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HEDONIC PRICING MODEL (HPM) ON SOUTH TANGERANG RESIDENTIAL PROPERTY VALUE

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Abstract

This study investigates the effects of location, structural, and environmental attributes on residential property values in South Tangerang City, Indonesia. The research employs the Hedonic Pricing Model (HPM), formulated mathematically using the multiple linear regression approach to determine the relative contribution given by these attributes. To achieve the objective, data were collected from information on residential properties in South Tangerang City which is accessible on various property buying and selling websites. The data collection was limited from July 2023 to January 2024. The results showed that some variables affected the value of residential properties, such as distances to KRL stations, public parks, top high schools, and the Central Business District (CBD), as well as building areas, land areas, and the number of rooms (bathrooms and bedrooms). However, other variables, such as distances to malls, hospitals, universities, and population density, had no partial effect on residential property values. If we look at the types of variables, the standardized coefficient beta test revealed that building areas were the most dominant variable affecting the property values in the region. This finding is different from other results, showing that property values are local. The influence of property attributes can vary across regions, so the impacts and relationships are different, too.

Keywords: Hedonic Pricing Model (HPM), property value, residential property

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INTRODUCTION

Many studies have explored factors affecting the property values of land and buildings. Simply put, the studies agree that the building's location, environment, and character attributes are variables that shape the value of a property (Riyanto *et al*., 2021). These variables are then incorporated into the Hedonic Pricing Model (HPM). According to previous studies, HPM is commonly used in property valuation research to determine the factors that affect the price of a property (Güler et al., 2019; Sa'at et al., 2021). This model expresses that the price of a property is the sum of its individual attribute values (Lisi, 2019). The attributes or characteristics attached to the property include location, size, age, and quality (Price, 2017).

Appraisers must be able to analyze the relationship between property attributes and the value of the property. International Valuation Standards or IVS (2022) states that identifying and analyzing the characteristics of the appraised property enables appraisers to obtain an accurate estimate of the property value. Moreover, as property transactions increase, the need for accurate value estimation from appraisers will be increasingly needed.

Bartke and Schwarze (2021) state that appraisers have a role as "information intermediaries" in a real property transaction. The appraiser analyzes the characteristics of the property and the existing market risk to estimate the property value and then conveys this estimate to the buyer or seller. This information serves as the basis for buyers and sellers in negotiating and making decisions related to property transactions. By providing this information, appraisers help reduce information gaps and uncertainty in the real property market. Otherwise, buyers and sellers must rely on their own knowledge and expertise to estimate the value of a property, which can be time-consuming and complex.

This motivated the authors to conduct research on attributes or factors that affect residential property values in South Tangerang City. South Tangerang City was chosen due to its location in the Jabodebek-Banten area. It is one of the areas with increasing residential property buying and selling transactions in Indonesia. In addition, the development of the construction sector in this city has triggered demand for residential properties in the area. The results of this study will provide an overview for appraisers of how certain factors affect the value of residential properties in South Tangerang City so that the valuation results can be more accurate.

LITERATURE REVIEW

Hedonic Pricing Model (HPM)

The hedonic model was first introduced by Court (1939) in his research to analyze automobile prices in the United States. He stated that the hedonic model can be used to measure the value of an item with complex attributes, such as a car.

Court's results were further developed by other researchers, such as Lancaster (1966) and Rosen (1974).

Although the hedonic model was introduced by Court (1939), the theoretical basis for this model was first put forward by Lancaster (1966) through hedonic utility theory. He argued that the utility of a good is not derived from the good itself. Rather, it is the individual "characteristics" of a good that create its utility. In other words, the utility of an item is simply the combination of the individual utility of each of its characteristics.

Hedonic utility theory was used by Rosen (1974) as a basis for developing HPM. He argued that the value of a good is an aggregate of characteristics that produce utility. In other words, the total price of a good should be the sum of the individual prices of its characteristics. This implies that HPM can be used to "dissect" the price of an item into smaller parts of that item using certain analytical tools (e.g. regression). In this way, the contributions of each part to the overall value of the item can be identified (Sopranzetti, 2010).

Of many items, residential property is one type that uses HPM as a frame of reference (Sopranzetti, 2010). The price of a residential property depends heavily on its intrinsic and extrinsic attributes, each of which can be evaluated independently (Lisi, 2019). He noted that the monetary value of residential property attributes is implicit and cannot be observed directly. However, these attributes can be assessed through the selling price of the property and their relative contributions. Typically, these contributions can be measured using regression models

Linear regression is the most often used model to express the mathematical formulations of HPM on residential properties (Crespo & Gret-Regamey, 2013; Lisi, 2021). As previously explained, the monetary value of property attributes is implicit, but through regression models, the monetary contribution of each property attribute to property prices can be identified by estimating the coefficient of these attributes (Lisi, 2021; Rosen, 1974). The value of a residential property is analyzed based on its independent variables, which are usually a collection of structural characteristics, accessibility, and environment.

Factors Affecting Residential Property Value

Research suggests that location, structural, and environmental functions are the main attributes widely used in HPM for real property (Riyanto et al., 2021). These attributes can be further divided into several variables or factors, each of which can have a positive or negative impact on property values (Kauko, 2003). The contribution made by each variable also varies.

The first attribute is the location of the property. The immobility nature of residential property makes the location one factor that determines property value because buyers not only buy physical land and buildings but also the location (Kiel & Zabel, 2008). Not surprisingly, there is a common saying that the three things that determine a house's price are location, location, and location.

Location is closely related to the monocentric model. The monocentric model states that residential property prices depend on the distance between the property location and the Central Business District (CBD) (Riyanto et al., 2021). Surianto et al. (2019) stated that CBD is the center of comfort needed by humans. Hence, properties near the CBD tend to have higher economic capabilities. However, the concept of location is not limited to knowing the relationship between property values and their distance to the CBD only. Some studies try to find out the relationship between property values and their distance to other objects, such as subway stations (Crespo & Gret-Regamey, 2013; Dai et al., 2020; Hong & Ryu, 2021; Mathur, 2020), shopping malls (Berawi et al., 2020; Farber & Yeates, 2006; Mathur, 2020; Surianto et al., 2019; Yilmazer & Kocaman, 2020), or public parks (Berawi et al., 2020; Hong & Ryu, 2021; Olanrele et al., 2023; Park et al., 2017; Sander & Haight, 2012). Thus, the value of residential properties is influenced not only by their distance to the CBD but also by their closeness to other important places.

The second attribute affecting the property value is the characteristics of the building. These characteristics can be the age of the building, design quality, area of space, number of spaces, quality of building materials, and room layout. Likewise, the physical and structural factors of the building can have a positive or negative effect on property prices (Moses & Yusoff, 2018).

The environment is the third property attribute. Price (2017) explained that although landscapes are not a common type of private item, their presence on a property can increase the marketability of the property. This opinion is in line with the results of a study by Cetintahra and Cubukcu (2014), mentioning that the aesthetics of the property environment can arouse a sense of joy, cohesiveness, and pleasure. Hence, it will affect the value of the property. In addition to landscape, other factors related to the environment also affect the value of a property, such as exposure to pollution and health (Price, 2017) or security and safety (Dai et al., 2020)

The three attributes described earlier indicate that the value of the residential property is local. Local factors such as location, environment (neighborhood), and available amenities have a greater influence on property value than global factors. In addition, residential property attributes can impact different areas in different ways due to cultural, economic, and social differences in each region.

RESEARCH METHODOLOGY

Model Building

This section outlines the methodology used in this study to analyze the factors influencing residential property prices. To do so, this study used the basic model developed by Berawi et al. (2020), as illustrated in Figure 1. The model was developed to identify variables that affect residential property prices for landed houses and apartments near the first phase of the Jakarta MRT station construction project. The model has considered the influence of location attributes, property characteristics, and environment on residential property prices.

However, the author made adjustments to some variables. First, the authors adjusted the distance variable to the MRT station. In order for the variables to be more relevant to the local conditions, the condition variable was changed from the MRT station to the Commuter Line Train (KRL) station. The adjustment was made because KRL is the only type of train used as public transportation in South Tangerang City. In addition, the variables of apartment area, apartment communal land area, and apartment communal space area were also not used because the type of residential property analyzed in this study was limited to landed houses.

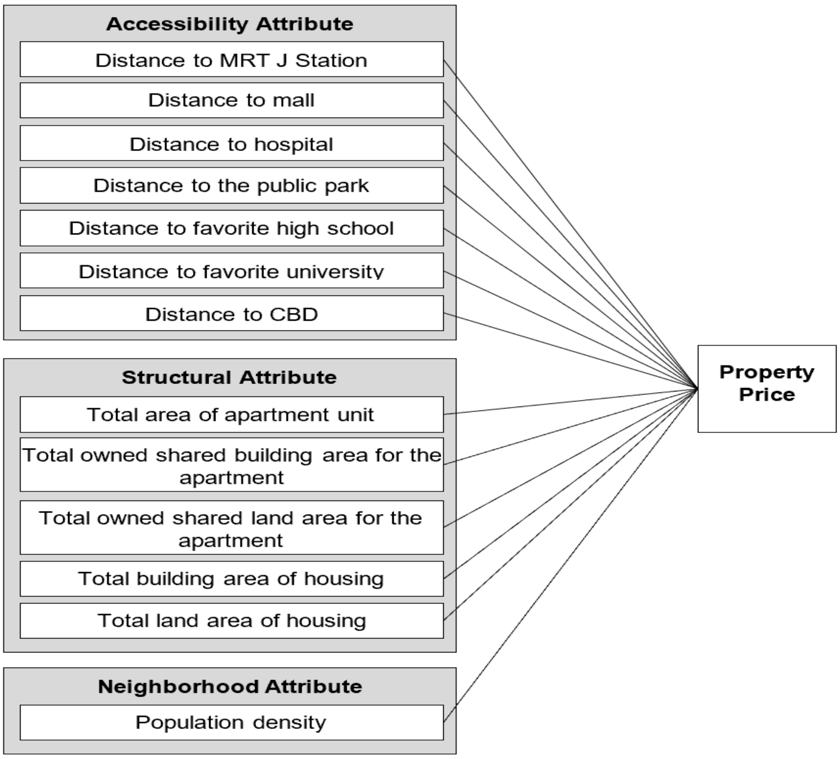

Figure 1: Base Model
Source: Berawi et al. (2020)

In addition to the model developed by Berawi et al. (2020), this study added several new variables that were relatively relevant to the study's objectives. New variables were added, including the number of bathrooms and bedrooms. Several studies have found a significant positive relationship between the number of bathrooms and residential property value (Bujanda, 2014; Hong & Ryu, 2021; Mathur, 2014; Mathur, 2019; Metz, 2015). Nevertheless, it is important to note that research also found a significant negative relationship between the two variables (Mathur, 2014; Mathur, 2019). The final model, which serves as the research framework, is shown in Figure 2.

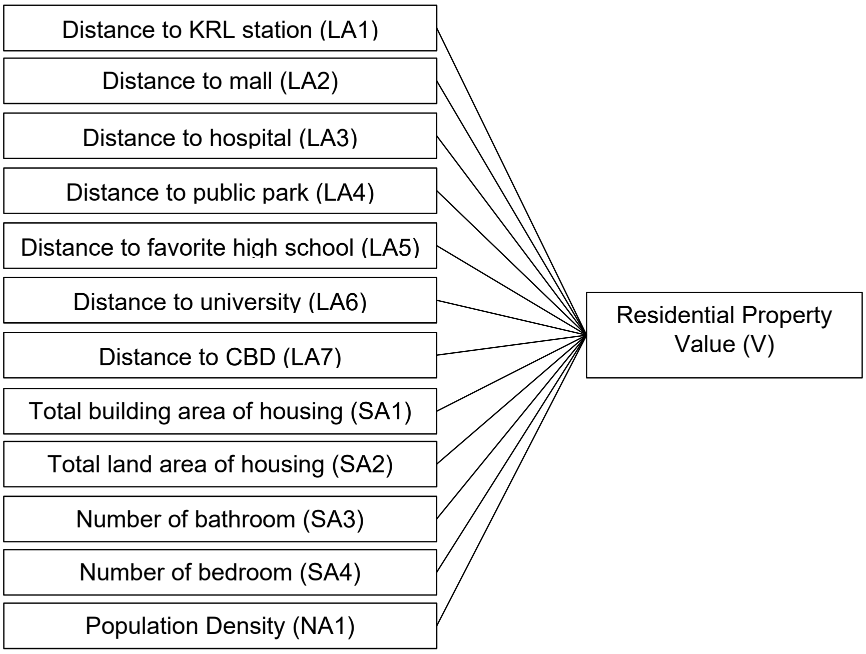

Figure 2: Final Model

Data Description

This research was conducted in South Tangerang and employed primary and secondary data. The primary data involved variable data related to property location, collected from Google Maps and measured based on actual distance. Meanwhile, the secondary data were information on residential property obtained from property buying and selling websites on the internet. The search was listed from July 2023 to January 2024. Secondary data in this study also included information about the population obtained from Statistics Indonesia.

The dependent variable in this study is the estimated property value in South Tangerang City. Before using this variable, the data needed adjustments because the price was still in the form of the property offer price. To convert the offer price to the estimated transaction value, the offer price was reduced by a certain percentage, reflecting the difference between the offer and the transaction price. The study used a 6% adjustment to convert the offer price into an estimated residential property value. This percentage was obtained from research conducted by Riyanto et al. (2023). The study found that the offer price of residential properties in Jakarta is, on average, 6% higher than the transaction price. The variables used in this study are further described in Table 1.

Table 1: Description of Variables

Code	Description	Unit
Dependent Variables		
V	Estimated property value obtained from property buying and selling websites on the internet	Rupiah
Independent Variables		
Location Attributes (LA)		
LA1	Distance from residential property to the nearest KRL station	Meter
LA2	Distance from residential property to the nearest mall	Meter
LA3	Distance from residential property to the nearest hospital	Meter
LA4	Distance from residential property to the nearest public park	Meter
LA5	Distance from residential property to the nearest favorite high school	Meter
LA6	Distance from residential property to the nearest university	Meter
LA7	Distance from residential property to CBD	Meter
Structural Attributes (SA)		
SA1	Total building area of residential property	m2
SA2	Total land area of residential property	m2
SA3	Number of bathrooms owned by a residential property	Fruit
SA4	Number of bedrooms owned by a residential property	Fruit
Neighborhood Attributes (NA)		
NA1	Population density in the neighborhood around residential properties	Person/m^2

After collecting the data, multiple linear regression analysis was used to analyze and predict the value of the dependent variable from one or more independent variables (Saunders et al., 2019). A statistical application, Stata 14.2, was used to perform the multiple linear regression models.

Following that, classical assumption testing was applied to ensure the models' accuracy, consistency, and unbiased nature (Mardiatmoko, 2020). These tests included normality tests, multicollinearity tests, and heteroscedasticity tests. In addition, the authors also conducted simultaneous parameter tests (F-test) and measurement of the coefficient of determination (RSquare). The standardized coefficient beta test was also carried out to determine which independent variable has the most dominant influence on the dependent variable.

ANALYSIS AND DISCUSSION

Table 2 shows the results of the multiple linear regression of the dependent variable. It shows an estimated value of residential property and twelve independent variables that have been previously selected.

Table 2: Results of multiple linear regression analysis

V	Coef.	p-value	Beta	Sig
LA1	-82.134	0.013	-0.1197	*
LA2	-128.140	0.102	-0.1454	
LA3	21.481	0.769	0.0181	
LA4	-73.049	0.175	-0.0651	
LA5	92.644	0.063	0.0825	
LA6	209.091	0.001	0.2262	*
LA7	-177.479	0.002	-0.1593	*
SA1	8.707.070	0.000	0.5674	*
SA2	3.905.898	0.000	0.2310	*
SA3	3,185e+08	0.000	0.2977	*
SA4	-2.543e+08	0.000	-0.2709	*
NA1	33.375	0.257	0.0497	
Constant	4.364e+08	0.298		
Number of obs				136
Prob > F				0.0000
R-squared				0.8112
Adj. R-squared				0.7928

**p<0.05*

Source: Author's Calculation

In addition, to provide an alternative interpretation of the influence of the independent variable on the dependent variable, the author also transformed the linear model into a natural logarithm model (Ln), as shown in Table 3. The Ln model helps avoid heteroscedasticity, identifies coefficients that indicate elasticity, and bring the data scale closer. In a study on property valuation, Ishijima and Maeda (2015) stated that the application of linear models to property data does not always yield reliable results. Thus, the Ln model can improve the explanatory ability of the model, making it a widely used model among researchers for provides more accurate results.

Table 3: Results of multiple linear regression analysis (Natural Logarithm Model)

LnV	Coef.	p-value	Beta	Sig
LnLA1	-0.1263	0.035	-0.0986	*
LnLA2	0.0981	0.288	0.0836	
LnLA3	-0.0739	0.174	-0.0659	
LnLA4	-0.1449	0.010	-0.1224	*
LnLA5	0.1228	0.004	0.1194	*
LnLA6	0.0670	0.183	0.0796	
LnLA7	-0.1886	0.005	-0.1478	*
LnSA1	0.4995	0.000	0.4609	*

LnV	Coef.	p-value	Beta	Sig
LnSA2	0.3179	0.000	0.2320	*
LnSA3	0.4417	0.000	0.3544	*
LnSA4	-0.2842	0.018	-0.1763	*
LnNA1	0.1822	0.082	0.0725	
Constant	17.499	0.000		*
Number of obs				136
Prob > F				0.0000
R-squared				0.8255
Adj. R-squared				0.8085

_*p<0.05_

Source: Author's Calculation

Table 4 summarizes the classical assumption tests for both regression models. Of the three tests, the linear model only satisfied the multicollinearity test. It failed to meet the normality and heteroscedasticity tests. Conversely, the Ln model met the normality, multicollinearity, and heteroscedasticity tests. Based on the results of these tests, the author decided to use the Ln model as the basis for analyzing the influence of location, structural, and environmental attributes on residential property values.

Table 4: Classical assumption testing

Classical Assumption Test	Testing	Model Linear	Model Ln
Normality	_Skewness and Kurtosis Tests_	0.0016	0.4014
Multicollinearity	_Variance Inflation Factor_	2.51	2.65
Heteroscedasticity	_Breusch-Pagan/Cook-Weisberg Test_	0.0000	0.5582

Source: Author's Calculation

Based on Table 3, the F-test results from the multiple linear regression analysis show that the twelve selected independent variables simultaneously affect the dependent variable. The results showed that 80.85% of the estimated value of residential properties in South Tangerang City could be explained by variables, such as distances to KRL stations, malls, hospitals, public parks, top high schools, universities, CBD, building area, land area, number of the bathrooms, number of the bedrooms, and population density. The remaining 19.15% was explained by other variables outside the twelve independent variables. Additionally, the standardized coefficient beta revealed that the building area variable (LnSA1) had the most dominant independent variables affecting the estimated residential property value (LnV).

Of the seven independent variables related to location attributes, four independent variables had a significant effect on the dependent variable. The four independent variables included distance to the nearest KRL station (LnLA1), distance to the nearest public park (LnLA4), distance to the nearest top high school (LnLA5), and distance to the CBD (LnLA7). Three other independent variables – distance to the nearest mall (LnLA2), distance to the nearest hospital (LnLA3), and distance to the nearest university (LnLA6) – were found to have no significant influence on the dependent variable.

Among the significant variables, there was a significant relationship between the distance of residential property to the nearest KRL station (LnLA1) and the estimated value of residential property (LnV). Under conditions of other variables, the fixed value, a 1% increase in the distance to the nearest KRL station, reduced the estimated value of residential property by 0.1263%. This negative coefficient of LnLA1 confirms previous studies conducted at different locations (Crespo & Gret-Regamey, 2013; Dai et al., 2020; Hong & Ryu, 2021; Mathur, 2020). Mathur (2020) emphasizes that train stations are facilities that serve the entire surrounding community. Thus, their presence is a key factor affecting residential property values.

In addition to the proximity to KRL stations, Table 3 also shows the importance of public parks in determining property values. It shows that the distance of residential properties to the nearest public park statistically has a statistically significant and negative effect on the estimated value of residential properties at a 95% confidence level. The analysis indicates that a 1% increase in the distance to the nearest public park would reduce the estimated value of residential properties by 0.1449%. This result aligns with previous studies, such as Park et al. (2017) and Sander and Haight (2012). Public parks are perceived by the community as a place to provide education, entertainment, physical activities, and social interaction.

Similarly, the distance to the nearest top high school was another variable that significantly affected the estimated property value in South Tangerang City. The regression coefficient of the variable LnLA5 showed that a 1% increase in the distance between a residential property and the nearest top high school would increase the estimated value of the residential property by 0.1228%, assuming the value of the other variable is fixed. This finding differs from other studies that found a negative relationship between the distance to the nearest high school and the value or price of the property (Berawi et al., 2020; Hong & Ryu, 2021; Metz, 2015). However, Metz (2015) also found that residential properties that are too close to schools often have lower values due to the effects of disruption or congestion around the school.

Another critical attribute that might affect the property values was the distance to the Central Business District (CBD). This study revealed that this variable had a significant and negative influence on the estimated value of residential property. Each increase in the distance to the CBD by 1%, *ceteris paribus*, would reduce the estimated value of residential properties by 0.1886%. This finding confirms that the distance to the CBD is a consistently significant variable. Other studies conducted in different locations have shown that property values decrease farther from the CBD or city centre. (Batog et al., 2019; Berawi et al., 2020; Dai et al., 2020; Farber & Yeates, 2006; Forys, 2022; Hong & Ryu, 2021; Mathur, 2014; Mathur, 2019; Metz, 2015; Surianto et al., 2019). This shows that closeness to the CBD is important for determining property values.

In addition to location attributes, Table 3 shows the roles of structural attributes in determining property values. It was reported that variables such as building area (LnSA1), land area (LnSA2), number of bathrooms (LnSA3), and number of bedrooms (LnSA4) had significance values smaller than the confidence level of 95% (α = 5%). Thus, it can be concluded that partially all independent variables related to structural attributes have a significant influence on the estimated value of residential properties in South Tangerang City (LnV).

This study shows that building area significantly influences the estimated value of residential properties in South Tangerang City. Each 1% increase in building area resulted in a 0.4995 increase in the estimated value of the residential property, assuming other variables remain fixed. Numerous studies have also found that building area positively affects residential property values (Batog et al., 2019; Berawi et al., 2020; Bujanda, 2014; Crespo & Gret-Regamey, 2013; Farber & Yeates, 2006; Mathur, 2014; Mathur, 2019; Mathur, 2020; Metz, 2015). The building area is closely related to space availability for daily activities. The larger the building area, the more space there is for resting, cooking, working, and other activities.

The land area variable is another independent variable that significantly affects the estimated value of residential property in South Tangerang City. Similarly, a 1% increase in land area would increase the estimated value of residential property by 0.3179%. This finding is in line with other studies conducted in different locations, which suggest that more land or parcel in a residential property generally leads to higher property value (Batog et al., 2019; Bujanda, 2014; Farber & Yeates, 2006; Forys, 2022; Mathur, 2014; Mathur, 2019; Mathur, 2020; Metz, 2015). It can be concluded that the influence of land area seems to be consistent across different locations

Further, the results of the study in South Tangerang City show a significant and positive relationship between the number of bathrooms and the estimated value of residential properties. The regression coefficient in the LnSA3 variable indicated that every 1% increase in the number of bathrooms increased the estimated value of residential properties in South Tangerang City by 0.4417%. This is congruent with earlier studies, stating that the number of bathrooms has a positive relationship with property value (Bujanda, 2014; Hong & Ryu, 2021; Mathur, 2014; Mathur, 2019; Metz, 2015). This finding is also in line with that expressed by Sirmans et al. (2005), who claim that the number of bathroom variables in HPM studies mostly produces a positive relationship. This is understandable because the bathroom is an important facility that supports activities for bathing, washing, and lavatory.

Another interesting variable that is taken into account is the number of bedrooms. In contrast, this variable statistically had a significant and negative effect on the estimated value of residential property at a 95% confidence level. This study's finding indicates that each 1% increase in the number of bedrooms reduced the estimated value of residential property by 0.2842% under fixed, variable conditions. Some studies have also found a significant negative relationship between the number of bedrooms and property value (Mathur, 2014; Mathur, 2019). In particular, Mathur (2014) argued that this negative relationship occurs because increasing the number of bedrooms can reduce the overall living space in a property, as the total area is divided among more rooms.

Regarding environmental (neighborhood) attributes, the population density variable (LnNA1) did not have a significant influence on the estimated residential property value in South Tangerang City (LnV). These findings are consistent with studies by Dai et al. (2020) and Olanrele et al. (2023), who also found no significant effect between population density and property values. However, other studies have also found that higher population density can lead to a decrease in the property value in surrounding neighborhood (Berawi et al., 2020; Bujanda, 2014; Crespo & Gret-Regamey, 2013).

CONCLUSION

This study has shown that the Hedonic Price Model (HPM) can be used to identify which attributes affect the value of a residential property and analyze the relative contribution of these attributes. The results revealed that the value of residential properties in South Tangerang City was significantly influenced by variables such as distances to KRL stations, public parks, top high schools, CBD, building area, and land area, as well as the number of bathrooms and bedrooms. On the other hand, distances to malls, hospitals, universities, and population density were known to have no effect on property values in this region.

These findings highlight that property values are local, and the influence of property attributes may have different impacts and relationships in different regions. This variation happens due to cultural, economic, and social differences in each region.

In appraisal practice, especially when using the market data comparison approach, HPM offers an alternative method for property appraisers to consider the effect of certain attributes on property values. Despite the promising results, this study still has a limitation, as the adjustment process tends to be subjective based on the experience and knowledge of each assessor. HPM can overcome this subjectivity issue because adjustments to HPM methods are more data-driven.

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