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Prediction of Land Price for Sustainable Housing Development in the Capital of Thailand Using Deep Learning Techniques

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Abstract

Due to the high population density and limited land availability in Bangkok, the capital of Thailand, land values have been increasing every year, posing challenges to sustainable housing development. Accurate land valuation is critical not only for investment decisions but also for promoting economic efficiency, social equity, and sustainable urban land use. Inaccurate analysis can lead to losses for real estate developers, project residents, and surrounding communities. However, this process requires extensive knowledge and experience. This research presents an approach for analyzing land values in Bangkok using Deep Learning techniques, which can help real estate developers assess appropriate land values more accurately and precisely. The study collected data on vacant land in Bangkok from an online feasibility study database and analyzed them using Deep Learning techniques. The results showed 30 determinants categorized into five groups. The study conducted 80 parameter adjustments with a ratio of 128:64:32 using a Quadratic Loss Function. The model was validated using k-fold cross-validation to ensure robustness and a Model Simulator operator to test sensitivity analysis. The Deep Learning model resulted in an R-square value of 0.917 and an RMSE of 2620 USD. The results of this research can be used as an effective decision-making tool for real estate developers, landowners, and brokers in determining appropriate buying or selling prices for land to support real estate sustainable development.

Keywords: deep learning; land price prediction; land valuation; sustainable development; sustainable housing; urban sustainability

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1. Introduction

Bangkok, as shown in Figure 1, serves as Thailand's primary center of development and experiences consistent annual growth in land value. In this study, land value specifically refers to the market value, the price at which land is offered or traded in the open market as advertised through real estate brokerage platforms. This differs significantly from the official assessed value provided by the Treasury Department, which is primarily used for taxation and legal purposes. By focusing on market-driven data, this research captures the real-time economic dynamics and collective valuation of urban land as perceived by active market participants. The Real Estate Information Center [1] reported that the undeveloped land price index reached 407.8 points in the first quarter of 2024, a 5.7% year-on-year increase.

The city's spatial dynamics are characterized by a clear stratification into inner, middle, and outer areas. According to the Treasury Department's 2025–2026 appraisal update [2], prime locations such as Ploenchit, Witthayu, and Siam Square have reached official valuations of 32,135 USD per square wa, reflecting the intense concentration of value in the city's

core. This disparity arises from a complex interplay of localized determinants. Data from the Treasury Department [3] further indicate that areas near mass transit rail lines in the city center have seen the highest price increases. This aligns with a report from Bangkokbiznews [4], which identifies the BTS On Nut area as a highly desirable residential location, particularly due to the Green Line project, the first mass transit line to pass through the heart of Bangkok.



Figure 1. Map of the Bangkok area.

While the existing literature has provided a foundational understanding of land value determinants, and prior studies have successfully utilized traditional models, such as regression models, to establish these relationships [5], the increasing complexity of a rapidly evolving megacity presents new analytical challenges. To complement these established methods, this study investigates the use of Deep Learning to better capture the intricate spatial heterogeneity and high-dimensional interactions that characterize Bangkok's current real estate landscape. Similarly, the authors of some recent studies have adopted Deep Learning techniques, such as Tochaiwat & Budda [6], who investigated construction prices, and Yang et al. [7], who studied household electricity consumption.

However, a significant research gap remains in the context of Bangkok's land market: while accurate valuation is critical for project feasibility [8], the nonlinear relationships and synergistic effects between high-dimensional urban determinants are often difficult to isolate using linear frameworks alone. This can lead to significant value discrepancies, particularly for inexperienced developers. The incremental value of this research lies in its integrated approach—combining 30 multidimensional variables categorized into five specific groups: (1) Location, (2) Infrastructure, (3) Local Economy, (4) Legal Regulations, and (5) Site Characteristics—to provide a more nuanced predictive framework than previous site-specific studies. To address these gaps, the primary objectives of this study are (1) to identify and analyze the impact of 30 multidimensional determinants on market-driven land prices in Bangkok; (2) to develop and optimize a Deep Learning (DL) architecture capable of capturing complex, nonlinear patterns within these high-dimensional datasets; (3) and to evaluate the model's stability and precision through rigorous k-fold cross-validation, providing a reliable tool for urban planning and development.

This transition to a Deep Learning framework is prompted by the increasing complexity of the 30-variable dataset. As high-dimensional data can present challenges such as multicollinearity in linear contexts, Deep Learning offers a complementary approach adept at capturing nuanced, nonlinear patterns [9] and complex interaction effects. This approach aligns with recent urban studies that utilize diverse non-parametric frameworks to enhance

the accuracy of infrastructure and resilience assessments [10]. Through continuous hyperparameter tuning and k-fold cross-validation, the model was refined to ensure precision. By enhancing the precision of land value forecasting, this study serves as a sophisticated supplement for developers and urban planners, reducing information asymmetry that often leads to speculative overpricing. Ultimately, this data-driven approach contributes to better housing affordability and more inclusive urban development within the Bangkok land market.

2. State of the Art

2.1. Determinants of Land Value

In the context of the Bangkok Metropolitan Area, land value is influenced by a multitude of independent factors that often exhibit nonlinear and complex relationships. A primary driver of escalating land values is the public transportation system, which has radically transformed Bangkok's urban landscape in recent decades. Traditionally, a "prime location" was defined by its proximity to the Central Business District (CBD); however, modern definitions have shifted towards proximity to mass transit stations (BTS/MRT), which is now viewed as a critical factor for quality of life [11]. Furthermore, urban planning regulations and zoning restrictions impose varying constraints on land use, leading to significant disparities in land valuation across different areas. The variables used in this study were identified and derived from a comprehensive review of previous studies related to the research topic, similarly to the approaches used by Phuong et al. (2026) and Tochaiwat & Budda (2026) [5,6]. Land value depends on various factors that are the components of land price evaluation. In studying various studies, multiple factors were found to affect land value. These variables can be categorized into the following groups: (1) Location, (2) Site Characteristics, (3) Infrastructure Facilities and Community Services, (4) Surrounding Physical Environment, (5) Local Economy, and (6) Legal Regulations. The references for these factors are shown in Table 1.

Table 1. Factors influencing land value from the literature.

Factors	Authors
Location	[12–39]
Site Characteristics	[12–14,16,40–45]
Infrastructure Facilities and Community Services	[12,14,16,19,41,46–54]
Surrounding Physical Environment	[40,55–65]
Local Economy	[14,22,33,37,40,58,65–70]
Legal Regulations	[13,14,33,37]

The categorization into these six dimensions represents a holistic approach to land valuation. While Location and Infrastructure define accessibility, Legal Regulations (e.g., zoning and FAR) act as a catalyst or constraint on the land's highest and best use. These factors are intrinsically linked; for instance, the synergy between transport expansion and zoning density directly impacts housing affordability and urban inclusion in Bangkok. Although other intangible factors exist, such as market speculation, this study focuses on these six quantifiable pillars to ensure model robustness and interpretability.

2.1.1. Location

A comprehensive review of the literature revealed that location is the paramount factor in determining land value ([12,14–16,19,25–27,31,32,39]). The proximity of land

to key points of interest and the overall quality and convenience of the surrounding area significantly influence its value. The impact of location on land value manifests in several ways. The following key location factors affect land value: (1) Distance from city center or community hub typically correlates with higher land value, with prices generally decreasing as distance increases [21,25]. (2) The location within a municipal boundary or local administrative area is significant because it offers access to different levels of public utilities, infrastructure, and government services [38]. (3) Distance from roads and transportation routes, including highways, main roads, secondary roads, alleys, or public transit lines, affects convenient access to the area [15,19,24,26,27,39]. (4) The conditions of roads passing through the land, including their type, width, surface quality, etc., are important because high-quality roads indicate area prosperity and facilitate access for many private vehicles and public transportation [21,32]. (5) Accessibility and the convenience of commuting to workplaces and public utilities, such as government offices, markets, shopping centers, banks, schools, universities, hospitals, religious places, and highway access points, significantly affect land value ([12,18,22,25,32,36,37]). The availability of diverse transportation options, the ease and speed of commuting, and lower associated travel costs all contribute positively to land value. Moreover, the potential for pedestrian access and foot traffic has gained recognition as a value-enhancing factor. Land in areas with high walkability to important locations or those experiencing substantial pedestrian flow often see an increase in value. This trend reflects growing appreciation for pedestrian-friendly urban environments. Properties with limited external access or those requiring difficult travel conditions often experience a depreciation in value [29,30,38].

2.1.2. Site Characteristics

A comprehensive review of the literature, including the Treasury Department [14], Jetsadawan [16], Asavaphanthip [41], Srisomboon & Charnwasununth [42], Abdulla et al. [31], and Gao & Asami [43], highlights several key physical factors that influence land value: (1) Plot size is a crucial factor. Land should be appropriately sized for its intended use [45]. Larger plots may be suitable for agriculture, industrial plants, or golf courses, while medium and smaller plots are ideal for residential developments like single homes or condominiums, office buildings, hotels, or shopping centers. (2) The shape of the land also impacts its value. Square or rectangular plots typically have higher values due to their efficient use potential. Conversely, irregular shapes, like triangles or trapezoids, and plots with indentations often decrease land value. (3) Topographic features play a significant role. Natural characteristics such as lowlands, basins, valleys, hills, slopes, and plains affect land value based on their potential for development and use. (4) Surface elevation relative to the road frontage is another crucial factor. The difference in elevation can significantly impact land value due to the potential costs of land filling or leveling for construction or real estate development projects [41,42]. (5) The width of the land along the road is particularly important for commercial properties or residential developments. Land with wide frontage along a main road, allowing for easy vehicular access, tends to have a higher value [34,41]. (6) Special physical features can greatly enhance land value. These may include multiple access points, proximity to parks, golf courses, rivers, lakes, mountains, waterfalls, or beautiful natural views [43,44].

2.1.3. Infrastructure Facilities and Community Services

Based on previous studies, such as the Treasury Department [14], Jetsadawan [16], Aziz et al. [19], Somantri [39], Asavaphanthip [41], Ruksasri et al. [46], Long [48], Yuan, Wei & Xiao [49], Feng & Humphreys [51], Wang et al. [52], Kim et al. [53], and Ahlfeldt & Kavetsos [54], factors related to public utilities, facilities, and community services in

the land area can be summarized as follows: (1) Infrastructure such as roads, electricity, water supply, telephone, and drainage systems should be considered in terms of whether they are available in the land area while assessing land value. The better the quality and availability of these factors, the higher the land value will be. (2) The availability of public facilities such as markets, shops, public parks, clubs, and sports fields in the land area should be considered, and their quality and convenience of use should be evaluated. The more abundant these facilities are and the better their quality, the higher the land value will be [47,51,53,54].

2.1.4. Surrounding Physical Environment

According to Lake et al. [56], Kim et al. [57], Liang [58], Nakamura [59], Asavaphanthip [41], Yuan, Wei & Wu [60], and Nicholls [63], the physical environmental conditions of the land location, such as area hygiene, wind direction, temperature (hot or cold), odors, noise, lighting, water source conditions, tree shade, and panoramic views, affect land value. For example, air quality that impacts future habitability of the land, which may be affected by nearby locations such as industrial factories, influences land prices [65]. Traffic noise disturbance from highways is considered noise pollution [62]. Additionally, traffic congestion also affects land value [61]. In the specific context of Bangkok, the city has become increasingly affected by severe $PM_{2.5}$ particulate matter pollution. Consequently, there is growing public and academic interest in Urban Green Spaces, which serve as vital infrastructure for promoting public health and enhancing the urban environment. Beyond their ecological functions, these green spaces act as essential recreational and cultural hubs. They facilitate diverse communal activities, such as walking, cycling, and social gatherings, thereby fostering community cohesion and improving the overall quality of urban life [64].

2.1.5. Local Economy

The presence of land in prime locations within areas characterized by diverse economic activities indicates the potential or tendency for cities to expand and grow significantly in the future. This phenomenon can be attributed to various factors such as population growth, the development of roads and public utilities, government infrastructure projects, and investments in residential and other real estate projects by the private sector [22,40,70]. Moreover, land in city centers, where there is a high density of economic activities and diverse economic forms, tends to have higher values. This increase in land value can lead to the migration of workers from the city center to lower-valued outskirts, resulting in the dispersion of labor and economic activities. Consequently, land that is currently low-valued in areas farther from the city may increase in value in the future [67,69]. Additionally, policies that reduce the value of industrial land can further contribute to urban expansion [68].

2.1.6. Legal Regulations

Each urban planning zone is subject to different legal regulations, which in turn affect the potential for land development. Generally, areas with fewer legal restrictions are more favorable for development compared to those with numerous legal constraints. For example, zoning laws that dictate land use and building height restrictions significantly influence the ability to set land prices [22,33]. Additionally, limitations on project development, such as the construction of single-detached houses, semi-detached houses, and townhouses, can pose further constraints [21]. Conversely, land situated in legally suitable zones for commercial projects tends to have higher values [37].

The six categories of determinants discussed above do not operate in isolation but are deeply interconnected in a nonlinear manner. For instance, the value-enhancing effect of infrastructure, such as a new MRT line, is heavily moderated by legal regulations such as

Floor Area Ratio (FAR) bonuses. Similarly, site characteristics, such as plot size, only become significant when the local economy demands large-scale commercial development.

2.2. Property Value Appraisal

Property valuation depends on the type of property and the purpose of the valuation. There are three main approaches to property valuation, as outlined in the Thai Government Gazette [17]: (1) Market Comparison Approach: This approach involves evaluating the property by comparing it with similar properties in the vicinity. This method relies on market data from comparable land sales to establish a benchmark. Factors influencing land value, such as location, accessibility, and local amenities, are considered to provide a fair comparison. By analyzing these elements, valuers can determine a market-based valuation that reflects current conditions [34,70]. (2) Income Approach: This approach focuses on the potential income that the property can generate. This method is particularly useful for valuing commercial properties and rental units. The valuation process involves estimating the property's value through direct capitalization, where projected income and expenses are considered. (3) Cost Approach: This approach assesses the property by calculating the total value of the land and the depreciated value of any structures on it. This method is often used for new construction or properties with unique features. The land is valued using the Market Comparison Approach, while the structures are evaluated based on their construction costs. The unit-in-place method and the quantity survey method are commonly employed to estimate building costs. By subtracting depreciation, valuers can determine the current value of the property. This approach is particularly useful for insurance purposes and for valuing specialized properties [46].

While these three traditional approaches remain the industry standard in Thailand (as per the Government Gazette), they rely heavily on human judgment and linear assumptions. In a volatile market like Bangkok, where data are high-dimensional and spatial factors are complex, there is a clear shift toward "Automated Valuation Models" (AVMs) and Deep Learning. This research fills the gap by integrating these traditional appraisal pillars into a sophisticated Deep Learning framework, providing more objective and scalable predictions for large-scale housing developments.

2.3. Bangkok Context

The Bangkok Metropolitan Area is characterized by a high degree of spatial heterogeneity and diverse urban fabrics, resulting from decades of rapid development and densification. While Bangkok invests heavily in large-scale urban redevelopment projects to position itself as a global city, it simultaneously exhibits extensive urban informality [12]. This dual nature creates a complex landscape where informal settlements often coexist with modern transit-oriented developments near the Central Business District (CBD).

Furthermore, the city's sociocultural profile is equally multifaceted; some districts serve as multicultural hubs inhabited by both local and international residents [71], while peri-urban zones function as critical logistics and industrial corridors connecting the capital to neighboring provinces. These areas are further transformed by the ongoing expansion of the mass transit system (MRT/BTS), which reshapes infrastructure demands and triggers significant demographic shifts among both long-standing communities and new residents [11]. Additionally, the geographical prominence of the Chao Phraya River, which bisects the city, introduces a complex socio-environmental dynamic. While the riverfront has evolved into a premier destination celebrated for its esthetic appeal, cultural landmarks, and high-end tourism developments, these same areas remain susceptible to significant environmental challenges. Despite their status as prime real estate, these low-lying urban

pockets and riverfront properties continue to face high vulnerability to seasonal flooding, tidal surges, and long-term climate-related risks [13].

In summary, the urban landscape of Bangkok is defined by a delicate balance between rapid modernization, socio-spatial diversity, and environmental vulnerability. The paradox of the riverfront—where high commercial value meets high environmental risk—exemplifies the nonlinear complexity of Bangkok's spatial dynamics. These multifaceted characteristics, ranging from transit-driven growth to climate-related vulnerabilities, create a highly heterogeneous environment. For researchers and stakeholders, capturing these intricacies is essential, as they exert a profound yet varied influence on land valuation, tourism-related pricing, and the overall resilience of the urban economy.

2.4. Deep Learning Technique

Deep Learning (DL) represents an advanced evolution of Artificial Neural Networks (ANNs), characterized by its multilayered architecture designed to perform hierarchical feature learning. Unlike traditional machine learning, DL's strength lies in its ability to automatically extract high-level features from complex data samples without extensive manual feature engineering. In the context of property valuation, DL can capture the nonlinear and synergistic effects between various determinants, such as the interaction between proximity to transit hubs and specific urban zoning regulations, which are often lost in conventional linear models [72]. Deep Learning was built upon the concept of Artificial Neural Networks (ANNs), which is a subset of Machine Learning techniques. It simulates the neural networks in the human brain by stacking multiple layers. Each layer consists of the following components: the first layer, called the input layer; the middle layers, called the hidden layers; and the final layer, called the output layer.

Deep Learning techniques enhance the functioning of ANNs by increasing the number of stacked Hidden Layers to achieve more accurate results. The challenge in using Deep Learning techniques is finding the appropriate neural network and identifying variables that affect the teaching performance of the computer network [73,74]. The more complex the layer system used in processing, the deeper the structure becomes, resulting in more complex outcomes. For example, a neural network with four stacked layers can synthesize and process information more complexly than a neural network with only two layers. Finally, several entrepreneurs have applied Deep Learning techniques in their business process because of their high accuracy and efficiency. This research employs a deep neural network where 30 distinct determinants serve as input features. The model leverages multilayered hidden architectures to extract nonlinear representations from the data sample. Through systematic parameter tuning and robustness checks, the framework yields a highly precise predictive model for land prices, effectively addressing the complexities of urban property valuation. The proposed architecture is shown in Figure 2.

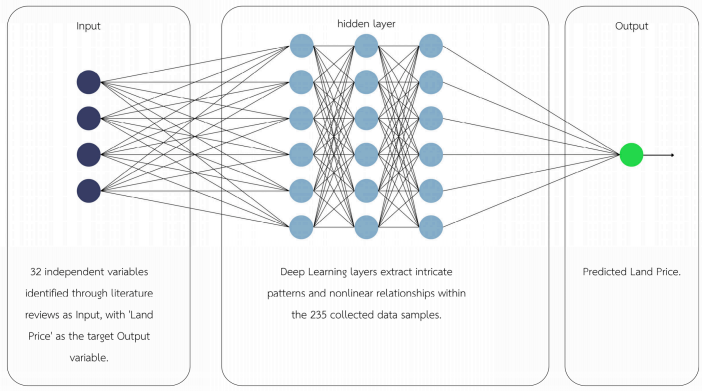

Figure 2. The proposed Deep Learning architecture for land price prediction.

3. Research Methodology

3.1. Data Source

This research employed a quantitative approach utilizing Deep Learning techniques. The model required high-quality input data for supervised learning, which was sourced from www.feasy.com, an online platform that specializes in real estate data aggregation that provides standardized information by consolidating data from the Thai Property Valuation Association, a widely recognized and authoritative body for real estate valuation in Thailand. Unlike general property listing websites, this platform ensures data consistency and reliability by integrating multiple layers of geographical and legal constraints, including city planning zones (color-coded zones), expropriation lines, building restrictions, and mass transit networks. To eliminate the scale effect and facilitate objective comparisons across different plot sizes, the target variable (dependent variable) was defined as the unit land value per square meter (THB/sq.m.) rather than the total transaction price.

This centralized database allows for cross-referenced validation within a single standardized framework. A total of 235 land plots across Bangkok were identified and meticulously collected for the analysis, ensuring that each data point represents a verified market offering rather than unverified amateur listings.

3.2. Research Process

Following a comprehensive literature review, this study initially identified five determinant groups influencing land prices: Location, Site Characteristics, Infrastructure/Facilities, Surrounding Physical Environment, and Local Economy/Community Services. The feature selection process followed a systematic filtering approach to ensure methodological rigor. First, variables were pre-screened based on their theoretical significance in urban economics and the land valuation literature. Second, a correlation analysis was performed to identify and remove redundant or highly collinear variables that could lead to overfitting. Third, the remaining features were evaluated using feature importance ranking within the RapidMiner environment. This step ensured that only the variables with the highest predictive power and relevance to the Bangkok land market were retained, resulting in a final set of 30 independent variables. However, due to the constraints of digital data collection via the Feasy.com platform, variables within the "Surrounding Physical Environment" group, which require primary onsite surveys, were excluded to maintain data consistency and reliability. Ultimately, 30 independent variables were selected for model input. While traditional appraisal often relies on a limited set of heuristics or primary factors, this high-dimensional approach was intentionally adopted to capture the hidden, nonlinear interdependencies within Bangkok's complex urban ecosystem that human intuition might overlook.

The land price forecasting model was developed using RapidMiner (version 10.1, RapidMiner GmbH, Dortmund, Germany). RapidMiner was selected for its computational efficiency and its ability to provide performance comparable to Python-based environments [75]. To ensure robust model performance and prevent issues related to data distribution or small sample sizes, this study implemented 10-fold cross-validation. This process involved three steps: (1) Data Splitting: The dataset was divided into 10 equal subsets (k = 10). (2) Training and Testing: In each iteration, 90% of the data ($k - 1$) were used for training, while the remaining 10% served as the test set. (3) Rotation: This process was repeated 10 times, ensuring every data point was used for both training and testing, thereby reducing bias and enhancing the model's generalizability. To ensure optimal performance of the Deep Learning architecture, all numerical input variables were standardized using Z-score transformation. This step was crucial to prevent features with larger scales from biasing the weight initialization and gradient updates,

ensuring each of the 30 determinants contributed proportionately to the learning process. Furthermore, hyperparameter tuning was conducted to optimize the neural network's architecture. The outcomes were then compared with results obtained from an automated program system (AutoModel) to validate performance. To address the "black box" nature of Deep Learning, we utilized the Model Simulator within RapidMiner. This approach enhanced model transparency by perturbing input variables to observe changes in the output, identifying how each of the 30 features supports or contradicts the final land price prediction. This granular analysis bridges the gap between high-dimensional data and human-interpretable logic, demonstrating that the model does not merely process numbers but simulates the multifaceted valuation logic inherent in a dynamic real estate market.

4. Results

4.1. Related Variables

The researchers defined a total of 30 variables, derived from a comprehensive literature review, and compared them with the data available from the website, as shown in Table 2.

Table 2. Variables used in the research.

Row	Factor Group Name	Variable Name	Meaning	Unit	Level of Measurement
1	Location in Bangkok area	Inner area	High-density Central Business Districts (CBDs) and historical cores characterized by intensive land use, premium commercial activities, and primary transportation hubs.	1/0 (1 = Yes)	Dummy
2		Middle area	Transitional urban zones surrounding the inner core, consisting of established residential neighborhoods and emerging secondary business districts with high connectivity.	1/0 (1 = Yes)	Dummy
3		Outer area	Suburban regions primarily characterized by low-density residential developments, industrial zones, and agricultural greenbelts.	1/0 (1 = Yes)	Dummy
4	Shape of land	Square shape	Land parcels with an approximately equal length and width.	1/0 (1 = Yes)	Dummy
5		Rectangle shape	Land parcels where one pair of opposite sides is longer than the other, maintaining a regular four-sided structure.	1/0 (1 = Yes)	Dummy
6		Other shape	Land parcels with irregular geometries, such as trapezoids, triangles, or asymmetrical polygons, that do not fit standard categories.	1/0 (1 = Yes)	Dummy
7	Land details	Square wa	Land area in square wa units.	Square wa (1 square wa = 0.000988 acre)	Ratio
8		Width	Land frontage width.	Meter	Ratio
9		Length	Land depth.	Meter	Ratio
10		Road width	Width of the road adjacent to the land frontage.	Meter	Ratio
11		Bridge nearby land	Land parcel is located in the immediate vicinity of a road overpass, an elevated interchange, or a river-crossing bridge.	1/0 (1 = Yes)	Dummy
12	Position of land	Corner plot	Number of roads adjacent to the land that makes the land a corner plot.	1/0 (1 = Yes)	Dummy
13		Side road	Land parcel that is adjacent to a secondary road or positioned along the side of a major thoroughfare.	1/0 (1 = Yes)	Dummy
14	Land use	Land use type	Classified land designations (residential, commercial, agriculture).	Categorical	Nominal
15	Public road next to land	Amount of public road	Amount of public road next to land.	1/2/3/4 (amount of road)	Ratio
16		River width near land	Width of public river near land.	Meter (1 m = 3.280 Ft)	Ratio

Table 2. *Cont.*

Row	Factor Group Name	Variable Name	Meaning	Unit	Level of Measurement
17	Adjacent land use	Commercial building	Adjacent land area is used for a commercial building.	1/0 (1 = Yes) (0 = No)	Dummy
18		Apartment	Adjacent land area is used for apartments.	1/0 (1 = Yes) (0 = No)	Dummy
19		Single building	Adjacent land area is used for a single building.	1/0 (1 = Yes) (0 = No)	Dummy
20		Warehouse	Adjacent land area is used for a warehouse.	1/0 (1 = Yes) (0 = No)	Dummy
21		Temple	Adjacent land area is used for a temple.	1/0 (1 = Yes) (0 = No)	Dummy
22		Housing estate	Adjacent land area is used for housing.	1/0 (1 = Yes) (0 = No)	Dummy
23		Tall building	Adjacent land area is used for a high-rise building.	1/0 (1 = Yes) (0 = No)	Dummy
24		Farm	Adjacent land area is used for farming.	1/0 (1 = Yes) (0 = No)	Dummy
25		Gas station	Adjacent land area is used for a gas station.	1/0 (1 = Yes) (0 = No)	Dummy
26	Amenities within 1 km radius	Mall	Distance from a mall is not more than 1 km.	1/0 (1 = Yes) (0 = No)	Dummy
27		Market	Distance from a market is not more than 1 km.	1/0 (1 = Yes) (0 = No)	Dummy
28		Academic	Distance from school or college is not more than 1 km.	1/0 (1 = Yes) (0 = No)	Dummy
29		Hospital	Distance from a hospital is not more than 1 km.	1/0 (1 = Yes) (0 = No)	Dummy
30		Public transport	Distance from public transportation (BTS/MRT/BRT/ARL) is not more than 1 km.	1/0 (1 = Yes) (0 = No)	Dummy

4.2. Model Development and Systematic Tuning

The development of the land price forecasting model involved evaluating 80 experimental configurations within the RapidMiner environment. To address the nonlinear complexities of Bangkok's land market, the optimization focused on hidden layer architectures and loss functions, including Quadratic, Huber, Absolute, and Quantile. As detailed in Table 3, various multilayer perceptron structures were tested, showing that incremental adjustments in the hidden layer ratio significantly impact predictive power. The empirical results identify the 128:64:30 architecture with a Quadratic Loss Function as the optimal configuration, achieving the highest R^2 of 0.917 and the lowest RMSE of 2620.

Table 3. List of top 5 models developed through parameter adjustments.

Deep Learning Parameter Adjustments			
Hidden Layers	**Loss Function**	**R^2**	**RMSE (USD)**
128:64	Quadratic	0.845	3580
127:65	Quadratic	0.848	3542
129:63	Quadratic	0.843	3600

Table 3. *Cont.*

Deep Learning Parameter Adjustments			
Hidden Layers	**Loss Function**	**R^2**	**RMSE (USD)**
128:65:31	Quadratic	0.900	2877
128:64:32	Quadratic	0.917	2620
128:64:32	Huber	0.830	3598
128:64:32	Absolute	0.738	4462
128:64:32	Quantile	0.689	4866

4.3. Comparative Performance and Model Justification

To further justify the necessity of this optimized Deep Learning (DL) approach, a comparative benchmark was conducted against traditional machine learning methods. According to Table 4, the proposed DL model significantly outperformed Linear Regression (R^2 = 0.438), Random Forest (R^2 = 0.607), and XGBoost (R^2 = 0.575). While Random Forest yielded a slightly lower MAE, indicating its efficiency in predicting the majority of land price clusters, the DL model's superior R^2 and lower RMSE confirm its robust capability in capturing complex, nonlinear spatial dynamics and extreme value fluctuations across the 30 determinants. This systematic manual tuning also proved far more effective than the AutoModel (R^2 = 0.709), validating that the tailored architecture is essential for high-accuracy property technology applications. This performance is consistent with established benchmarks in the literature, such as Tochaiwat (R^2 = 0.918) [76] and Sitthikankun et al. (R^2 = 0.914) [77].

Table 4. Comparative performance analysis of land value forecasting models.

Models	**R^2**	**RMSE (USD)**	**MAE (USD)**
Linear Regression	0.438	7200	4265
Random Forest	0.607	5484	2978
(XGBoost) Gradient Boosted Tree	0.575	6343	3722
Deep Learning	0.917	2620	3998
Auto Model	0.709	3600	12,272

4.4. Analysis of Research Results

The input data for the model show the factors affecting land prices (market price), ranked from highest to lowest weight. These feature weights were calculated using the correlation-based weighting method, which measures the absolute linear relationship between each determinant and the land price. The results were subsequently normalized to a scale of 0 to 1 to allow for a direct comparison of relative importance across all variables. The factors, shown in Figure 3, are as follows: (1) inner area, (2) public transportation, (3) mall, (4) academic area, (5) outer area, (6) middle area, (7) land use, (8) rectangle shape, (9) hospital, (10) other shape, (11) warehouse, (12) road width near land, (13) commercial building, (14) tall building, (15) width, (16) length, (17) bridge near land, (18) farm, (19) river width near land, (20) square shape, (21) temple, (22) housing estate, (23) side road, (24) gas station, (25) corner plot, (26) market, (27) apartment, (28) amount of public road, (29) single building, and (30) square wa. The definition of each factor is described in Table 2 above. The hierarchy of these 30 determinants provides a quantitative mapping of Bangkok's land value drivers. The dominance of inner area (Rank 1) and public transportation (Rank 2) indicates that spatial accessibility remains the primary value multiplier in a monocentric urban structure. Interestingly, while physical traits like "square wa" (Rank 30) show a

lower linear correlation with unit price, their high absolute sensitivity in the subsequent model simulation reveals a critical nonlinear scaling effect that traditional linear models often fail to capture.

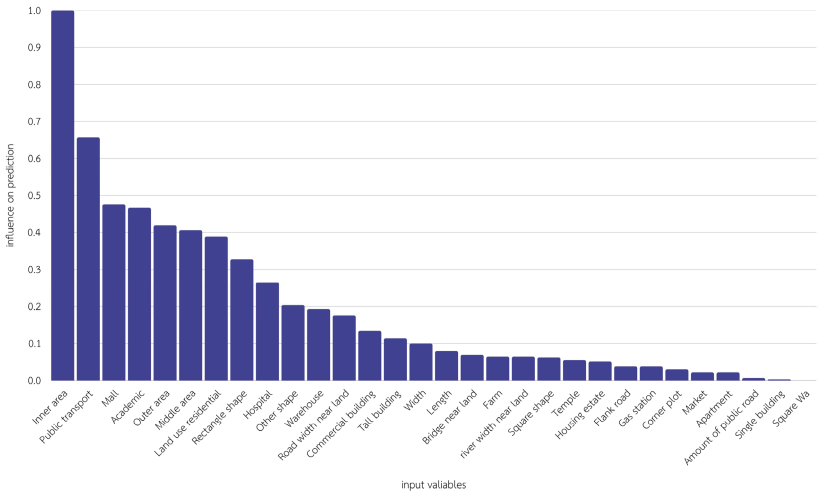

Figure 3. Weights of factors affecting land value.

To provide a deeper understanding of the model's decision-making process, local explanation analysis was conducted using the Model Simulator, a core functional operator within the RapidMiner environment. While SHAP or LIME are alternative frameworks for model interpretability, the Model Simulator was selected as it is natively integrated into the research workflow, allowing for a seamless and robust sensitivity analysis of the 30 urban determinants. This approach effectively translates the Deep Learning "black box" into an interpretable tool for observing how land values respond to specific spatial changes. Figure 4 illustrates how specific determinants influence the predicted land value for a representative case.

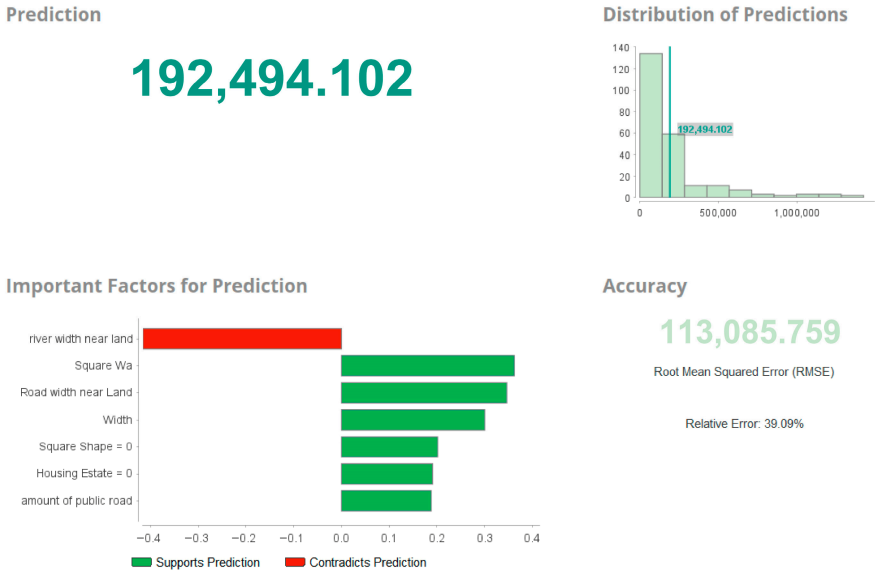

Figure 4. Land price prediction results and feature importance using Model Simulator in RapidMiner.

In Figure 4, the model predicted a land value of 192,494.102 USD. According to the "Distribution of Predictions" analysis, this case is highly representative of the broader dataset, as the predicted value aligns with the highest-frequency bin (primary cluster). While the Relative Error is 39.09%, this figure is consistent with the model's overall perfor-

mance metrics and reflects the inherent volatility of the Bangkok land market. Crucially, the prediction remains within the expected distribution range, confirming that the model captures general market trends without generating erratic outliers. The localized analysis reveals the underlying logic of the prediction: (1) Positive Drivers (Supports Prediction): Key variables such as land area (square Wa) and road accessibility (road width near land) demonstrate the strongest positive influence. This aligns with urban economics theories where plot size and infrastructure connectivity are primary determinants of land value. Physical attributes, including plot width and regular shape, further enhance the valuation. (2) Negative Drivers (Contradicts Prediction): Notably, proximity to wide water bodies (river width) shows a negative correlation in this instance. This suggests that for certain residential zones in Bangkok, excessive river width may be perceived through the lens of environmental risk (e.g., flood susceptibility) or regulatory constraints (e.g., setback requirements) rather than as a premium amenity, thus moderating the final valuation.

To further validate the model's reliability and practical utility, a sensitivity analysis was performed using the Model Simulator. This approach transitioned the Deep Learning model from a black box output to an interpretable decision support tool. As illustrated in Figure 5, the simulator allowed for real-time adjustments of input variables to observe their dynamic impact on land value predictions. The simulation, which adjusted the river width near land and optimized spatial constraints, predicted a value increase to 241,220.750 USD. This variation demonstrates the model's high sensitivity to micro-locational determinants. Notably, while physical attributes, such as square wa, and infrastructure factors, such as road width near land, remained consistent positive drivers, the model also identified negative constraints, such as the absence of nearby amenities.

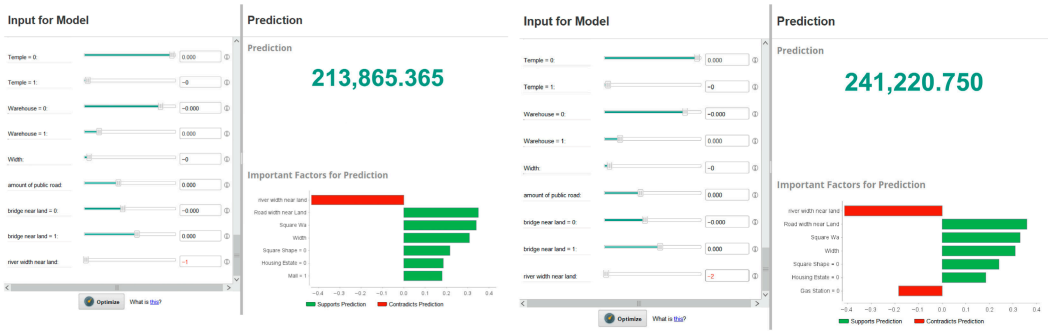

Figure 5. Sensitivity analysis and scenario simulation (negative drivers test).

To evaluate the model's responsiveness to physical land characteristics, a comparative simulation was conducted by adjusting the square wa variable. As illustrated in Figure 6, In the first scenario with a smaller land size, the model predicted a value of 233,016.845 USD. In this context, while land size remains a positive driver, the proximity to the river (river width near land) acts as a significant negative constraint on the valuation. In contrast, in the second scenario, upon increasing the land area (square wa), the predicted value rose exponentially to 2,777,805.367 USD. Notably, as the scale of the land increases, the importance of square wa becomes the dominant positive driver, significantly outweighing other spatial factors. This simulation confirms that the Deep Learning model accurately captures the nonlinear relationship between land size and total value, which is a common characteristic in the Bangkok real estate market. It also demonstrates that the model does not merely apply a flat rate but dynamically recalculates the weight of each determinant based on the specific attributes of the property. Regarding the substantial variations observed in the simulations, such as the increase to 2,777,805.367 USD for larger land plots, these figures remain consistent with documented market transactions in

Bangkok's prime commercial districts. In these high-density areas, the premium for large, developable land parcels often results in exponential value increases, reflecting the extreme spatial heterogeneity of the local market.

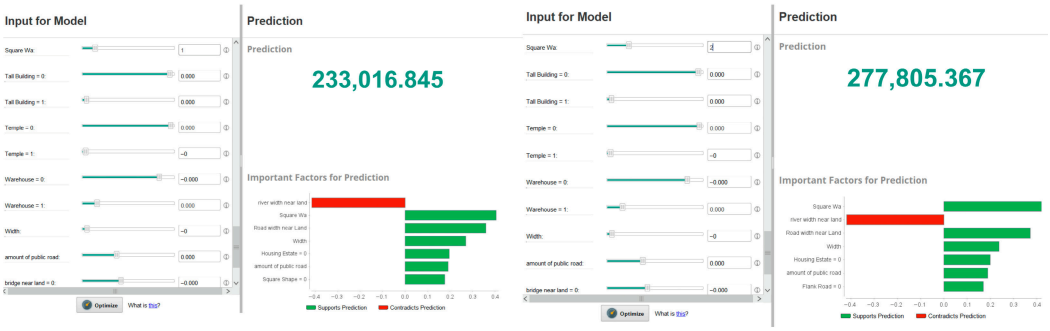

Figure 6. Sensitivity analysis and scenario simulation (positive drivers test).

5. Discussion

The experimental results demonstrate that the proposed Deep Learning model is highly effective in capturing the complex, nonlinear dynamics of Bangkok's real estate market, achieving a robust R^2 of 0.917 and an RMSE of 2620 USD. These performance metrics significantly outperform the baseline automated models (AutoModel), which yielded an R^2 of 0.709. This disparity justifies the necessity of manual parameter tuning and a specialized multilayer architecture (128:64:32 hidden layers) to accurately process high-dimensional urban data.

5.1. Hierarchy of Determinants and Urban Dynamics

The model identifies a clear hierarchy among the 30 determinants. The top 10 variables, namely (1) inner area, (2) public transportation, (3) mall, (4) academic area, (5) outer area, (6) middle area, (7) land use residential, (8) land use agriculture, (9) rectangle shape, and (10) hospital, align with the spatial economic theories of Subongkoch [38] and Techrochanapakin [78]. These findings confirm the established conclusions of previous studies in the Bangkok context [34,37], reinforcing that accessibility is the primary driver of value. However, this study supplements the existing literature by quantifying the relative importance of 30 variables simultaneously—a scale rarely addressed in traditional linear studies. Specifically, the high weight of "inner area" and "public transportation" reflects the actual urban planning dynamics of Bangkok, where the government's transit-oriented development (TOD) policies and the concentration of high Floor Area Ratio (FAR) incentives in the Central Business District (CBD) have created a steep value gradient. This spatial disparity, as captured by the model, highlights a critical challenge for urban affordability; as transit-oriented development (TOD) drives prices upward, the model serves as a vital tool for policymakers to identify areas where inclusive residential zoning or subsidies are most needed to prevent social exclusion in the inner city. By aligning these 30 diverse variables with actual city planning constraints, the model proves to be a valid proxy for the multidimensional logic of the Bangkok real estate market.

5.2. The Paradox of Land Size: Global Weight and Local Sensitivity

A notable finding in this study is the contrast between the global weight and the local sensitivity of the square wa variable. Although it is ranked lowest (30th) in terms of overall feature weight, it exhibited the highest sensitivity in scenario simulations. This phenomenon can be attributed to the scale effect and the nonlinear interaction inherent in Deep Learning. While the marginal weight per unit of area is relatively small com-

pared to locational dummies (e.g., inner area), land size acts as a primary multiplier for locational premiums. In the simulator, an increase in square wa exponentially scaled the total predicted value, reflecting complex real-world appraisal logic where total value is a product of unit price (driven by location) and total quantity (land area). Interestingly, our findings regarding "river width" potentially contradict some Western urban theories where waterfront proximity is universally viewed as a luxury premium. In the context of Bangkok's urban planning and environmental history, the model's negative sensitivity toward excessive river width may reflect a localized risk perception related to flood susceptibility and the stringent setback requirements mandated by the Bangkok Building Control Act. This demonstrates that the Deep Learning model does not merely process numbers but aligns with the actual regulatory and physical constraints of the Bangkok Metropolitan Area.

The application of Deep Learning proved highly appropriate for this analysis, as it successfully captured the diversity of human-driven market behaviors, which are often nonlinear and multidimensional [76–79]. Despite the inherent volatility of real estate data, the R^2 value achieved is considered exceptionally high for social scientific research involving human behavior and urban needs, which typically yields lower coefficients than controlled scientific experiments [80,81].

5.3. Bridging Mathematical Modeling and Social Constructs

A critical consideration in this study is the capacity of an Artificial Neural Network (ANN), a mathematical tool to forecast "market value", which is inherently a social construct shaped by human behavior and collective perception. The robust performance of the model ($R^2 = 0.917$) suggests that while market prices are socially driven, they are not arbitrary. Instead, they follow complex, nonlinear patterns resulting from the interaction of spatial, economic, and infrastructural determinants. By employing a Deep Learning architecture, this research effectively uses ANN as a "social simulator" that captures the aggregate outcome of thousands of individual market decisions. The model's ability to align 30 diverse variables with established spatial economic theories confirms that Deep Learning is a valid proxy for understanding the multidimensional logic of urban land valuation. Beyond its mathematical validity, the application of ANN serves as a transformative tool for urban sustainability. By decoding the nonlinear interdependencies of 30 determinants, this study provides a quantitative foundation for spatial planning and land policy. Specifically, by identifying the value premiums driven by mass transit, the model acts as a strategic instrument for policymakers to address housing affordability through inclusive zoning or targeted subsidies ensuring that transit-oriented developments do not lead to social displacement.

Furthermore, this high-dimensional approach promotes rational resource management by providing an objective "shadow price" for urban land, which can effectively curb unregulated speculation and the resulting price distortions that drive urban sprawl. Ultimately, by transitioning the Deep Learning "black box" into an interpretable decision support system, this research enhances market transparency. It reduces information asymmetry, fostering an equitable and resilient real estate ecosystem that aligns with the global imperatives of sustainable urban governance and inclusive economic growth.

6. Conclusions and Recommendations

This study analyzed the determinants impacting residential land values in Bangkok through an optimized Deep Learning model ($R^2 = 0.917$). The 30 variables were categorized into five primary groups: (1) Location, (2) Infrastructure and Services, (3) Local Economy, (4) Legal Regulations, and (5) Site Characteristics. The findings reveal that inner area

and public transportation are the most influential factors, reinforcing the significance of transit-oriented connectivity in urban land valuation. Additionally, the study highlighted a scale effect where land size (square wa) acts as a critical multiplier in total valuation, despite having a lower global weight than locational factors.

6.1. Generalizability and Replicability

While the specific weights and findings of this study are calibrated to the unique spatial dynamics of Bangkok, the methodological process is designed to be highly replicable. This research provides a standardized framework, from feature engineering of 30 multidimensional variables to Deep Learning architecture optimization, that can be reutilized for assessing land values in other locations. Specifically, the model and its underlying logic are highly applicable to other rapidly urbanizing regions and megacities in Southeast Asia (e.g., Jakarta, Manila, or Ho Chi Minh City) or nations that share similar characteristics, such as high population density, transit-oriented development trends, and complex land use regulations.

The determinants identified in this study are broadly consistent with factors commonly reported in the land price literature, including land details, land use, and adjacent amenities. This suggests that the general relationships between these determinants and land prices may also be relevant in other urban contexts. However, the magnitude and spatial distribution of these effects are likely influenced by the specific urban structure of Bangkok, particularly the concentration of economic activities in the Central Business District and the significant impact of mass transit systems and the city's transportation network. Therefore, while the identified determinants reflect widely recognized mechanisms affecting land values, the empirical results of this study should primarily be interpreted within the Bangkok metropolitan context.

As for the sustainability perspective, the proposed model contributes to sustainable real estate development in multiple dimensions. From an economic perspective, it reduces uncertainty and improves investment efficiency. Socially, more accurate land valuation can help mitigate pricing distortions, thereby supporting housing affordability and equitable access. From an urban sustainability standpoint, the model provides valuable insights for more efficient land use planning and balanced urban growth. Therefore, this research not only advances predictive modeling in real estate but also supports the broader goal of sustainable urban development in rapidly growing cities.

6.2. Research Contributions and Stakeholder Benefits

1. Real Estate Developers: The forecasting model and Model Simulator serve as strategic tools for project feasibility analysis. Developers can utilize these tools to compare land options, optimize project locations, and estimate pricing with higher precision, thereby reducing financial risks during the initial development phases. However, developers should complement these data-driven insights with qualitative market sentiment to account for fluctuations not captured by the historical dataset.
2. Urban Planners and Policymakers: The sensitivity analysis provides a technical basis for understanding infrastructure-led appreciation. This supports more transparent land use policies, though policymakers must consider the broader social implications of land value increases on housing affordability and urban inclusion.
3. Researchers and Academics: This study further validates the effectiveness of Deep Learning techniques in analyzing complex real estate data. It demonstrates that even with nonlinear relationships, systematic parameter tuning and k-fold cross-validation can produce highly reliable results that contribute to the existing body of knowledge in property technology.

7. Limitations

While this study provides significant insights into land valuation using Deep Learning, several limitations must be acknowledged.

7.1. Data and Scope Limitation

The primary limitation of this research is its reliance on a single data platform, www.feasy.com. This choice was made to ensure data consistency and reliability, as land prices for the same plot can vary across different listing websites due to fluctuating commission rates and unverified amateur postings. Furthermore, the sample size was constrained to 235 verified plots within the Bangkok Metropolitan Area, reflecting the specific geographical scope and the timeframes of this research. Additionally, the dataset represents a temporal snapshot specifically from the year 2025. Consequently, the model's predictive logic is calibrated to the market dynamics, interest rates, and urban development status of that particular period. While this ensures the study's relevance to the current "new normal" real estate landscape, it may limit the immediate generalizability of the findings to other regions or different economic cycles with different market dynamics. Additionally, the dataset relies on market listing prices (asking prices) from the Feasy.com platform; while these reflect current market sentiment and expectations, they may deviate from final actual transaction prices due to private negotiations and varying seller urgency. This introduces a potential "sentiment premium" that the model captures as part of the valuation logic.

7.2. Methodological and Software Constraints

From a methodological perspective, the use of RapidMiner as the primary modeling environment presents specific trade-offs that must be acknowledged.

First, regarding interpretational limitations, while RapidMiner provides a robust and accessible interface for neural network modeling, it offers less transparency in extracting granular mathematical transitions of neural weights compared to low-level coding frameworks like Python (e.g., TensorFlow or PyTorch). This "black box" nature can limit the depth of interpretability regarding how specific hidden layers process spatial nonlinearity.

Second, to address the susceptibility to overfitting often associated with high-level automated tools, this study strictly implemented a 10-fold cross-validation framework. This ensures that the model's high accuracy is rooted in generalizable patterns rather than data memorization.

Third, concerning hyperparameter exploration, RapidMiner's standardized optimization suite, while efficient, lacks the extreme architectural flexibility of Python for developing highly customized loss functions or non-standard neural layers from scratch.

Despite these constraints, the choice of RapidMiner was strategic; it ensures workflow reproducibility and minimizes manual coding errors. Previous comparative studies [75] have demonstrated that its predictive integrity remains comparable to manual coding environments when rigorous validation protocols, such as the ones used in this research, are applied.

7.3. Variable Scope and Proxy Indicators

While the literature underscores the importance of the Surrounding Physical Environment, such as esthetic quality and micro-level neighborhood atmosphere, these variables were excluded from the current model. This decision was based on the necessity of maintaining data homogeneity and reliability by prioritizing verified digital parameters over subjective onsite surveys. However, it is important to note that the high predictive accuracy (R^2 = 0.917) suggests that many environmental qualities are effectively captured through

surrogate indicators within the "Location" and "Infrastructure" groups (e.g., proximity to public parks, mass transit access, and urban zoning).

7.4. Future Research

To build upon the foundations established in this study, future research should evolve toward a more dynamic and multidimensional understanding of urban land value.

Spatiotemporal Analysis: Future studies should incorporate time-series data to observe how land values evolve following the completion of new transit lines (e.g., the Pink and Yellow monorail lines in Bangkok).

Advanced XAI: Subsequent research could integrate SHAP (SHapley Additive exPlanations) or LIME within Python environments to provide even more granular mathematical transparency than the current Model Simulator.

Visual Analytics: Integrating Computer Vision and Street View imagery to quantify "esthetic quality" could fill the gap left by the exclusion of physical environment variables.

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