and Number of Units in the Project (X_{10}) indicate the potential of the project in terms of residents' comfort. These factors motivate buyers' decision to purchase when considered alongside other project factors.

5. **Common areas and management factors**

Project common areas including their management, i.e., Swimming Pool (X_{11}), Fitness Center (X_{12}), Multipurpose Room (X_{13}), Security System (X_{14}), Dining Area (X_{15}), Workspace (X_{16}), Garden (X_{17}), Sauna (X_{18}), Playground (X_{19}), Cinema (X_{20}), Retail Zone (X_{21}) and Laundry (X_{22}), are examples of facilities that can be standout features for a condominium project. These facilities not only enhance convenience but also shape the lifestyle of condominium residents, driving increased interest in living in the project and fostering satisfaction in the decision to purchase a unit.

6. **Location-related factors**

Finally, the Geographical Location (X_{23}) and distance from significant places, such as the proximity of a project to important landmarks, i.e., Distance from a Highway (X_{24}), Distance from a Public Transportation Station (X_{25}), Distance from a Shopping Mall (X_{26}), Distance from a Public Park (X_{27}), Distance from an Electrical Train Station (X_{28}), Distance from a Market (X_{29}), Distance from a Hospital (X_{30}), Distance from a Major Road (X_{31}), Distance from a Temple (X_{32}) and Distance from a Gas Station (X_{33}), are the indicators for convenience of living and transportation for residents. These factors influence the routes chosen for commuting and the daily lives of residents, as well as their ability to access various essential destinations. Such aspects can play a significant role in facilitating residents' decision-making when considering a condominium purchase.

It was found that the coefficient of determination, R^2, was 0.703 while the RMSE was 0.539. The R-squared value is a statistic used to assess the goodness of fit of the obtained mathematical model data, serving as a coefficient that indicates the level of determination. The 0.703 R^2 value indicates that the determinants all together explain about 70.3 percent changes in the sales rate, which is accurate enough for planning purposes. This indicates that the Deep Learning network model is capable of identifying the factors that significantly affect the sales rate and is a reliable tool for predicting future sales rates of residential projects. The accuracy value is considered the measure that most closely represents the true value of the data. This is even in cases of a limited number of data, as revealed by Morano et al. (2015); Zainun et al. (2010). A high accuracy value of the model indicates that the model is precise and can be applied effectively, as it reflects the actual relationships among the various influencing factors. For instance, the price factor is the most significant in determining selling prices, as it results in competitive advantages, which in turn affects other factors within the group (Guan & Cheung, 2023). Meanwhile, the characteristics and number of rooms were found to be significant, consistent with the research by Yoshida and Kato (2022), which revealed that the features of rooms and internal space have a considerable impact on the consideration of purchasing a residence across all economic and social conditions. Similarly, the importance of location was found to significantly influence purchasing considerations, as it is crucial for the distance to various key destinations, as previously noted in the literature of Li et al. (2020).

CONCLUSION AND RECOMMENDATIONS

It was found that the most influential factors on the sales rate are: (1) Price-related factors, (2) Entrepreneur-related factors, (3) Room-related factors, (4) Project structure-related factors, (5) Common area and management-related factors, and (6) Location-related factors. These findings are mainly in accordance with the influential factors of the projects (Issarasak et al., 2021; Tochaiwat et al., 2023). In other words, when compared to previous literature, it is evident that the price factor has a significant influence, as it can motivate buyers in constrained economic conditions. Meanwhile, the factor related to the developer impacts credibility, while the characteristics of the rooms affect the preferences of the residents. Additionally, the project structure and management greatly influence purchasing decisions. Lastly, the location factor is crucial in terms of travel distance to various key destinations for residents. All of these factors collectively contribute to an increase in sales rates, resulting in the project's success.

All of these can be used as recommendations for stakeholders. This expands on the section regarding stakeholders, as the results of this research yield a model that stakeholders can utilize for pricing strategies, interior design elements of the project, and marketing strategies. Consequently, the findings can be categorized into recommendations beneficial to stakeholders, as follows:

1. **Project Developer**

In terms of practical application, project developers can leverage the insights gained from studying the determinants of condominium sales rates to plan and execute condominium projects with satisfactory sales outcomes. Like a conductor, the project developer shall control all important factors contributing to project success: reasonable price, a trustworthy brand, residential units and common areas, as well as the location that responds to the demands of the buyers. This is in line with the literature review by Wen et al. (2019) which discusses the relationship between the facilities in a project and their impact on the sales rate. An understanding of entrepreneurial factors enables real estate developers to analyze and adopt an appropriate competitive strategy that aligns with their type of company. Price-related factors assist in decision-making regarding market segmentation and project design, while location-related factors give useful information for the land acquisition process. Additionally, project-structure-related factors, room-related factors and common area and management factors contribute to designing projects that better meet buyers' expectations. This is consistent with the research of Kumar and Khandelwal (2018).

In addition, project developers can utilize the acquired model to predict the possible sales rate of their projects. The sales rate is crucial data for assessing the feasibility of a project, comparing alternatives to find the one that enhances the highest sales rate, or performing resource allocation and operation planning, including unit inspections, handovers, and property transfers. This contributes to making condominium projects more efficient and enhancing a high level of buyer satisfaction. Successful projects build long-term trust in the brand among buyers.

2. **Designer**

When designing the condominium project, designers can use the determinants, especially the project-structure-related factors, room-related factors and common area and management factors, to select project designs that align with buyers' needs, resulting in favorable sales outcomes for the condominium projects they are designing. This is consistent with the research of Chia et al. (2016). Professional designers shall design residential units and common areas that can respond to the buyers' demands with construction costs not exceeding those assumed in the project feasibility study phase. This is in line with the findings presented in the research of Rinchumphu et al. (2013). It should be noted that the approach adopted by the majority of developers in pricing residential units in a condominium project is pricing by the project cost. This implies that when the construction cost is high, the price will be also high, and the sales rate will become low conversely. Moreover, similar to project developers, designers can also use the acquired model as a prototype to compare the design alternatives to find the one that enhances the highest sales rate.

3. **For those continuing their studies**

In further research applications, researchers can perform a similar research methodology with the different types of real estate projects in order to find the determinants and prediction models of the different types of projects. This information shall be highly beneficial for the stakeholders in enhancing project success, as mentioned above. Alternatively, researchers may use other analysis techniques or tools and compare the results between the different analysis tools like Nghiep and Al (2001), who compared Artificial Neural Network (ANN) and Multiple Regression Analysis (MRA), or Laszlo and Ghous (2020), who compared RapidMiner with Python, to compare the ability of each tool in defining the sales rate determinants and predicting the sales rate for condominiums. Moreover, those interested could further explore how this model might evolve with larger datasets or more complex, real-time data inputs to enhance its practicality. For example, demographic factors of the project's target groups can be input into the model to gain additional insights that real estate developers can apply in their planning and decision-making processes.

Finally, it should be noted about the research limitations. Because the sales rate of condominium projects is important data for marketing strategic planning of their competitors, it is normally treated as confidential (Agency for Real Estate Affairs, 2021). Therefore, this research gathered data from the market survey reports. However, this approach seems to have a limited number of data that may affect the accuracy of the results. In future studies, this approach can be adapted for large datasets that are relevant to the specific time periods, allowing for the examination of complex factor relationships and the resolution of issues pertinent to each timeframe.

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