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A long short-term memory model for forecasting housing prices in Taiwan in the post-epidemic era through big data analytics

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A B S T R A C T

This study aims to analyse housing prices in Taiwan in the post-epidemic era, identify the crucial factors influencing them, and develop a suitable method for analysing and forecasting them. This study collects relevant data such as Taiwan's housing price index data from 2002 to 2020 to identify the crucial factors affecting Taiwan's housing prices; this is achieved by constructing a regression model, forecasting Taiwan's housing prices through a constructed long short-term memory (LSTM) model that employs big data analytics, and verifying the efficiency of the proposed models through *R-square* and root mean square error values. The results indicate that the top 10 factors affecting Taiwan's housing prices are mostly related to mortgage interest rates, suggesting that in Taiwan, the effect on housing prices in the post-epidemic era may be non-significant. This study collects data on Taiwan's housing price for the period from the first quarter of 2002 to the fourth quarter of 2020 to construct an LSTM for forecasting Taiwan's housing prices. The results indicate that the proposed LSTM exhibits good fitness, indicating that the model is suitable for analysing and forecasting housing prices. Given that analysing and forecasting quantity is also crucial in housing market analyses and that this study focuses only on predicting housing prices, future research should explore the simultaneous prediction and analysis of both price and quantity.

1. Introduction

Housing prices have always been a key topic for the public and among local and foreign governments, and abundant research regarding this topic has been published. Since 1949, due to political policies, the housing market in Taiwan has experienced three to seven rent reductions following events such as the release of the commons in 1951, the 823 artillery exchange in 1958, Taiwan's withdrawal from the United Nations in 1971, and the first presidential election in 1996. Subsequently, national elections, the 921 earthquake in 1999, and the first transfer of power to an opposition party in 2000 no longer shocked Taiwan's housing market. The influence of cross-strait relations on housing prices is also a unique factor influencing Taiwan's real estate market. Taiwan's housing prices have undergone various changes in the past two decades. For example, Taiwan's housing prices temporarily stopped increasing during the 921 earthquake in 1999 and the first transfer of power to an opposition party in 2000, denoting a wait-and-see market. Subsequently, housing prices increased again in anticipation of a business recovery. In 2003, when the severe acute respiratory syndrome (SARS) outbreak occurred, housing prices stopped increasing but exhibited an upward trend of recovery, after which they stabilised when the epidemic was successfully controlled. Taiwan's housing prices continued to increase until October 2007, when the subprime mortgage crisis in the United States created a global financial tsunami, causing Taiwan's housing prices to decrease sharply. With the subsequent stabilisation of the global financial market, the upward trend of Taiwan's housing prices was reverted. After a decade of prosperity, which ended in 2013, Taiwan's housing prices bottomed in 2015. In 2019, Taiwan's housing prices recovered, but the emergence of the coronavirus disease 2019 (COVID-19) pandemic in early 2021 created a panic in Taiwan.

From the perspective of the currency market, the high reliance

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of consumers on housing loans to address the lack of short-term capital creates an inseparable link between the housing market and the rapidly changing currency market. Therefore, the number of housing loans and the corresponding interest rates warrant further investigation in housing industry research. On March 16, 2020, the Dow Jones Industrial Average decreased by 2997.1 points (12.93%), which was the largest 1-day decline since the Black Monday event on October 19, 1987. This economic shock, which was caused by noneconomic factors (primarily the COVID-19 pandemic), caused a global stock market crash at the beginning of 2020. However, the global economic climate quietly recovered in 2021. Given this history, the present study focuses on forecasting future housing market fluctuations in Taiwan. It aims to collect data on Taiwan's housing market to identify crucial factors affecting housing prices in Taiwan, construct a big data analytics and prediction model for housing prices in Taiwan, and verify and compare the constructed model with other models.

2. Literature review

This section provides a discussion of the general economic cycle of Taiwan's housing market and a review of the literature on housing price analysis, forecasting models, big data analytics, and deep learning (DL) models in the context of Taiwan's housing market.

2.1. Overview of business cycle of Taiwan's housing market

The present study aims to use big data analytics and DL methods to establish a model for predicting housing prices in Taiwan. In the model, the dependent variable "housing price" is analysed using housing price index data. For the quarterly data on Taiwan's housing price index, the sampling period is from the first quarter of 2001 to the third quarter of 2020, with the first quarter of 2001 serving as the base time point. The trend for the Taiwan House Pricing Index from the first quarter of 2001 to the first quarter of 2021 is presented in Fig. 1, and the corresponding growth rate is presented in Fig. 2. The housing price trends of several cities in Taiwan from the first quarter of 2001 to the first quarter of 2021 are presented in Fig. 3 (Interior Taiwan, 2021; Stock-AI, 2021). Fig. 3 reveals that the housing prices in Taiwan grew year by year from 2012 to 2020 but decreased slightly in the fourth quarter of 2016. This trend in the fourth quarter of 2016 may be due to political factors leading to a wait-and-see attitude in the market. However, after 2016, housing prices began to increase slowly. In early 2020, the COVID-19 pandemic occurred, which was more severe than the SARS outbreak. During this period, all global economic indicators indicated a general decline. The global economic impact of the COVID-19 pandemic began to gradually subside in late 2020, and global economic indicators seem to have picked up again at beginning of 2021. How this trends affected Taiwan's housing prices is the focus of this study.

2.2. Literature on factors affecting housing prices

Regarding the factors influencing housing market prices, numerous studies have explored housing prices on the basis of changes in financial and monetary markets. Fortura and Kushner (1986) discovered that expected inflation causes an increase in housing demand, which in turn causes housing prices to increase. McCue and Kling (1994) employed a vector self-regression model to identify the direct relationships of price levels, nominal interest rates, real output, and private investment activities with changes in real estate returns, and they discovered that nominal interest rates have the greatest influence. Barras, Bourgeois, and Handley (1994) indicated that U.K. housing prices are affected by the overall economy, real estate market, and currency market of the United Kingdom. Quan and Titman (1999) conducted a regression analysis, and they proposed that real estate compensation is correlated with stock prices, and that real estate prices are affected by a country's gross national product.

Sanders (2008) explored housing price index trends based on mortgage balance, subprime mortgage ratios, and mortgage interest rates. Croce and Haurin (2009) constructed a forecasting model for housing price business cycles based on four indicators, namely the number of housing construction licenses issued, the number of houses built, the number of new houses sold, and the number of existing homes sold (the volume of housing intermediaries); notably, their model made predictions and was modified using the Bayesian probability method. Shi, Young, and Hargreaves (2009) adopted the sale appraisal ratio (SPAR) method to measure housing prices; in their model, the main variable was the ratio of the current announced value of a house to its sale price. Oikarinen (2009), constructed a dynamic model for predicting housing prices on the basis of average per capita national income, population, and mortgage balance. Zhou (2018) employed a sentiment index to explore housing prices in mainland China.

Meyer (2019) conducted a relative operating characteristic analysis to predict housing operating rates in the United States. Kou and Gedik (2019) used big data analytics, a vector self-reversion model, and other methods to explore the housing price trend in Australia after the 2008 financial tsunami from the perspective of human behaviour and Internet voice volume (Google Trends; GT). Lee and Kim (2019) performed auto-regressive integrated moving average analysis (ARIMA) and employed a regression model to predict housing prices in South Korea; in their analysis, the main predictive variable was the Internet search volume.

Through the use of an artificial neural network model, Rahman, Maimun, Razali, and Ismail (2019) successfully predicted the housing prices in Malaysian cities. Rahman et al. (2019) built a neural network–based nonlinear model to explore the relationships of traditional economic indicators (e.g., income and interest rates) with housing prices in Malaysia.

2.3. Literature on models for forecasting housing prices

To predict housing prices by using big data analytics, Kou and Gedik (2019) built a model for forecasting housing prices in Australian cities by conducting self-regression analysis and employing the big data analytics features of GT. Lee and Kim (2019) built an ARIMA model that used the Internet volume to predict housing prices in South Korea. Rostami and Hansson (2019) used a long short-term memory (LSTM) model and a support vector machine (SVM) to analyse housing prices.

LSTM is a DL method. DL involves using multilayer neural networks and the related training methods. Specifically, a large amount of matrix data is input, weights are calculated nonlinearly, and the output is generated. This information processing mechanism is similar that of a neural network formed from brain nerves. A neural network flow chart is presented in Fig. 4 (Rostami & Hansson, 2019).

DL can be used to extract features and learn from sample data with diverse characteristics (Fawaz, Forestier, Weber, Idoumghar, & Muller, 2019; Fischer & Krauss, 2018; Sadaei, e Silva, Guimarães, & Lee, 2019; Thompson & Li, 2019; Yu, Chen, Li, Ji, & Wu, 2019). Commonly used DL methods include the convolution neural network (CNN), which is mainly used for processing images, and the recurrent neural network (RNN), which is often used to process sequential data. A RNN mainly adds the weight obtained from a previous input to the next layer to complete the sequential

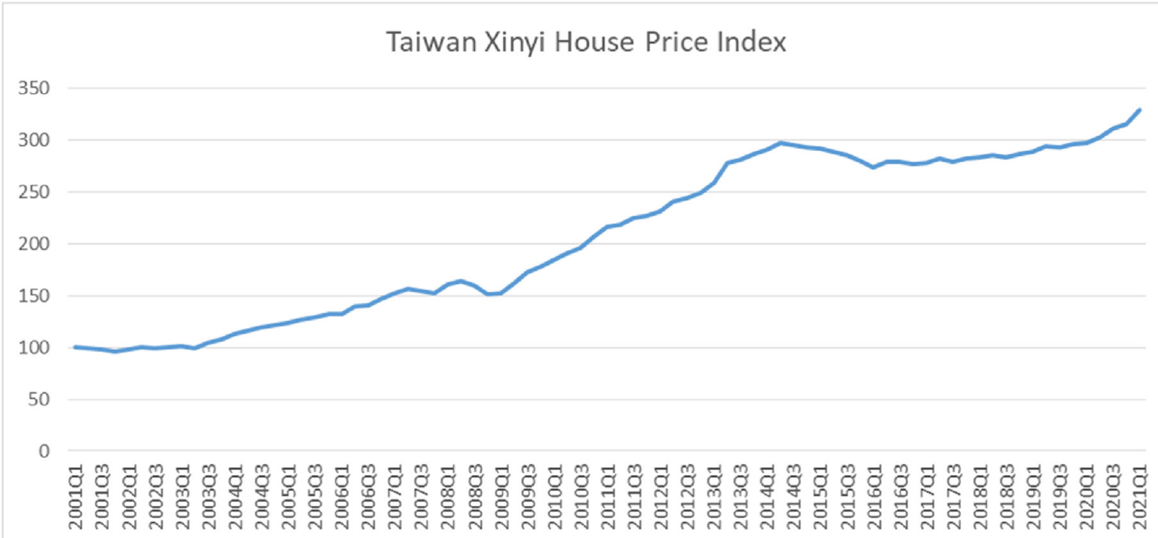

Fig. 1. Taiwan's housing price index from first quarter of 2001 to first quarter of 2021.
Source:a. Stock AI, Taiwan Xinyi House Price Index (2021), cite from: https://stock-ai.com/grp-Mix-twSinyi.php.b. Real Estate Information Platform of the Ministry of the Interior of Republic of China (Taiwan).c. This study drawing based on the first quarter of 2001.

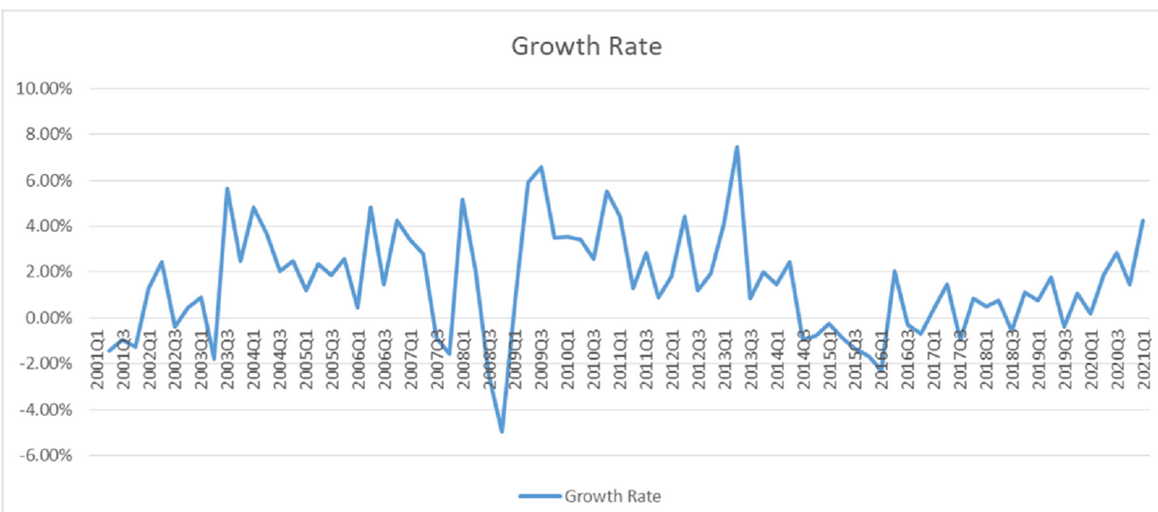

Fig. 2. Growth rate of Taiwan's housing price index from first quarter of 2001 to first quarter of 2021.
Source:a. Stock AI, Taiwan Xinyi House Price Index (2021), cite from: https://stock-ai.com/grp-Mix-twSinyi.php.b. Real Estate Information Platform of the Ministry of the Interior of Republic of China (Taiwan).c. This study drawing based on the first quarter of 2001.

calculation of data (Wang, 2020). An RNN extracts key information from the beginning and end of an article and performs cyclic repetitions (i.e., the same operation is repeated for each variable of the sequence data). Because the output of an RNN is dependent on previous calculations, it is suitable for predicting future housing prices on the basis of past housing prices.

Traditional RNNs, in practice, have limitations in terms of their ability to the process long-term memory. Therefore, numerous studies have developed LSTM models to improve the capabilities of RNNs (Chang, 2019). As a type of RNN, the first LSTM model was proposed by Hochreiter and Schmidhuber (1997). The model is characterised by its greater number of control units relative to that in other models and can thus analyse time-series data. LSTM is often used to forecast prices in the financial market because it can be used to analyse the interrelationships between data points before and after a given time point, thereby clarifying the interrelationships within time-series data. Fischer and Krauss (2018) used LSTM to forecast the S&P 500 stock market. Temür, Akgün, and Temür (2019) used LSTM and ARIMA to construct an analysis model for predicting housing prices in Turkey. Ge (2019) used LSTM and CNNs to analyse housing prices in Beijing and New York.

Numerous international studies have used LSTM to analyse housing prices, demonstrating the feasibility of constructing LSTM-based housing price prediction models. However, construction investment primarily affects domestic or regional markets, and in research on housing prices in multiple cities, local data are still required. This study uses the LSTM model to construct and validate a model for forecasting housing prices in Taiwan in the post-COVID-19 era.

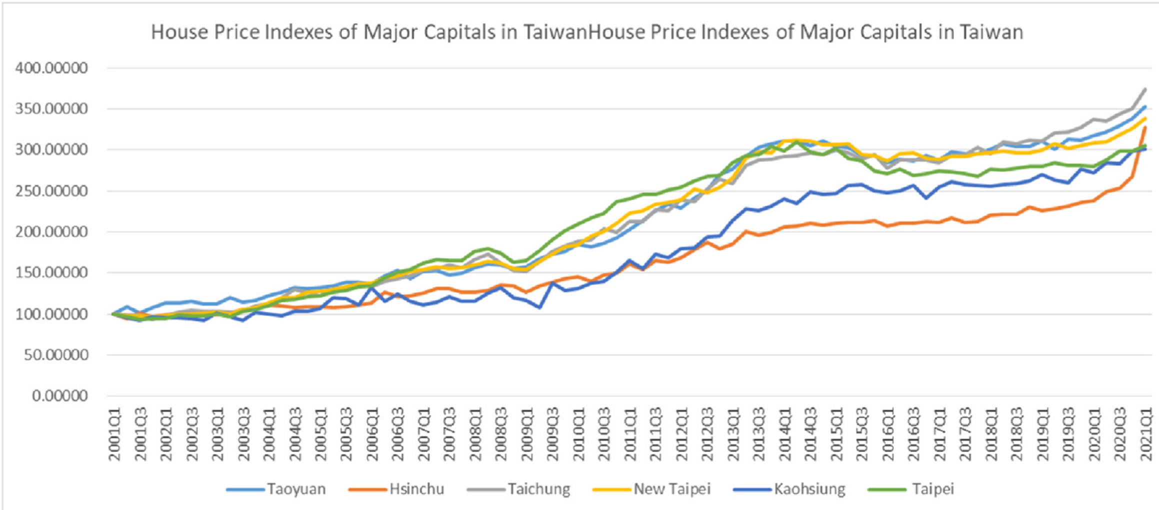

Fig. 3. Housing price indices of major cities in Taiwan from first quarter of 2001 to first quarter of 2021.
Source:a. Stock AI, Taiwan Xinyi House Price Index (2021), cite from: https://stock-ai.com/grp-Mix-twSinyi.php.b. Real Estate Information Platform of the Ministry of the Interior of Republic of China (Taiwan).c. This study drawing based on the first quarter of 2001.

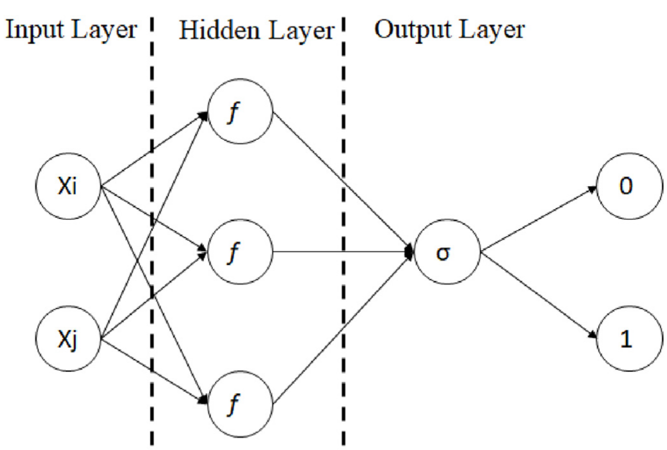

Fig. 4. Neural network flow chart (Rostami & Hansson, 2019).

3. Methodology

3.1. Regression model

This study collected data on more than 30 variables through a literature survey, and through correlation analysis, this study extracted 10 independent variables that were significantly correlated with Taiwan's housing prices, including the Taiwan Housing Price Index, TWSE capitalisation weighted stock index, Taiwan's economic growth rate, consumer price index, average mortgage interest rate, M1b money supply, housing loan burden rate, and housing price income ratio; and volatility index futures (VIX). The notations used in the present study are presented in Table I.

The present study employed the Phillips–Perron (PP; Phillips & Perron, 1988) test to construct the model. Phillips and Perron (1988) proposed the PP test to overcome the limitations of the augmented Dickey–Fuller test (ADF) which proposed by Dickey and Fuller (1979). The PP test allows for the presence of weak dependencies and heterogeneity in residual terms, and it applies the distribution and critical values used in the ADF test. The PP test is similar to the ADF test in that it can be distinguished by the conditions of an intercept (ω_0) and a time trend (t). An equation that contains only the intercept (ω_0) can be expressed as equation (1).

$$y_t = \omega_0 + \omega_1 y_{t-1} + \theta_t \quad (1)$$

The present study used the PP test to conduct a regression analysis and to explore the key factors affecting housing prices in Taiwan. Specifically, the Taiwan Housing Price Index (Xinyi Housing Price Index) was used as a criterion variable, the forecast variables were gradually selected through gradual regression analysis, and a regression model of crucial factors affecting housing prices in Taiwan was constructed. The concept of this model is expressed in equation (2), where Y_{t+1} is the Taiwan House Pricing Index for the period $t+1$, X_t is the value of the independent variable for period t, a is the intercept term, and ε is the residual term.

$$Y_{t+1} = a + b_0 Y_t + b_1 X_1 + b_2 X_2 + \ldots + \varepsilon \quad (2)$$

3.2. DL model

The present study also used a DL method to construct a model for forecasting housing prices in Taiwan. This model is primarily based on the housing price prediction model developed in another study (Rostami & Hansson, 2019), which used an RNN, a LSTM model, and an SVM to analyse housing prices; the concept of the RNN model is presented in Fig. 5. In the presented equation, y is the predicted Taiwan Housing Price Index, t is the data collection period, y_{t-k} is the Taiwan Housing Price Index for each period in the data set, x comprises the independent variables that affect housing prices, and x_{it-k} represents the data in each period of each variable in the data set.

Compared with other RNN models, an LSTM model incudes the additional three steps of forgetting, updating, and outputting to a neural unit, which is presented in Fig. 6, where ⊗, tanh, and ⊕ are in the circle; σ is in the box; and tanh is the gate. The function of the LSTM model is to calculate the amount of data updated to the cell state through mathematical functions. The top horizontal line connects all neural units (Chang, 2019). The symbol descriptors in the LSTM model (Fig. 6) are presented in Table II.

Table 1
Notations used in this study.

Symbol	Illustration	Unit
THPI	Taiwan House Price Index	
TAIEX	TWSE Capitalization Weighted Stock Index	
EGR	Economic Growth Rate of Taiwan	%
CPI	Consumer Price Index of Taiwan	%
AMIR	Average Mortgage Interest Rate of Taiwan	%
M1b	M1b money supply of Taiwan	100 million NT dollar
THLBR	Taiwan Housing Loan Burden Rate	%
THPIR	Taiwan Housing Price Income Ratio	times
VIX	Volatility Index Futures (VIX)	
ln_THPI	Taiwan House Price Index takes the logarithm	
ln_TAIEX	TWSE Capitalization Weighted Stock Index takes the logarithm	
ln_CPI	Consumer Price Index of Taiwan takes the logarithm	
ln_AMIR	Average Mortgage Interest Rate of Taiwan takes the logarithm	
ln_M1b	M1b money supply of Taiwan takes the logarithm	
ln_THLBR	Taiwan Housing Loan Burden Rate takes the logarithm	
ln_THPIR	Taiwan Housing Price Income Ratio takes the logarithm	
ln_VIX	Volatility Index Futures takes the logarithm	
nor_THPI	Normalized Taiwan House Price Index	
nor_TAIEX	Normalized TWSE Capitalization Weighted Stock Index	
nor_EGR	Normalized Economic Growth Rate of Taiwan	
nor_CPI	Normalized Consumer Price Index of Taiwan	
nor_AMIR	Normalized Average Mortgage Interest Rate of Taiwan	
nor_M1b	Normalized M1b money supply of Taiwan	
nor_THLBR	Normalized Taiwan Housing Loan Burden Rate	
nor_THPIR	Normalized Taiwan Housing Price Income Ratio	
nor_VIX	Normalized Volatility Index Futures	

4. Results

The present study collected data pertaining to Taiwan's housing prices and other related factors from the first quarter of 2002 to the fourth quarter of 2020. Table III presents the data from the final 5 years of this study period.

4.1. DL model for housing prices in Taiwan

Two-thirds of the collected data were used for training, and one-third was used for testing to obtain predictions regarding housing prices in Taiwan for the subsequent quarter. The results are presented as a fluctuation graph in Fig. 7, where the *X* axis is the period, which starts from the beginning of the first quarter of 2002 and is divided into quarters, and the *Y* axis is the normalized Taiwan Housing Price Index. In Fig. 7, the blue line represents the actual value, the orange line displays the predicted value, and the proposed LSTM model for predicting housing prices in Taiwan exhibits a good fit.

4.2. Regression model for housing prices in Taiwan

In the present study, the independent variables used to forecast housing prices in Taiwan were identified on the basis of the relevant studies that explored factors affecting housing prices. The correlation coefficient and significance of each variable are presented in Table IV. The variables initially identified through correlation analysis were the Taiwan Housing Price Index ($p^{***} < 0.01$), TWSE capitalisation weighted stock index ($p^{***} < 0.01$), economic growth rate ($p^{*} < 0.1$), consumer price index ($p^{***} < 0.01$), average

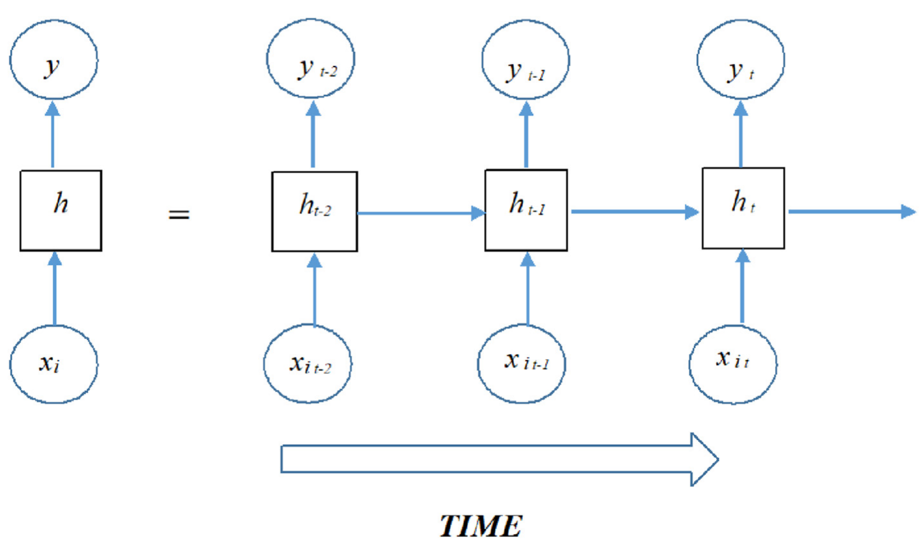

Fig. 5. The RNN model for housing prices prediction provided by (Rostami & Hansson, 2019).

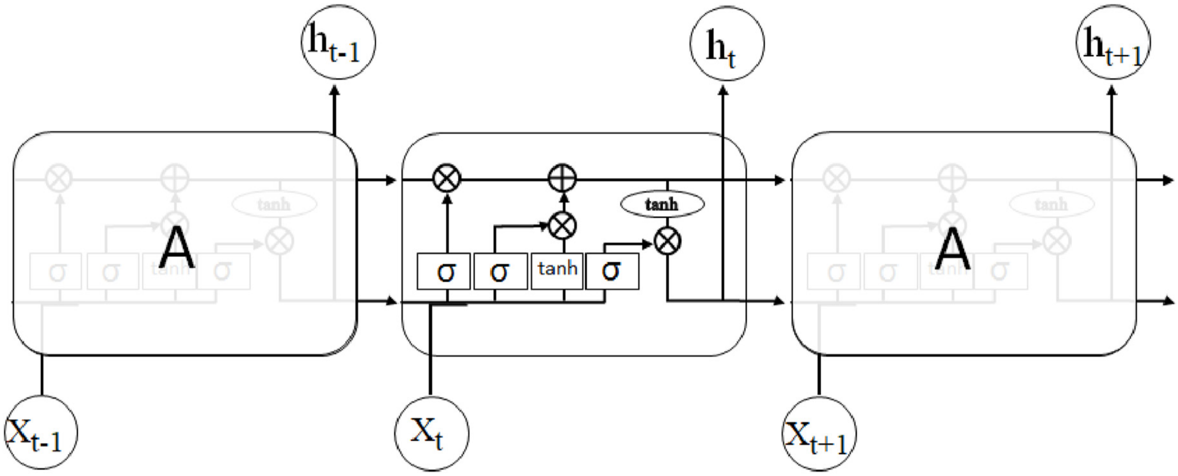

Fig. 6. Visualisation of deep learning concept (Olah, 2015).

Table 2
Notations of deep learning model.

symbol	Illustration
⊗	modified information
⊕	added information
σ	Sigmoid layer
tanh	tanh layer
$h(t-1)$	The output of the previous LSTM unit
$c(t-1)$	The memory of the previous LSTM unit
$X(t)$	Input
$c(t)$	Latest memory
$h(t)$	Output

mortgage interest rate ($p^{***} < 0.01$), M1b money supply ($p^{***} < 0.01$), housing loan burden rate ($p^{***} < 0.01$), and housing price income ratio ($p^{***} < 0.01$) of Taiwan; and VIX ($p^{*} < 0.1$).

The correlation coefficients of the normalized values of these variables are expressed as a visual matrix (Fig. 8).

The present study further constructed a regression model to identify the key factors affecting the Taiwan Housing Price Index. Four key factors affecting the current Taiwan Housing Price Index ($THPI_t$) were extracted: Taiwan's housing price income ratio ($THPIR_t$), Taiwan's M1b money supply ($M1b_t$), Taiwan's housing loan burden rate ($THLBR_t$), and Taiwan's average mortgage interest rate of Taiwan ($AMIR_t$). Stepwise regression analysis was performed using the current Taiwan Housing Price Index ($THPI_t$) as the dependent variable, and the results are presented in Table V.

The *R-square* of the proposed regression model reached 0.970, indicating its simplicity and accuracy. The regression model for $THPI_t$ can be expressed as equation (3) (nor means normalized data).

$$nor\_THPI_t = 0.363 - 1.879 \times (nor\_THPIR_t) + 0.588 \times (nor\_M1B_t) + 2.107 \times (nor\_THLBR_t) - 0.665 \times (nor\_AMIR_t) \tag{3}$$

The regression model was then used to produce predictions regarding the current Taiwan Housing Price Index, and a comparison of the prediction results with the actual data revealed the perfect fit of the model (Fig. 9).

Two key factors affecting the Taiwan Housing Price Index in the subsequent period ($THPI_{t+1}$) were then extracted, namely the current Taiwan Housing Price Index ($THPI_t$) and Taiwan's average mortgage interest rate ($AMIR_t$). Stepwise regression analysis was performed using the Taiwan Housing Price Index in the subsequent period ($THPI_{t+1}$) as the dependent variable, and the results are presented in Table VI.

The *R-square* of this model reached 0.996, indicating its perfect fit. The regression model for $THPI_{t+1}$ can be expressed as equation (4).

$$nor\_THPI_{t+1} = 0.300 + 0.925 \times (nor\_THPI_t) - 0.051 \times (nor\_AMIR_t) \tag{4}$$

The results revealed that the key factor affecting the Taiwan Housing Price Index was the average mortgage interest rate. The performance of the proposed regression model is described in Fig. 10.

4.3. Model evaluation

Furthermore, the present applied the comparison criteria for root mean squared error (*RMSE*) and *R-square* to evaluate the effectiveness of the proposed models and to compare them with other models.

(1) The *RMSE* is the square root of the mean square error (*MSE*); *MSE* measures the deviation between actual and predicted values. In the present study, *MSE* is expressed in equation (5), and *RMSE* is expressed in equation (6).

$$MSE = \frac{\sum_{t=1}^{n} (\widehat{Y_t} - Y_t)^2}{n}; \tag{5}$$

Table 3
Data pertaining to Taiwan's housing price index and other related factors from last 5 years.

Time	THPI	TAIEX	EGR	CPI	AMIR	M1b	THLBR	THPIR	VIX
2016Q1	274.200	8412.197	−0.300	99.183	1.837	154004.667	35.350	8.460	20.486
2016Q2	279.740	8526.690	1.010	99.593	1.730	154130.667	37.140	8.970	15.676
2016Q3	278.970	9073.370	2.040	100.057	1.683	157332.000	38.490	9.350	13.234
2016Q4	277.060	9261.443	2.770	101.170	1.667	159663.333	38.340	9.320	14.098
2017Q1	278.240	9669.980	2.640	99.957	1.670	161809.333	38.040	9.240	11.692
2017Q2	282.360	10102.597	2.280	100.157	1.660	160842.667	38.900	9.460	11.426
2017Q3	279.620	10447.684	3.180	100.797	1.637	164713.667	37.840	9.220	10.944
2017Q4	281.960	10665.700	3.420	101.577	1.630	166274.667	37.580	9.160	10.308
2018Q1	283.340	10941.826	3.150	101.513	1.633	169394.333	37.250	9.080	17.355
2018Q2	285.550	10789.917	3.290	101.877	1.627	170031.333	36.900	9.000	15.338
2018Q3	283.980	11042.597	2.380	102.480	1.623	173683.333	36.170	8.820	12.857
2018Q4	287.200	9805.857	1.800	102.050	1.627	175295.667	35.120	8.570	21.054
2019Q1	289.330	10320.823	1.830	101.837	1.633	181018.667	35.530	8.660	16.469
2019Q2	294.460	10732.350	2.400	102.707	1.620	182832.667	36.060	8.790	15.183
2019Q3	293.350	10757.180	3.030	102.903	1.620	186746.000	34.730	8.470	15.960
2019Q4	296.480	11615.140	3.310	102.767	1.617	188547.333	35.150	8.580	13.986
2020Q1	297.060	10831.776	2.510	102.387	1.607	194333.667	35.300	8.620	31.225
2020Q2	302.610	11185.180	0.350	101.700	1.363	199064.667	34.640	8.660	34.494
2020Q3	311.230	12590.620	4.260	102.417	1.360	207831.333	36.760	9.190	25.809
2020Q4	315.750	13667.253	5.090	102.720	1.363	217038.667	36.810	9.200	25.622

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(\widehat{Y_t} - Y_t)^2}{n}}. \tag{6}$$

where $\widehat{Y_t}$ is the predicted value of the Taiwan Housing Price Index at time t, Y_t are the actual values of the Taiwan Housing Price Index at time t, and n is number of observations.

(2) *R-square* measures how successful the fit is in explaining a variation of the data, and it can be expressed in equation (7).

$$Rsq = 1 - \frac{\sum_{t=1}^{n}(\widehat{Y_t} - Y_t)^2}{\sum_{t=1}^{n}(Y_t - \overline{Y_t})^2}. \tag{7}$$

For the proposed LSTM model, its training model had an *RMSE* of 0.019, and its test model had an *RMSE* of 0.033. The *R-square* of the proposed LSTM was 0.995. For the proposed regression model, its *RMSE* and *R-square* for forecasting the current Taiwan Housing Price Index were 0.058 and 0.970, respectively, and its *RMSE* and *R-square* for forecasting the subsequent-period Taiwan Housing Price Index were 0.270 and 0.996, respectively.

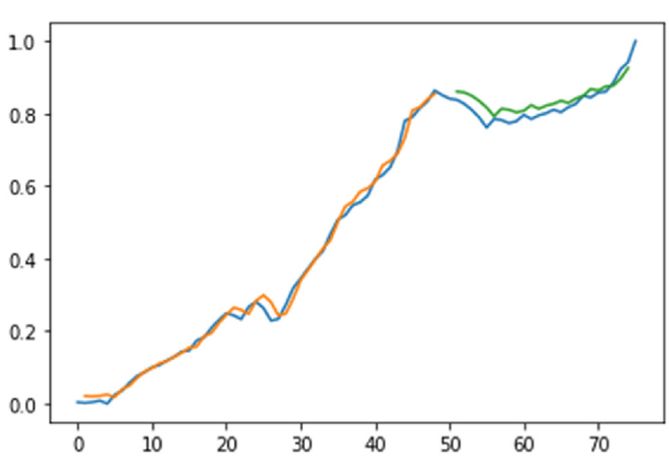

Fig. 7. Performance of proposed long short-term memory model for predicting housing prices in Taiwan.

Furthermore, the fitting results of the proposed models were compared with those of the models developed by Rahman et al. (2019) in accordance to the *RMSE* and *R-square* comparison criteria, and the results are presented in Table VII. The comparison revealed that the proposed the Taiwan Housing Price Index LSTM model exhibited a good fit and favourable performance.

5. Discussion

In practice, the proposed model can be used to predict housing price trends, which can be used as a basis for making real estate investment decisions. First, four-season data are converted into annual data by calculating averages, and annual housing price index forecasts are produced using the proposed model. The overall accuracy of the model is 83.33% (Table VIII).

Table VIII provides the predicted increase in the Taiwan Housing Price Index in 2021. The present study aims to extract factors related to housing prices in Taiwan through a correlation analysis. It also aims to identify the key factors affecting housing prices in Taiwan by constructing a regression model, predict the housing prices in Taiwan in the post-epidemic era by constructing a LSTM model through big data analytics, and verify the model's efficiency on the basis of *R-square* and *RMSE* results.

The results revealed the top 10 factors affecting housing prices in Taiwan, which included the Taiwan Housing Price Index, TWSE capitalisation weighted stock index, economic growth rate, consumer price index, average mortgage interest rate, M1b money supply, housing loan burden rate, housing price income ratio of Taiwan, and VIX. The current-period data of these variables were significantly related to the subsequent-period housing price index. Furthermore, four key factors affecting the current Taiwan house pricing index were extracted through regression analysis, namely the housing price income ratio, M1b money supply, housing loan burden rate, and average mortgage interest rate of Taiwan. These factors can be regarded as overall economic and financial indicators. They demonstrated that housing prices were substantially affected by the overall economic and financial performance of a country. Furthermore, two key factors affecting the subsequent-period housing prices in Taiwan were extracted through a constructed regression model, namely the current housing prices and

Table 4
Correlation coefficient and significance of each variable.

		THPI	TAIEX	EGR	CPI	AMIR	M1b	THLBR	THPIR	VIX
THPI	Pearson	1	.845***	−.225*	.966***	−.724***	.948***	.965***	.975***	−.220*
	Sig.		.000	.051	.000	.000	.000	.000	.000	.056
TAIEX	Pearson	.845***	1	.034	.854***	−.677***	.910***	.789***	.820***	−.286**
	Sig.	.000		.770	.000	.000	.000	.000	.000	.012
EGR	Pearson	−.225*	.034	1	−.276**	.100	−.198*	−.265**	−.249**	−.343***
	Sig.	.051	.770		.016	.388	.087	.020	.030	.002
CPI	Pearson	.966***	.854***	−.276**	1	−.743***	.953***	.949***	.966***	−.116
	Sig.	.000	.000	.016		.000	.000	.000	.000	.318
AMIR	Pearson	−.724***	−.677***	.100	−.743***	1	−.739***	−.638***	−.742***	.236**
	Sig.	.000	.000	.388	.000		.000	.000	.000	.040
M1b	Pearson	.948***	.910***	−.198*	.953***	−.739***	1	.902***	.932***	−.161
	Sig.	.000	.000	.087	.000	.000		.000	.000	.164
THLBR	Pearson	.965***	.789***	−.265**	.949***	−.638***	.902***	1	.989***	−.182
	Sig.	.000	.000	.020	.000	.000	.000		.000	.115
THPIR	Pearson	.975***	.820***	−.249**	.966***	−.742***	.932***	.989***	1	−.199*
	Sig.	.000	.000	.030	.000	.000	.000	.000		.084
VIX	Pearson	−.220*	−.286**	−.343***	−.116	.236**	−.161	−.182	−.199*	1
	Sig.	.056	.012	.002	.318	.040	.164	.115	.084	

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

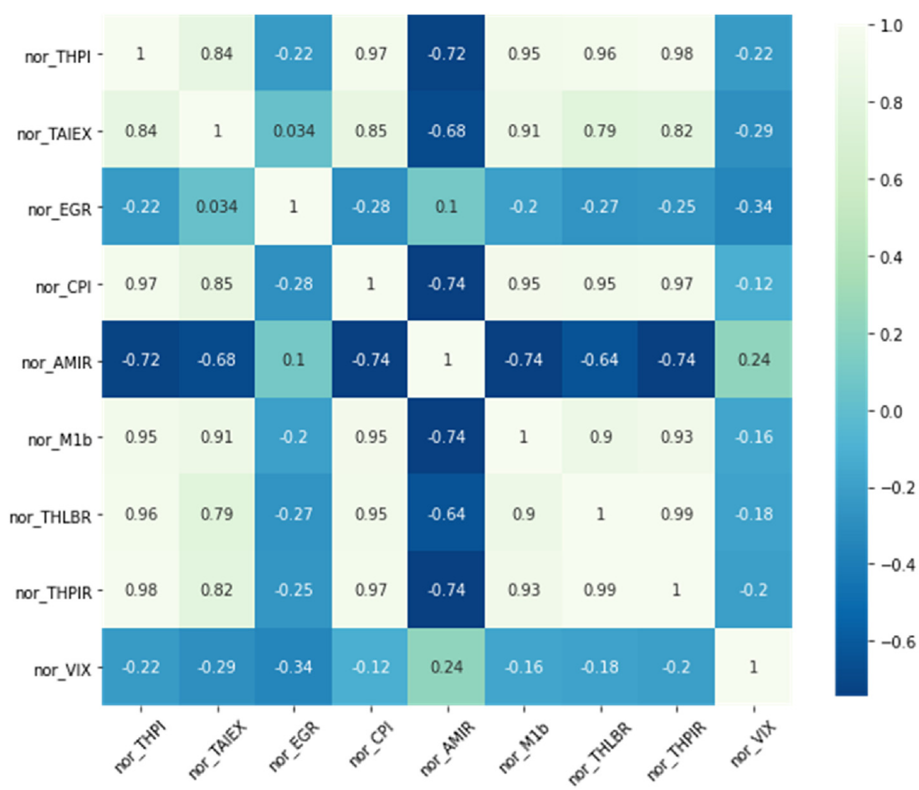

Fig. 8. Correlation analysis of studied variables.

Table 5
Results for $THPI_t$ as obtained using proposed regression model.

Dependent variable nor_$THPI_t$	Unstandardized coefficient B	Standard deviation	Standardized coefficient Beta	*t*	*Sig*
(constant)	.363	.104		3.494	.001
nor_THPIR	−1.879	.643	−1.807	−2.921	.005
nor_M1b	.588	.087	.466	6.732	.000
nor_THLBR	2.107	.515	2.080	4.087	.000
nor_AMIR	−.665	.184	−.393	−3.620	.001

average mortgage interest rate of Taiwan. They demonstrated that housing prices in Taiwan were mainly affected by mortgage interest rates and VIX, which are related to public sentiment and do not significantly influence housing prices in the proposed regression

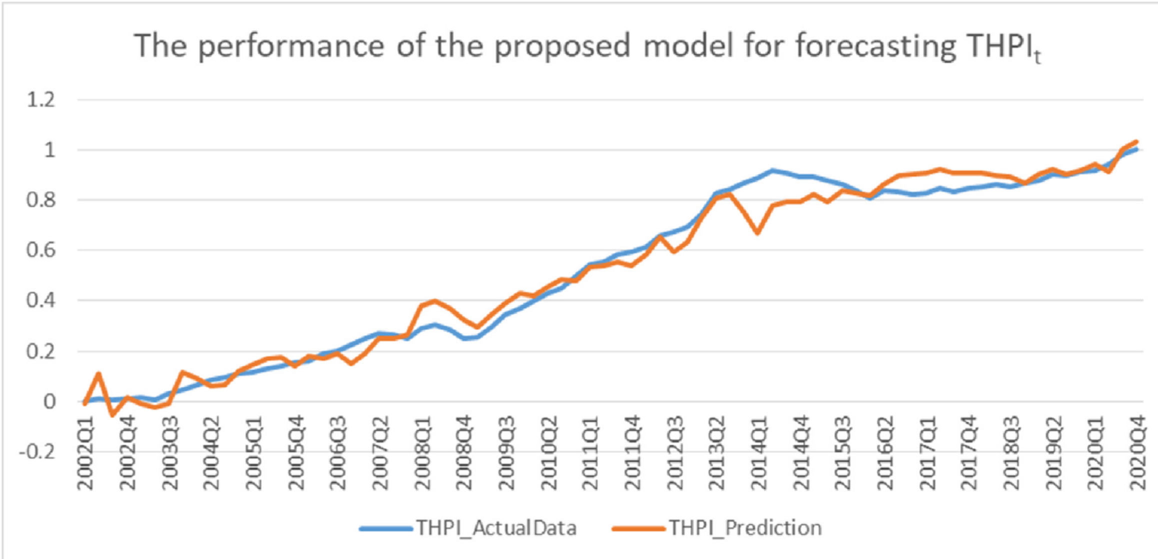

Fig. 9. Performance of proposed model for forecasting $THPI_t$.

Table 6
Proposed regression model for forecasting $THPI_{t+1}$.

Dependent variable nor_ $THPI_{t+1}$	Unstandardized coefficient B	Standard deviation	Standardized coefficient Beta	*t*	*Sig*
(constant)	.030	.008		3.750	.000
nor_THPI	.925	.009	.975	99.280	.000
nor_AMIR	−.051	.016	−.032	−3.224	.002

model. This result suggests that in Taiwan, the effect of housing prices in the post-epidemic era may be non-significant.

The *R-square* of the proposed regression model for predicting $THPI_t$ was .970, indicating the simplicity and accuracy of the model, and the *R-square* of the proposed regression model for predicting $THPI_{t+1}$ was 0.996. Both values indicate the perfect fit and high efficiency of the proposed regression models. For the LSTM model for forecasting housing prices in Taiwan, the *RMSE* and *RMSE* of the

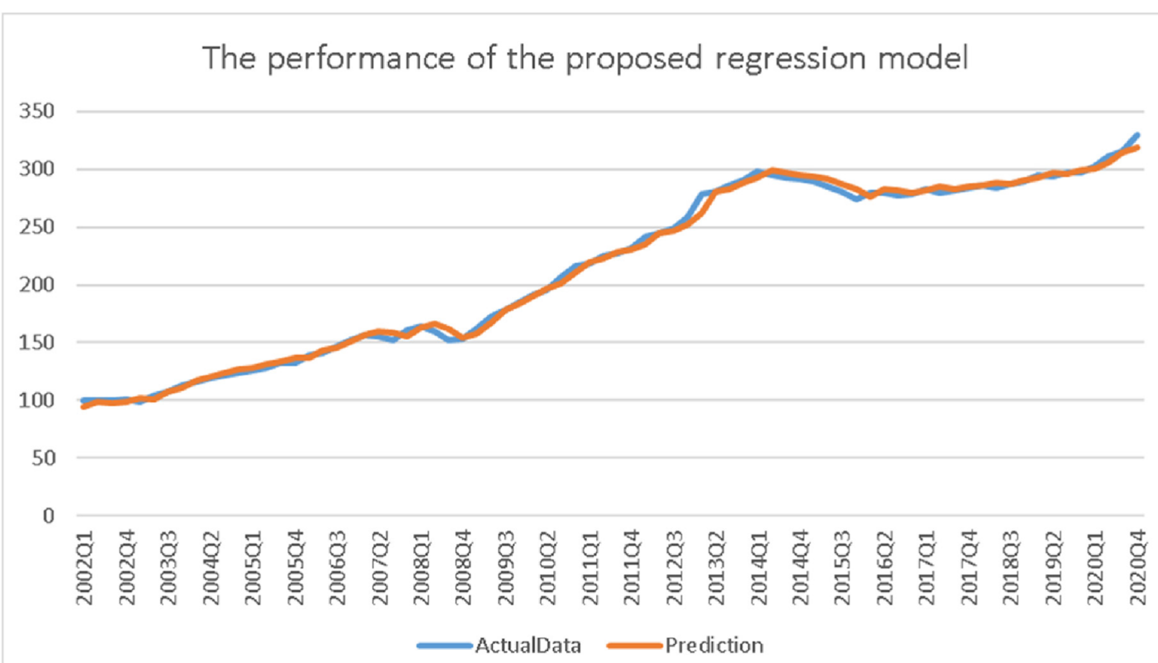

Fig. 10. Performance of proposed model for forecasting $THPI_{t+1}$.

Table 7
Comparison of model performance.

Comparison criteria	The model of (Rahman et al., 2019)				The proposed models		
	Set1		Set2		LSTM	Regression Model 1	Regression Model 2
	Taman Mutiara Rini	Taman Bukit Indan	Taman Mutiara Rini	Taman Bukit Indan	LSTM	Regression Model for $THPI_t$	Regression Model for $THPI_{t+1}$
RMSE	0.110	0.040	0.130	0.040	0.019	0.058	0.270
R-square	0.990	0.930	0.960	0.890	0.995	0.970	0.996

Table 8
Application of proposed model.

Time	$THPI_t$	$THPI_{t+1}$	$THPI_{t+1}$	Fluctuation		
Year	Actual	Actual	Prediction	Actual	Prediction	Correctness
2002	99	100	97	△	▼	0
2003	103	106	106	△	△	1
2004	118	120	122	△	△	1
2005	128	130	132	△	△	1
2006	140	145	144	△	△	1
2007	154	156	158	△	△	1
2008	159	157	161	▼	△	0
2009	166	174	172	△	△	1
2010	195	202	200	△	△	1
2011	222	225	225	△	△	1
2012	241	248	245	△	△	1
2013	276	284	278	△	△	1
2014	294	294	296	△	△	1
2015	287	282	289	▼	△	0
2016	277	279	280	△	△	1
2017	281	282	284	△	△	1
2018	285	287	288	△	△	1
2019	293	295	296	△	△	1
2020	307	NA	310	NA	△	NA

training model and test model were 0.02 and 0.03, respectively. These results indicate that the proposed LSTM model for forecasting housing prices in Taiwan has a good fit, and that LSTM is a suitable method for analysing housing prices.

6. Conclusion

Because the demand for houses (i.e., home purchases) in Taiwan is based on factors such as festivals (e.g., the Ghost Festival), future research should consider seasonal factors and explore models for forecasting the housing price index by season. By contrast, self-occupation demand is a type of regional demand, which can be used to predict the housing price index of each city, and the key factors affecting the housing prices in each city can be explored. These findings can serve as references for urban development and housing planning.

In summary, to stabilise housing prices in an economy, the regulation of mortgage interest rates is an operational tool that can influence current and future housing prices. Although the COVID-19 pandemic affected stock prices in the short term, it was a short-term event with limited effect on the long-term stability of investments in the housing market. The findings of the present study indicate that from an academic perspective, LSTM is a suitable method for analysing housing prices. For the market, financial indicators, such as the housing price income ratio, M1b money supply, housing loan burden rate, and average mortgage interest rate of Taiwan, are the main factors affecting housing prices. From the policy perspective, mortgage interest rates are the key factor affecting the housing market, and the COVID-19 could have slightly produced short-term housing price fluctuations. However, in the long term, the adjustment of mortgage interest rates is still a useful tool for stabilising housing prices.

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