PACIFIC RIM PROPERTY RESEARCH JOURNAL
2021, VOL. 27, NO. 1, 55–74
https://doi.org/10.1080/14445921.2021.1961182

Routledge
Taylor & Francis Group

What is in a name? A modern interpretation from housing price in Hong Kong

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ABSTRACT

Hong Kong is a metropolitan city. Owing to its historical background as a former British colony, it is characterised by a mixture of Chinese and Western cultures. While most housing estates' names are bilingual in Chinese and English, many recent large scale housing estates have an English name only. Do housing estates with an English name only associate with higher prices than bilingual ones? To the best of our knowledge, none have studied that before. We attempted to fill this research gap. Four large-scale residential projects in Yuen Long District were selected, two are bilingual and two have English names only. 253,605 data points, including macroeconomic variables and housing characteristics, were included in this study. The results of the hedonic price model showed that properties with English names only were associated with a higher price than bilingual ones. We also utilised a long short-term memory (LSTM) housing price prediction model to predict housing price. Our research results show that housing estates with English names only are associated with higher housing price. It provides a new perspective on real estate housing estates' brand management and provide a reference for real estate buyers in the future.

ARTICLE HISTORY
Received 05 May 2021
Accepted 24 July 2021

KEYWORDS
Chinese and English name; Real Estate; House Price; Brand Management; Hedonic Regression; LSTM

1 Introduction

Limited supply and huge demand drive housing price up in Hong Kong. Skyrocketting housing price is also supported by good economic development and an increase in population. While unaffordable housing lowers living quality of city dwellers, frequent and large transactions in this small city provide an ideal example for real estate market research (Funke and Paetz, 2013).

Previous studies have shown that housing price is affected by a basket of factors: population growth (Moallemy and Melser, 2019), land supply and economy (Upadhyaya etal., 2017; Chen, Long and Qin, 2020), interest rates and employment opportunities (Sanae and Shimizu, 2015; Yang and Pan, 2020), income and housing supply (Wang and Richman Dan, 2019), finance and building capacity (Su et al., 2019), external environment (Dai etal., 2020), government regulations and policies, and property taxes and fees

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(Tang and Coulson, 2016). Compared with Singapore, the United States and other countries, Hong Kong has a lower home ownership rate. Even so, it fell from 50.4% in 2016 to 49.20% in 2017 (Jayanta and Oladinrin, 2019).

Naming is an important issue in marketing strategy. If the name is good, it can increase sales and profitability. Real estate developers usually choose a name, which is easy to remember and can attract consumer attention, for their housing estates. The number of properties in Hong Kong with English names only, rather than traditional bilingual names, has increased in recent years. We speculate that this branding strategy is linked to higher housing prices. However, as far as we know, there is no research in this area. Therefore, our goal is to fill this gap, contributing to the existing housing research.

We systematically analyze the impact of various factors on housing prices, the current use of hedonic pricing model (HPM), vector regression, and LSTM model for housing price prediction. We wish to provide insights to homeowners, appraisers and mortgage bankers when they conduct house price valuation and prediction.

The rest of this article is organized as follows: Section 2 systematically examines the factors that affect house prices. Section 3 provides an overview of the Hedonistic Price Model (HPM) to examine various factors' correlation with housing price and long short-term memory (LSTM) for housing price prediction. Section 4 shows the results of HPM and LSTM. Section 5 summarizes the research and make suggestions for further study.

2. Literature review

2.1 Factors that affect house prices

Factors that affect real estate prices include macro and micro factors (Zhang, 2019). Macro factors include political, legal and economic (Wan etal., 2020; Chan, 2011; Shi, Jou, and Tripe, 2014; Zhang et al.; Li, 2016) and social and cultural (Moallemi and Melser, 2019). Micro-factors include property conditions, household disposable income, buyer preferences, and financial policies. By using empirical evidence from 285 cities obtained between 2005 and 2013, Chen reveals the relationship between urban housing prices and capital deepening (Chen etal.,2020). This provides a new perspective for explaining the increase in housing prices and regulating urban housing prices. Zhou and Xia (2018) summarize the literature of scholars on the factors that influence housing prices with regard to research method.

As the convenience of public transport units is mainly reflected in the cost of transportation and the accessibility of shopping centers, the frequency of public transport services affects house prices (Geng, Bao, Liang, 2015) Ayuso and Restoy, 2006; Ossokina and Verweij, 2015; Facilities accessibility in schools and shopping centres has a positive impact on house prices (Zhang et al., 2020; Zhang, Zhou and Hui, 2020). Buyers prefer beautiful landscapes such as lakes and valleys affect house prices (Fu etal., 2019). Previous research also finds that environmental externalities such as air quality and smog (Zhang etal., 2019; Chasco and Le Gallo, 2013; Li, and Chau, 2016; Nicholls, 2019), direction of wind blows from landfill affect house prices (Li etal.,2018).

Other studies were conducted from five main perspectives: supply and demand, personal consumption (Bischoff, 2012), housing characteristics, government policies, and spillover effects. With the emergence of housing bubble, people are increasingly concerned about the impact of personal consumption factors on housing prices; so far, the research methods are mostly empirical, taking time and space information into account (Pace etal. 2000). utilsing linear and nonlinear and spatial research methods (Bao and Wan, 2010), focusing on the introduction of new methods for analysis (Li etal., Lin, 2017). According to the supply and demand framework, Xiong (2019) analyzes the impact of global real estate prices on China's real estate price from the perspectives of the macro-control system, local fiscal expenditure control, land resource supply, bank credit supply, project cost, population urbanisation, monetary economy, population, and residents' income expectations. Del Giudice etal. (2017) and Del Giudice and De Paola (2014) assess environmental externalities that affect property prices, such as traffic noise. Celineand Arthur (2014) study the impact of accident risks in hazardous industrial facilities and petrol stations on house prices.

2.2 Influence of name on product value and brand management

Name is the discriminator for identifying goods, distinguishing enterprises from each other, the first advertisement of enterprises, and the first aspect for consumers to evaluate. A name is also a symbol of quality and credibility. Branding reflects the image of an enterprise and bears the cognitive function of consumers. The popularity and the reputation of a brand affects the profitability of an enterprise. In essence, consumers' understandings and associations about acertain property are linked with the brand name. Name is the first component of a brand, and the product name directly affects the value of the brand (Hendrasto & Utama, 2019).

Hendrasto and Utama (2019) study the inconsistency of brand names and their influence on the consumers' preferences. They think that brand name is a decisive factor of brand success. Brand name is a very valuable asset of a company (Hendrasto and Utama, 2019; Li, 2012). The importance of brand name highlights the importance when a company gives a name to its products, as that inevitably connects to a company's goals. Previous studies have tested the consistency in different branding environments. Melnyk, Klein, and Völckner (2012) tested the use of non-native languages in developed countries and several brands in developing countries. Foreign brand names are found to be associated with high-quality products. This is evidenced in the increase in the use of foreign brand names (Melnyk, Klein, and Völckner, 2012).

To consumers, brand names provide information about the products' quality. Brand name affects people's evaluation on a product's quality and subsequently their purchase intentions. (Leuthesser, Kohli, and Harich, 1995). Therefore, brand names are usually built based on many factors' consideration. This is because brand equity depends on brand value, and brand value comes from the brand name itself.

2.3 Research hypothesis

The implicit effect of the name of real estate is reflected on people's cognition and association of real estate. First, the buyer has a preliminary impression of the property through its name; secondly, the preliminary impression associates with the property; finally, the buyer has a direct experience (Leuthesser, Kohli, and Harich, 1995). Name is an important feature of a product's branding, and the preferred function of any property name is to promote public awareness or make it easier for consumers to choose properties which is capitalised as the property price. The theoretical framework centred in Hong Kong where most people live in the high-rise apartments.

The official languages of Hong Kong are Chinese and English, and the government's language policy is "biliterate and trilingual", i.e. written in Chinese vernacular and English, and spoken in Cantonese (commonly known as Cantonese), Putonghua, and English. Cantonese is mainly used by the Chinese population in Hong Kong, while English is the main language of many non-Chinese including ethnic minorities.

In Hong Kong, students, parents, and schools prefer to use English as the medium of instruction instead of Chinese because Hong Kong is an international trade and financial centre, there is a need for good command of English which is also a prerequisite for university admissions in Hong Kong. Graduates with good English also have a higher chance of getting high-pay jobs (Jayantha and Lam, 2015).

Against the backdrop of current research and literatures, however, we have not found any empirical research with regard to the impact of pure English names only as compared to bilingual ones on housing prices. As there is an increasing number of housing estates with names in English only, does that imply housing estates with English names only are sold at higher price? In order to fill this research gap, we formulated a hypothesis:

H1: Housing units with English name only exhibits higher house price than bilingual ones.

To study the hypothesis, we utilised hedonic housing price model to illustrate its impact on present and past transaction data. We then utilised big data and LSTM model to predict housing price in future. The statistical analysis and empirical results shall provide insights in other cities which were once colonies.

3. Research methods

In this study, HPM was used to study the housing prices and LSTM was applied for housing price prediction.

3.1 Hedonic price model (HPM)

HPM, also known as the characteristic price model and utility valuation method, holds that real estate is composed of many different characteristics, and real estate price is determined by the utility brought by all features (Bao and Wan, 2010), such as area, floor, building materials used in housing, the construction cost and infrastructure cost, location, environmental externalities of housing (Yue, 2019; Li etal., 2016; Li and Huang, 2020). Because each of the housing unit is unique with different features, housing price is different. If these features can be decomposed, each factor's impact on housing price can be calculated.

The application of HPM to housing price analysis is based on several assumptions. First, housing market operates under perfect competition: producers and consumers can freely enter and exit the market, buyers and sellers have complete information on housing products and prices. The housing market reaches equilibrium, the intrinsic prices of attributes do not interact with each other, all consumers have the same understanding of the characteristics of each product. It is also assumed that many differentiated products can be obtained in the market, so that the selection for various commodity bundles is continuous. Based on these assumptions, the HPM has been widely used in housing market research (Nicholls, 2019).

3.2 House price prediction based on machine learning

In recent years, there is a huge progress in artificial intelligence, machine learning and deep learning methods which could be applied to various assets' price prediction (Wu and Deng, 2015; Gao, 2020). By using various attributes of housing as well as economic factors from September 2013 to May 2020, we propose to use LSTM for housing price prediction.

LSTM is a type of time-cycle neural network where memory units are added to each neural unit in the hidden layer, so that the memory information in the time series can be controlled, making this network suitable for processing and predicting time-series problems (Yang, Li, and Zhang, 2020). An LSTM neural network adjusts the memory and the forgetting degree of previous information and current information through control gates (input gate, forgetting gate, and output gate). It combines short-term memory with long-term memory, which makes the circulating neural network process long-term memory ability and solves the problem of gradient disappearance (Gao, 2020). We used the LSTM method to predict housing price and the process are listed as follows:

(1) The forgetting gate in the LSTM model filters information and forgets useless information.

$$f_t = \sigma\left(W_f x_t + V_t h_{t-1} + b_t\right)$$

(2) The input gate updates the status according to the input information and the memory information.

Enter information: $i_t = \sigma(W_i x_t + V_i h_{t-1} + b_i)$

Memory cells: $\hat{c}_t = tanh(W_c x_t + V_c h_{t-1} + b_c)$

Long-term memory: $c_t = i_t \hat{c}_t + f_t c_{t-1}$

(3) The output gate outputs the current information.

$$o_t = \sigma(W_o x_t + V_o h_{t-1} + b_o)$$
$$h_t = o_t * \tanh(c_t)$$

where x_t represents the input vector at time t and h_{t-1} represents the vector output by the LSTM before time t, i.e., short-term memory information. Furthermore, c_t represents the long-term memory information at time t, σ is the sigmoid activation function, W and V represent the weight matrix, and b represents the offset vector (Gao, 2020).

To establish a housing price prediction model, we firstly cleared the data, filled the missing data by using interpolation methods. Then, the data variables were normalised with a value range between [0, 1], and the normalised mathematical expression is as follows:

$$x^* = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Here, x_{max} is the maximum value of each of the housing price feature in the sample data after cleaning, and x_{min} is the minimum value of each housing price feature in the sample data after cleaning. We input all the relevant data of the housing price characteristics at time t and output the housing price at time t+ 1(Wen & Yan, 2020).

The collected original housing price data were pre-processed, the combined data $\{\cdots, x_{t-1}, x_t\}$ were obtained through multidimensional data processing. Next, the training samples were trained by the LSTM model. Finally, the sample data was tested by the trained LSTM model to predict the housing price series $\{\tilde{x}_{t+1}, \tilde{x}_{t+2}, \cdots\}\tilde{x}_{t+1} = W_2 \cdot h_t + b$ in the future. The mathematical expression of stock price in the next moment is as follows: (Yang etal., 2020).

The LSTM algorithm was processed via Python. We utilise the housing transaction data in the past as the input parameters and two sets of case data as the training sets. Multi-dimensional data makes full use of the time series data and its own changing trend, reducing the noise interference in experimental sample data, improving the data information, ensuring more accurate prediction results (Wen & Yan, 2020).

3.3 Data acquisition

There is an increase in the number of people who realise the importance of big data in our society (Du, Li, and Zhang, 2014; Hromada, 2016). In this research, we used big data to study the impact of various factors on housing price based on HRM and future housing price prediction based on LSTM (Wu, Jiao, & Yu etal., 2018). With an increase in the usage of Internet and mobile phone, housing search for rent and purchase has evolved from using mouth of word in the past to real estate websites and mobile applications search (Dietzel etal., 2014), such as https://hk.centanet.com, https://data.28hse.com and https://www. midland. com.hk.

We identified Yuen Long District in Hong Kong as the research area. Yuen Long locates in the northwest of Hong Kong, China. It has one of the largest number of high-rise residential buildings amongst all the districts in Hong Kong. Choosing housing estates in Yuen Long only eliminates the impact of housing prices differences due to location differences of the housing estates. We only select high-rise buildings more than 15 floors with high transaction data, and exclude buildings that required residents to walk up flight of stairs. Then, two pairs of large-scale housing estates with names in both bilingual Chinese and English names and with English names only in Yuen Long were identified: Yoho Town (with English names only), Grand Yoho (with English names only), The Reach (with bilingual names), and Park Signature (with bilingual names).

All the unusual or unstated transaction records were excluded. All the residential transaction records, from September 2013 to May 2020, consisted of 253,605 data points. The usable area of the study sample units ranged from 272 to 2038 ft. Prices ranged from 1883 USD to 28,804 USD per feet.

All the transaction data about real estate used in this study, such as developers, housing conditions, total area, price history, and other detailed transaction records, were obtained from Centaline Property Agency. Economic data, such as personal average salary index, money supply M2, unemployment rate, comprehensive consumer price index, and the best lending rate, were obtained from the Census and Statistics Department of the HongKong Special Administrative Region.

3.4 Model establishment

In this study, hedonic price model (HPM) was established. The following specific HPM was estimated based on the selected housing attributes that have a significant impact on the housing prices in the data collection. These attributes were summarised according to previous literatures. The model took the form of semi-logarithm where the actual housing price was a function of basket of attributes. The model is expressed as follows:

$$\begin{aligned}\log(HP)_{it} &= \delta_0 + \delta_1 \log(Floor)_i + \delta_2 \log(Area)_i + \delta_3(NOP)_i + \delta_4(Traffic)_i \\ &+ \delta_5 \log(TOV)_i + \delta_6 \log(APSI)_i + \delta_7 \log(M2)_i + \delta_8 \log(HM)_i \\ &+ \delta_9 \log(CC)_i + \delta_{10} \log(IC)_i + \delta_{11} \log(Population)_i + \delta_{12} \log(UR)_i \\ &+ \delta_{13} \log(CPI)_i + \delta_{14} \log(BLR)_i + \varepsilon_i\end{aligned}$$

where $\log(HP)_{it}$ is the real transaction price of housing i at time t (measured in US dollars), $\delta_1 \cdots \delta_{14}$ represent the coefficients of variables to be estimated, δ_0 represents a constant term, and ε_i indicates the error term of the model. Details of the variables are listed in Table 1. Table 1 Selected variables for this model.

3.5 Data description

To explore the research problem (or hypothesis) of the impact of Chinese and English names on the house prices, transaction records of housing units in large residential estates were included in the model. Four large housing estates were divided into two groups. The first group is Yoho Town (with English name only) and The Reach (with bilingual names). The second group is Grand Yoho (with English name only) and Park Signature (with bilingual names). The These two groups located nearby, eliminating the differences in prices due to differences in location, transportation and facilities differences in that particular location. Through an empirical analysis of two groups of cases, we answered the research questions.

(1) Yoho Town

Yoho Town is located at No.8 Yuen Long Street, southeast end of Yuen Long Town Center. The development is Sun Hung Kai. There are 2 phases in Yoho Town, with 16 buildings and 5,504 units. The usable area of Yoho Town ranges from 362 feet to 1231 feet. (http://hk.centanet.com/transaction/ptest.aspx?type=3&code=BEPPWPPAPK&ref=CD2_Detail_Nav)

(2) Grand Yoho Estate

Grand Yoho is located in 9 Long Yat Road, Yuen Long Station. The development has two phases, consists of seven blocks and 1,954 units. The usable area of properties in Grand Yoho ranges from 397 to 2,125 square feet.

(http://hk.centanet.com/transaction/ptest.aspx?type=3&code=BESPWPPJPK&ref=CD2_Detail_Nav)

(3) The Reach

The Reach is located in 11 Shap Pat Heung Road, southeast of YuenLong . The development is in Henderson/New World. There are 12 buildings in The Reach, providing 2,580 units. The usable area of properties in The Reach ranges from 354 to 1,940 square feet.

(http://hk.centanet.com/transaction/ptest.aspx?type=2&code=BEPPWPPHPW&ref=CD2_Detail_Nav)

Table 1 Selected variables for this model.

Abbreviation	Variable	Rationale and Source of Data
HP	Housing price	Housing price and all the related housing data was collected from real estate transaction data of Centaline Property Agency.
Floor	Floor	The air quality and scenery on the upper floors are usually better than those on the lower floors, with less odour and pollutants from restaurants and traffic, respectively.
Area	Usable area of the housing unit	According to the "Residential Property (First-Hand Sales) Ordinance", residential property is counted as the saleable area. The area of balcony, utility platform, and balcony are counted as the usable area.
NOP	Property name	If the housing estate is named in English only, it is 1; otherwise, it is 0.
Traffic	Distance to the MTR station	The shorter the distance between the residential area and the MTR station, the more convenient it is for the residents. It is 1 if the walking distance to MTR station within 5 minutes; otherwise 0. The data was collected from the real estate transaction data of Centaline Property.
TOV	Gross domestic product	Production activities of all residents in a certain period is often considered as the best indicator to measure the economic situation of aregion. Data was obtained from the Census and Statistics Department of Hong Kong.
APSI	Average personal salary index	The personal salary index reflects the income of residents. High income increases the proportion of housing purchases, which will lead to an increase in the housing prices. Data are obtained from the Census and Statistics Department of Hong Kong.
M2	Money supply	Previous literature showed that money supply affected the real estate market, and the inflow of hot money (including that from mainland China) affected Hong Kong real estate market. Data was obtained from Hong Kong Monetary Authority.
HM	Number of households	Number of domestic households by housing type, including home ownership households, public rental housing units and interim housing households, and subsidised sale units under the Tenant Purchase Scheme (TPS). The number of households reflects the housing demand and indirectly affects the housing price. Data was obtained from the Census and Statistics Department of Hong Kong.
CC	Housing construction cost	The cost of housing construction directly affects the first-hand housing's price. Data was obtained from the Census and Statistics Department of Hong Kong.
IC	Infrastructure cost	Residential infrastructure, including transportation, post and telecommunications, water supply and power supply, greenery, environmental protection, culture and education, and health services, are the material basis of life. Well-equipped infrastructure can enhance the residential experience, and the increase in infrastructure cost will lead to an increase in the housing price. Data was obtained from the Census and Statistics Department of Hong Kong.
Population	Number of permanent residents	The population data in this study was obtained from the permanent residents and floating residents data from the Census and Statistics Department of Hong Kong.
UR	Unemployment rate	Unemployment rate refers to the proportion of unemployed working population. A high unemployment rate leads to fewer people invest in the real estate market, causing to a decrease in housing price. The data was obtained from the monthly unemployment rate of the Census and Statistics Department of Hong Kong.
CPI	Comprehensive consumption index	Composite CPI is one of the CPI indicies in Hong Kong. An index reflects the impact of changes in consumer prices on the overall household. It is compiled by the Census and Statistics Department of Hong Kong according to the overall expenditure pattern of all the households covered by CPI (A), CPI (B), and CPI (C) (accounting for 90% of the households in Hong Kong).
BLR	Best lending rate	The best lending rate represents the interest rate. This is the interest rate charged by the bank to the most creditworthy customers. Empirical evidence shows that the money market interest rate is closely related to the best lending rate. When the best loan interest rate increases, the mortgage payment will increase. Then, the demand for buying real estate declines, so the value of real estate declines. The best lending rate in this study refers to the interest rate quoted by The Hong Kong and Shanghai Banking Corporation Limited, and the data was obtained from the Hong Kong Monetary Authority.

(4) Park Signature

Park Signature is located in 68 Gum Um Road, the developer is New World Development Company Limited. There are nine buildings, providing 1,620 units. The usable area of properties in Park Signature ranges from 272 to 1,382 square feet.

3.6 Variables included in the study

Our HPM model includes variables of the floor and the usable area of the housing units, Chinese and English names of real estate, transportation, GDP, average personal salary index, money supply, number of households, housing construction cost, infrastructure cost, resident population, unemployment rate, comprehensive consumption index, best loan interest rate, and housing price. The most important variable in this study was the name of the property (NOP) which is 1 if the residential unit used an English name, otherwise denotes as 0.

4. Research findings and discussions

4.1 Statistical interpretation of HPM model

The interpretation of the HPM and the multivariate return model is usually based on some standard statistical tools, such as simple t-statistics, F-statistics, and adjusted R^2. The hypothesis of a single parameter of an explanatory variable is tested by using a simple t-test. Simple t-statistics are used to test whether a specific attribute has a significant impact on the housing prices. In this study, the dependent variable was real housing prices.

Null hypothesis refers to the independent variable has nothing to do with the dependent variable (H0). If the absolute value of the t-statistic of a parameter (i.e. empirical t-statistic) is greater than the critical value, the zero hypothesis is denied, indicates that a specific variable is significant. This means that a specific independent attribute/variable has an important influence on the dependent variable.

The performance of the whole model is determined on the basis of the F-statistics. If the empirical F-value is greater than the critical value, the model is considered to perform well, or the overall performance of the model is good. This means that the selected set of independent variables/attributes is suitable for the model. Another very important statistical tool to explain the return model is the adjusted R^2, which showed the explanatory power of the model. It tells us to what extent the data conform to the model or to what extent the changes in the dependent variables are explained by the selected independent variables. Adjusted R^2 value ranges from 0 to 1, the higher the adjusted R^2, the better the model.

4.2 Study findings

The data collection was carried out to analyse the relationship between Chinese and English names and the housing price. Housing price as a dependent variable, while the other variables are independent variables, shows the above relationship and the influence on housing price. In all, 253,605 observations, including transaction prices, macroeconomic data, and architectural features, were collected.

4.2.1 Group 1: Yoho town (with English name only) and the reach (with bilingual names)

The first set of data includes Yoho Town (with English name only) and The Reach (with bilingual names) is presented in Table 2. Table 4 lists the correlation analysis of the first group, and the estimated feature model displays a very good data fit, explaining approximately 76% of the total change in the actual housing prices (adjusted R^2 of 0.765). The estimated F-value was 15,430, indicating that the overall performance of the model was good.

4.2.2 Group 2: grand Yoho (with English name only) and park signature (with bilingual names)

The second group consisted of Grand Yoho (with English name only) and Park Signature (with bilingual names). The descriptive statistics of this group of data are shown in Table 3 below.

Table 4 shows the correlation of Group 1: Yoho Town (with English name only) and The Reach (with bilingual names). Table 5 lists the correlation analysis of Grand Yoho (with English name only) and Park Signature (with bilingual names). The estimated feature model has a very good data fit. Adjusted R^2 of 0.801 indicated that the model can explain 80%. The estimated F-value was 2050, showing that the overall performance of the model was good.

4.2.3 Estimation result of HPM model

Tables 6 and 7 list the estimated results of two groups of HPM models. Two sets of data showed that housing estates with English names are associated with higher housing prices (NOP=1 when housing estates have English names only and NOP=0 when housing estates have bilingual names). The correlation coefficients of the two tests results are 0.383 and 0.431, respectively. Compared with the data of the first group, the coefficients of the second group were relatively large. This showed that the second group of properties with English name only was capitalised at a higher value than the first group.

After conducting HPM, we move one step forward to predict the housing prices based on the abovementioned factors. Figure 1 showed the influence of each variable on the model. Figure 2 showed the variables' influence on the model. After comparative analysis, the results in Figure 2 show that the comprehensive price index and population have great influence on model's prediction accuracy.

In order to evaluate the performance and prediction accuracy of the model, we select RMSE, MAE and MAPE model evaluation according to the predicted value and the actual value of the housing prices. They are equal to 0 when the predicted value is completely consistent with the actual value, the formulas are as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i^{,} - y_i)^2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i^{,} - y_i\right|$$

Table 2. Descriptive statistics of the Yoho town (with English name only) and The Reach (with bilingual names).

Abbreviation	Variable	Mean	Median	Standard Deviation	Minimum	Maximum
Floor	Floor	19.73	19.00	11.463	1	52
Area	The usable area of the housing unit	495.30	440.00	151.342	354	1426
NOP	Property name	0.71	1	0.452	0	1
Traffic	The distance to the MTR station	0.71	1	0.452	0	1
TOV	Gross domestic product (millions of Hong Kong dollars)	212.833	220.979	17.767	164.125	251.206
APSI	Average personal salary index	111.693	112.800	7.261	99.2	131.7
M2	Money supply (millions of Hong Kong dollars)	8109.898	7136.271	3271.752	3813.442	14,745.872
HM	Number of households ('000)	2335.316	2331.320	135.803	2127.4	2652.5
CC	Housing construction cost	3693.989	3565.667	699.175	2639.000	5285.667
IC	Infrastructure cost	2255.941	1777.333	1033.991	697.667	3923.000
Population	Number of permanent residents ('000)	7069.261	7052.100	216.410	6764.2	7057.4
UR	Unemployment rate	4.659	3.700	1.773	2.8	8.4
CPI	Comprehensive consumption index	86.451	82.900	11.808	71.7	111.6
BLR	Best lending rate	5.134	5.000	0.525	5	8
HP	Housing price	373.51	353	228.849	74	2260

Table 3. Descriptive statistics of the grand Yoho (with English name only) and park signature (with bilingual names).

Abbreviation	Variable	Mean	Median	Standard Deviation	Minimum	Maximum
Floor	Floor	19.82	18.00	11.835	2	51
Area	Usable area of the housing unit	595.47	553.00	174.610	272	2038
NOP	Property name	0.39	0	0.487	0	1
Traffic	Distance to the MTR station	0.39	0	0.487	0	1
TOV	Gross domestic product (millions of Hong Kong dollars)	206.131	209.426	19.385	175.398	251.206
APSI	Average personal salary index	117.541	117.200	5.150	109.8	131.7
M2	Money supply (millions of Hong Kong dollars)	12,011.545	11,618.441	1461.465	10,056.437	14,745.872
HM	Number of households ('000)	2483.866	2505.250	58.892	2419.0	2652.5
CC	Housing construction cost	4295.615	4220.333	644.352	3303.667	5285.667
IC	Infrastructure cost	3406.733	3458.000	526.744	1672.000	3923.000
Population	Number of permanent residents ('000)	7324.434	7291.300	91.993	7210.9	7057.4
UR	Unemployment rate	3.271	3.300	0.2389	2.8	5.2
CPI	Comprehensive consumption index	100.871	103.100	4.949	92.4	111.6
BLR	Best lending rate	5.005	5.000	0.025	5	5.13
HP	Housing price	690.72	616.00	374.975	250	4382

$$MAPE = \frac{1}{N}\sum_{1}^{N}\left|\frac{y_i^{,} - y_i}{y_i}\right|$$

Here, $y_i^{,}$, is the predicted housing price, y_i is the actual housing price, and N is the number of experimental data samples. The smaller the RMSE, MAE and MAPE values, the better the performance of the prediction model, and the smaller the error between the predicted housing price.

The training and test results of this model are shown in Figure 3. Due to the large amount of experimental data, in order to show the output results of model more clearly, 300 consecutive housing price data are selected as the display data. It can be seen from Figure 3 that the training output of LSTM housing price forecasting model is close to the

Table 4. Correlation of the Yoho town (with English name only) and the reach (with bilingual names).

Variables	Floor	Area	NOP	HP	Traffic	TOV	APSI	M2	HM	CC	IC	Population	UR	CPI	BLR
Floor	1	0.161**	0.222	0.081***	0.222	0.162*	0.068**	0.077**	0.064**	0.109**	−0.130**	0.076**	0.063**	0.090**	0.004*
Area	0.161**	1	0.169**	0.911***	0.169**	0.161**	0.024**	0.089**	0.094**	−0.148**	−0.070**	0.083**	−0.089**	0.058**	0.081*
NOP	0.222	0.169**	1	0.383**	0.216	0.730**	0.451*	0.577*	0.526*	0.294**	0.276**	0.566*	0.510	0.589*	0.157*
HP	0.081***	0.911***	0.383**	1	0.385**	0.206***	0.600*	0.457***	0.464***	0.081**	0.503**	0.448**	−0.208**	0.428**	−0.225**
Traffic	0.222	0.169**	0.216	0.385**	1	0.730**	0.231**	0.577**	−0.526**	0.294**	0.676**	0.566**	0.510*	0.589**	0.157
TOV	0.162*	0.161**	0.730**	0.206***	0.730**	1	0.251**	0.319**	0.721**	0.012*	−0.572**	0.260**	0.326**	0.281**	0.123**
APSI	0.068**	0.024**	0.451*	0.600*	0.231**	0.251**	1	0.720*	0.711	0.146	0.463*	0.711*	0.063*	0.726**	0.113**
M2	0.077**	0.089**	0.577*	0.457***	0.577**	0.319**	0.720*	1	0.090**	0.523*	0.627*	0.191*	−0.637**	0.980**	0.174**
HM	0.064**	0.094**	0.526*	0.464***	−0.526**	0.721**	0.711	0.090**	1	0.244	0.573	0.396*	−0.298*	0.479*	0.175*
CC	0.109**	−0.148**	0.294**	0.081**	0.294**	0.012*	0.146	0.523*	0.244	1	0.554**	0.306**	−0.055	0.377**	−0.205**
IC	−0.130**	−0.070**	0.276**	0.503**	0.676**	−0.572**	0.463*	0.627*	0.573	0.554**	1	0.634**	0.025**	0.687*	−0.426**
Population	0.076**	0.083**	0.566*	0.448**	0.566**	0.260**	0.711*	0.191*	0.396*	0.306**	0.634**	1	0.711**	0.990**	0.185**
UR	0.063**	−0.089**	0.510	−0.208*	0.510*	0.326**	0.063*	−0.637**	−0.298*	−0.055	0.025**	0.711**	1	−0.866**	−0.004
CPI	0.090**	0.058**	0.589*	0.428**	0.589**	0.281**	0.726**	0.980**	0.479*	0.377**	0.687*	0.990**	−0.866**	1	0.220**
BLR	0.004*	0.081*	0.157*	−0.225**	0.157	0.123**	0.113**	0.174**	0.175*	−0.205**	−0.426**	0.185**	−0.004	0.220**	1

"***" Significant at 99% level, "**" significant at 95% level and "*" significant at 90% level.

Table 5. Correlation of the GRAND Yoho (with English name only) and park signature (with bilingual names).

Variables	Floor	Area	NOP	HP	Traffic	TOV	APSI	M2	HM	CC	IC	Population	UR	CPI	BLR
Floor	1	0.099***	0.560	0.476**	0.560	0.322**	0.117**	0.289**	0.297**	0.283**	−0.022**	0319**	0.008*	0.281**	0.056*
Area	0.099***	1	0.103**	0.926***	0.103*	0.080**	0.052***	0.162**	0.091**	−0.320**	−0.113**	0.122**	−0.116**	0.150**	0.113**
NOP	0.560	0.103**	1	0.431**	0.356	0.630**	0.175**	0.568*	0.569**	0.651**	0.108**	0.650*	0.111*	0.568**	0.076**
HP	0.476**	0.926***	0.431**	1	0.631**	0.585*	0.230**	0.583***	0.557**	0.395**	0.251**	0.608**	−0.172**	0.550**	0.268**
Traffic	0.560	0.103*	0.356	0.631**	1	0.630**	0.175	0.568**	−0.569**	0.651**	0.108**	0.650**	0.111*	0.568**	0.076*
TOV	0.322**	0.080**	0.630**	0.585*	0.630**	1	0.354**	0.828**	0.883***	0.705**	−0.296**	0.906**	−0.228**	0.839**	0.388**
APSI	0.117**	0.052***	0.175**	0.230**	0.175	0.354**	1	0.557**	0.475	0.415*	−0.303	0.481*	−0.023***	0.594**	0.166**
M2	0.289**	0.162**	0.568*	0.583***	0.568**	0.828**	0.557**	1	0.941*	0.728	0.444*	0.973*	−0.460*	0.961**	0.363*
HM	0.297**	0.091**	0.569**	0.557**	−0.569**	0.883***	0.475	0.941*	1	0.610	−0.568	0.982**	−0.186**	0.929**	0.417**
CC	0.283**	−0.320**	0.651**	0.395**	0.651**	0.705**	0.415*	0.728	0.610	1	0.205**	0.748	0.041*	0.751*	−0.041**
IC	−0.022**	−0.113**	0.108**	0.251**	0.108**	−0.296**	−0.303	0.444*	−0.568	0.205**	1	−0.442*	0.587	0.368**	−0.527**
Population	0.319**	0.122**	0.650*	0.608**	0.650**	0.906**	0.481*	0.973*	0.982**	0.748	−0.442*	1	−0.446**	−0.097**	0.411**
UR	0.008*	−0.116**	0.111*	−0.172**	0.111*	−0.228**	−0.023***	−0.460*	−0.186**	0.041*	0.587	−0.446**	1	−0.097**	−0.400**
CPI	0.281**	0.150**	0.568**	0.550**	0.568**	0.839**	0.594**	0.961**	0.929**	0.751*	0.368**	−0.097**	−0.097**	1	0.356**
BLR	0.056*	0.113**	0.076**	−0.268**	0.076*	0.388**	0.166**	0.363*	0.417**	−0.041**	−0.527**	0.411**	−0.400**	0.356**	1

"***" Significant at 99% level, "**" significant at 95% level and "*" significant at 90% level.

Table 6. Estimated results of group 1,2.

Independent variable	Yoho Town (with English name only) and The Reach(with bilingual names)	Grand Yoho (with English name only) and Park Signature(with bilingual names)
Constant	−3.299	−4.482
log (Floor)	0.487**	0.477**
log (Area)	0.562**	0.685***
NOP	0.461**	0.541**
Traffic	0.335**	0.501**
log (TOV)	0.300**	0.145*
log (APSI)	0.259	0.105
log (M2)	0.329***	0.198***
log (HM)	0.449**	0.445**
log (CC)	0.307**	0.426**
log (IC)	0.282*	0.461*
log (Population)	0.877**	0.897**
log (UR)	−0.296	−0.455*
log (CPI)	0.428**	0.550**
log (BLR)	−0.206**	−0.281*
Adjusted R-squared	0.791	0.832
F-statistic	12,484	2540

"***" Significant at 99% level, "**" Significant at 95% level, and "*" significant at 90% level.

Table 7. Comparison of case data between two groups.

	Coefficient	t-statistics
Yoho Town (with English name only) andThe Reach (with bilingual names)	0.383	178.022
Grand Yoho (with English name only) andPark Signature (with bilingual names)	0.431	51.873

significant at 95% level.

actual housing price data. It indicates that the model is suitable for housing price prediction and has strong learning ability. The predicted results fit the actual values well, with high prediction accuracy and fitting curves, in particular when we deal with housing price data with large fluctuations. The predicted results are basically consistent with the changing trend of real housing price data.

Table 8 lists the RMSE, MAE and MAPE values of LSTM housing price prediction model with multi-dimensional data. The experimental results showed that LSTM housing price prediction with multi-dimensional data is practical and superior, but it does not rule out the model has room for further improvement.

4.2.4 Comparison results and analysis with another model

To further test the superiority of LSTM housing price prediction model with multi-dimensional data, LSTM housing price prediction model and ARMA housing price forecasting model are selected for comparison, and two sets of case data are also used as experimental sample data to train and test the models. In order to show the comparison results of the model training output, housing price data of the last 10 months is selected as the output results of ARMA model and LSTM housing price prediction model with multidimensional data processing. Figure 4 clearly shows the comparison results between the test outputs of two housing price forecasting models and the actual data. Compared with ARMA housing price forecasting model, the LSTM housing price

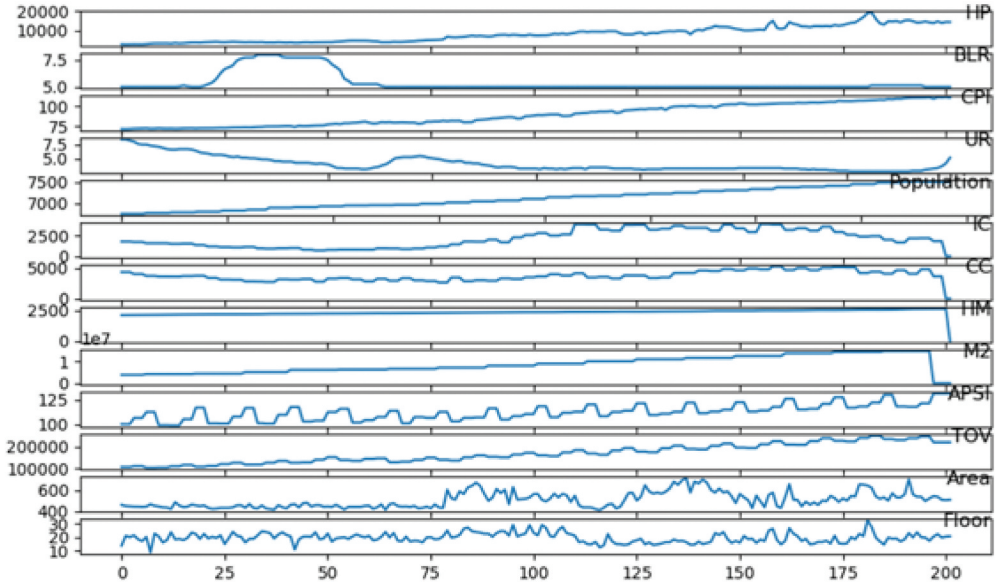


Figure 1. The influence of each variable in LSTM model.

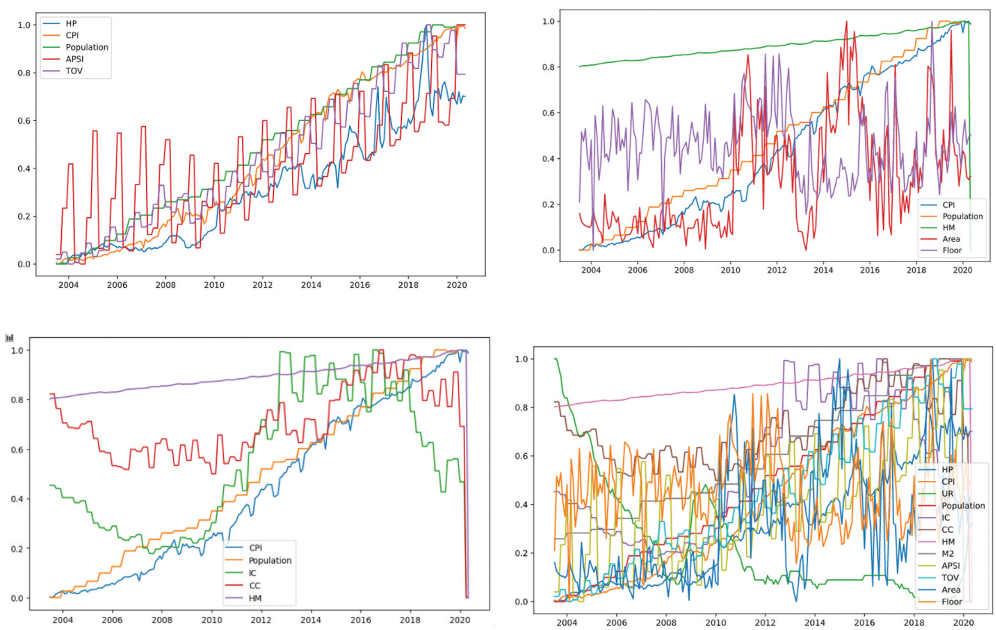


Figure 2. The top variables that impact the model.

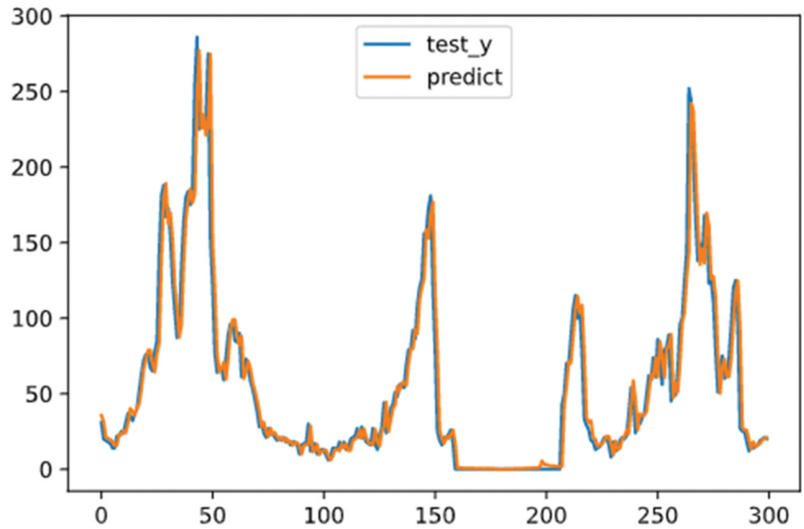
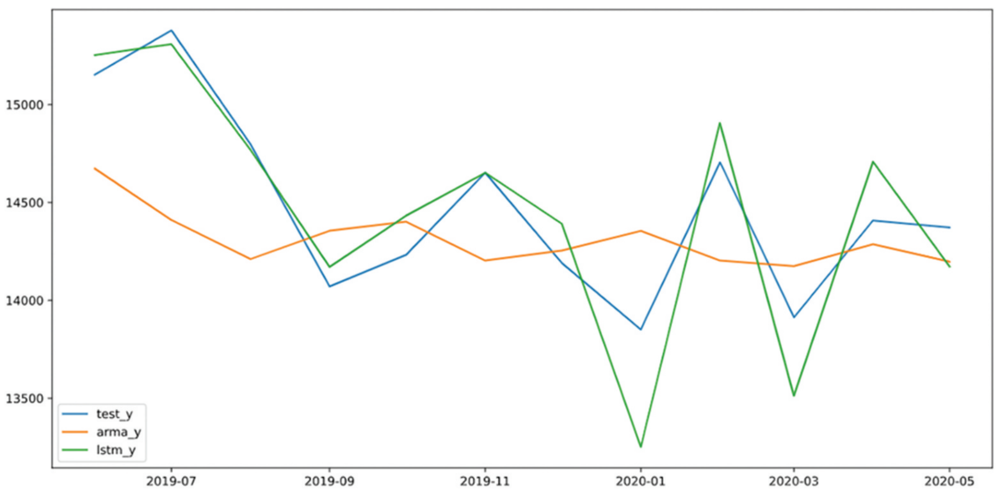


Figure 3. Housing price forecast chart based on LSTM.

Table 8. Test error of LSTM model for multidimensional data processing.

Evaluation index	RMSE	MAE	MAPE
LSTM forecasting model with multidimensional data processing	0.1817	0.1336	0.0107



ARMA model

Figure 4. Test output comparison results of LSTM model for multidimensional data processing.

prediction model with multi-dimensional data in this research is closer to the actual housing price data. ARMA model's forecasting results are bad when the housing price fluctuates greatly. Yet, the predicted value of LSTM model is very close to the actual housing price even when the data fluctuates substantially. Table 9 lists the RMSE, MAE

Table 9. Comparison of test errors between LSTM model for multidimensional data processing and ARMA model.

s	RMSE	MAE	MAPE
LSTM forecasting model with multidimensional data processing	0.1817	0.1336	0.0107
ARMA forecasting model	0.4631	0.3683	0.0254

and MAPE values of LSTM housing price prediction model and ARMA housing price forecasting model.

It can be seen from Table 9 that the LSTM housing price prediction model with multidimensional data has relatively small errors and superior performance. Compared with ARMA housing price forecasting model, the RMSE of root mean square error is reduced by 60.76%, the MAE of average absolute error is 63.72% less, and the MAPE of average absolute percentage error is reduced by 57.87%. Therefore, the LSTM housing price prediction model in this paper can perform better even in times of high volatility. Thus, LSTM is useful in housing price prediction.

5. Conclusion

The purpose of this study was to explore the impact of Chinese and English names of properties on housing prices. Because of many recent housing estates are named in English instead of traditional bilingual with English and Chinese, we speculated that properties with English names only might be associated with higher housing prices. By using big data analysis, and the classic HPM, we analysed 253,605 transaction data points, compared two large pairs of residential estates' transactions in Yuen Long District, and found that housing estates with English names are associated with higher housing prices. This phenomenon might be attributed to the norms that housing estates with pure English names are associated with prestige branding among Hong Kong people.

The empirical results also showed that the influence of English name in the second group (Grand Yoho (with English name only) and Park Signature (with bilingual names) was greater than that of the first group (Yoho Town (with English name only) and The Reach (with bilingual names). This might be attributed to factors that were not included in this study.

Another finding was that in terms of the housing characteristics, the usable area of housing units was the most important factor affecting housing prices, which was closely related to the limited housing resources in Hong Kong. For every increase in the usable area of a housing unit, the housing price increases by 91.1% to 92.6%. In addition, transportation (referring to the MTR station in this study) had an important impact on housing prices, particularly in the second group. In terms of economic factors, both money supply (M2) and GDP showed a strong correlation with the housing prices. With regard to social factors, there was a positive correlation between the resident population and the number of families and housing prices, which was also in line with the law of social development. The increase in population and the number of families led to a stronger housing demand, leading to housing shortage and higher housing prices. Besides, the comprehensive consumption index of residents had a significant positive correlation with the housing prices. For every unit increase in the comprehensive consumption index, the housing price increases by 42.8% to 55%.

In this article, we utilised big data and artificial intelligence for analysing factors that impact housing price. Therefore, we could better understand the structure and dynamics of the urban real estate market. There are many factors that affect housing prices. Under the influence of external economic factors such as cyclical changes in the market, news release regarding major economic policies, and sudden epidemics outbreak, the number and types of model factors can be adjusted to improve the performance of the LSTM model and provide more valuable information to investors. Finally, because it is almost impossible to include all the variables in our model, we omitted some variables. In the future, our present models can be enlarged with more housing transaction data and incorporate other variables.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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