INTERNATIONAL JOURNAL OF eBUSINESS AND eGOVERNMENT STUDIES
Vol: 16 **No:** 4 **Year:** 2024 **ISSN:** 2146-0744 (Online) (**pp.**215-231) **Doi:** 10.34109/ijebeg.2024160411
Received: 15.06.2023 | **Accepted:** 11.12.2024 | **Published Online:** 30.12.2024

-RESEARCH ARTICLE-

DETERMINANTS OF PRICING FOR NEW CONDOMINIUMS IN BANGKOK: A MULTI-LEVEL ANALYSIS USING WEB-BASED DATA

Chatpong Tangmanee*

Chulalongkorn Business School, Chulalongkorn University
ORCID: https://orcid.org/0000-0001-6805-2921
Email: chatpong@cbs.chula.ac.th

Nuttirudee Charoenruk

Chulalongkorn Business School, Chulalongkorn University
ORCID: https://orcid.org/0000-0003-4262-6960
Email: nuttirudee@cbs.chula.ac.th

—Abstract—

Previous studies have demonstrated that the listing prices of residential units are influenced by both unit-specific characteristics (such as the number of bedrooms) and broader building-level attributes (such as proximity to train stations). However, these unit-level characteristics are frequently embedded within the building attributes, leading to potential violations of the assumptions underpinning many conventional analytical techniques. To address this issue, the present research employed a multi-level analytical approach to examine the extent to which the listed prices of newly developed condominiums in Bangkok are determined by these two categories of factors—unit features and building attributes. Drawing on a dataset comprising 1,372 condominium units obtained from a real estate website, the multi-level analysis revealed that both sets of variables significantly influenced pricing. Furthermore, statistical outcomes affirmed the appropriateness of the multi-level method for the dataset under investigation. Beyond contributing to methodological discussions concerning price determinant analysis, the study also offers practical guidance for a range of stakeholders. For example, the total number of units within a building and the number of floors were found to significantly impact unit prices. Accordingly, property developers are advised to take these aspects into account when determining pricing strategies.

Keywords: New Condominium Pricing; A Multi-Level Analysis; Web-Based Data

Citation (APA): Tangmanee, C., Charoenruk, N. (2025). Determinants of Pricing for New Condominiums in Bangkok: A Multi-Level Analysis using Web-Based Data. *International Journal of eBusiness and eGovernment Studies, 16*(2), 215-231. doi:10.34109/ijebeg.2024160411

INTRODUCTION

Condominium development plays a crucial role in supporting the Thai national economy. Developers must recognise the significance of the housing sector, which acts as a catalyst for demand across numerous associated industries. During the construction stage, condominium projects require substantial volumes of construction materials, equipment, and labour inputs (Bahamid et al., 2022). Upon completion, these developments contribute residential units to the real estate supply chain, thereby enhancing broader economic activity. Extant literature on real estate consistently affirms that the price of a residential unit is influenced by two primary groups of determinants. One group pertains to the physical and functional characteristics of the unit itself, while the second encompasses locational and contextual factors representing building-level attributes. Empirical investigations have shown that variables such as gross floor area, bedroom count, and the allowance for pets can positively affect price formation (Bhor et al., 2020). In addition, advanced analytical approaches such as machine learning have corroborated the role of bedroom quantity in shaping price levels, as demonstrated in the study by Li, Wang and Ding (2020). Supporting earlier findings by Cassetti (1992), Orford (2000) further validated the application of multi-level modelling as a more contextually suitable approach than traditional regression models in forecasting property prices.

With respect to locational and structural elements, variables such as the total number of floors within a building have been found to significantly influence listing prices of new condominiums in Bangkok (Tangmanee, 2023), suggesting that high-rise units tend to command premium prices compared to those in low-rise developments. Furthermore, access to on-site facilities—such as fitness centres, swimming pools, or shared workspaces—has been shown to significantly impact property prices, with evidence drawn from both Malaysian (Dziauddin, 2019) and Thai (Techakumphu, 2015) contexts. In major urban centres with chronic traffic congestion, proximity to commuter train stations has also been repeatedly identified as a critical pricing factor (Tangmanee, 2023; Xiao et al., 2019).

A critical review of prior literature reveals two principal gaps in research. The first concerns methodological limitations, particularly in the way explanatory variables influencing listed prices are conceptualised. Much of the earlier work presumes (1) linear associations between variables (Liang et al., 2018) and (2) independence among observations. However, these assumptions may be flawed, as many unit-level attributes—such as furnishing status or bedroom count—are inherently nested within broader building-level factors like the number of floors or the proximity to transit infrastructure. This nesting structure compromises the assumption of observational independence, rendering conventional linear regression techniques inadequate. In response, scholars have advocated for the use of multi-level modelling to better account

Vol: 16 **No:** 4 **Year:** 2024 **ISSN:** 2146-0744 (Online) (**pp.**215-231) **Doi:** 10.34109/ijebeg.2024160411

for such data hierarchies (Aguinis et al., 2013; Gelman & Hill, 2006). Supporting this recommendation, Choi et al. (2019) demonstrated the significant influence of both lower-level variables (i.e., housing characteristics) and higher-level variables (i.e., residential environment) on housing prices in Korea.

The second gap pertains to data reliability and contextual specificity within the Thai property market. Given the strategic importance of pricing in marketing, firms are generally reluctant to disclose the methods underpinning their pricing strategies. Consequently, relying on survey instruments targeting real estate professionals may not produce valid or reliable data. To circumvent this limitation, numerous studies have instead utilised pricing data extracted from online property listings (Dai & Güleryüz, 2019; Dziauddin, 2019). While the accuracy and granularity of such data have reportedly improved, the procedures involved in data harvesting remain largely undocumented. Moreover, limited academic attention has been paid to the pricing of newly constructed condominiums in Bangkok, particularly in relation to building-level characteristics or proximity to mass transit (Sirikolkarn, 2008; Tochaiwat, 2020). Given the pressing need for empirical evidence in this domain, the primary objective of the present study was to apply a multi-level analytical approach to web-sourced data, with the aim of identifying which variables—carefully selected from the categories of unit features and building attributes—significantly influence listed condominium prices. In this framework, unit features are conceptualised as nested within building-level attributes. The remainder of the paper is structured into five main sections. The next section provides a review of relevant literature on condominium pricing. This is followed by the methodology, which outlines data acquisition and preparation for multi-level modelling. The results are presented in the third section, with the final two sections offering the discussion and conclusion.

LITERATURE REVIEW

The number of newly developed condominium projects is recognised as a significant indicator of economic health. The methods adopted in pricing condominium units for sale are particularly critical in the housing market, as they directly affect affordability for prospective homebuyers (Hwang & Quigley, 2004). Despite the inherently illiquid nature of real estate, condominium valuations continue to influence both business operations and international market dynamics (Paramati & Roca, 2019). A wide array of factors underpins these prices, typically categorised into two main groups. The first group pertains to the unit's intrinsic characteristics, including gross floor area, whether the unit is fully furnished, and the number of bedrooms. The second encompasses the building's locational context, such as proximity to commuter train stations or the presence of shared facilities like swimming pools.

Vol: 16 **No:** 4 **Year:** 2024 **ISSN:** 2146-0744 (Online) (**pp.**215-231) **Doi:** 10.34109/ijebeg.2024160411

Numerous studies have affirmed that unit-specific features significantly influence listed prices. For example, Lowrance (2015) demonstrated that interior design plays a crucial role in shaping pricing in the New York housing market. Similarly, Kaya and Atan (2014), drawing on data from a Turkish bank, established a significant relationship between the number of bedrooms and house prices in Turkey. In Bangkok, Tochaiwat (2020) confirmed the number of bedrooms to be a decisive factor in the pricing of second-hand condominium units. Room size was also highlighted as a notable determinant in pricing new condominiums in the city (Sirikolkarn, 2008). Regression analysis by Tochaiwat et al. (2017) further validated the role of unit characteristics in pricing, although the study focused on the second-hand market and did not provide detailed information regarding data collection procedures. Other notable influences on pricing in Bangkok include parking capacity and the availability of fitness centres (Chullabodhi et al., 2020), though it remains unclear whether these studies considered listed prices or final transaction values. Research by (Pitt et al., 2016), focusing on studio-type condominiums in Bangkok, found that various spatial configurations, including living area, dining space, and corridor dimensions, contributed significantly to listed prices. Using price data obtained from Booli Search Technologies, Dai and Güleryüz (2019) corroborated the positive influence of the number of building floors on unit prices, though the total unit count within buildings did not yield significant results.

RESEARCH METHODOLOGY

Data Preparation

Given that the principal aim of this research is to apply a multi-level analytical approach to determine whether ten selected variables significantly influence the listed prices of newly developed condominium units in Bangkok, Thailand, a quantitative methodology has been adopted. The unit of analysis is defined as an individual newly listed condominium unit. Among the ten independent variables considered in this study, two (designated as X1 and X2 in Table 1) are classified under level one, representing lower-level attributes of individual units. The remaining eight variables fall under level two, reflecting higher-level characteristics associated with the broader context of the building or its location. To collect the relevant data, a Python-based web scraping tool was developed and utilised to systematically extract listing information from a real estate website. Although the identity of the website is intentionally withheld as part of the research protocol, it is recognised among the top ten online property platforms in Thailand (Umbelina, 2019). This platform serves as an intermediary, facilitating transactions between property owners and potential buyers.

Vol: 16 **No:** 4 **Year:** 2024 **ISSN:** 2146-0744 (Online) (**pp.**215-231) **Doi:** 10.34109/ijebeg.2024160411

Table 1: Definitions of Key Variables

Variables	Definitions
Dependent Variables	
Y: Listed Price of Condominium Units (Baht)	The price of a condominium listed for sale on the website.
Independent Variables	
Level-One (Room) Variables	
X1: The Number of Bedrooms	The total number of bedrooms in the unit for sale.
X2: The Number of Bathrooms	The total number of bathrooms in the unit for sale.
Level-Two (Building) Variables	
X3: The Number of Floors	The total number of floors in the building where the condominium is listed for sale.
X4: The Number of Condominium Units	The total units of condominiums in the building where the unit is listed.
X5: Percentage of Parking (%)	The number of parking spots divided by the total number of condominium units.
X6: Availability of a Swimming Pool	Whether the project has a common pool which residents can use.
X7: Availability of Fitness Facilities	Whether the project has common fitness facilities which residents can use.
X8: Availability of a Business Room	Whether the project has a common business area to serve its residents.
X9: Walking Distance to the Nearest Station	The walking distance from the building to the nearest station on a commuter train line (km).
X10: Euclidean Distance to the Nearest Station	The direct distance (or displacement) from the building to the nearest station on a commuter train line (km).

The Python-based crawler was programmed to access the "new condominiums" section of the selected real estate platform, retrieving all entries advertising newly available condominium units from November 2021 through January 2022. From the full set of extracted listings, the dataset was refined to include only those condominium buildings that had three or more units listed for sale. This selection criterion is supported by sample size recommendations in previous literature (Asparouhov, 2006; McNeish & Stapleton, 2014), which emphasise the need for adequate variability within lower-level data (individual sale units) nested within each higher-level group (the respective buildings) to ensure reliable analysis. Although the multi-level modelling technique is suited for hierarchical data structures, it is not without its challenges. One of the primary limitations lies in its reduced capacity to account for the variation among lower-level observations within a single higher-level entity, which may impose constraints on its implementation. Orford (2000) describes this as the contextualisation limitation of regression models which, while effective in handling spatial autocorrelation, may limit the generalisability of multi-level techniques when sample diversity is insufficient.

Upon completion of data extraction, a total of 1,372 new condominium units were successfully recorded, distributed across 303 buildings. This implies that 303 of the total units serve as building-level anchors, while the remaining 1,069 units share those same contextual attributes, suggesting interdependence among observations. Nonetheless, the total number of observations meets the adequacy threshold for multi-level modelling as established by McNeish and Stapleton (2014). The collected listing details enabled us to identify and record for each unit its listed price (Y), number of bedrooms (X1), number of bathrooms (X2), total number of floors in the building (X3), total number of units in the project (X4), parking availability expressed as a percentage (X5), and the presence of shared amenities such as a swimming pool (X6), a fitness facility (X7), or a business room (X8). Moreover, using the geographical coordinates (latitude and longitude) of each building, we computed two measures of distance to the nearest commuter train station: walking distance (X9) and straight-line (Euclidean) distance (X10).

Data Analysis

Alongside the descriptive statistics generated for all variables, the results of the multi-level analysis were reported to identify which variables significantly accounted for the variation in the listed prices of newly built condominiums. The analytical procedure was carried out in three primary stages. The initial step focused on assessing the suitability of the multi-level modelling approach by employing two diagnostic tools: the intraclass correlation coefficient (ICC) and the likelihood ratio (LR) test (Hoffman, 2015). Specifically, the ICC was calculated based on the empty means and random intercept model (often referred to as the baseline model), and it quantified the proportion of variance in listed prices attributable to differences between buildings relative to the overall variance. The formulation of this concept is illustrated in Equation (1).

$$ICC = \frac{Between - Building\ Variation}{Between - Building\ Variation + Within\ Building\ Variation} = \frac{\tau_{U_0}^2}{\tau_{U_0}^2 + \sigma_e^2} \quad \ldots (1)$$

Where:

σ_e^2 = The Variance within Building
$\tau_{U_0}^2$ = The Variance between Buildings

In the second step, the value of the ICC obtained from the basic model was interpreted as the proportion of total variance in listed prices that could be attributed to differences between buildings. This statistic was instrumental in determining whether incorporating a random effect was justified within the model. The LR test was then conducted to assess whether the multi-level model, which includes random effects, provided a better fit to the data compared to a traditional fixed effect model. A statistically significant LR test outcome indicated that the multi-level model offered superior explanatory power over the fixed effect alternative (Hoffman, 2015). Additionally, both fixed and random effects were estimated, allowing for an assessment of lower-level direct effects as well as cross-level direct effects, following the specifications outlined in Equations (2) and (3). The final step of the analysis involved evaluating whether any of the selected independent variables had a statistically significant influence on the listed prices of condominium units.

Level 1: $\ln(Y_{ij}) = \beta_{oj} + \beta_{1j}X1_j + \beta_{2j}X2_j + e_{ij}$ ... (2)

Level 2: $\beta_{oj} = \gamma_{oo} + \gamma_{o1}X3_j + \gamma_{o2}X4_j + \gamma_{o3}X5_j + \gamma_{o4}X6_j + \gamma_{o5}X7_j + \gamma_{o6}X8_j + \gamma_{o7}X9_j + \gamma_{o8}X10_j + U_{oj}$ ... (3)

Where:
Yij = A Listed Price of the Condominium Unit i in the Building j
e_{ij} = A Room-Specific and Building-Specific Within-Building Residual
U_{0j} = A Random Intercept

RESULTS

Table 2 presents the distribution of observed condominium units according to the number of bedrooms. As anticipated, units with one bedroom constitute the largest proportion, accounting for 40.0% of the total. It is important to highlight two key points: first, 317 out of the 1,372 observed listings did not specify the number of bedrooms; and second, the penthouse category is included based on the classification provided by the sellers, although this type may comprise three or more bedrooms.

Table 2: Observed Condominium Units, Classified by Bedroom Counts (n=1,055 due to 317 entries missing data)

Number of Bedrooms	Counts (%)
Studio	117 (11.1)
One	422 (40.0)
Two	329 (31.3)
Three	105 (9.9)
Penthouse	69 (6.5)
Four or More	13 (1.2)
Total	1,055 (100)

Table 3 illustrates the number of condominium units categorised by their nearest commuter train station. Given the relative length of the train lines, it is unsurprising that the majority of the observed listings are located along the green line, while the smallest proportion is situated near the ARL.

Vol: 16 No: 4 Year: 2024 ISSN: 2146-0744 (Online) (pp.215-231) Doi: 10.34109/ijebeg.2024160411

Table 3: Observed Condominium Units Classified by Proximity to the Nearest Station of One of the Four relevant Bangkok Commuter Train Lines

Commuter Train Lines	Total Number of Stations on the Relevant Line that were Close to Buildings Included in the Study (%)	Total Number of Observed Units Listed (%)
Airport Rail-Link	5 (7.7)	103 (7.5)
Blue Line	15 (23.1)	288 (21.0)
Green Line	31 (47.7)	634 (46.2)
Purple Line	14 (21.5)	347 (25.3)
Total	65 (100)	1,372 (100)

As indicated in Table 4, the mean listed price of the sampled condominium units was 10.37 million baht. On average, these units featured 1.64 bedrooms and 1.53 bathrooms. At the building level, the average number of floors was 25.64, with each building comprising approximately 541.87 units. The average ratio of available parking spaces to the total number of units stood at 58.52%.

Table 4: Descriptive Statistics or Quantitative Variables (n=1,372)

Variables	Mean	Standard Deviation	Minimum Value	Maximum Value	Skewness	Kurtosis
List Price (Baht): Y	10,372,083.92	22,858,828.149	638,000	315,000,000	6.83	61.76
The Number of Bedrooms: X1	1.64	0.826	1	6	1.43	2.52
The Number of Bathrooms: X2	1.53	0.890	1	7	2.26	6.62
The Number of Floors: X3	25.64	16.173	5	77	0.59	0.01
The Number of Units: X4	541.87	513.722	30	3036	1.71	2.97
Percentage of Parking (%): X5	58.52	30.787	16	232	2.10	6.49
Walking Distance to the Nearest Train Stations (km): X9	1.42	1.374	0.05	10.40	2.57	9.56
Euclidean Distance to the Nearest Train Stations (km): X10	0.81	0.676	0.05	2.97	1.47	1.53

Furthermore, the average walking distance from the observed condominium buildings to the nearest commuter train station was 1.42 kilometres, while the average straight-line (Euclidean) distance was 0.81 kilometres. The distributions of three binary variables—namely, the availability of a swimming pool, a fitness facility, and a business room—are summarised in Table 5. Nearly all buildings offered a swimming pool (94%) and a fitness facility (99%), whereas fewer than 10% provided a business room.

Table 5: Frequency Distribution of Dichotomous Variables

Variables	Frequency (%)
Availability of a Swimming Pool (X6)	No (6%)
	Yes (94%)
Availability of a Fitness Facility (X7)	No (1%)
	Yes (99%)
Availability of a Business Room (X8)	No (91%)
	Yes (9%)

Table 6 reports the Pearson correlation coefficients (r), the majority of which were statistically significant, thereby supporting the rationale for including these variables in the model to examine their ability to explain the listed prices of newly developed condominium units in Bangkok.

Although the dataset was compiled from 303 buildings, each comprising a minimum of three units listed for sale, the mean number of units per building was 4.52. Consequently, while unit-level features such as the number of bedrooms remain independent across the total of 1,372 condominium units, locational characteristics (for instance, the distance to the nearest commuter train station) exhibit interdependence, as they are shared by units within the same building. This dependence among observations, combined with the hierarchical structure of the data, would have potentially breached the core assumptions of conventional regression techniques had they been applied (Pedhazur & Schmelkin, 1991). Therefore, a multi-level modelling approach was adopted. Supporting this choice, the calculated ICC of 0.79 confirms considerable variance between buildings, underscoring the appropriateness of the multi-level method over traditional regression. The precise ICC metrics are detailed in the subsequent section.

The multi-level analysis conducted on the 1,372 condominium units yielded two principal findings. First, in assessing the suitability of the multi-level model, an empty-means random intercept model was estimated using maximum likelihood estimation. The outputs of this model are presented in Table 7. The variance of the level-two random intercept $\tau_{U_0}^2$ was estimated at 0.789, while the level-one residual variance σ_e^2 was calculated as 0.206. These values yield an ICC of 0.79. This indicates that 79% of the total variance in listed condominium prices is attributable to differences between buildings, reflecting the consistent mean variations across projects. The remaining 21% is explained by within-building variation, representing deviations from the project-specific averages. To assess whether the ICC of 0.79 is statistically different from zero, a likelihood ratio test was conducted. The resulting test statistic was 1,461.77, with a p-value below 0.01, demonstrating that the inclusion of the random intercept significantly enhances model fit when compared to a model that includes only fixed effects. These findings confirm the necessity of employing a multi-level model that accounts for

Vol: 16 **No:** 4 **Year:** 2024 **ISSN:** 2146-0744 (Online) (**pp.**215-231) **Doi:** 10.34109/ijebeg.2024160411

random effects.

Table 6: Correlation Matrix (* Significant at the Level of .05 or Less)

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
List Price (Baht): Y	.486*	.508*	.311*	-.161*	.553*	.224*	.025	.036	-.246*	-.141*
The Number of Bedrooms: X1	1	.767*	.143*	-.127*	.314*	.109*	.047	.047	-.056*	-.062*
The Number of Bathrooms: X2		1	.177*	-.147*	.368*	.076*	.007	.026	-.059*	-.058*
The Number of Floors: X3			1	.312*	.301*	.226*	-.003	.191*	-.279*	-.237*
The Number of Units: X4				1	-.194*	.137*	.009	.042	-.024	.037
Percentage of Parking (%): X5					1	.128*	.009	.176*	.200*	-.154*
Availability of a Swimming Pool: X6						1	.162*	.075*	-.097*	.075*
Availability of a Fitness Facility: X7							1	-.029	-.004	-.029
Availability of a Business Room: X8								1	-.082*	-.094*
Walking Distance to the Nearest Train Stations (km): X9									1	.706*
Euclidean Distance to the Nearest Train Stations (km): X10										1

Second, the inferential results from the multi-level model are summarised in Table 7. As anticipated, several variables exhibited positive associations with the listed price of condominium units, including the number of bedrooms, number of bathrooms, total floor count, and the proportion of parking spaces. Conversely, an inverse relationship was observed for the total number of units and the walking distance to the nearest station. Moreover, units within developments offering a swimming pool were priced higher on average than those in buildings without this feature. However, the availability of a fitness centre, business room, or the Euclidean distance to the nearest commuter train station did not display a significant relationship with unit price. Notably, the positive correlation between floor count and price, alongside the negative association between unit count and price, suggests that higher-rise buildings with fewer total units may attract premium pricing. These implications are further elaborated in the Discussion and Conclusion sections.

Vol: 16 **No:** 4 **Year:** 2024 **ISSN:** 2146-0744 (Online) (**pp.**215-231) **Doi:** 10.34109/ijebeg.2024160411

Table 7: Results from a Multilevel Model

	Empty Means and Random Effect Model		**Full Model**	
	Coefficient (SE⁺)	**T-Value**	**Coefficient (SE⁺)**	**T-Value**
γ_{oo}	15.478 (0.053)	292.21	13.556 (0.224)	60.47
The Number of Bedrooms: X1			0.297 (0.023)	12.81
The Number of Bathrooms: X2			0.203 (0.024)	8.59
The Number of Floors: X3			0.014 (0.002)	6.58
The Number of Units: X4			-0.0004 (0.000067)	-5.56
Percentage of Parking (%): X5			0.012 (0.001)	10.52
Availability of a Swimming Pool: X6			0.481 (0.145)	3.30
Availability of a Fitness Facility: X7			-0.072 (0.204)	-0.35
Availability of a Business Room: X8			-0.191 (0.097)	-1.97
Walking Distance to the Nearest Train Station (km): X9			-0.112 (0.029)	-3.87
Euclidean Distance to the Nearest Train Station (km): X10			0.009 (0.055)	0.16
$\tau^2_{U_0}$	0.789 (0.069)		0.156 (0.016)	
σ^2_e	0.206 (0.009)		0.101 (0.005)	

* $p<0.05$, ⁺ SE Stands for Standard Error

DISCUSSION

This study set out to examine whether nine selected variables, encompassing unit-level and building-level characteristics, could significantly account for variations in the listed prices of condominium units by employing a multi-level analytical approach. Through a programmed script, data were extracted on the listed prices of 1,372 condominium units available for sale via a well-established real estate platform. Among the sampled units, the most prevalent configuration was one-bedroom units, comprising 40.0% of the sample, followed by two-bedroom units at 31.3%. These findings are consistent with prior surveys which reported the predominance of one-bedroom condominiums in the Bangkok market (DDproperty, 2017). As illustrated in Table 4, the average asking price for the observed units was approximately 10.3 million baht. The 303 buildings sampled had an average height of 25.64 floors and contained, on average, 541.87 units per building. Additionally, more than 94% of these units were located in developments featuring swimming pools or fitness centres, whereas fewer than 10% were in buildings that included a shared business space. Regarding accessibility, the average walking distance to the nearest commuter train station was 1.42 kilometres, with an average straight-line (Euclidean) distance of 0.81 kilometres. The green line accounted for the highest proportion of units (46.2%), which is to be expected given that it was the first commuter line operational in the network since its launch in 1999 (Vichiensan et al., 2021). Overall, the observed condominium features align well with those documented in earlier studies of the Bangkok real estate market (Kulkosa, 2016; Pimon, 2023), supporting the representativeness of the sample.

Analysis of the dataset reveals two notable features. First, the structure of the data is inherently hierarchical: unit-level attributes such as the number of bedrooms and bathrooms are nested within building-level factors, including parking provisions and proximity to train stations. This data arrangement substantiates the use of a multi-level modelling technique over traditional regression. Second, the ICC value of 0.79 further validates this methodological decision, indicating that a substantial share of the total variance in listed prices originates from differences between buildings. Despite the suitability of the data structure for multi-level analysis, several limitations should be acknowledged, particularly those related to the method of data collection. The use of a web crawler introduced two primary concerns. First, the reliability of the data depends on the credibility of the source. This was addressed by selectively harvesting information from a highly regarded real estate website and implementing stringent data cleaning protocols to ensure acceptable quality standards. Second, the data reflect a single time frame, thus providing a static view of market conditions. Although data integrity was ensured, the temporal limitation means that market dynamics may not be fully captured. It is therefore recommended that future studies replicate this approach across multiple periods to assess the consistency of findings.

Three principal insights emerge from the multi-level analysis. First, six of the independent variables demonstrated statistically significant positive relationships with the listed prices, a result consistent with previous literature (Tangmanee, 2023; Xiao et al., 2019). Specifically, the number of bedrooms, number of bathrooms, availability of parking, and presence of a communal swimming pool were all positively associated with higher prices, reinforcing earlier findings (Lowrance, 2015; Tochaiwat, 2020). In metropolitan contexts, proximity to commuter train infrastructure is a key consideration for buyers, which explains the observed negative correlation between walking distance to the nearest station and unit price (Xiao et al., 2019). Shorter distances typically translate into increased market value due to enhanced accessibility.

Second, a nuanced pattern emerged in relation to building-level features: while the total number of floors was positively correlated with unit prices, the total number of units showed a negative association. These results suggest that units in high-rise buildings with fewer total units tend to command higher asking prices compared to those in lower-rise developments with greater unit density. This trend may be explained by several factors. High-rise buildings frequently offer superior panoramic views, which are often valued at a premium, particularly in dense urban areas. Moreover, upper-floor units are frequently perceived as more prestigious, which further elevates their market value. The construction of tall buildings also involves higher development costs due to the need for sophisticated engineering solutions and luxury facilities, which may be reflected in the pricing of units (Patni & Sadhu, 2023). Although limited research has addressed the influence of building typologies on pricing structures, this study potentially offers a valuable contribution to this underexplored area.

Third, the lack of significance for variables representing the presence of a fitness centre or a shared business lounge in determining listed prices was unexpected. Developers often incorporate fitness amenities to enhance a project's market appeal, and earlier empirical work has reported positive effects of such facilities on residential pricing (Chullabodhi et al., 2020; Tajima, 2019). However, this was not corroborated by the current findings. As relevant literature offering comparable results was not identified, the interpretation of these outcomes remains speculative. One plausible explanation lies in the binary measurement of these amenities, which, coupled with limited variability (see Table 5), may have diminished their explanatory power. In particular, with fewer than 10% of buildings offering business lounges, the scarcity of this feature may have contributed to its statistical insignificance in price determination.

CONCLUSION

A total of 1,372 condominium units in Bangkok, Thailand, were examined in this study. The unit listings, along with relevant details concerning unit and building characteristics, were collected from a single real estate platform through the use of a Python-based data extraction script. From these data, ten variables were identified—two relating specifically to individual units and the remainder associated with building-level features. Due to the nested nature of the data, where units are grouped within buildings, the use of a multi-level analytical approach was deemed more suitable than conventional regression analysis, which assumes independence across observations. The multi-level analysis produced several key findings. It was determined that seven of the ten variables significantly influenced listed prices. The number of bedrooms, number of bathrooms, building height (in terms of storeys), the proportion of available parking, and the presence of a communal swimming pool were all positively associated with higher prices. Conversely, the total number of units within a building and the walking distance to the nearest commuter train station were negatively related to pricing. The remaining three variables—availability of a fitness facility, presence of a business room, and the direct distance to the nearest train station—were not found to significantly affect the listing prices.

This study offers two important contributions. The first is theoretical. The hierarchical structure of the data highlights the limitations of traditional regression and supports the adoption of multi-level modelling as a more appropriate method for analysing such datasets. Through this approach, two insights emerge. First, the physical design of buildings appears to influence pricing. Specifically, units in taller buildings with fewer overall units are typically listed at higher prices. This suggests that building configuration may be a factor in perceived value and could be deliberately leveraged by developers. Second, while direct distances to train stations did not have a significant effect, walking distance did. This suggests that actual accessibility on foot may be more relevant to buyers than geometric proximity alone. The second contribution is practical and addresses the interests of two stakeholder groups. For developers, the findings offer guidance on pricing strategies. In particular, attention should be given to building height and total unit count, as both have a measurable impact on pricing. Optimising these aspects may enhance the appeal and market competitiveness of new developments. For prospective buyers, the results provide a framework to assess whether listed prices align with key structural and locational attributes. Buyers may find it useful to evaluate the floor count and overall building density when considering the value of a particular unit.

One limitation of the study relates to the data collection method. Although efforts were made to ensure the accuracy and completeness of the extracted data, inconsistencies in webpage formatting may have resulted in the omission of certain details. While units may appear uniformly displayed, differences in their underlying structure could have affected data capture. This constraint should be taken into account when interpreting the study's findings.

REFERENCES

Aguinis, H., Gottfredson, R. K., & Culpepper, S. A. (2013). Recommendations for estimating cross-level interaction effects using multilevel modeling. Academy of Management Proceedings, https://doi.org/10.5465/ambpp.2013.10839abstract

Asparouhov, T. (2006). General multi-level modeling with sampling weights. *Communications in Statistics—Theory and Methods*, *35*(3), 439-460. https://doi.org/10.1080/03610920500476598

Bahamid, R. A., Doh, S. I., Khoiry, M. A., Kassem, M. A., & Al-Sharafi, M. A. (2022). The current risk management practices and knowledge in the construction industry. *Buildings*, *12*(7), 1016. https://doi.org/10.3390/buildings12071016

Bhor, V. B., Gaikwad, M. S., & Zende, P. S. (2020). Implementation of housing price prediction. *International Journal of Innovative Research in Technology*, *6*(11), 118-122. https://www.academia.edu/42686072

Cassetti, E. (1992). The dual expansion method: an application for evaluating the effect of population growth on development. *Applications of the Expansion Method*, 10-41. http://dx.doi.org/10.4324/9780203405383

Choi, Y., Seo, M. J., & Oh, S. H. (2019). The correlates between walkable environments and housing price using multi-level model. *KSCE Journal of Civil Engineering*, *23*(10), 4516-4524. https://doi.org/10.1007/s12205-019-1894-0

Chullabodhi, C., Chalermpong, S., Ratanawaraha, A., & Kato, H. (2020). Assessing minimum parking requirements and parking capacities of residential development in the bangkok metropolitan region. *Transportation Research Record*, *2674*(11), 593-605. https://doi.org/10.1177/0361198120947716

Dai, E., & Güleryüz, L. (2019). Factors that influence condominium pricing in Stockholm: A regression analysis: A regression analysis. In.

DDproperty. (2017). How Consumers View Each Of Bangkok's Condo Segments. https://www.ddproperty.com/en/property-news/2017/4/150528/how-consumers-view-each-of-bangkoks-condo-segments

Dziauddin, M. (2019). An Investigation of Condominium Property Value Uplift around Light Rail Transit Stations Using a Hedonic Pricing Model. IOP Conference Series: Earth and Environmental Science, http://dx.doi.org/10.1088/1755-1315/286/1/012032

Gelman, A., & Hill, J. (2006). *Data analysis using regression and multilevel/hierarchical models*. Cambridge university press. http://dx.doi.org/10.1017/CBO9780511790942

Hoffman, L. (2015). *Longitudinal analysis: Modeling within-person fluctuation and change*. Routledge. https://doi.org/10.4324/9781315744094

Hwang, M., & Quigley, J. M. (2004). Selectivity, quality adjustment and mean reversion in the measurement of house values. *The Journal of Real Estate Finance and Economics*, *28*, 161-178. https://doi.org/10.1023/B:REAL.0000011152.40485.12

Kaya, A., & Atan, M. (2014). Determination of the factors that affect house prices in Turkey by using hedonic pricing model. *Journal of Business Economics and Finance*, *3*(3), 313-327. https://dergipark.org.tr/en/pub/jbef/issue/32410/360453#article_cite

Kulkosa, T. (2016). A hedonic pricing analysis: Evaluating prices of Bangkok's new condominiums along BTS Skytrain. *Master), Thammasat University. Retrieved from http://ethesisarchive. library. tu. ac. th/thesis/2016/TU_2016_5702042077_5533_4047. pdf.* https://ethesisarchive.library.tu.ac.th/thesis/2016/TU_2016_5702042077_5533_4047.pdf

Liang, X., Liu, Y., Qiu, T., Jing, Y., & Fang, F. (2018). The effects of locational factors on the housing prices of residential communities: The case of Ningbo, China. *Habitat International*, *81*, 1-11. https://doi.org/10.1016/j.habitatint.2018.09.004

Li, X., Wang, C., & Ding, L. (2020). A hybrid deep learning approach for analyzing residential housing prices. *Neural Computing and Applications, 32*, 11299–11312. https://doi.org/10.1007/s00521-019-04538-z

Lowrance, R. E. (2015). *Predicting the market value of single-family residential real estate*. New York University. https://cs.nyu.edu/media/publications/lowrance_roy.pdf

McNeish, D. M., & Stapleton, L. M. (2014). The effect of small sample size on two-level model estimates: A review and illustration. *Educational Psychology Review*, *28*, 295-314. https://doi.org/10.1007/s10648-014-9287-x

Orford, S. (2000). Modelling spatial structures in local housing market dynamics: A multilevel perspective. *Urban Studies*, *37*(9), 1643-1671. https://doi.org/10.1080/00420980020080301

Paramati, S. R., & Roca, E. (2019). Does tourism drive house prices in the OECD economies? Evidence from augmented mean group estimator. *Tourism Management*, *74*, 392-395. https://doi.org/10.1016/j.tourman.2019.04.023

Patni, S., & Sadhu, V. K. K. (2023). Investigating Cost Overrun Factors in High-Rise Housing Projects in India. *The Asian Review of Civil Engineering*, *12*(1), 29-33. https://doi.org/10.51983/tarce-2023.12.1.3666

Pedhazur, E. J., & Schmelkin, L. P. (1991). *Measurement, design, and analysis: An integrated approach (Student ed.).Lawrence Erlbaum Associates, Inc.* https://psycnet.apa.org/record/1991-98078-000

Pimon, T. (2023). Startling: What's the average Cost of a Bangkok Condo in 2023. https://www.fazwaz.com/advice/startling-whats-the-average-cost-of-a-bangkok-condo-in-2023

Pitt, M., Chotipanich, S., Issarasak, S., Mulholland, K., & Panupattanapong, P. (2016). An examination of facility management, customer satisfaction and service relationship in the Bangkok healthcare system. *Indoor and Built Environment*, *25*(3), 442-458. https://doi.org/10.1177/1420326X14555420

Sirikolkarn, P. (2008). The effect of mass transit systems on price of condominium in Bangkok. *Undergraduate Honor Thesis, Department of Economics University of California Berkeley*. https://econ.berkeley.edu/sites/default/files/peson_sirikolkarn_thesis.pdf

Tajima, K. (2019). Shared amenities' impacts on condominium resale values. *International Journal of Housing Markets and Analysis*, *13*(2), 281-297. https://doi.org/10.1108/IJHMA-03-2019-0038

Tangmanee, C. (2023). An Empirical Study on the Factors Driving the Pricing of New Condominiums in Proximity to Bangkok Commuter Train https://doi.org/10.33168/JSMS.2023.0617

Systems. *Journal of System and Management Sciences*, *13*(6). https://doi.org/10.33168/JSMS.2023.0617

Techakumphu, J. (2015). Legal problems involving mixed-use condominium in one building. *Thammasat Business Law Journal*, *5*. https://so05.tci-thaijo.org/index.php/TBLJ/article/view/112481

Tochaiwat, K. (2020). *Hedonic price model of secondhand condominium units in Bangkok*. International Transaction Journal of Engineering, Management, & Applied …. http://dx.doi.org/10.14456/ITJEMAST.2021.1

Tochaiwat, K., Likitanupak, W., & Kongsuk, S. (2017). Location selection models for low-rise condominium development in bangkok. *Veridian E-Journal, Silpakorn University (Humanities, Social Sciences and arts)*, *10*(5), 266-280. https://www.researchgate.net/publication/322220371

Umbelina, J. (2019). Thailand property portals ranking by traffic in July 2019. https://www.linkedin.com/pulse/thailand-property-portals-ranking-traffic-july-2019-joseba-umbelina

Vichiensan, V., Wasuntarasook, V., Hayashi, Y., Kii, M., & Prakayaphun, T. (2021). Urban rail transit in Bangkok: Chronological development review and impact on residential property value. *Sustainability*, *14*(1), 284. https://doi.org/10.3390/su14010284

Xiao, Y., Hui, E. C., & Wen, H. (2019). Effects of floor level and landscape proximity on housing price: A hedonic analysis in Hangzhou, China. *Habitat International*, *87*, 11-26. https://doi.org/10.1016/j.habitatint.2019.03.008