ACCSCIENCE PUBLISHING

International Journal of Systematic Innovation

ARTICLE

Reframing spatial housing models: A lateral thinking approach to real estate valuation in Taichung, Taiwan

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Abstract

Internal structural attributes and external locational factors are commonly used as predictive variables in housing price models, enabling the identification of key determinants for assessing whether a property is fairly priced or represents a good investment. However, prior research has largely overlooked alternative applications of such models that could further enhance the identification of advantageous purchase opportunities. This study addresses this gap by applying lateral thinking to identify a "green zone", thereby supporting more informed housing purchase decisions. This study investigates the impact of geographic features on housing prices, based on 229 transactions recorded between September 2023 and September 2024 in the North District of Taichung City, Taiwan, using data from the Ministry of the Interior's real estate platform. Building upon an existing regression model that includes structural variables, such as the lot size, number of rooms, age, number of floors, availability of an elevator, and the presence of a garage, we introduced six additional geographic variables that reflect the proximity to a metro station, hospital, museum, CBD, funeral home, and clothing outlets. The revised model demonstrates improved explanatory power, with the R^2 increasing from 0.756 to 0.791. Among the newly included variables, proximity to the CBD and the museum exhibit the strongest positive effects on housing prices, contributing increases of TWD 9.8834 million and TWD 6.1644 million, respectively. These effects are both statistically significant. In contrast, proximity to a metro station has a significant negative impact of – TWD 7.2272 million , a finding attributed to a boundary constraint, since only sales south of the station fall within the district, creating a data bias. Using the escape technique of lateral thinking, these results also provide practical guidance for buyers by identifying cost-effective areas located just outside the 500 m proximity zones of high-value amenities. One such example is located near the intersection of Zhongming Road and Section 1, Zhongqing Road, with price savings of at least TWD 7.36 million. A residual analysis reveals clustering in the Yizhong Business District, suggesting that other unobserved value factors may warrant future investigation.

Keywords: Housing prices; Geographical features; Regression analysis; Amenity proximity; Lateral thinking

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Citation: Chan, H. Y., Lai, Y. C., Huang, Y. X. & Deng, J. J. (2026). Reframing spatial housing models: A lateral thinking approach to real estate valuation in Taichung, Taiwan. *Int J Systematic Innovation* 10(2):1981.
https://doi.org/10.6977/IJoSI.202604_10(2).0004

Received: August 27, 2025

Revised: January 2, 2026

Accepted: February 19, 2026

Published online: April 22, 2026

1. Introduction

Ensuring that every resident has a home is a fundamental responsibility of governments. This is particularly relevant in numerous Asian societies, where traditional values, such as the Chinese proverb "owning land brings wealth," continue to shape people's perceptions. This belief underscores the idea that land ownership is the cornerstone of financial security and prosperity, although as land is increasingly being transformed into housing, the adage is evolving into "owning a house brings wealth."

With rising living standards and evolving environmental conditions, the demand for an ideal place to live is increasing. Purchasing a house is not only a significant personal milestone but also a decision with long-term financial implications. Amid persistent increases in housing prices, public concern over price rationality and the factors driving market fluctuations has intensified. The issue of housing prices affects not only individual purchasing decisions but also bears broader implications for national economic stability: high housing prices can exacerbate financial stress and social inequality, thereby hindering young people's ability to enter the market. Consequently, the need to accurately and reasonably estimate housing prices has become an urgent topic for policy and research.

This study explores the influence of geographic factors on housing prices, using empirical data from a district in northern Taichung, Taiwan, as an example. This study focuses on the North District of Taichung City as the primary area of analysis. As a region undergoing rapid development, the North District has garnered considerable attention from real estate investors and prospective homebuyers. The area is characterized by well-established infrastructure and a wide range of urban amenities, including the North District Civil Sports Center, five major urban renewal projects, and five prominent department store commercial zones. Moreover, the district offers abundant educational resources, including 21 schools spanning elementary to university levels, as well as a comprehensive healthcare system. These features collectively position the North District as a desirable residential environment for diverse age groups. Notably, the combination of these advantages has contributed to a consistently stable population, which currently stands at approximately 147,000 residents.

For this analysis, transaction data on townhouse properties in the North District of Taichung City from September 2023 to September 2024 were used. The dataset included sale prices and associated property characteristics, such as land area (in pings, 1 ping ≈ 3.3 m^2), total floor area, number of rooms, living rooms, bathrooms, number of floors, presence of an elevator, building age, number of garages, and geographical coordinates (latitude and longitude). The coordinates were used to identify the spatial location of each property, while the remaining variables served as independent variables that influence the sale price.

A linear regression model is applied to examine the effects of these independent variables on housing prices. Furthermore, a spatial analysis is conducted to assess the influence of geographic factors, such as proximity to commercial centers, museums, funeral homes, and medical facilities, on property values. The objectives are to identify the critical determinants of housing prices and to provide empirical evidence that can support future price evaluations and urban planning decisions.

2. Literature review

This study draws on several key scholarly works on housing sale prices. These studies, which span various regions and time periods, offer valuable insights into price prediction models and the factors that influence them, thereby providing a foundation for the research design. Furthermore, to overcome the limitations often encountered in conventional housing analyses, the concept of lateral thinking is incorporated to explore novel applications and perspectives. The primary references for this study include studies by De Bono (1971), Engle *et al.* (1985), Pardoe (2008), De Cock (2011), Sheppard (2013), Borgoni *et al.* (2018), and Duan *et al.* (2021). The following section presents a chronological overview of the content and contributions of these works.

2.1. De Bono (1971)

Thinking can be broadly categorized into two types: vertical thinking and lateral thinking. Vertical thinking refers to the conventional, logical progression of thought—moving systematically from one piece of information to the next, much like stacking blocks to build a tower. This type of thinking, rooted in ancient Greek philosophy, has profoundly shaped modern societal reasoning. However, vertical thinking tends to limit exploration to sequential, predictable paths and often fails to break out of established frameworks. As a result, it may overlook creative or unconventional solutions.

To address this limitation, lateral thinking offers an alternative approach. Introduced by Edward de Bono, lateral thinking comprises two core techniques: escape and provocation. Escape involves identifying a dominant assumption or idea and then deliberately setting it aside to explore new perspectives. Provocation, on the other hand, facilitates a non-logical leap away from prevailing thought patterns. While the initial connection to the original goal may seem unclear, this technique often reveals new and reasonable paths to problem-solving upon further reflection.

In the present study, lateral thinking techniques are applied to the regression analysis of housing prices. This approach is intended to uncover novel perspectives and strategic insights that may assist prospective homebuyers—insights that conventional vertical thinking may fail to reveal.

2.2. Engle *et al.* (1985)

Engle *et al.* (1985) proposed a housing price prediction model based on hedonic equations, using housing transaction data from San Diego, California, from January 1973 to January 1980. The model incorporated both internal structural attributes and external locational factors, while also accounting for inflation, tax policies, mortgage conditions, and the capitalized impact of future rents and costs.

The internal structural variables included the building's age, number of rooms, land area, and number of bathrooms. The study also explored both linear and quadratic effects for building age, land area, and number of rooms. In terms of external geographical factors, the model considered distances to transportation hubs and shopping centers. The detailed specification of variables offers valuable insights into the complex determinants of housing prices.

2.3. Pardoe (2008)

Using housing price data from Eugene, Oregon, in 2005, Pardoe (2008) analyzed the interactive effects of multiple variables on property values. The model placed particular emphasis on the quadratic effect of the building age, the interaction between the number of rooms and bathrooms, and factors such as the number of garages and proximity to parks. By integrating both locational attributes and internal structural characteristics, the study provides a comprehensive variable framework that serves as a valuable reference for regional housing price analysis.

2.4. De Cock (2011)

This study used housing price data from Ames, Iowa, covering 2006 to 2010, and analyzed a dataset comprising 2,930 housing transaction records. The dataset includes 80 detailed variables and is widely regarded as a classic resource for housing price prediction. It has also been widely used on the Kaggle platform for machine learning competitions.

Key variables highlighted in the study included the lot size, total building area, number of garages, presence of a fireplace, and basement area. However, the dataset does not account for the effects of inflation or tax rates on housing prices. In addition, the wide range of building ages (from less than a year to over 50 years) poses challenges for accurate valuation.

2.5. Sheppard (2013)

Cultural amenities, such as museums, have long been considered beneficial to residential communities. Sheppard (2013) investigated the direct impact of cultural amenities on housing prices. In that study, a hedonic price analysis was conducted using data from four US cities to evaluate the effect of museum locations on nearby property values.

The findings reveal that establishing a museum has a significant positive influence on housing prices. Properties closest to the museum tend to have their value increases of 20%–50%, and this positive effect diminishes with distance from the museum. The maximum distance of measurable positive influence, denoted as D, ranges from 0.72 km to 22.7 km across the cities studied.

2.6. Borgoni *et al.* (2018)

A unique feature of this paper is its classification of urban structures into amenities and disamenities, which are then incorporated into the hedonic pricing model. Urban amenities are features that enhance household utility, whereas disamenities negatively affect it. Although the case study of Milan presented in the paper did not include any disamenities, the concept was highly relevant to the present case study, where we examined the impact of a funeral home on housing prices.

The paper reported the radius of influence for each amenity considered, such as parks, metro stations, and museums. Specifically, the radius of influence for a museum is estimated to be 200 m, determined by inverting the impedance function at a threshold value of 0.02. This implies that if a location is farther than 200 m from the museum, its influence on housing prices becomes negligible. For metro stations, the radius of influence is 680 m.

The paper also investigated the effect of floor level on housing prices, but adopts a dichotomous approach: rather than treating floor as a continuous numerical variable, buildings are categorized based on whether or not the floor is above the first level. This methodology differs from our previous approach, and we aim to explore the implications of this distinction in our analysis.

Finally, the natural logarithm of the housing price is employed as the dependent variable in the hedonic model. This transformation reduces the variability of the dependent variable, thereby minimizing the deviation between predicted and actual housing prices and improving the overall model fit.

2.7. Duan *et al.* (2021)

This study focused on housing prices in the metropolitan area of Beijing, China, using the unit price per m^2 as the dependent variable; this approach represents a departure from most existing research, which typically employs the total sale price. Duan *et al.* (2021) argued that due to the scarcity of land resources in Beijing, the unit price is a more meaningful indicator for market analysis.

The study examined a range of influencing factors, including regional economic indicators (such as gross domestic product, average income, and population density), locational attributes (such as distances from the city center, schools, and hospitals), and internal housing characteristics (including floor area, building orientation, interior decoration, total built area, age of the building, and number of rooms). This unique design highlighted the significant role of geographic location and regional economic conditions in shaping housing prices, while also offering a novel perspective by selecting the dependent variable.

Based on the review of the aforementioned literature, four research gaps merit further exploration, as detailed in Sections 2.8–2.11.

2.8. Selection of the form of the dependent variable

In housing price research, there is no consensus on whether the plain total sale price or its natural logarithm should be used as the dependent variable, and the most appropriate choice depends on the specific characteristics of the study area and the research objectives. A logarithmic transformation is often employed to reduce skewness in price distributions and to improve the model performance, but its applicability must be evaluated on a case-by-case basis.

2.9. Impact of geographic factors on housing prices

Existing research has established that geographic factors significantly influence housing prices; however, their contributions to the predictive accuracy of pricing models remain under-quantified. A key challenge lies in representing geographic variables, particularly the influence of metro accessibility. Several measurement approaches have been proposed, including: (i) calculating the Euclidean distance from a property to the nearest metro station; (ii) counting the number of metro stations within a specified radius of the property; and (iii) creating a dummy variable to indicate whether the property falls within a defined service radius of a metro station.

2.10. Impact of the interior attributes of the house

As an example of the interior attributes, we consider the floor variable. This can be treated in multiple ways: as a continuous variable reflecting the actual floor number; as a binary variable distinguishing intermediate floors from others (with a value of one for intermediate floors, and 0 otherwise); or as another type of dichotomous variable, such as identifying ground-floor units (one for a ground-floor unit, 0 otherwise). The modeling choice should align with the empirical context and theoretical expectations of how the floor level affects buyer preferences.

2.11. Escape from conventional thinking in deploying the housing model

Upon completing a housing price analysis, attention is often narrowly directed toward interpreting model outputs—particularly coefficient estimates and significance levels. However, this conventional focus may overlook alternative areas of insight that hold strategic value for stakeholders, such as prospective homebuyers. This study aims to move beyond the confines of traditional regression analysis by exploring the potential to identify high-opportunity housing zones that are not readily apparent through standard modeling approaches. In doing so, it seeks to enhance the practical utility of the housing price model through the application of lateral thinking, thereby opening new pathways for informed decision-making.

The above discussion provides both theoretical grounding and a clear direction for this study, underscoring the importance of further exploring the role of geographic variables and selecting appropriate dependent variables in housing price analysis.

3. Construction of the model and analysis

The data for this study were obtained from the Ministry of the Interior's Real Estate Transaction Price Inquiry Service Platform. Transaction records of townhouses in the North District of Taichung City were collected, covering the period from September 2023 to September 2024, totaling 229 transactions. Key variables such as the address, total sale price, total floor area, layout, building age, and number of floors were organized and compiled in Excel (Version 365, Microsoft Corporation, USA) to serve as a foundation for analysis.

3.1. Construction features

A basic statistical analysis was conducted using Python, and a multiple regression model was used to evaluate the predictive power of various housing characteristics. The total sale price served as the dependent variable. The independent variables included the age of the building, total floor area (in pings), land area (in pings), number of bedrooms, living rooms, and bathrooms, as well as the presence of an elevator, availability of a parking space, and the number of floors. The resulting multiple regression model had an R^2 of 0.72, indicating a reasonably good fit.

The estimated regression equation is shown in **Equation 1**, and Table 1 summarizes the variable definitions along with their corresponding means and standard deviations.

$$TP = -163.1511 - 8.7645\ Age + 21.7176\ TFA + 53.0085\ Lot + 8.6874\ Room + 100.7942\ LR - 49.2486\ Bath + 330.0840\ Elev + 189.0562\ Gar + 9.9621\ Fl \quad (1)$$

When quadratic effects of age, bedrooms, and lot size were considered in addition to the interaction between bedrooms and bathrooms, the resulting model yielded an R^2 of 0.756. The estimated regression equation is presented in **Equation 2**.

$$TP = 1390.1220 - 49.5911\ Age + 29.9131\ TPA + 9.3040\ Lot - 67.8640 Room + 112.9973\ LR + 42.8904\ Bath + 207.122\ Elev + 56.8216\ Gar - 190.0540\ Fl + 0.5451\ Age^2 + 7.8135\ Room^2 + 0.3263\ Lot^2 - 8.9020\ Room_{Bath} \quad (2)$$

The largest residuals (i.e., the differences between actual housing prices and predicted values) are not clustered around the central business district (CBD), suggesting that geographical proximity to the CBD may not significantly influence housing prices. This observation was further examined in the analysis conducted in our study.

3.2. Geographical features

In the current study, six key areas within the North District were selected to represent significant geographical features: museums, hospitals, the CBD, clothing outlets, funeral homes, and metro stations. These locations were considered to have potential impacts on housing prices and were discussed in subsequent sections. An overview of the landmark locations is presented in Figure 1.

3.2.1. National Museum of Natural Science

This museum integrates technology, living experiences, art, and human-centered exhibitions, reflecting the characteristics of a modern natural science museum. It is located between Boguan Road and Jianxing Road, as illustrated in Figure 2, showing its relative position in

Table 1. Descriptive statistics for variables used

Variable	Description	Mean	Standard deviation
Dependent variable			
TP	Total housing price, in TWD 10,000	2,166.4306	1,757.1401
Independent variables: Structural attributes			
Age	Age of the house, in years	40.6924	15.8678
TFA	Floor area of the house, in pings[a]	56.1482	38.8117
Lot	Land area of the parcel, in pings[a]	25.0211	16.5635
Room	Number of bedrooms in the house	5.0480	3.3037
LR	Number of living rooms in the house	2.2882	1.3491
Bath	Number of bathrooms in the house	3.8384	3.2532
Elev	Dummy variable indicating whether there is an elevator (1 = Yes; 0 = No)	0.0480	0.2143
Gar	Number of garages in the house	0.0480	0.2339
Fl	Number of floors in the house	3.0218	1.1256

Notes: [a]1 ping ≈ 3.3 m^2. Abbreviation: TFA: Total floor area; TP: Total price.

 https://doi.org/10.6977/IJoSI.202604_10(2).0004

the North District. A circular buffer with a 500 m radius, representing the museum's area of influence, was generated using ArcGIS Online (2024, Environmental Systems Research Institute, Inc., USA). A total of 28 houses included in our study, marked by small circles, fall within the area of influence of the museum.

3.2.2. China Medical University Hospital Business District

This hospital provides high-quality medical services in key areas of human health. In addition to healthcare, the surrounding compound offers several commercial amenities typically found in business districts, such as convenience stores and food courts. As shown in Figure 3, a circular buffer with a 500 m radius representing the hospital's area of influence was generated using ArcGIS Online. A total of 57 houses included in our study, marked

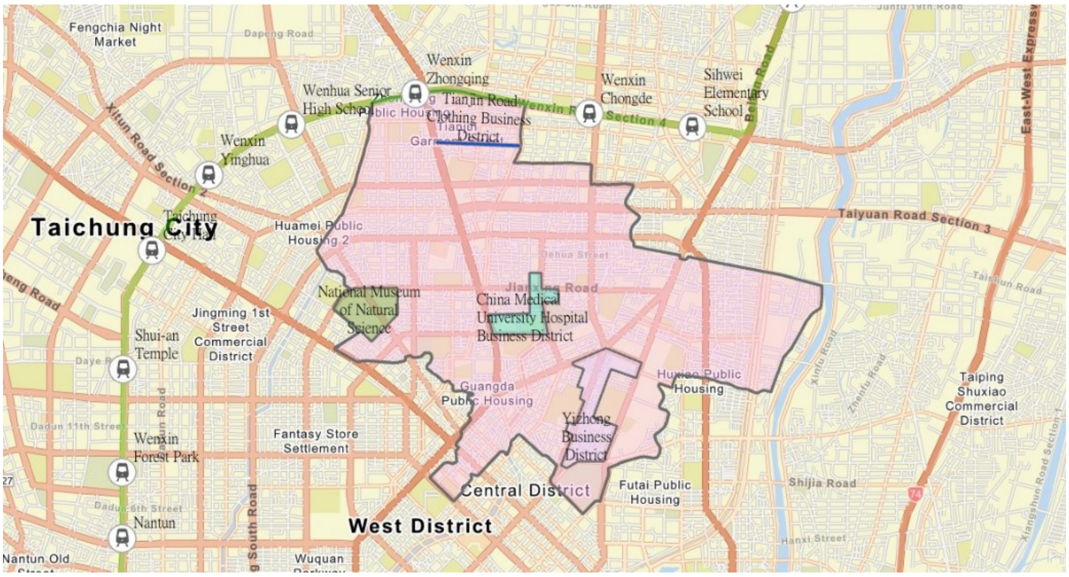

Figure 1. Overview of landmark locations

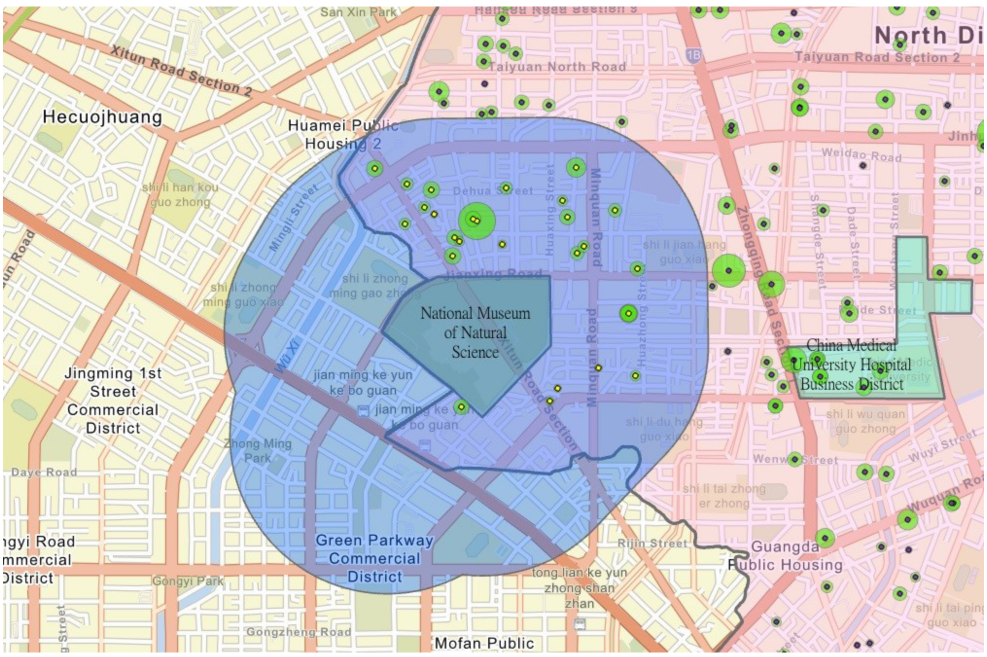

Figure 2. Location of the museum in the North District. The varying sizes of the green circles indicate the residual size of the houses in the regression model. The yellow dots indicate houses within the circular buffer boundary. The black dots indicate the houses outside the buffer boundary.

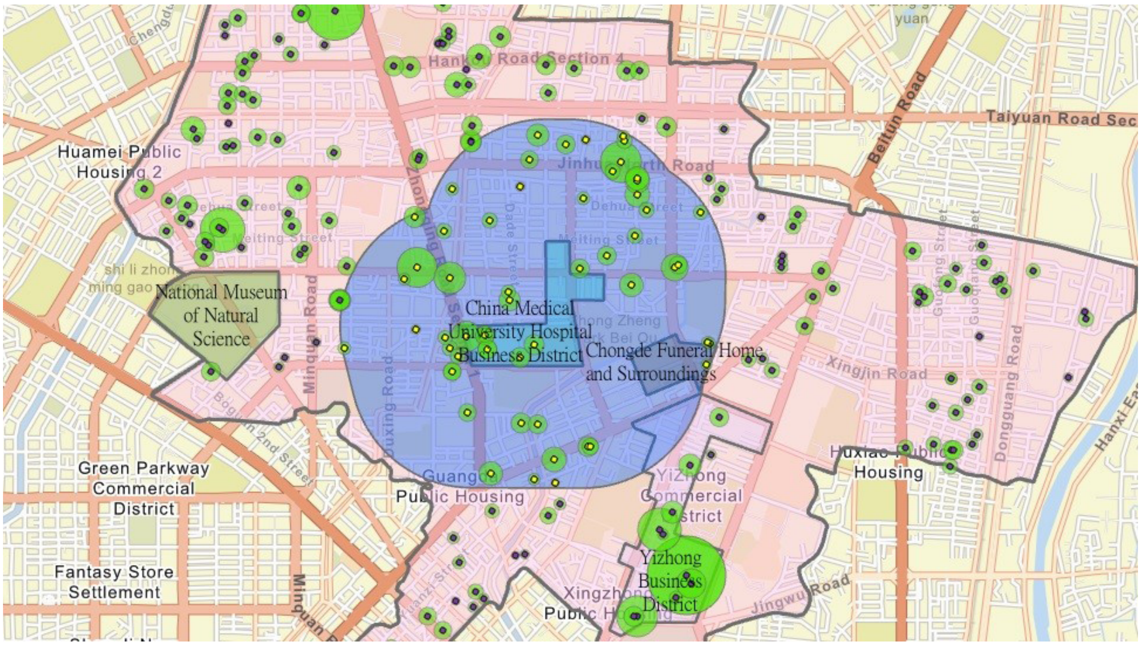

Figure 3. Location of the hospital and its area of influence. The varying sizes of the green circles indicate the residual size of the houses in the regression model. The yellow dots indicate houses within the circular buffer boundary. The black dots indicate the houses outside the buffer boundary.

by small circles, fall within the hospital's area of influence.

3.2.3. Yizhong Business District

The Yizhong Business District offers a variety of food courts, playgrounds, and entertainment facilities, making it a popular destination for young people. The name "Yizhong" refers to the Taichung First Senior High School, which is located within the district. Figure 4 illustrates its location. A circular buffer with a 500 m radius representing the business district's area of influence was generated using ArcGIS Online, resulting in a lobe-shaped buffer zone. Within this zone, there are 29 houses included in our study, marked by small circles.

3.2.4. Tianjin Road Clothing Business District

This district offers a wide variety of outlets for fashion apparel. Figure 5 shows the location of the district. A circular buffer with a radius of 500 m, representing the district's area of influence, was generated using ArcGIS Online, producing a rod-shaped buffer zone. Within this zone, there are 40 houses included in our study, indicated by small circles.

3.2.5. Chongde Funeral Home and surroundings

In Taiwan, funeral homes are commonly regarded as disamenities, due to their association with death, which is considered inauspicious in traditional culture. These facilities are places where the deceased are memorialized by family and relatives, and the process often involves rituals that generate noise and are perceived to bring bad luck. One such facility is located in the North District, as shown in Figure 6. A circular buffer with a radius of 500 m, representing the district's area of influence, was generated using ArcGIS Online, resulting in a rough, round buffer zone. A total of 27 houses included in our study, marked by small circles, fall within the district's area of influence.

3.2.6. Metro stations

The presence of a metro station on the green line can significantly boost the prosperity of nearby shops and houses, since the metro has made transportation within Taichung city quick and reliable. Figure 7 shows the location of the metro stations in the study area. Only Wenxin Zhongqing station affects house prices in the North District. A circular buffer with a radius of 500 m, representing the district's area of influence, was generated using ArcGIS Online, resulting in a perfectly round buffer zone. Within this zone, there are seven houses included in our study, marked by small circles.

3.3. Proposed models

In this study, three models were constructed to incorporate geographical feature data. We first extended **Equation 2** by adding dichotomous variables to represent six geographical features. Next, based on this extended specification (Model 1), we modified the structural variable Fl by converting it

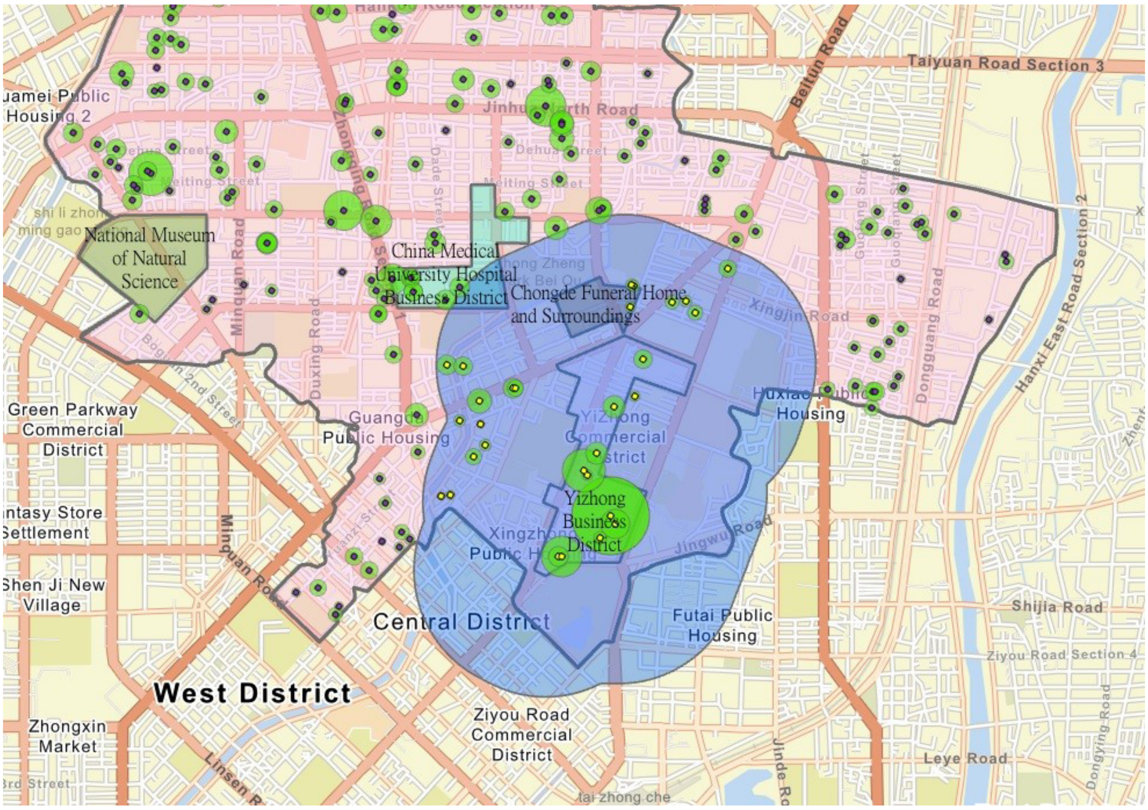

Figure 4. Location of the Yizhong Business District in the North District. The varying sizes of the green circles indicate the residual size of the houses in the regression model. The yellow dots indicate houses within the circular buffer boundary. The black dots indicate the houses outside the buffer boundary.

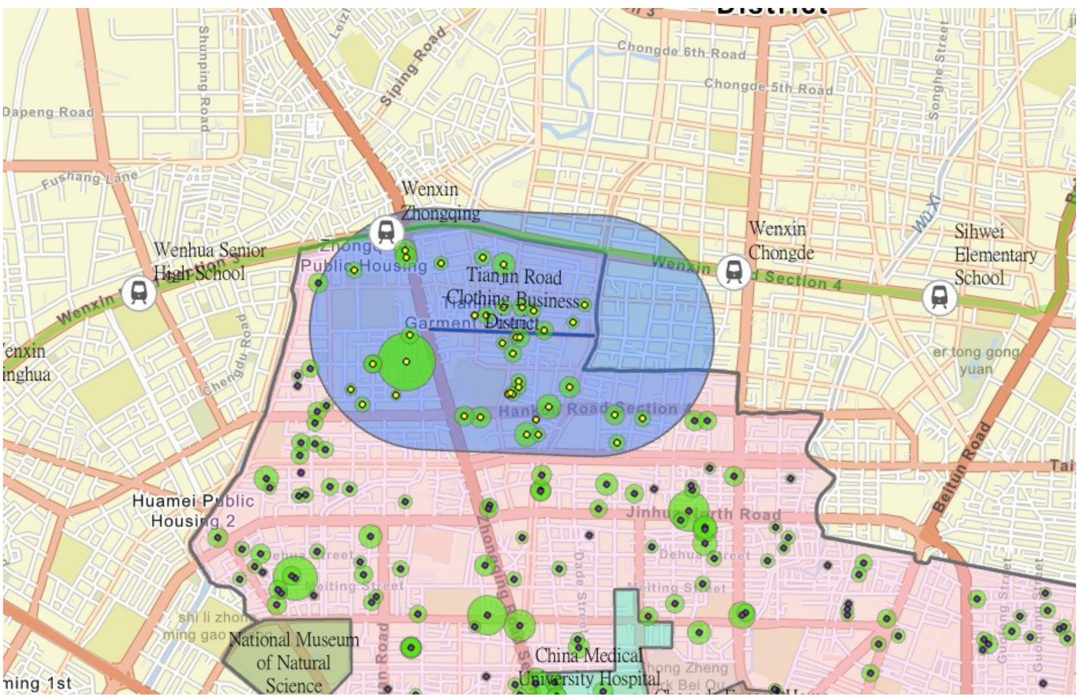

Figure 5. Location of the Tianjin Road Clothing Business District in the North District. The varying sizes of the green circles indicate the residual size of the houses in the regression model. The yellow dots indicate houses within the circular buffer boundary. The black dots indicate the houses outside the buffer boundary.

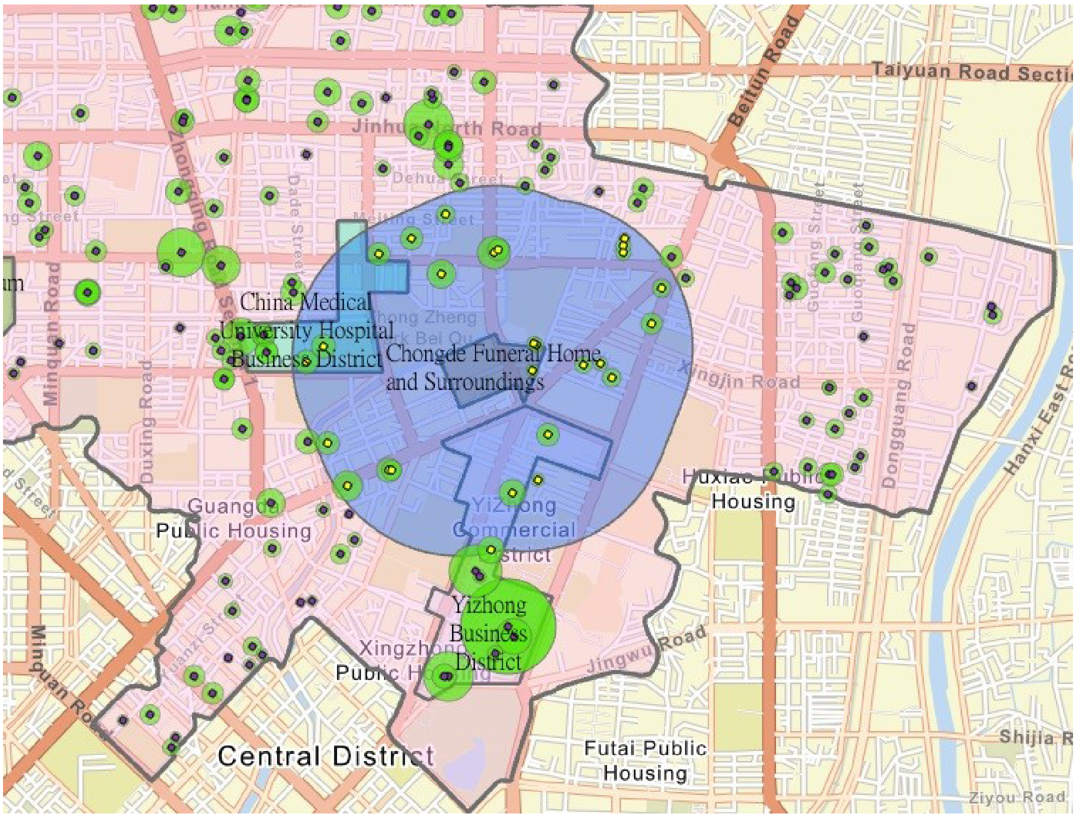

Figure 6. Location of the Chingde Funeral Home in the North District. The varying sizes of the green circles indicate the residual size of the houses in the regression model. The yellow dots indicate houses within the circular buffer boundary. The black dots indicate the houses outside the buffer boundary.

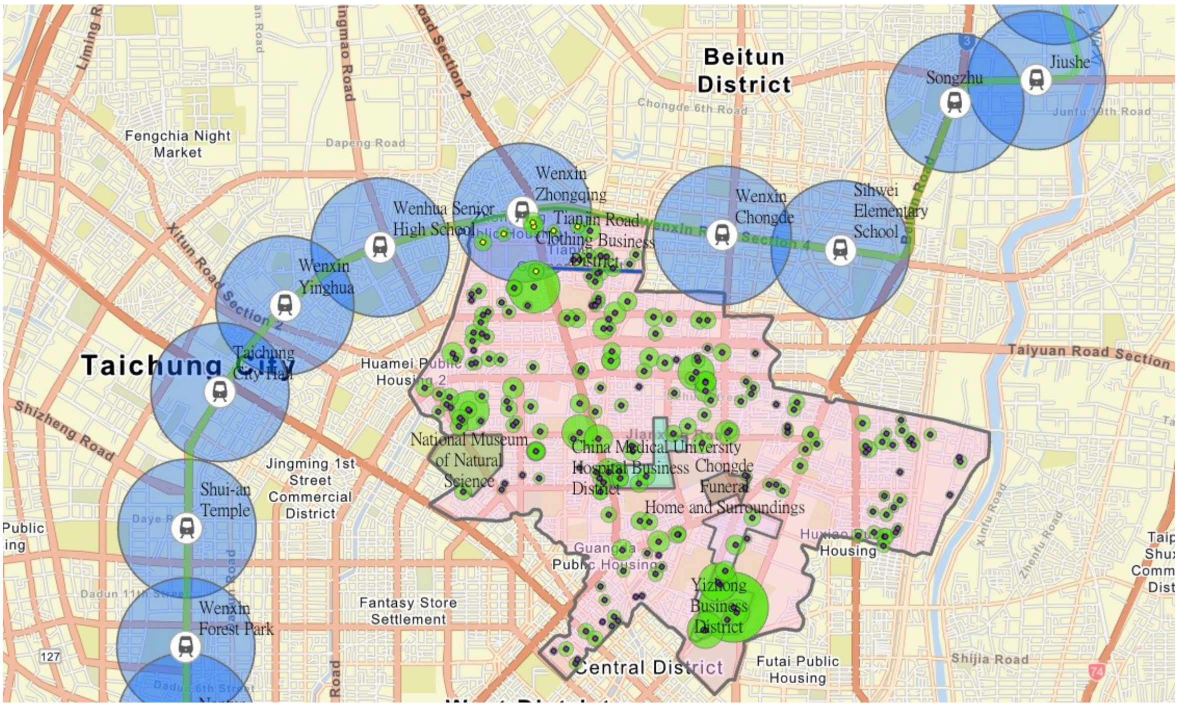

Figure 7. Location of the metro stations in the North District. The varying sizes of the green circles indicate the residual size of the houses in the regression model. The yellow dots indicate houses within the circular buffer boundary. The black dots indicate the houses outside the buffer boundary.

from an integer variable to a binary variable that is assigned a value of one if the housing unit consists of only one floor, and 0 otherwise (Model 2). Finally, building on Model 2, we transformed the dependent variable "total price" (TP) by taking its natural logarithm to reduce variance in housing prices (Model 3). The specifications of these models are described in the following sections.

3.3.1. Model 1

If we add the geographical features representing the museum, hospital, CBD, clothing outlets, funeral home, and metro station to **Equation 2**, the resulting model yields an R^2 of 0.791. The estimated regression equation is presented in **Equation 3**. Table 2 presents the variable definitions along with their means and standard deviations.

$$\begin{aligned} TP = {} & 920.0865 - 32.8042 \text{ Age} + 29.4750 \text{ TPA} + 18.0749 \text{ Lot} - 56.3120 \text{ Room} + 143.5576 \text{ LR} \\ & + 17.3155 \text{ Bath} + 195.0357 \text{ Elev} + 81.2810 \text{ Gar} - 216.3338 \text{ Fl} + 0.2723\, Age^2 + 5.5680\, Room^2 \\ & + 0.2666\, Lot^2 - 5.9683 \text{ Room}_{\text{Bath}} - 722.7214 \text{ Metro} + 120.1756 \text{ Hospital} + 616.4406 \text{ Museum} \\ & + 988.3381 \text{ CBD} - 259.2006 \text{ FH} + 198.7997 \text{ Outlet} \end{aligned} \tag{3}$$

3.3.2. Model 2

In Model 2, the structural variable Fl was modified by converting it from an integer variable to a binary variable Fl1, which was assigned a value of one if the housing unit consists of only one floor and 0 otherwise. The resulting model yielded an R^2 of 0.787, indicating that Model 2 performed slightly worse than Model 1, which had an R^2 of 0.791. The estimated regression equation is presented in **Equation 4**.

$$\begin{aligned} TP = {} & 304.5060 - 29.2208 \text{ Age} + 25.2810 \text{ TPA} + 26.9859 \text{ Lot} - 73.1954 \text{ Room} + 131.3572 \text{ LR} \\ & - 7.4514 \text{ Bath} + 122.0725 \text{ Elev} + 126.6469 \text{ Gar} - 24.7364 \text{ Fl1} + 0.2888\, Age^2 + 5.4195\, Room^2 \\ & + 0.2212\, Lot^2 - 4.2798 \text{ Room}_{\text{Bath}} - 759.2528 \text{ Metro} + 116.7875 \text{ Hospital} + 605.6245 \text{ Museum} \\ & + 967.9731 \text{ CBD} - 246.3844 \text{ FH} + 256.3872 \text{ Outlet} \end{aligned} \tag{4}$$

3.3.3. Model 3

In Model 3, we built upon Model 2 and transformed the dependent variable TP by taking its natural logarithm, aiming to reduce the variance in housing prices. The resulting model yielded an R^2 of 0.679, indicating that Model 3 performed much worse than Model 1, which has an R^2 of 0.791. The estimated regression equation is presented in **Equation 5**.

$$\begin{aligned} \text{Ln(TP)} = {} & 6.3630 - 0.0207 \text{ Age} + 0.0058 \text{ TPA} + 0.0418 \text{ Lot} + 0.0271 \text{ Room} + 0.0199 \text{ LR} \\ & + 0.0432 \text{ Bath} - 0.2506 \text{ Elev} + 0.2839 \text{ Gar} - 0.4185 \text{ Fl1} + 0.0002\, Age^2 + 0.0007\, Room^2 \\ & - 0.0002\, Lot^2 - 0.0037 \text{ Room}_{\text{Bath}} - 0.0682 \text{ Metro} + 0.1223 \text{ Hospital} + 0.2957 \text{ Museum} + 0.1125 \text{ CBD} \\ & + 0.0758 \text{ FH} + 0.1173 \text{ Outlet} \end{aligned} \tag{5}$$

Table 3 summarizes the regression results of the three models, showing their performance in terms of R^2 values, the dependent variable used in each model, and the corresponding regression coefficients. Of the three, Model 1 performed best, with the highest R^2 value of 0.791, while Model 3 performed the worst, with the lowest R^2 of 0.679.

Although numerous studies have adopted the natural logarithm of TP as the dependent variable, our findings suggest that this approach may not be appropriate for a homogeneous dataset in which variation across districts and time spans is minimal, and only structural and geographical features influence housing prices. In such contexts, the raw TP appears to yield better model performance.

Furthermore, our models provide strong evidence that both structural features and geographical features significantly influence housing prices. For instance, in Model 1, the coefficient for the age of the house is negative (– TWD 328,042), while the coefficient for the square of the age is positive (TWD 2,723). This indicates that housing prices decline with age, but at a decreasing rate, suggesting that older houses retain a residual value and do not depreciate to 0. This can be seen in Figure 8, where a baseline showing the quadratic age function is superimposed on the actual price. In addition, the total floor area positively affects the price (TWD 294,750), as does the presence of an elevator (TWD 1.9504 million) and a garage (TWD 812,810).

With respect to geographical features, a surprising finding is that proximity to the metro station is negatively associated with housing prices (– TWD 7.2272 million), possibly due to noise or congestion. The effects of the other five geographical features are aligned with expectations. The presence of a funeral home negatively affects prices (– TWD 2.5920 million), while proximity to a museum, CBD, hospital, and retail outlet positively influences housing prices.

For a comprehensive investigation, we also re-estimated the model by modifying Model 3, replacing the binary floor variable (Fl1) with the original integer variable (Fl), resulting in an R^2 of 0.677. The difference between the

Table 2. Descriptive statistics for the variables in Model 1

Variable	Description	Mean	Standard deviation
Dependent variable			
TP	Total housing price, in TWD 10,000	2166.4306	1757.1401
Ln(TP)[a]	Natural logarithm of TP	7.4299	0.7650
Independent variables: Structural attributes			
Age	Age of the house, in years	40.6924	15.8678
TFA	Floor area of the house, in pings[b]	56.1482	38.8117
Lot	Land area of the parcel, in pings[b]	25.0211	16.5635
Room	Number of bedrooms in the house	5.0484	3.3037
LR	Number of living rooms in the house	2.2882	1.349103
Bath	Number of bathrooms in the house	3.8384	3.253218
Elev	Dummy variable indicating whether there is an elevator (1 = Yes; 0 = No)	0.0480	0.2143
Gar	Number of garages in the house	0.0480	0.2339
Fl	Number of floors in the house	3.0218	1.1256
Fl1	Binary variable with a value of one if the house is single-story (i.e., one floor), and 0 otherwise	0.0349	0.1840
Age^2	Square of Age	1906.5560	1194.7658
$Room^2$	Square of Room	36.3493	78.2749
Lot^2	Square of Lot	899.2052	2090.9514
Room_Bath	Interaction between the number of bedrooms and bathrooms	28.5022	72.6965
Independent variables: Geographical features			
Metro	Dummy variable with a value of one if within 500 m of a metro station, and 0 otherwise	0.0306	0.1725
Hospital	Dummy variable with a value of one if within 500 m of a hospital, and 0 otherwise	0.2489	0.4333
Museum	Dummy variable with a value of one if within 500 m of a museum, and 0 otherwise	0.1223	0.3283
CBD	Dummy variable with a value of one if within 500 m of Yizhong Business District, and 0 otherwise.	0.1266	0.3333
FH	Dummy variable with a value of one if within 500 m of a funeral home, and 0 otherwise	0.1179	0.3232
Outlet	Dummy variable with a value of one if within 500 m of Tianjin Road Clothing Business District, and 0 otherwise	0.1747	0.3805

Notes: [a]Values are calculated in TWD 10,000; [b]1 ping ≈ 3.3 m^2.
Abbreviations: CBD: Central business district; FH: Funeral home; LR: Living room; TFA: Total floor area; TP: Total price.

Table 3. Comparison of the three proposed models

Variables	Model 1	Model 2	Model 3
Performance index			
R^2	0.7910	0.7870	0.6790
Dependent variable	TP	TP	Ln(TP)
Independent variables: Structural attributes			
Constant	920.0865	304.5060	6.3630
Age	−32.8042	−29.2208	−0.0207
TFA	29.4750	25.2810	0.0058
Lot	18.0749	26.9859	0.0418
Room	−56.3120	−73.1954	0.0271
LR	143.5576	131.3572	0.0199
Bath	17.3155	−7.4514	0.0432
Elev	195.0357	122.0725	−0.2506
Gar	81.2810	126.6469	0.2839
Fl	−216.3338	N/A	N/A
Fl1	N/A	−24.7364	−0.4185
Age2	0.2723	0.2888	0.0002
Room2	5.5680	5.4195	0.0007
Lot2	0.2666	0.2212	−0.0002
Room_Bath	−5.9683	−4.2798	−0.0037
Independent variables: Geographical features			
Metro	−722.7214	−759.2528	−0.0682
Hospital	120.1756	116.7875	0.1223
Museum	616.4406	605.6245	0.2957
CBD	988.3381	967.9731	0.1125
FH	−259.2006	−246.3844	0.0758
Outlet	198.7997	256.3872	0.1173

Abbreviations: CBD: Central business district; FH: Funeral home; LR: Living room; N/A: Not applicable; TFA: Total floor area; TP: Total price.

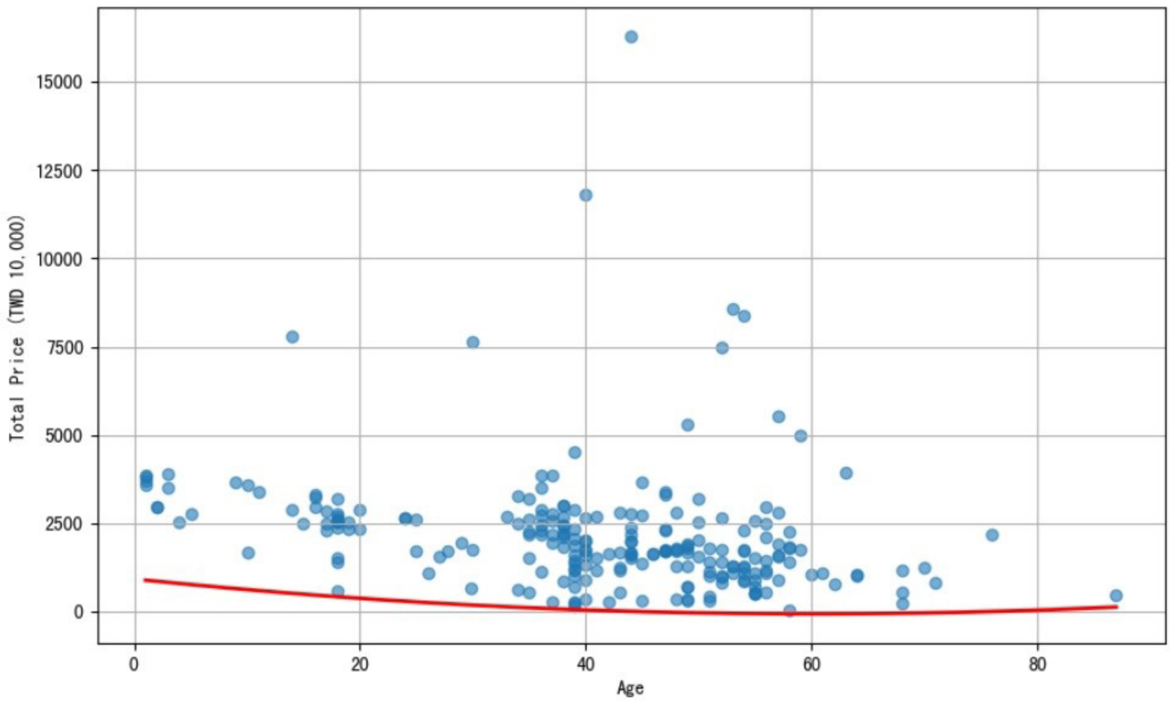

Figure 8. Baseline effect of age on house price

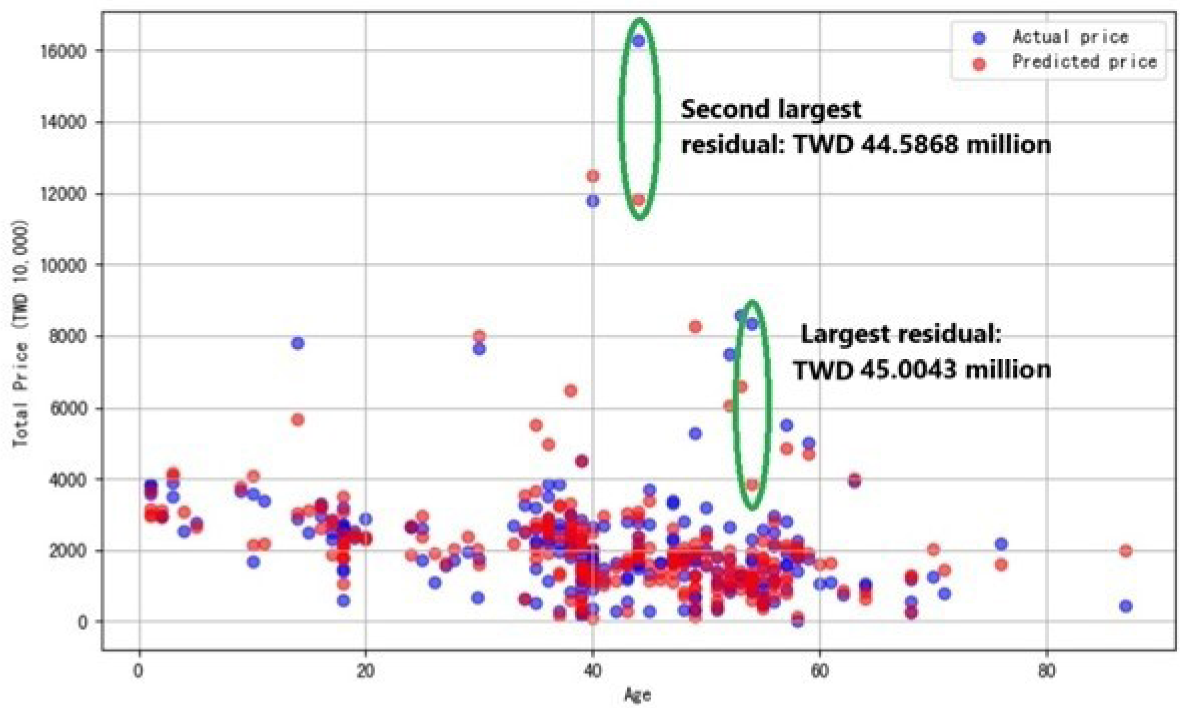

Figure 9. Scatter plot of actual and predicted house prices based on age

Table 4. Linear regression for Model 1

Variables	Coefficient	Standard error	*t*	*p*-value
Constant	920.0865	532.828	1.727	0.086*
Age	−32.8042	14.989	−2.188	0.030**
TFA	29.4750	3.141	9.384	<0.001****
Lot	18.0749	9.918	1.823	0.070*
Room	−56.3120	74.385	−0.757	0.450
LR	143.5576	44.803	3.204	0.002***
Bath	17.3155	72.432	0.239	0.811
Elev	195.0357	328.240	0.594	0.553
Gar	81.2810	252.812	0.322	0.748
Fl	−216.3338	110.966	−1.950	0.053*
Age2	0.2723	0.194	1.406	0.161
Room2	5.5680	4.812	1.157	0.249
Lot2	0.2666	0.066	4.013	<0.001****
Room_Bath	−5.9683	4.979	−1.199	0.232
Metro	−722.7214	350.301	−2.063	0.040**
Hospital	120.1756	144.728	0.830	0.407
Museum	616.4406	187.035	3.296	<0.001****
CBD	988.3381	210.824	4.688	<0.001****
FH	−259.2006	207.586	−1.249	0.213
Outlet	198.7997	177.517	1.120	0.264

Notes: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; ****$p < 0.001$.
Abbreviations: CBD: Central business district; FH: Funeral home; LR: Living room; TFA: Total floor area.

predicted and actual house prices is illustrated in Figure 9, based on the data fitted using Model 1. The largest residual occurs for buildings with an age of 54 years, with a value of TWD 45.0043 million, while the second-largest residual occurs at the age of 44, with a residual of TWD 44.5868 million.

Finally, we present the linear regression results along with their statistical significance in Table 4. This table offers managerial insights into the influence of structural and geographical features on housing prices.

In terms of structural features, the number of living rooms emerges as the most influential factor. An additional living room is associated with an increase of TWD 1.4356 million in housing price. House age is the second most influential factor, with each additional year resulting in a decrease of TWD 328,042. The third most significant factor is the total floor area, where each additional ping corresponds to an increase of TWD 294,750. These three variables have both substantial effect sizes and strong statistical significance, and can therefore be considered crucial structural features inherent to every housing unit.

Other structural elements, such as an elevator and a garage, are optional (i.e., not present in every house). Although they may increase the value, their estimated effects are not statistically significant and should be interpreted with caution.

Among the geographical features, the most notable positive impact emerges from proximity to the Yizhong Business District, which increases house prices by TWD 9.8834 million. In contrast, proximity to a metro station shows a negative effect, reducing house prices by TWD 7.2272 million. A location near the National Museum of Natural Science contributes positively, increasing the house value by TWD 6.1644 million. Other geographical features do not show statistical significance and are therefore considered less relevant in this context.

Using Model 1 to predict housing prices, we calculated the residuals as the differences between the actual prices and the predicted values. As a visualization of the spatial distribution of these residuals in the North District, a bubble plot is presented in Figure 10, where three sets of symbols are used: blue squares represent the five smallest residuals, red triangles indicate the five largest residuals, and purple circles denote the remaining residuals. The size of each symbol corresponds to the magnitude of the residual, with larger symbols indicating larger values.

For the blue squares, the smallest residual is – TWD 3,473.32, shown as the smallest blue square located at the

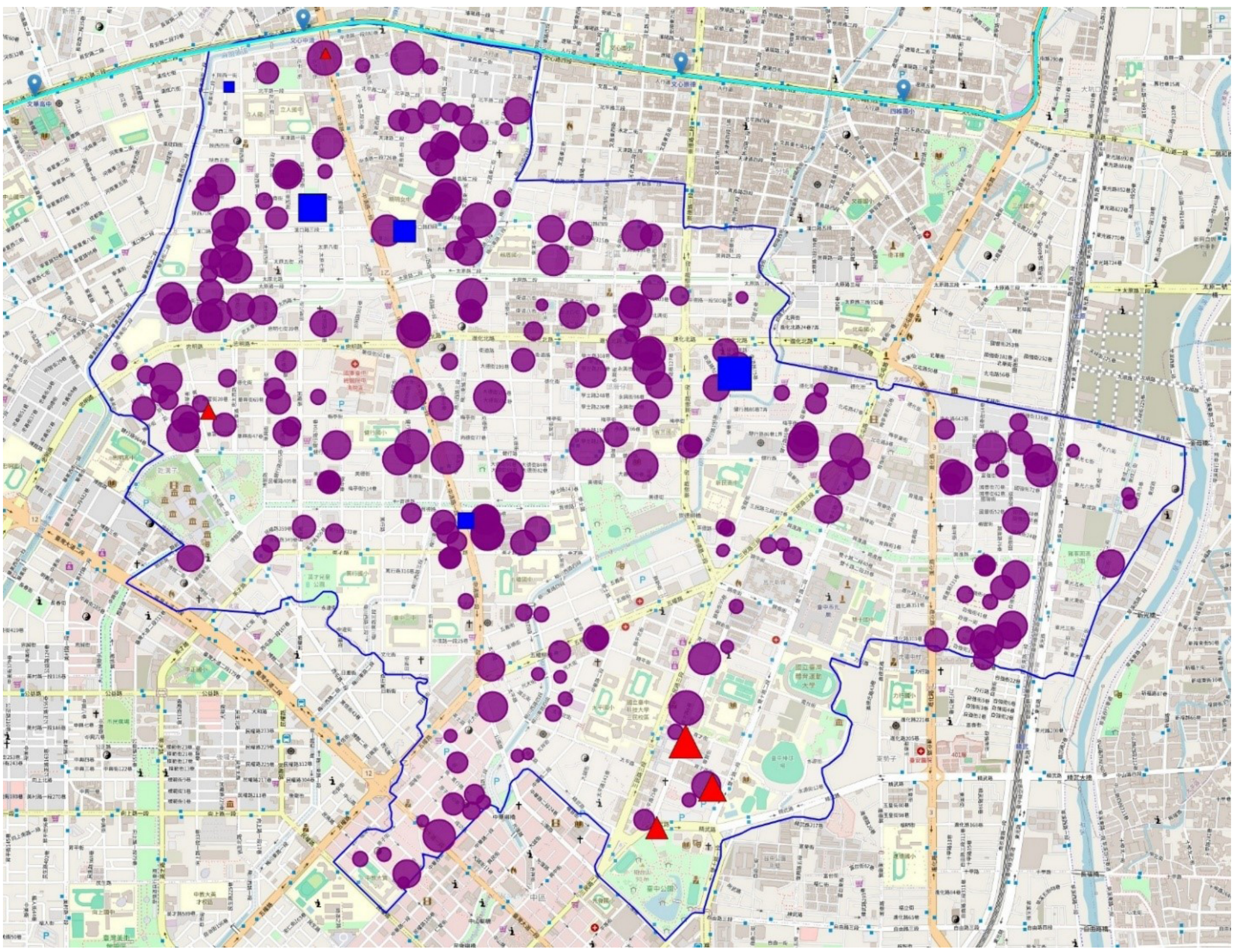

Figure 10. Residual map for properties in the North District

top left corner of Figure 10. The fifth smallest residual is – TWD 1,538.26, represented by the largest blue square in the middle-right portion of the figure.

For the red triangles, the largest residual is TWD 4,500.43, indicated by the largest red triangle positioned at the top of the three clustered red triangles near the bottom of Figure 10. The fifth largest residual is TWD 1,428.45, shown at the top of the figure as the smallest red triangle.

The purple circles represent residuals that fall between – TWD 1,538.26 and TWD 1,428.45. Of these, the largest purple circle corresponds to a residual close to TWD 1,428.45, while the smallest one represents a residual of approximately – TWD 1,538.26.

Overall, the residuals appear to be randomly distributed throughout the North District, with no clear spatial clustering. This suggests that Model 1 effectively accounts for the influence of geographical features, yielding well-balanced predictions across the region.

Finally, we examined the residuals in relation to the locations of amenities, as illustrated in Figure 11. The teardrop icons along the perimeters of the amenities indicate the boundary corners of each amenity. Notably, the three largest residuals, represented by red triangles, are all situated in the southern section of the Yizhong Business District. Their close clustering suggests that the additional value associated with being located within this district may exceed TWD 9.8834 million, or alternatively, that other unaccounted-for factors may be exerting upward pressure on house prices in this area. This observation warrants further investigation. It is also important to note that apart from the Chongde Funeral Home complex (marked in black), all amenities are displayed in cyan, indicating that they are classified as positive amenities.

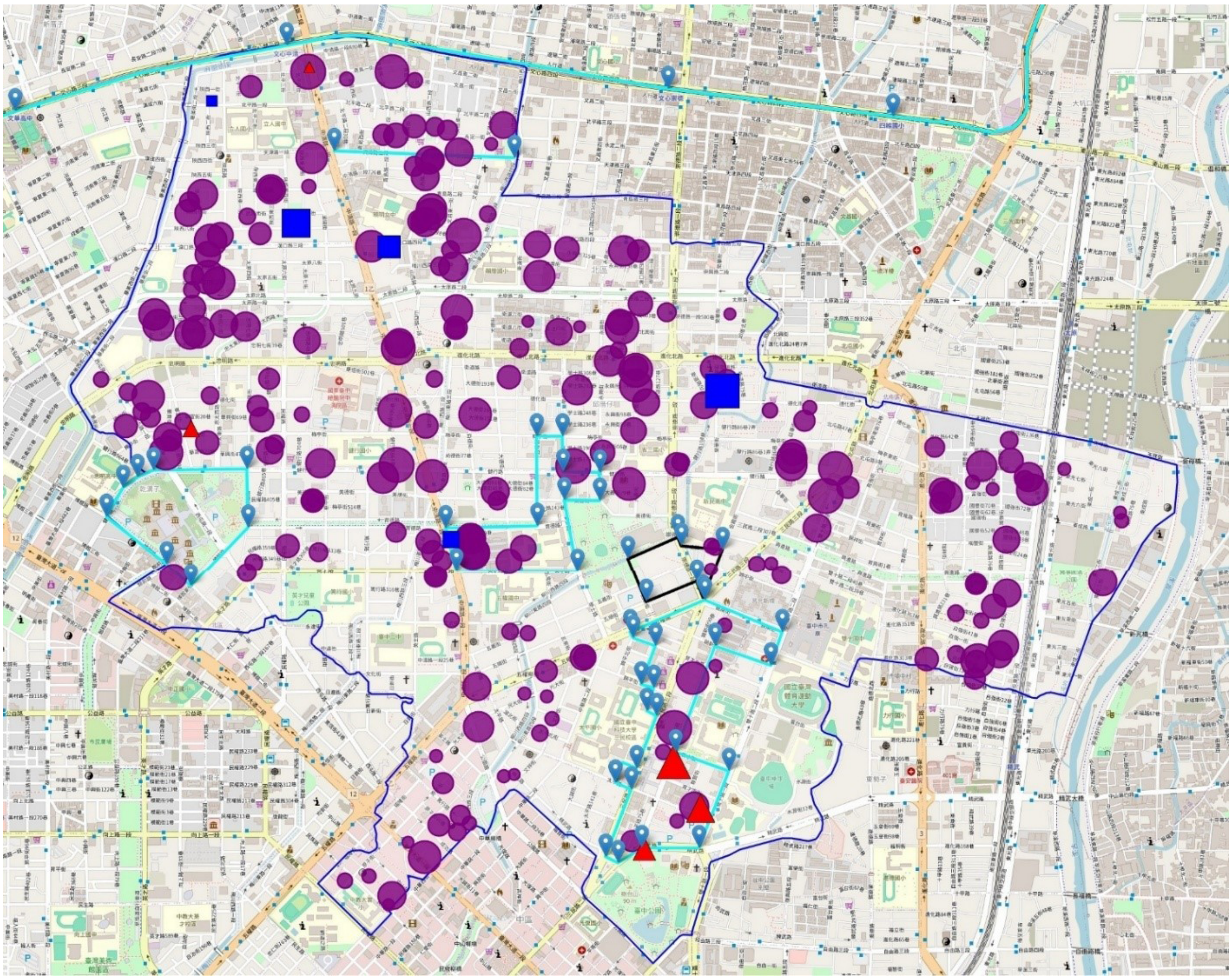

Figure 11. Residual map for properties in the North District, superimposed with amenities

 https://doi.org/10.6977/IJoSI.202604_10(2).0004

Contrary to expectations, proximity to the metro station exhibited a statistically significant negative effect on housing prices, with an estimated impact of – TWD 7.2272 million. This unexpected result may be attributed to the spatial distribution of the sample data. Specifically, the Wenxin Zhongqing Metro Station is the only station situated at the boundary of the North District. As a result, all sampled housing transactions near the station were located to its south, while properties to the north—although likely influenced by the station—fell outside the study area and were thus excluded. This geographic constraint represents a key limitation of the current analysis and may contribute to the observed negative effect. Figure 12 provides a close-up view of the metro station's area of influence. Notably, only seven properties are located within the buffer zone, all of which lie south of the station. In principle, the metro station should affect all properties within the buffer zone. However, due to the defined scope of the study, only properties within the North District were included in the analysis.

4. Lateral thinking insight

To explore novel housing value dynamics, this study incorporates two core techniques from lateral thinking: escape and provocation, as proposed by De Bono (1971). These approaches challenge conventional regression assumptions and open up new directions for identifying strategic housing opportunities—particularly those beyond the 500 m buffer zones of known amenities.

4.1. Escape: Reframing "outside the buffer zone" as value zones

Traditional spatial modeling assumes that properties within the buffer zones of positive amenities—such as museums, hospitals, and business districts—hold superior value due to accessibility. However, by escaping this assumption, we investigate the green zones, defined as areas located just outside the 500 m radius of high-value amenities. These areas potentially offer:

- Reduced noise and congestion,
- Greater privacy and tranquility,
- Moderate accessibility without a premium price.

Figure 13 shows an example near the intersection of Zhongming Road and Section 1, Zhongqing Road, where property values are at least TWD 7.3600 million lower despite still being within a short walking distance of both the museum and the hospital.

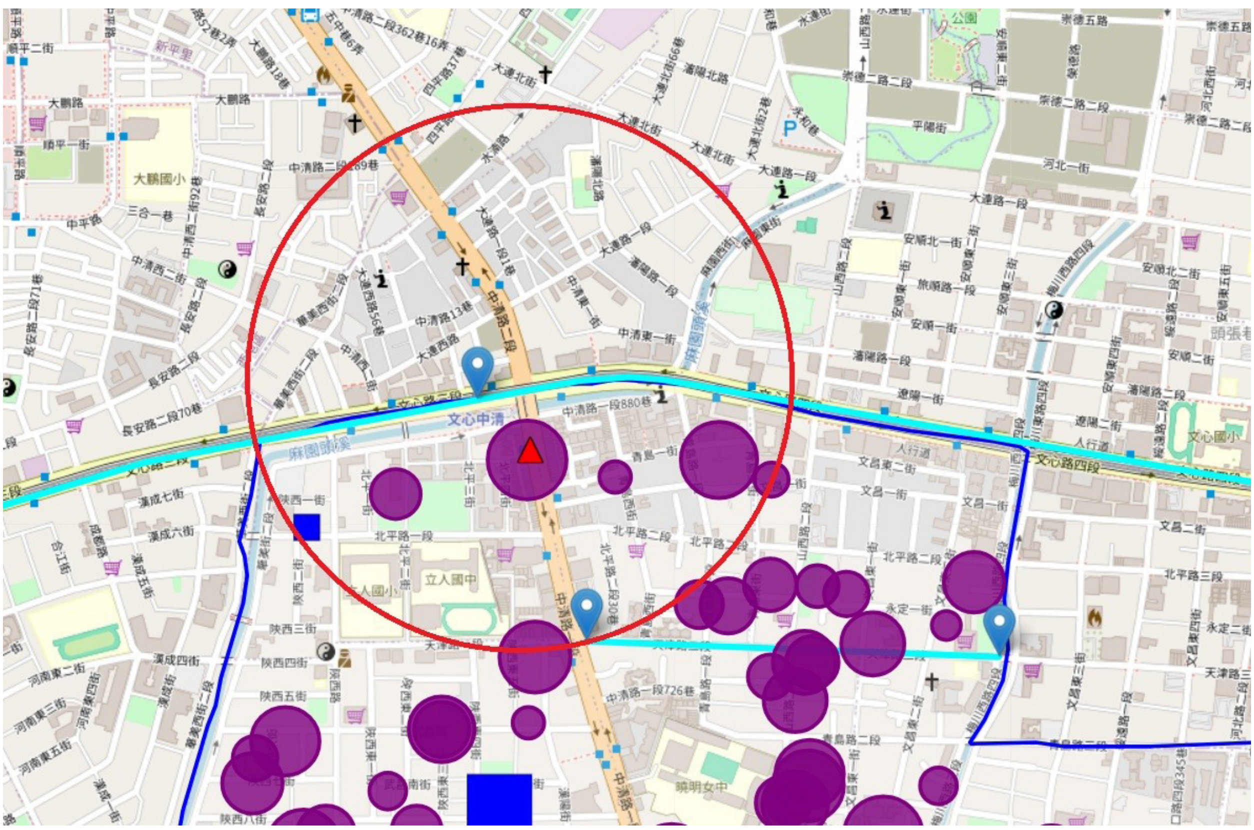

Figure 12. Enlarged map of the buffer zone around the metro station

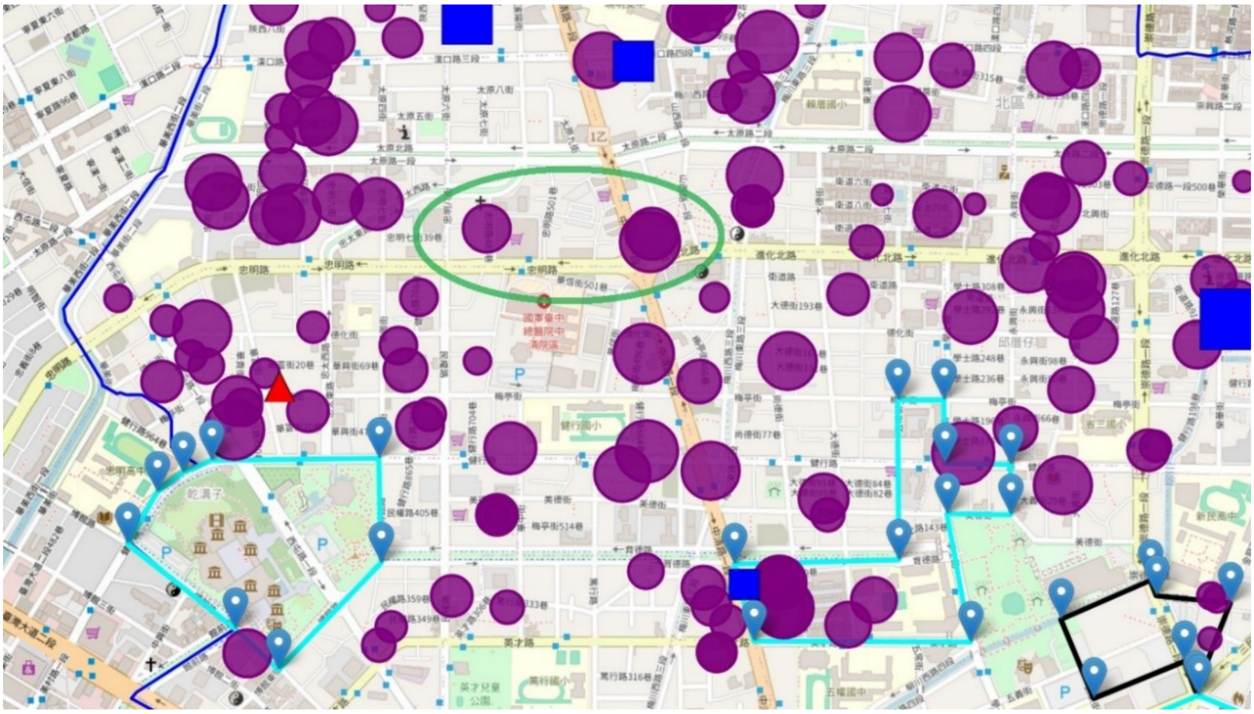

Figure 13. Green zone—areas located just outside the 500 m buffer zones of high-value amenities

4.2. Provocation: Introducing new dimensions of value

The provocation technique asks, "What if housing value increases when a house is not near anything?" This contrarian question directs attention to unmodeled yet significant value drivers, such as:

- Quietness (low traffic, distance from busy roads),
- Environmental quality (greenness, views, altitude),
- Social ambiance (community cohesion, safety, spiritual environment).

These dimensions prompt a rethinking of the current regression framework, which primarily centers on tangible,

Table 5. Value dimension and proxy variable

Value dimension	Proxy variable	Data source
Noise exposure	Distance to arterial roads	GIS road network data
Green environment	NDVI greenness index	Remote sensing/Google Earth
Air quality	Elevation or air monitoring stations	Digital elevation model
Spiritual ambiance	Density of temples or churches nearby	POI database or OpenStreetMap
Community feel	Distance to public parks or libraries	City planning datasets

Abbreviations: GIS: Geographic information system; NDVI: Normalized difference vegetation index; POI: Point of interest.

proximity-based features. To operationalize this thinking, we propose integrating proxy variables in future studies, as shown in Table 5.

These result in an expansion from "where is it located?" to "what is the sensory and social experience of living there?" In particular, regarding air quality in Table 5, two studies are worth noting: Anselin and Le Gallo (2006) and Cai *et al.* (2024). The former examined the ozone factor, while the latter focused on fine particulate matter.

5. Conclusion

This study has examined the impact of geographical features on housing prices, based on 229 housing transactions recorded between September 2023 and September 2024 in the North District of Taichung, Taiwan. A regression analysis revealed that proximity to the museum increases housing prices by TWD 6.1644 million, while proximity to the CBD results in an even higher increase of TWD 9.8834 million. Proximity was defined as being within 500 m of the boundaries of these amenities. Both effects were statistically significant.

Contrary to expectations, proximity to the metro station exhibited a statistically significant negative effect on housing prices, with an estimated impact of – TWD 7.2272 million. This unexpected result may be attributed to the spatial distribution of the sample data. More specifically, the Wenxin Zhongqing Metro Station is the only metro station located at the boundary of the North District. Consequently, all sampled housing transactions near the station were located to its south, while those to the north, although potentially influenced by the station, fell outside the study area and were therefore excluded. This geographic limitation represents a key constraint of the current analysis and may account for the observed negative effect.

When selecting the period and region of study for the house sale model, we carefully excluded unnecessary fluctuation factors, such as a long period (e.g., more than 13 months) or larger regions (e.g., the entire Taichung City). If a longer period is selected, house prices may fluctuate, and broader economic fluctuations may bias the true effect of the construction and geographical features of the buildings. If a larger region is chosen, the spatial characteristics may impact the house prices. Hence, we limited our research to a period of 13 months and focused solely on the North District, which represents the second limitation.

Regarding geographical features, the results confirmed that proximity to the museum and the CBD served as significant positive factors affecting housing prices, as discussed above. This finding also has practical implications for prospective homebuyers; for instance, areas just outside the 500 m proximity zones, although still within a reasonable distance from both the museum and the hospital, represent cost-saving opportunities. One such area, highlighted by the green ellipse in Figure 13, lies near the upper left region of the intersection between Zhongming Road and Section 1, Zhongqing Road. According to Model 1, housing prices in this area may be at least TWD 7.3600 million lower than in closer-proximity zones, offering both accessibility and economic advantage. Similar high-potential locations can be identified by applying the same spatial principles.

Finally, it is worth noting that the three largest positive residuals in predicted housing prices are all clustered in the southern part of the Yizhong Business District. This pattern suggests that other unobserved factors may be influencing housing prices in this area, warranting further investigation.

6. Limitation/Recommendation

The first issue is whether we can replace "TP" with "total value." Our answer is that it is possible, but it would complicate the problem because the value of a house varies among buyers. If we want to measure the total value of a house, we must ask potential buyers for their opinions and take the average as the value of that house. This approach increases the uncertainty of the problem.

Second, as with any data-fitting technique (such as regression, machine learning, adaptive control, or neural modeling), adding parameters improves accuracy but also risks overfitting. This paper does not claim to provide the best-fitting results for house price prediction; instead, it highlights several important points that are often overlooked in research on data fitting. Specifically, it identifies the missing main parameters of value in the Theory of Inventive Problem Solving literature, beyond just money, when evaluating houses for sale. This is why the "escape" method plays a crucial role in this research. De Bono (1971) proposed the escape method; however, despite proposing various ways to escape the mainstream of thought, none of his techniques can be systematized. Further research is warranted.

Third, this section addresses the importance of connecting the dots. Research from different fields seldom exchanges ideas, as each discipline builds its own tower. However, stones from other mountains can be used to polish jade. In other words, insights drawn from external sources can be applied to remedy one's deficiencies. The regression model analyzing house prices in relation to key amenities is similar to adaptive control studies that analyze hidden dynamics. The similarity lies not in what is being modeled (house prices vs. dynamic systems) but in how unknown influences are handled under structural assumptions. Both a regression model for house prices and an adaptive control scheme analyze hidden factors indirectly through observable outcomes, using a shared analytical logic. Both frameworks treat hidden dynamics not as mysteries to be fully uncovered, but as latent influences constrained by structure and inferred through their observable effects. Thus, the adaptive control method can be used to address the issue of new dimensions in evaluating house prices. For example, the new dimension regarding air quality can be treated as a hidden dynamic. Two studies on adaptive control are highly recommended: Rigatos *et al.* (2023) proposed a nonlinear optimal control approach for the dynamic model of a gas centrifugal compressor driven by an induction motor, using Lyapunov analysis to prove the global stability properties of the control method; Boulkroune *et al.* (2025) studied control and synchronization of chaotic systems, employing fuzzy logic systems within synchronization schemes to estimate continuous functional uncertainties.

Acknowledgments

None.

Funding

None.

Conflict of interest

The author declares no conflicts of interest.

Author contributions

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Investigation: Hsun-Yu Chan, Yu-Chen Lai, Yu-Xin Huang
Methodology: Jyh-Jeng Deng
Writing–original draft: Jyh-Jeng Deng
Writing–review & editing: Jyh-Jeng Deng

Availability of data

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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