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Google Maps amenities and condominium prices: Investigating the effects and relationships using machine learning

Viriya Taecharungroj

Mahidol University International College, 999 Phutthamonthon 4 Road, Salaya, Nakhon Pathom, 73170, Thailand

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ABSTRACT

Neighbourhood amenities significantly impact condominium prices and attract population to the area. Despite evidence of improved accuracy, studies that use machine learning to assess the effects of amenities on condominium prices are limited. The purpose of this research is to investigate the relationship between neighbourhood amenities and the prices of 500 condominiums in Bangkok, Thailand using data from Google Maps. An eXtreme gradient boosting (XGB) algorithm identified 36 important amenity factors, while the multiplicity of relationships between amenities and condominium prices as *bounded positive, accelerated positive, limited positive, humped* and *negative* was elucidated. Results showed that the popularity and other features of amenities drive condominium prices in several non-linear ways, while an attractive urban environment requires multiple amenities. Public and private organisations in Bangkok should collaborate to develop integrative plans that improve and sustain the diversity and availability of urban amenities.

1. Introduction

Condominiums are examples of high-density buildings that can improve city sustainability by reducing urban expansion into natural ecosystems and improving energy efficiency (Belcher, Suen, Menz, & Schroepfer, 2019). Condominiums provide functional, emotional and social benefits to their owners, while their locations offer accessibility to economic opportunities and *urban amenities* (G. Rosen & Walks, 2013). Agglomerations of amenities have become increasingly valued by the public due to the convenience of pedestrian life (Hidalgo, Castañer, & Sevtsuk, 2020). They also attract the creative class to the city, leading to growth of metropolitan areas (Li, Wei, & Wu, 2019). As such, amenities were found to influence housing and real estate prices. A comprehensive understanding of how urban amenities and the environment affect patterns and dynamics of condominium prices can improve sustainable city planning and housing policies (Hu et al., 2019).

The *hedonic approach* is favoured to quantify the effects of urban amenities on housing prices by applying linear regression analysis (Crespo & Grêt-Regamey, 2013). However, limitations of this method include the inability to discover non-linear relationships and multicollinearity issues that arise when using numerous explanatory variables (Schläpfer, Waltert, Segura, & Kienast, 2015). These limitations can be overcome through machine learning (ML) as an emerging artificial intelligence (AI)-based technology (Wang & Li, 2019). Compared with the traditional approach, ML algorithms can explore multilevel factor interactions and discover non-linear associations. ML algorithms are also more flexible, with fewer statistical assumptions and no requirement on data distribution (Y. Chen, Liu, Li, Liu, & Xu, 2016; Hu et al., 2019). However, despite evidence of improved accuracy (Abidoye & Chan, 2018; Hong, Choi, & Kim, 2020; McCluskey, Daud, & Kamarudin, 2014; Selim, 2009), few studies have used ML algorithms to assess the effects of amenities on the housing prices (Hu et al., 2019).

The existing literature has many data limitations related to this topic including costly and labour-intensive processes, infrequent update cycles and difficulties in obtaining data from official sources (Y. Chen et al., 2016). Recently, research focus has shifted to utilising open data on the Internet (Hu et al., 2019). With more than a billion active monthly users (Russel, 2019), Google Maps has become the most popular platform containing a large volume of point of interest (POI) information. Some recent studies have utilised POI data to evaluate housing price/rent using digital platforms (Y. Chen et al., 2016) but none have taken advantage of the ubiquitous, recent and rich data source provided by Google Maps.

To fill the gaps in this research lacuna, the first objective was to identify and analyse the important neighbourhood amenities that impacted condominium prices in Bangkok, Thailand using Google Maps and machine learning. Five hundred condominiums in Bangkok were selected. Bangkok is a major metropolitan area in Southeast Asia and

E-mail address: viriya.tae@mahidol.edu.

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recorded significant growth in condominium demand at over six hundred thousand units in 2020 (Suwannatat, 2021). However, a comprehensive understanding of the important neighbourhood amenities that affect condominium demand and prices in Bangkok and Thailand is limited (Bangbon, 2021; Tochaiwat, Likitanupak, & Kongsuk, 2017). The second research objective was to elucidate the relationship characteristics between amenities and condominium prices. Results will assist property developers through an awareness of amenities that increase condominium demand and suggest appropriate neighbourhood amenity development directions for city planners.

2. Literature review

2.1. Factors that influence condominium price and demand

Studies on the factors that affect housing prices and demand originated from *residential location theory* (Ball, 1973) and evolved into the field of *housing/property valuation* (see Binoy, Naseer, Kumar, & Lazar, 2021). Seminal works by Ball (1973) and Richardson, Vipond, and Furbey (1974) outline several broad categories of factors as housing types/characteristics, location including general spatial characteristics, accessibility and environmental quality. While some factors have been widely studied, a comprehensive understanding of the multiplicity of *amenities* — the focus of this research — remains limited.

The first important category of factors that affect housing prices and demand was their *structural* or physical characteristics such as total number of units, year built and number of floors (Belcher et al., 2019; Diao, 2015; Hong et al., 2020; Sunkpho & Ramjan, 2021; Wen & Tao, 2015). Despite being understudied, the *marketing strategy* of developers influenced condominium demand, especially in Bangkok (see Sunkpho & Ramjan, 2021; Wongleedee, 2017), while *location* was also highly important (Bangbon, 2021; Tochaiwat et al., 2017; Wongleedee, 2017). This research summarised three sub-categories of location as *accessibility* to the city, *environmental* characteristics and neighbourhood *amenities*.

Accessibility to the city refers to the distance of the condominium from the central business districts (CBDs). This was found to significantly influence prices (Belcher et al., 2019; Huang, Chen, Xu, & Zhou, 2017; Pettit et al., 2020; G.; Rosen & Walks, 2013; Wen & Tao, 2015). As a city grows geographically, residential areas are connected to CBDs via urban rail transit networks (URTNs) such as the Metro, Subway or the Underground. URTNs provide outlying residential areas with vital accessibility to the city centres. Many studies found a linkage between distance to URTNs and housing price/demand (Belcher et al., 2019; Diao, 2015; Duncan, 2011; Geng, Bao, & Liang, 2015; Krause & Bitter, 2012; Torres, Greene, & Ortúzar, 2013; Wen & Tao, 2015). *Environmental* characteristics refer to locational factors such as air quality, population density, road density, socioeconomic status, crime rate and tax rate (Ball, 1973; Su et al., 2021; Xiao et al., 2017).

2.2. Neighbourhood amenities that affect condominium prices

Neighbourhood amenities are an important locational factor and significantly affect housing prices by attracting population to the area (Adair, McGreal, Smyth, Cooper, & Ryley, 2000; Waltert & Schläpfer, 2010). Following Hu et al. (2019), neighbourhood amenities were categorised as educational, healthcare, natural, commercial, cultural, service facilities and others.

First, *educational facilities* were shown to affect the value of housing (Sadayuki, 2018). Research found that housing prices were influenced by availability, quality and proximity to high schools (Kim, Park, Lee, & Xue, 2015), secondary schools (Belke & Keil, 2018), primary and middle schools (Geng et al., 2015) and kindergartens and colleges (Wen, Zhang, & Zhang, 2014). The availability of *healthcare facilities* also drives housing prices in urban areas (Y. Chen et al., 2016; Liu et al., 2018). Hu et al. (2019) found that distance to the nearest top quality hospital was the most important price driver, while Su et al. (2021) determined that average distance to hospitals significantly affected house rentals.

Various types of *natural amenities* also positively affect housing prices such as green areas (Belcher et al., 2019; Torres et al., 2013), city parks (Ali, Bashir, & Ali, 2015; Jiao & Liu, 2010; Panduro & Veie, 2013; Wu, Ye, Du, & Luo, 2017), forest parks (Czembrowski & Kronenberg, 2016) and wetlands (Schläpfer et al., 2015). *Commercial facilities* are also important price determinants because they reflect economic prosperity and life convenience (Sadayuki, 2018; Torres et al., 2013). Examples of impactful commercial facilities are supermarkets (Geng et al., 2015), retail (Krause & Bitter, 2012; Matthews & Turnbull, 2007), convenience stores and shopping malls (Xiao et al., 2017).

Another important amenity type is *cultural facilities* such as libraries and museums. These were found to be even more important than commercial facilities (Hu et al., 2019). Gyms, sports and entertainment functions and leisure spaces also influence prices (Liu et al., 2018; Su et al., 2021; Wen & Tao, 2015; Xiao et al., 2017). Other important factors impacting housing prices were identified as services, social welfare functions and job opportunities (Hu et al., 2019; Liu et al., 2018).

The conventional *hedonic pricing model* or the *hedonic approach* (Crespo & Grêt-Regamey, 2013) has previously been used to assess the heterogeneity of housing prices. Housing units were divided into factors and the value of the house/condominium was estimated by applying regression analysis (Adair, Berry, & McGreal, 1996; Hu et al., 2019; Richardson et al., 1974; S.; Rosen, 1974). Housing value was estimated by the sum of the value of its combined characteristics (Belcher et al., 2019), while another stream of research assumed spatial heterogeneity and used various models such as global and locally weighted regression to predict prices (Helbich, Brunauer, Vaz, & Nijkamp, 2014).

However, the hedonic approach has major drawbacks including the inability to detect non-linear relationships and multicollinearity issues that arise from the interaction between multiple factors (Ali et al., 2015; Hu et al., 2019). The inability to include many factors limits a comprehensive understanding of the effect of various amenities on housing prices and demand. Without sufficient explanatory variables, some of the included variables may pick up the effects of the “omitted variables” leading to misinterpretation of causal effects (Schläpfer et al., 2015).

2.3. Housing price estimation using machine learning

To overcome these limitations of the traditional approach, machine learning (ML) techniques have recently gained popularity. Unlike traditional approaches, ML techniques do not start an analysis with a model but instead use an algorithm to learn the relationships between predictors and an outcome variable (McCluskey et al., 2014). Data are fed into the algorithm that is typically more rigorous and produces on average more accurate predictions than traditional methods (Abidoye & Chan, 2017). Previous literature details several ML techniques used to predict housing prices such as support vector machines, boosted regression trees, artificial neural network, random forest and gradient boosting trees.

Lam, Yu, and Lam (2009) used support vector machines (SVM) to perform property valuation in Hong Kong using 29 factors, while McCluskey et al. (2014) applied boosted regression trees (BRT) to analyse property prices in Malaysia using 13 factors. Abidoye and Chan (2018) used an artificial neural network (ANN) to predict housing prices in Lagos, while Sunkpho and Ramjan (2021) used deep learning, among other ML algorithms, to estimate condominium prices in Bangkok and Hong et al. (2020) used random forest (RF) to predict apartment prices in Seoul from 21 factors, of which 9 were locational. All these studies included amenity factors but they are not the main focus.

Some studies placed more emphasis on amenity factors. Y. Chen et al. (2016) analysed housing rents using 327,767 records in 67 Chinese cities. They used ensemble learning to accurately predict the rent but did not investigate the importance of each amenity factor. Two notable recent studies assessed differing degrees of importance of amenity factors. Liu et al. (2018) employed gradient boosting regression trees (GBRT) to predict housing prices in Nanjing, China and assessed the importance of structural and amenity factors using 20 categories of POI. To date, the most comprehensive study has been conducted by Hu et al. (2019) who analysed 2 structural, 6 accessibility and 52 amenity factors.

Recent studies have shown that ML can be used to assess the effects of various factors on both housing prices and demand. However, Hu et al. (2019) noted that studies identifying multilevel determinants and their relative importance were limited. Despite the plethora of research on housing prices and property valuation, a comprehensive understanding of the importance of amenities is still in the nascent stage.

One of the main reasons for the limited analysis of various amenities is data gathering (Hu et al., 2019), which can be labour-intensive and time-consuming, especially in developing countries (Taecharungroj, Boonchaiyapruek, & Muthuta, 2019). Recently, open and updated data extraction via social media has overcome this limitation and become a useful data source in this field of research (Hu et al., 2019). Data from electronic platforms could be extracted to approximate housing prices while amenities in the form of points of interest (POIs) can also be retrieved. This access has opened a new avenue for research on the importance of urban amenities. Here, data from Google Maps were retrieved to analyse the importance and relationships of amenities and condominium prices in Bangkok. Such a process facilitates both rapid data collection and insightful analyses of a wide range of amenities. Despite some limitations, Google Maps are an attractive source of information that were used to analyse amenities in previous studies (e.g., Hidalgo et al., 2020).

3. Data and methods

3.1. Data collection and processing

The first step of the research process is data collection (Fig. 1). Condominium price data were collected from ddproperty.com that contained the largest number of condominium listings in Bangkok (>150,000 in May 2021) compared with the two closest competitors, hipflat.com (>70,000) and livinginsider.com (>40,000). A Python script was used to scrape all condominium listings in Bangkok on ddproperty.com in May 2021. All listings were posted and/or updated between April and May 2021. In total, 152,512 listings were collected.

To assess prices, all listings were grouped into individual condominiums. Results identified 1911 condominiums in Bangkok on ddproperty.com. The top 500 condominiums were selected based on the number of listings; higher numbers of listings more closely approximate the actual prices. The numbers of listing ranged from 72 to 915. The author interviewed two industry experts who informed that the actual transaction price was generally closer to the minimum than to the mean or median value. Thus, the price of each condominium was estimated as "the 10th percentile" of the prices per sqm of all listings. Instead of the minimum price per sqm, "the 10th percentile" was used to exclude errors posted by sellers and remove outliers.

Google Maps' POI data were collected within a specified radius from each condominium. The existing literature was reviewed to determine an appropriate radius range of 300–600 m following Chalermpong and Ratanawaraha (2015) and Schläpfer et al. (2015). The neighbourhood radius was set at 400 m because this equated to a 5 min walk catchment area (Pongprasert & Kubota, 2017) and a good range for transit ridership (Guerra, Cervero, & Tischler, 2012). Townsend and Zacharias (2010) also stated that a 400 m radius was sufficient for recording built environmental characteristics.

Data as 96 types of POI[1] within each of the 500 condominium neighbourhoods were collected during June and July 2021 using the "googleway" package in R. Of the 96 POI types, no *light rail station* was recorded in any of the condominium neighbourhoods and this factor was excluded from the analysis. In total, 98,936 unique POIs were collected. Based on studies by Y. Chen et al. (2016) and Hu et al. (2019), important features of amenities were included in the models as (1) the frequency of each type of amenity in the neighbourhood and (2) the distance between the condominium and the nearest amenity of each type. There were two limitations. First, the Google API returned the maximum of 60 POIs of each type; therefore, the frequency of each type of POI was capped at 60. Second, it was not possible to compute the minimum distance between a condominium and a POI that did not exist in the neighbourhood. A radius of 400 m was imputed for missing values.

The Google API also provided information not previously studied in the existing literature — online reviews. Google Maps is the fastest growing online review platform (Mathayomchan & Taecharungroj, 2020) and allows users to leave reviews of POIs. The number of reviews of each POI is significant and can elevate offline *popularity* (Xie, Chen, & Wu, 2016). Therefore, this research also included *the average number of reviews* per *amenity* (*reviews* henceforth) as the third amenity feature in the models.

3.2. Extreme gradient boosting and random forest techniques

Machine learning (ML) was found to be superior to linear regression when assessing housing prices (Hu et al., 2019; Lam et al., 2009). Two ML algorithms — random forest (RF) regression and eXtreme gradient boosting (XGB) regression — were used. RF is a tree-based bagging algorithm that is effective and robust (Hu et al., 2019). It integrates many decision trees into a forest and gives a prediction based on a majority vote (Hong et al., 2020). RF can efficiently analyse a large dataset with many input factors, manage missing and categorical variables, handle unequal distribution and detect interactions and non-linear relationships with no requirement for detailed specification (Hong et al., 2020; Hu et al., 2019; Wang & Li, 2019).

The other algorithm used was XGB. This belongs to a family of boosted tree models. Unlike RF, which randomly and independently produces trees, boosting techniques create trees that are based on the residuals of the previous tree. A prediction is made when trees are built until the residuals are minimal or the maximum number of trees is reached. Wang and Li (2019) found that boosted tree models achieved higher accuracy and were faster than RF. Nevertheless, studies of housing prices using boosted tree models are limited (see McCluskey et al., 2014). XGB is a highly scalable and efficient implementation of a gradient boosting framework (for detail, please see T. Chen et al., 2015). It is faster than the preceding gradient boosting machine (GBM) models, with state-of-the-art predictive results and can be used for a wide variety of solutions (T. Chen & Guestrin, 2016). Therefore, both RF and XGB were selected as good candidates to model this dataset with many imputed and capped values.

Before testing the models, hyperparameter tuning was performed using a "random search" method in the *caret* package in R (Bergstra & Bengio, 2012). The dependent variable of the model was the condominium price, with independent variables as frequency, minimum distance and reviews of the 95 types of amenities — 285 independent variables in total. A hundred random combinations of hyperparameters were tested in each round. A five-fold cross validation was performed to avoid model overfitting and the process was repeated 10 times (Probst, Wright, & Boulesteix, 2019). The best model with the lowest root mean squared error (RMSE) was selected. For the RF model, the optimal *mtry* was 66. The optimal hyperparameters of the XGB model were 0.53 *colsample_bytree*, 0.02 *eta*, 6.32 *gamma*, 7 *max_depth*, 8 min_*child_weight*, 360 *nrounds* and 0.40 *subsample*. These hyperparameters were used in all subsequent models for consistency.

Some structural and accessibility factors were included as control variables. Structural factors — total units of condominium, number of floors, median unit size and year built — were collected from ddpro

[1] https://developers.google.com/maps/documentation/places/web-service/supported_types.

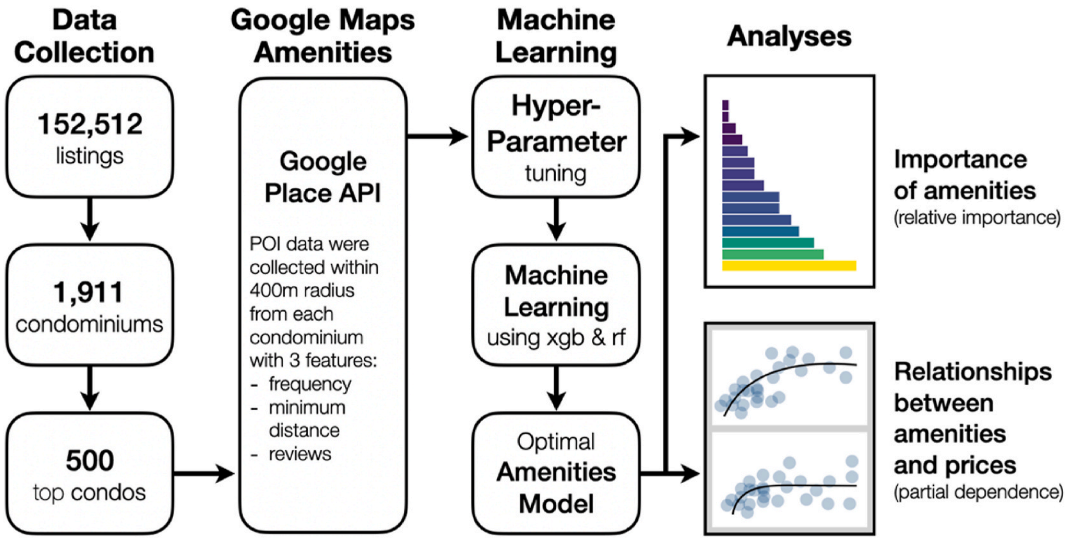

Fig. 1. Research process and methods.

perty.com and cross checked with information from another property listing portal, hipflat.com, for reliability. Accessibility factors included distance to the nearest URTN and the three main CBDs in Bangkok. In this study, the *Haversine method* was used to calculate the distances between two points using the "geosphere" package in R. Seven models were tested as *amenities, structural, accessibility, structural and accessibility, structural and amenities, accessibility and amenities* and *all models*. RMSE, R^2 and mean absolute error (MAE) were calculated as standard indicators of ML performance (Hu et al., 2019):

$$RMSE = \sqrt{\frac{1}{n}\sum (y_{i,o} - y_{i,p})^2}$$

$$R^2 = 1 - \frac{\sum (y_{i,o} - y_{i,p})^2}{\sum \left(y_{i,o} - \bar{y}_o\right)^2}$$

$$MAE = \frac{1}{n}\sum |y_{i,o} - y_{i,p}|$$

where n is the total number of condominiums, $y_{i,o}$ and $y_{i,p}$ are the observed and predicted prices of the *i*th condominium and $\bar{y}_o$ is the average observed price.

3.3. Analyses of amenities

The effects of amenities on condominium prices were represented by their *relative importance*, estimated by how much the prediction error increased when out-of-bag (OOB) data for the amenity was permuted when all others remained unchanged (Hu et al., 2019). The calculations were performed tree by tree as the model was constructed (Liaw & Wiener, 2002). To find the optimal number of factors, the relative importance of the 285 amenity factors in the model was first calculated. Then, the least important factor was removed one at a time to create a new model. In total, 285 models were created and compared using RMSE, R^2 and MAE to select the best *amenities* model. The same process was performed for the *all* model, including other structural and accessibility factors. The relative importance of each amenity on the condominium price was then revealed and ranked.

Next, the relationship between each important amenity and the predicted prices was visualised to observe the similarities and differences. Discovering the non-linear relationships is the key benefit of ML; thus, the *partial dependence* (PD) of each amenity factor was calculated using the "pdp" package in R. PD describes the specific effect of a single factor of condominium prices after accounting for the effects of others (Liu et al., 2018). PD curves assist in comprehensively understanding the interactive and complex relationships among factors (Hu et al., 2019). The LOESS smoothing function was fitted to visualise the trends.

4. Findings

Fig. 2 shows the locations of the 500 selected condominiums and their neighbourhoods within the 400 m radius. Most of the condominiums were concentrated in the city centres. The magnified area shows the three CBDs — *Sathorn, Pleonchit* and *Phromphong*. Some condominiums formed a branch out to the northern part of Bangkok in *Lad Phrao, Huay Kwang* and *Ari*. Many luxurious condominiums were concentrated in the south-eastern area as *Thong Lo*, *Ekkamai*, *Phra Khanong* and *Bang Na*. More expensive condominiums are represented by lighter dots. A number of less expensive condominiums were located in the western part of Bangkok — *Talat Phlu*.

4.1. XGB and RF results

Seven models were created using XGB and RF algorithms, with performances summarised in Table 1. All models produced acceptable performances with R^2 values ranging between 0.49 and 0.78. For both XGB and RF, the worst performing models were accessibility (Model 3), with RMSE of 43,788 and 43,388 respectively. By contrast, the best performing models for both algorithms were the structural and accessibility factors (Model 4), with RMSE of 29,004 (XGB) and 31,425 (RF).

Between structural, accessibility and amenities models, the structural model (Model 2) was the best performer. The amenities model (Model 1) performed slightly better than the accessibility model (Model 3). Model 7 that combined all factors performed worse than the best performing Model 4. More factors generate *noises* which, in turn, reduce model performance and predictability.

Although the performance of Model 1 — the focus of this research — was inferior to some other models, the results were still meaningful. Model 1 separated the effects of neighbourhood amenities from the other factors to better understand their importance. The R^2 value was 0.52 for both XGB and RF, implying that Model 1 explained 52% of the condominium price variance. Results also showed that the performance of XGB was superior to all RF models, except for Model 3. Therefore, further analyses were based on XGB models and results.

The magnitudes of Model 1 and Model 7–285 and 293 factors respectively, were further fine-tuned to determine the optimal factor

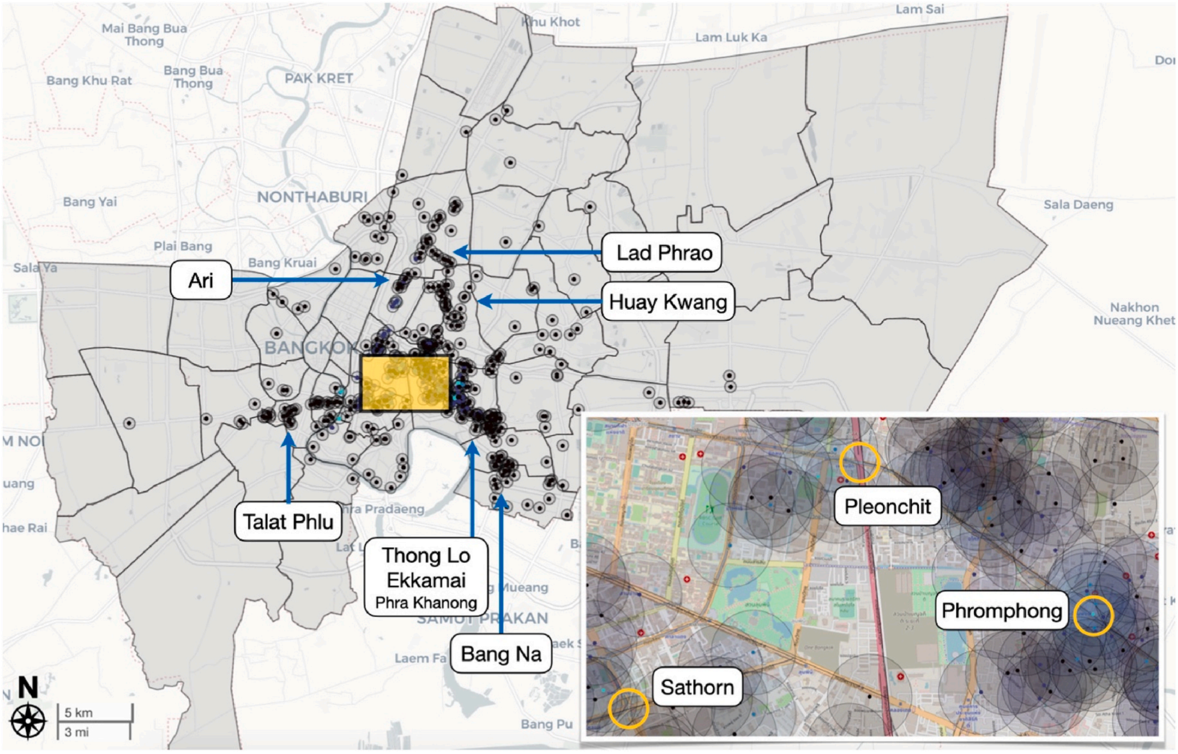

Fig. 2. Five hundred condominium locations and neighbourhoods.

Table 1
Model performance: XGB and RF.

No	Model	Extreme Gradient Boosting			Random Forest		
		RMSE	R^2	MAE	RMSE	R^2	MAE
1	95 (285 factors) Amenities (AME)	42,299	0.52	29,188	42,832	0.52	29,716
2	Structural (STR)	33,830	0.70	23,319	34,052	0.69	23,767
3	Accessibility (ACC)	43,788	0.49	29,904	43,388	0.50	29,734
4	STR + ACC	29,004	0.78	18,263	31,425	0.74	19,979
5	STR + AME	32,843	0.72	21,029	37,612	0.64	25,216
6	ACC + AME	41,680	0.54	28,010	41,814	0.54	28,467
7	All	32,159	0.73	20,249	36,804	0.66	24,427

number. The least important factor was removed one at a time to create a new model. Optimal models with minimal RMSE were selected. As a result, optimal *amenities model* contained 36 factors (RMSE 40,197, R^2 57% and MAE 28,274), with 12 factors for the *all model* (RMSE 28,700, R^2 78%, MAE 18,222). Both models also had the highest R^2 and performed better than the original models in Table 1.

4.2. Relative importance of factors

Fig. 3 displays the relative importance of the 12 factors in the *optimal all model*. Results showed that *distance to Pleonchit* had the highest relative importance (100%) followed by year built (70%), total number of units (56%) and number of floors (52%). Frequency of *gyms* and reviews of *restaurants* in the neighbourhood were the fifth (30%) and sixth (30%) most important factors. The factors were also separated into structural, accessibility and amenities. Out of the 12 most important factors, 4 were structural, 3 were accessibility and 5 were amenities-related.

To explore deeper into the role of amenities, the importance of the 36 amenities factors in the *optimal amenities model* was also specified. Notwithstanding the lower performance compared with the *optimal all model*, this model explained up to 57% of the variance in condominium

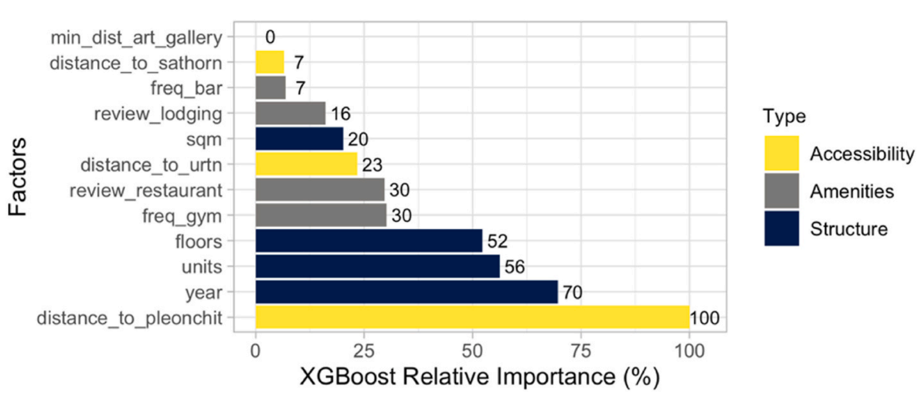

Fig. 3. Normalised relative importance of the optimal *all* model.

prices and helped to shed light on the unknown effects of amenities. Fig. 4 ranks the relative importance of the 36 amenities factors in this model. The most important amenity factor was the frequency of *bars* (100%) followed by reviews of *lodgings* (96%) and *restaurants* (92%). The fourth to the seventh most important amenity factors were frequency of *gyms* (43%), reviews of *spas* (29%), distance to the nearest *bar* (29%) and reviews of *beauty salons* (28%). The importance of the other 29 amenity factors ranged from 0% to 24%. Some amenities had more than one feature in the list such as bars (frequency and distance), clothing stores (review and distance) and art galleries (all three features). All descriptive statistics are shown in Table 2. Fig. 4 also categorised amenities based on the literature review as *commercial*, *cultural*, *healthcare*, *natural* and *services* amenities.

4.3. Relationships between amenities and condominium prices

The relationships between the 36 amenity factors and predicted condominium prices were fitted and visualised using PD. The relationships were categorised based on their shapes into five general types as *bounded positive, accelerated positive, limited positive, humped and negative relationships.*

Nine amenity factors were identified as having *bounded positive relationships* with predicted condominium prices. Fig. 5 shows amenities (X-axis) and predicted condominium prices (Y-axis). The PD curves showed these relationships as generally positive. The predicted prices either gradually increased (*freq_real_estate_agency*), strongly increased (*freq_park* and *review_lodging*), or displayed an S-shaped curve increase (*freq_gym*). One shared characteristic of these relationships was that the positive effects were "bounded" at a certain level above which amenity improvement did not further increase the predicted price.

Most of the amenities had modest effects on predicted prices, with only reviews of lodgings and frequency of parks showing substantial effects, with *ranges* of predicted prices according to the PD curves as 25,263 and 19,696 respectively and the two highest of all 36 factors. Thus, if reviews of lodgings were used as a sole determinant, the difference between the lowest predicted price (109,582 Baht at 0 reviews) and the highest predicted price (134,845 Baht at 393 reviews) was 25,263. PD results and other descriptive amenities statistics are shown in Table 2.

Seven amenity factors, as distances to the nearest amenity, were categorised as *accelerated positive relationships* (Fig. 6). A common characteristic of this type was the weak relationship between amenities and the predicted price at the beginning when the amenity was located at a distance from the condominium. However, when the amenity was near — from 200 to 0 m — the predicted price climbed upwards. The X-axis of minimum distance graphs was reversed to illustrate such an effect. From the PD curves, distances to the nearest subway, art gallery, bar and clothing store had the highest impact, with ranges of the predicted prices as 15,422, 13,464, 12,512 and 11,083 Baht respectively.

Ten amenity factors were categorised as *limited positive relationships* (Fig. 7). All of these factors, except the frequency of art galleries, were reviews. These curves shared a similar pattern that was the opposite of the accelerated positive relationship. There were strong positive effects at the beginning where the reviews increased from 0. After the number

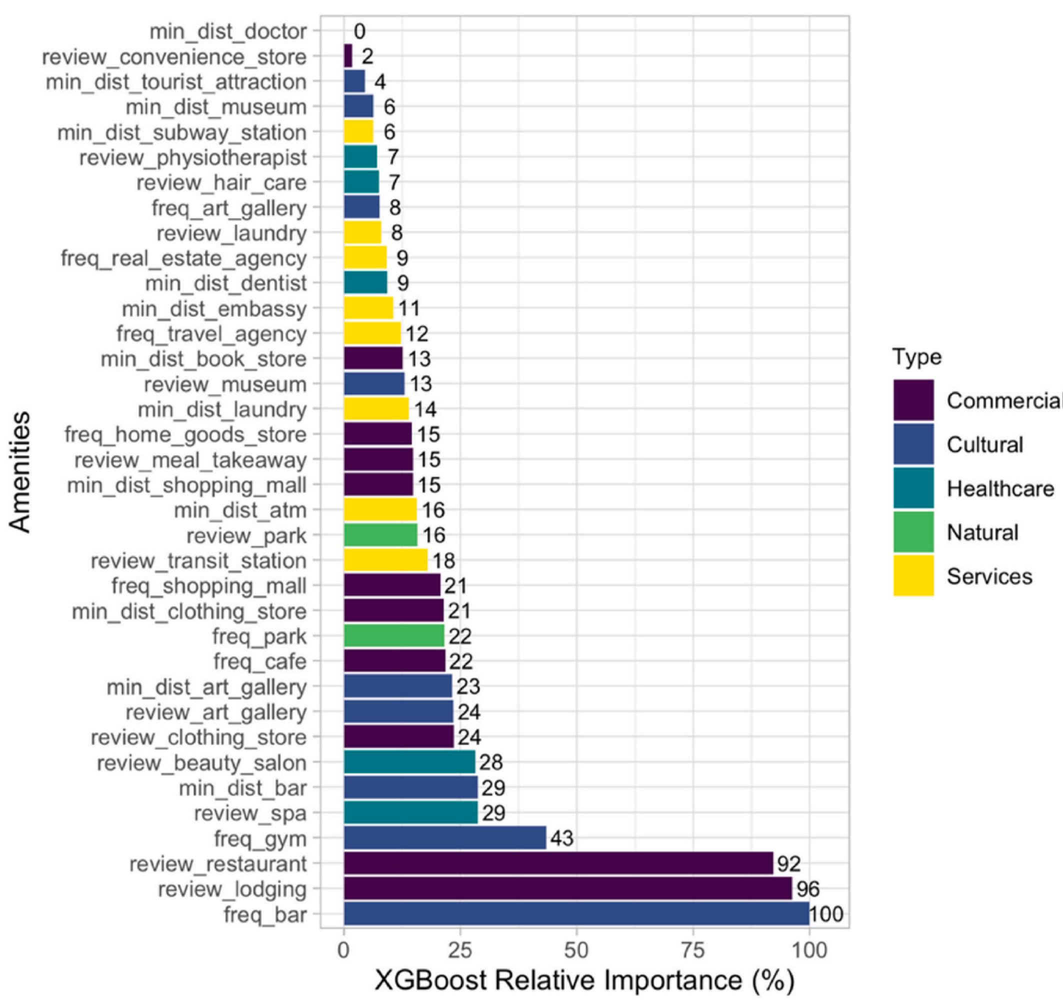

Fig. 4. Normalised relative importance of the optimal amenities model.

Table 2
Descriptive statistics and partial dependence results of the 36 amenities.

Amenity	XGB Importance	Descriptive Statistics				Results from Partial Dependence			
		Min	Max	Avg.	Median	Min Predict.	Max Predict.	Range	Avg. Predict.
freq_bar	100	0	60	15	7	113295	123606	10312	119103
freq_gym	43	0	26	6	4	113531	125881	12350	120207
freq_cafe	22	2	60	36	34	113632	118794	5161	116001
freq_park	22	0	12	1	1	114111	133807	19696	128495
freq_shopping_mall	21	0	56	9	5	113135	126340	13205	120750
freq_home_goods_store	15	0	60	18	15	114998	121766	6768	117384
freq_travel_agency	12	0	60	19	12	112815	119558	6743	116399
freq_real_estate_agency	9	0	58	11	7	114686	118985	4299	117545
freq_art_gallery	8	0	26	1	0	115203	119149	3946	118589
min_dist_bar	29	7	400	148	111	111263	123775	12512	113890
min_dist_art_gallery	23	20	400	320	400	114179	127643	13464	119519
min_dist_clothing_store	21	0	400	114	98	110958	122041	11083	114159
min_dist_atm	16	1	400	106	79	107349	118893	11544	116630
min_dist_shopping_mall	15	4	400	173	157	113486	119219	5733	115882
min_dist_laundry	14	0	400	107	87	114320	120474	6154	117591
min_dist_book_store	13	0	400	252	248	112688	120917	8229	116695
min_dist_embassy	11	44	400	339	400	115427	122873	7445	119244
min_dist_dentist	9	1	400	174	155	112749	120354	7606	115281
min_dist_subway_station	6	37	400	335	400	113505	128927	15422	120663
min_dist_museum	6	27	400	313	398	114025	124664	10639	118937
min_dist_tourist_attraction	4	28	400	328	400	109285	117714	8429	114374
min_dist_doctor	0	0	400	180	153	113837	118425	4589	115687
review_lodging	96	0	756	87	34	109582	134845	25263	129711
review_restaurant	92	1	351	75	46	110364	121399	11036	115704
review_spa	29	0	397	31	12	113290	123248	9958	117654
review_beauty_salon	28	0	41	6	4	114183	121501	7317	118593
review_clothing_store	24	0	364	5	1	114390	128167	13777	127521
review_art_gallery	24	0	291	6	0	114644	122770	8126	122336
review_transit_station	18	0	305	14	2	111418	121549	10130	121170
review_park	16	0	1522	45	0	113272	125494	12222	124768
review_meal_takeaway	15	0	1248	45	1	114715	123934	9219	122838
review_museum	13	0	1588	19	0	114910	127213	12304	126929
review_laundry	8	0	244	3	1	112262	119402	7141	117156
review_hair_care	7	0	138	11	5	114224	120248	6024	118837
review_physiotherapist	7	0	512	6	0	114882	133162	18280	131319
review_convenience_store	2	0	273	9	3	110032	116627	6595	110455

of reviews reached a certain point (e.g., 22 reviews of clothing stores and 47 reviews of art galleries), the PD curves remained flat. The results implied that some popularity of these amenities improved predicted prices; conversely, high popularity had no effect. For example, the predicted price increased from a minimum of 114,882 Baht when reviews of physiotherapy were 0 to a maximum of 133,162 Baht at 23 reviews and did not increase beyond that point.

As the name suggests, the six amenity factors that were categorised as *humped relationships* had a positive effect on the predicted prices until they reach a peak (Fig. 8). After the peak, the relationship became negative. For example, the predicted price reached a peak at 123,606 Baht when there were 22 bars in the neighbourhood and at 121,400 Baht when reviews of restaurants were 134. The predicted prices then declined beyond these points.

Lastly, four amenity factors had *negative relationships* with the predicted condominium prices (Fig. 9). They were regarded as *disamenities* that caused adverse effects (Schläpfer et al., 2015). The PD curves showed that predicted prices decreased when there were popular convenience stores nearby or when they were very close to an automatic telling machine (ATM) or a tourist attraction.

5. Discussions and conclusions

This research investigated the importance of neighbourhood amenities on condominium prices in Bangkok, Thailand, as the first to utilise data from Google Maps to assess and predict condominium prices. In total, 285 factors of 95 types of amenities were analysed. Also, as control variables, four structural and accessibility factors were included in the models. Two ML algorithms were used to assess the large number of factors instead of traditional hedonic modelling. Results showed that XGB outperformed RF in most models. Findings determined that 95 amenities from Google Maps explained 52% of the price variance, reinforcing the existing literature suggesting relationships between amenities and housing price/demand (Adair et al., 2000; Hu et al., 2019; Su et al., 2021; Waltert & Schläpfer, 2010).

To further investigate the amenities, the model was optimised with 36 amenity factors showing the best performance. The importance of each amenity factor was identified. Top ranked amenities were *cultural* (bars and gyms) and *commercial* (restaurants and lodgings). According to Hidalgo et al. (2020), *cultural* and *commercial* amenities are central nodes — that attracted people and other amenities — within networks of urban amenities or the so-called "amenity space". This research found that they also influence housing prices and demand. These results also reinforced a previous study by Liu et al. (2018) who found that entertainment and sports facilities were very important attractive factors for houses in city centres. Unlike a study by Hu et al. (2019), this current research did not find hospitals as important amenities. One probable reason is that Google Maps have yet to distinguish quality levels of healthcare and educational facilities, while cities have potentially different price/demand drivers.

Finally, PD was used to visualise non-linear relationships between amenity factors and predicted condominium prices as *bounded positive*, *accelerated positive*, *limited positive*, *humped* and *negative relationships*. Results illustrated that analysing POIs on Google Maps could become a valuable component for researchers and practitioners studying urban analytics, city science or regional intelligence (Batty, 2019; Vaz, 2016).

5.1. Theoretical contributions

Popularity of amenities drives condominium prices. Previous studies of

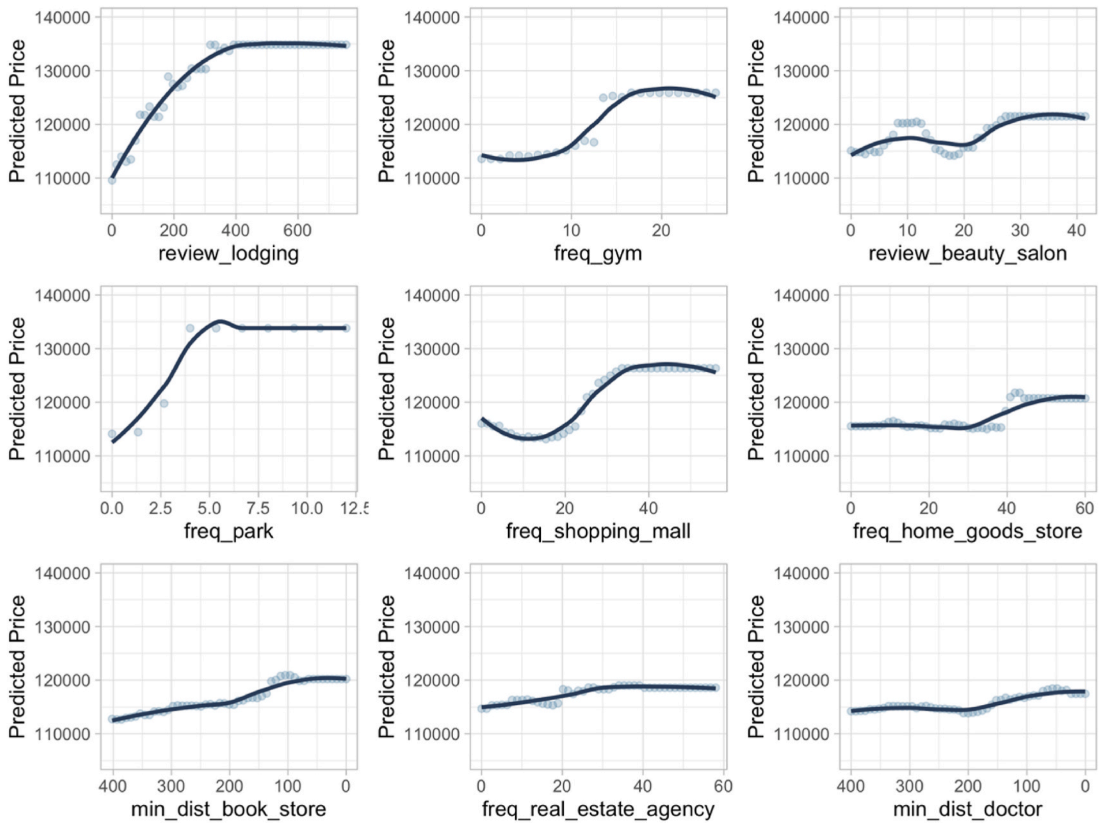

Fig. 5. PD curves of bounded positive relationships.

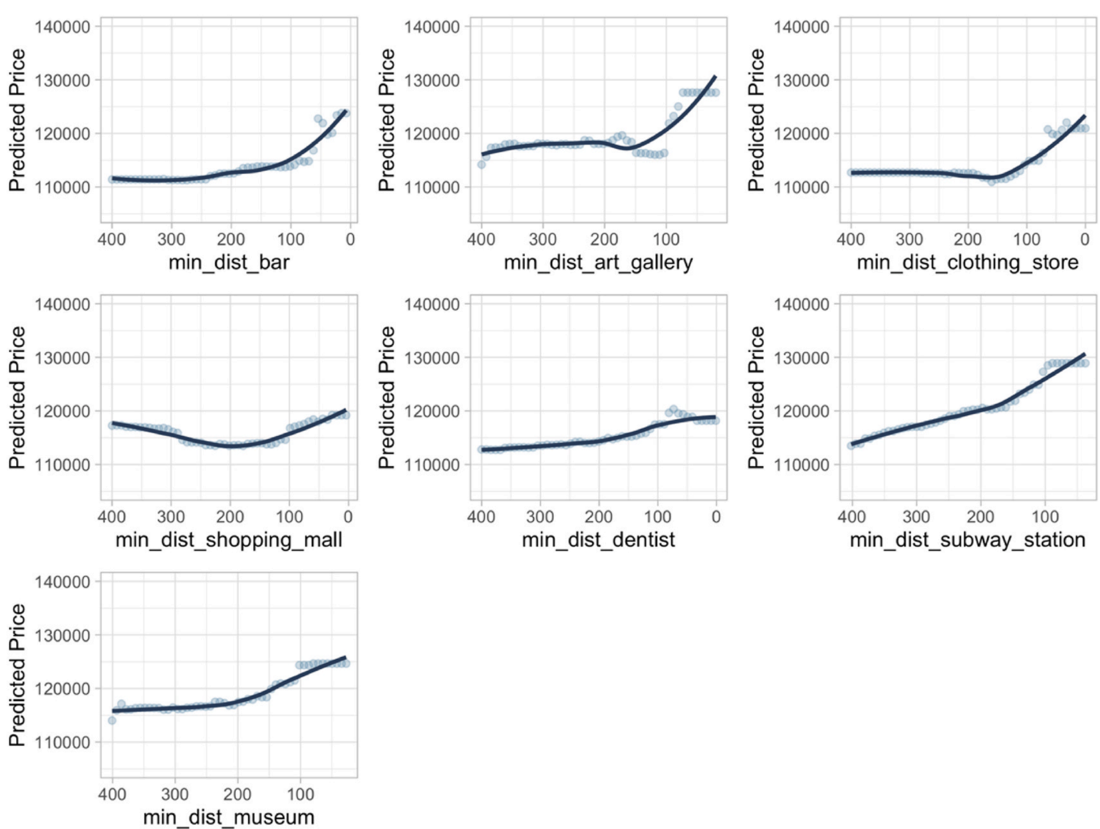

Fig. 6. PD curves of accelerated positive relationships.

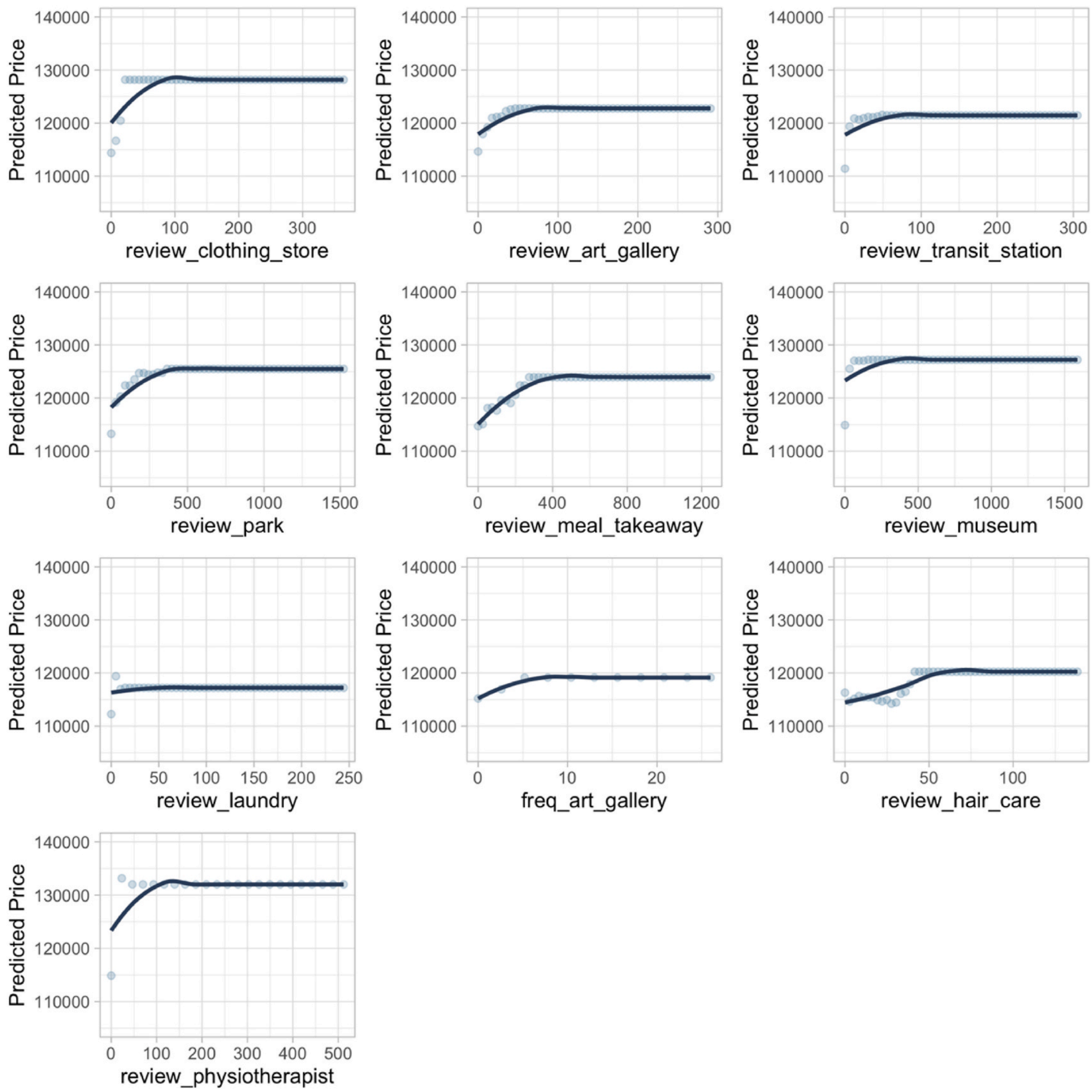

Fig. 7. PD curves of limited positive relationships.

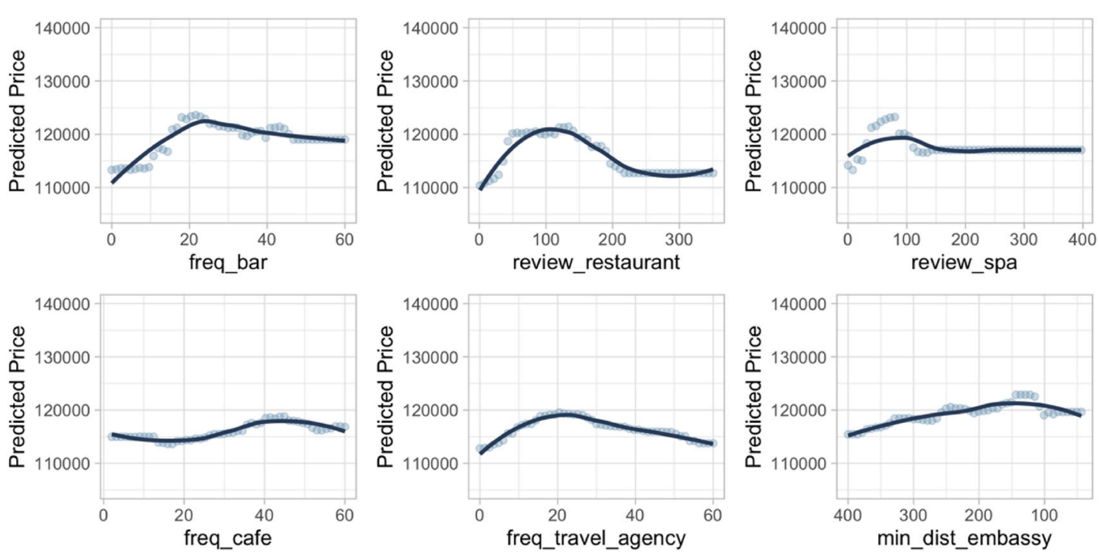

Fig. 8. PD curves of humped relationships.

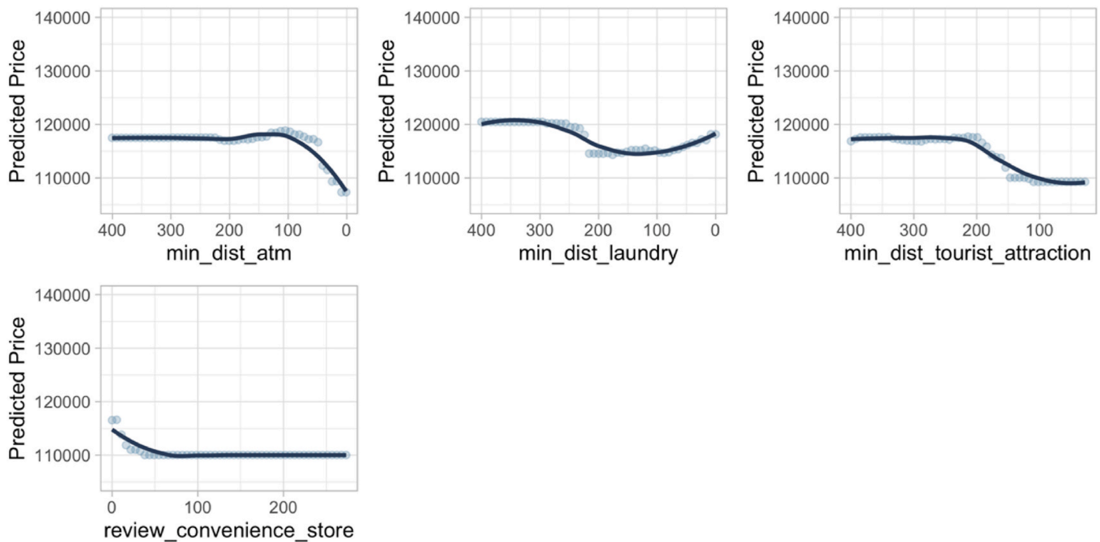

Fig. 9. PD curves of negative relationships.

neighbourhood amenities typically used features such as frequency, density and distance. This research introduced *reviews* as a feature to signify the *popularity* of POIs and investigate the popularity of amenities on housing prices. This aspect has not been previously studied in the existing literature. Findings showed that reviews of many amenities, especially *restaurants* and *lodgings*, were important determinants of condominium prices. However, they did not affect prices in the same way.

Amenities affect condominium prices in several non-linear ways. The ML algorithms discovered non-linear relationships. However, no existing study has explored the multiplicity of relationships between amenities and housing price/demand in detail. Here, PD curves showed that amenities affected predicted housing prices in several ways. Bounded positive relationships only influenced predicted prices to a certain level, while accelerated positive relationships demonstrated that for some amenities, the closer they were to the condominium, the more impact they had on the predicted price. By contrast, limited positive relationships for amenities — primarily reviews — pushed the predicted price up only at the beginning and showed no effect later. Some amenity factors showed humped relationships with the predicted price, while despite their high importance, a greater frequency of bars and reviews of restaurants did not necessarily increase predicted prices. Finally, some disamenities that negatively impacted predicted prices were identified.

An attractive urban environment requires multiple amenities. Although this research identified effects of individual amenity factors on predicted prices, it is important to improve multiple amenities in a neighbourhood. The PD curves show that individual amenity factors can potentially increase predicted prices between 3946 and 25,263 Baht at their optimal levels. Therefore, to further increase prices, improvements of multiple neighbourhood amenities are required. The existing literature identified diversity and agglomerations of amenities as important for urban vitality and viability (Hidalgo et al., 2020; Parker, Ntounis, Millington, Quin, & Castillo-Villar, 2017) and posited that mixed land use with several commercial and economic units increases housing prices (Jang & Kang, 2015). Results presented here support the significance of diversity and multiplicity of neighbourhood amenities and contend that multi-faceted amenity improvement — rather than focusing on individual amenity factors — is more likely to increase and sustain housing demand.

5.2. Practical implications

Integrative development of urban amenities: A nexus between public and private entities is crucial to foster more sustainable city planning. This research elucidated the role of public and private urban amenities on condominium prices. As such, the development of important amenities should play a central role in city planning. However, plans and actions of related entities in Bangkok are neither aligned nor integrated. The National Housing Authority (NHA) has included plans to develop affordable housing in several areas of Bangkok as part of their ten-year strategy (NHA, 2020). However, despite frequently mentioning urban regeneration and a smart, liveable inclusive city, the important neighbourhood amenities identified in this research are not evident part of their plans. Likewise, the Bangkok Metropolitan Administration (BMA), place limited emphasis on important urban amenities. Piecemeal projects included in their action plans aim to improve the capacities of local businesses and restaurants (BMA, 2021), while the strategic comprehensive planning and development of amenities are notably absent.

Continuous dialogue and collaboration between urban amenity providers (BMA and private businesses) and housing providers (NHA and property developers) are paramount, with the goal as an integrative plan to improve urban amenities in much-needed areas of Bangkok and catalyse residential demand which, in turn, will foster neighbourhood regeneration and deliver a more sustainable city in the long-term. Bangkok can also improve neighbourhoods in the short term through creative urban interventions or *tactical urbanism* (Mould, 2014). Neighbourhoods should assess which amenities they lack and introduce community-led initiatives such as pop-up bars and trendy restaurants, temporary market stalls or parklets (small artificial parks). Then, the community can evaluate the effects and whether to incorporate these suggestions as permanent features. A longer-term solution includes introducing public-private partnerships such as business improvement districts (BIDs), which collect levies from property/business owners, to develop suitable amenities for their neighbourhood (see Grail et al., 2020). A combination of small quick-wins and long-term collaborative/integrative frameworks could help Bangkok improve its amenity space.

5.3. Limitations and future research

Despite the notable contributions, this research had some limitations. The condominium prices used in the models were approximated from the listings on the portal. Although condominiums were selected based on the number of listings to improve price accuracy, prices may fluctuate in the property market over time. The Google API facilitated the rapid collection of massive data; however, data collection was limited to a maximum of 60 POIs per type. Also, the 96 selected types of POI did not include path-like infrastructures such as rivers and streets, contextual POIs such as Buddhist Temples that are ubiquitous in Thailand, or non-customer-facing POIs such as manufacturing (Hidalgo et al., 2020). Setting a 400 m radius offered a comparable scale among condominiums and improved data collection efficiency but disregarded amenities outside the boundary. The research scope was limited to 500 popular condominiums in Bangkok. More data input from within Bangkok or across various geographical areas would further strengthen the results and show alternative perspectives. XGB has not been further tested in the context of ML algorithms. Continuous testing and tuning are required to produce more robust results. This research posits new avenues for further research consideration, such as identifying the similarities and differences in the importance of amenities in various geographical areas. The ability of XGB to consistently outperform other ML algorithms in price prediction should be further tested, along with other possible practical ways to define non-linear relationships.

CRediT authorship contribution statement

Viriya Taecharungroj: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization.

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