J. Electrical Systems 20-3s (2024): 257-266

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Online Reviews Sentiment Analysis Based on High-Rise Residential Projects in Malaysia

Abstract: - The Malaysian property industry has suffered due to increasing numbers of unsold properties, especially high-rise residential types. Industry practitioners believed the absence of accurate market data for developers caused a mismatch where the developer failed to provide the right properties for the market demand. Thus, a crucial need to understand public opinion on sentiment and preferences for high-rise property. This study derived an online-reviews-based process for evaluating public sentiment and preferences to understand the reason behind the imbalances of supply and demand currently faced by the property industry in Malaysia. The present study introduced an alternative approach to the evaluation of public sentiments and preferences towards high-rise residential via sentiment analysis and interpreted the cause of positive and negative opinions via Term Frequency-Inverse Document Frequency (TF-IDF) analysis. To demonstrate the applicability of the proposed approach, an experiment based on multiple high-rise properties as a case study. The findings are expected to be employed by developers/government in the evaluation of their weaknesses and strengths on the high-rise properties project and how developers/government can improve certain areas.

Keywords: Sentiment Analysis, text mining, high-rise residential, user-generated data; Construction Industry.

I.INTRODUCTION

The current Malaysian property market situation with high numbers of unsold residential projects caused major concerns among developers and the government. Oversupply and unsold residential have been considered major issues that undermine the success of meeting housing needs (Swan Ng, 2019). Major property consultants such as Knight Frank Malaysia predicted that Malaysia’s property market to be moving slower in 2018 and will remain challenging even in 2019 (Zakariah, 2019). Currently, until February 2009, there is RM 29.47 billion value of unsold residential in Malaysia. The value of unsold residential projects was due to several reasons such as indiscriminate buildings by the developers, lack of market studies, and financial feasibility studies (Swan Ng, 2019). The performance of residential projects either success or failure also depend on the style of leadership and project manager’s emotional intelligence (Hanafi et al., 2022). Project managers who develop their emotional intelligence are more self-aware, can manage their emotions and behaviours, and build genuine friendships and connections with the people around them.

A lack of market studies leads mismatch where the developer fails to provide the right properties for the market demand. Industry practitioners believed the absence of accurate market data for developers caused the mismatch. If the situation continues, it could even affect Malaysia's economy. Therefore, to deal with these aforementioned issues in the Malaysian housing industry, the government and housing developers should investigate and regulate their housing activities to suit buyers’ needs and preferences (Swan Ng, 2019). The crucially need for Big Data analytics in the property industry in market studies has been strongly suggested by Malaysian industrial experts and later supported by the Minister of Housing and Local Government (Kay, 2018; Rosli, 2019).

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Public reviews on property shared through social media have become a very influential information source that impacts the property industry in many ways. In the We Are Social: Digital in 2018's report, the results show that 25 million Malaysians are Internet users and 95.7% of them are active social media users. Research indicates that Malaysians allocate approximately 8 hours daily to surfing social media platforms (Statista, 2019). Moreover, the survey done by the National Association of Realtors shows that 90% of home buyers now use the internet as their information source for searching and sharing information regarding real-estate products such as residential (Realtors, 2017). Although several researchers have utilized analysis of online reviews in the property domain, most of them have focused on investigating the Real Estate Investment Market (REIT) (Ruscheinsky, Lang, & Schäfers, 2018), housing market price changes (Walker 2014), housing location, neighborhood evaluation (Tan, Cheng, & Wei, 2017), and modelling of real estate investment (Fu et al., 2015). They do not provide public sentiment and preferences towards high-rise residential property.

In brief, this study has a contribution and differs from past studies in that it applies well-known sentiment analysis to identify public sentiment in Malaysian property and identify public sentiment and preferences in housing purchasing. The rest of this study is as follows: section 2 literature review of related studies, section 3 is a research methodology, and section experiment with case studies with the proposed method. Finally, section 5 concludes the findings.

II.HOME BUYERS' SENTIMENT AND PREFERENCES

Homebuyers' sentiment is playing a significant role in influencing the property market. Several researchers have investigated the relationship between homebuyers' sentiment and the property market (Dietzel, 2016; Hausler, Ruscheinsky, & Lang, 2018; Ruscheinsky et al., 2018). In short, the more positive homebuyers' sentiment will indicate a rising trend in homebuyers' confidence and add to an improving housing market. The output from investigating homebuyers' sentiment is significantly important as a very influential information source that impacts the property industry.

Meanwhile, the identification of homebuyers' preferences is also important for developers, government, and other stakeholders to effectively fulfil the market demand (Koklic & Vida, 2001; Kömürlü, Gürgün, & Arditi, 2013; Rahadi, Wiryono, Koesrindartoto, & Syamwil, 2013; M. I. Razak et al., 2013). Thus, name types of research on residential purchasing preferences have been carried out over the last few decades (Branigan & Brugha, 2014; Gawlik, 2016; Kauko, 2006; Kim, Yang, Yeo, & Kim, 2005; Raut, Kamble, & Jha, 2016). As a result, a variety of preference lists have been proposed based on several types of housing projects including high-rise residential projects. For example, location, transportation, neighbourhood, safety, price, accessibility, facilities, developer/brand, quality, surroundings, etc (Bangbon, Thanathanchuchot, Toprayoon, & Kongkawai, 2020; Chakraborty & Chakraborty, 2018; Ibrahim, 2017; Obeidat, Qasim, & Khanfar, 2018; Suwannaket, 2019). In conjunction with the literature, there is no fixed list of homebuyers' preferences in the house purchase decision-making process. Although numerous have been carried out to investigate public sentiment and preferences, most of them only focused on the traditional method of research such as survey and questionnaires which consists of a few limitations such as only being limited to a specific group of people, being costly, and being time-consuming. On the contrary, more information-rich data has been accumulated with the rapid development of Information Technology (IT) such as online reviews. Utilizing online reviews offered advantages of collecting opinions from various people in a short time and relatively low cost (Kang & Park, 2014; Omar, et al., 2014; J. Park, 2020; Manickam et al., 2021).

III.THE INFLUENCE OF ONLINE REVIEWS IN THE HOUSING INDUSTRY

The trend of using the Internet to aid home buyers' decision-making process keeps increasing over the years (Mcdonagh, 2006). This is also proven by findings from a survey done by the National Association of Realtors showing that 90% of home buyers now search the Internet as their information source in the housing purchasing process (Realtors, 2017). Based on the Realtor's report, most home buyers frequently search for five types of information through the internet such as property photo detail of property information, virtual tour, neighborhood information, and map. As a result, high numbers of real estate websites an available such as Zillow, iProperty, PropertyGuru, Trovit, and Propwall. The crucial influence of online reviews on purchasing has been profound in the literature on numerous purchasing types including housing purchasing decisions (Cheung & Thadani, 2012; M. Y. Cheung, Luo, Sia, & Chen, 2009; Erkan, 2016; Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004; Lim, 2015; Prasad, Gupta, & Total, 2017). Unlike before, most of the home buyer decision-making is influenced by references to a small group such as family, relatives, and friends. Through Web 2.0, the boundary of reference groups has extended the range of group references which is not only limited to strong ties such as family, relatives, or friends, yet also includes weak ties such as internet forum users. Nowadays, countless online communities exist in a variety of forms such as internet forums (IF) not only to communicate but also to interact and engage based on a topic of interest (Seng et al., 2020; Aghaei, Nematbakhsh, & Farsani, 2012; Barassi & Trere, 2012; Lee & Lan, 2007).

IV.OVERVIEW OF SENTIMENT ANALYSIS

Opinions are considered the main factor in controlling almost all human behaviors. Capturing the experiences and knowledge of others helps in making wise decisions. With the development of Web 2.0, people started sharing their opinions on the Web which creates the opportunity for exchanging experiences. The proliferation of people's opinions on various social networks in different domains has inspired many researchers to propose numerous approaches to mine the valuable knowledge from these opinions automatically to assist in the decision-making process, not only for probable customers but also for organizations. Sentiment analysis is a process within the field of NLP to analyze and determine the polarity of the opinion or emotion expressed in a text document, especially on the Web (Feldman, 2013; Liu, 2012; Pang & Lee, 2008). For the past decades, tremendous research on sentiment analysis has been conducted for the significant benefit it brings to the development of various domain areas such as education, economy, marketing, and politics (Kamarudin et la., 2023; Kang & Park, 2012; Ruscheinsky et al., 2018; Soelistio, Raditia, & Surendra, 2015; Ye, Zhang, & Law, 2009). The importance of this field has been acknowledged by the high number of approaches and techniques proposed in previous research and has become one of the reasons for its rapid development, as well as by the interest of companies and agencies that it raised over the past few years. Sentiment analysis (SA) can be carried out in the three-level as follows;

- Document-level: Define the opinion of the whole document based on one topic.
- Sentence level: Every sentence is considered a short document that can be subjective or objective.
- Aspect level: Enable to extract opinion towards aspects of entities.

With the objective of a fine-grained analysis, this study will be performed through sentence sentiment analysis to measure public sentiment and identify preference criteria for high-rise residential projects in Malaysia.

Table 1. Sentiment Analysis Method Studies For Investigated Public Opinions

Author	Year	Type	Tools / Corpus Source
J. Park	2020	Dictionary	SentiWordNet 3.0
Mathayomchan & Taecharungroj	2020	Dictionary	VADER
Liapakis et al.	2020	Corpus	Greek lexical resource for F&B domain.
E. Park et al.	2020	Dictionary	Linguistic inquiry and word count (LIWC).
Ara et al.	2020	Dictionary	SentiStrength
Y. Chen et al.	2020	Corpus	Senta system
Gan et al.	2020	Dictionary	AFINN
Kang & Park	2016	Dictionary	WordNet

V.SENTIMENT ANALYSIS IN THE CONTEXT OF REAL ESTATE

With the ability of SA to provide valuable information on people's opinions, numerous studies have been carried out in a variety of industry areas such as the movie industry, politics, tourism, products, and the stock market (González-Rodríguez, Martínez-Torres, & Toral, 2016; Schouten & Frasincar, 2016; Sridhar & Babu, 2014; Varghese & Jayasree, 2013). However, a survey is the only most common tool to measure homebuyer/investor sentiment in real estate which is costly and labor-intensive (Clayton et al, 2009; Freybote, 2016). The implementation of SA is slowly finding its way into the real estate industry.

The existence of online user-generated platforms which consist of a wealth of information has increased the influence of sentiment in real estate decisions. Several studies have successfully investigated the impact of SA on real estate. Such as Walker (2014) has performed dictionary-based sentiment analysis to investigate the housing market price changes in the United Kingdom through newspaper articles. Similarly, Soo (2015) also implemented SA based on 37, 000 local housing articles within the year 2000 to 2011 to investigate the local house price movement. The findings illustrated that sentiment has a significant influence on the housing price market. A more recent and intensive study was carried out by (Ruscheinsky et al., 2018) investigating the relationship between Real Estate Investment Market (REIT) and media sentiment. A dictionary SA has been performed based on 125, 000 newspaper articles in the United State (US). The empirical result shows a crucial influence of media sentiment in future REIT market movements.

Instead of focusing on identifying the relationship between sentiment and real estate, some studies utilized SA in modeling the real estate decision-making process. For example, has developed a decision support framework has been developed for real estate investment ranking based on the integration of online opinion and offline moving behavior data (Fu et al., 2015). Later on, another adoption of the sentiment analysis method in real estate modeling has been conducted by (Tan et al., 2017). With the preference for the educational environment in-house location, the authors have implemented SA as part of the proposed decision model. These studies provide evidence that the sentiment analysis method has a significant role in the property industry.

VI.METHODOLOGY

Figure 1 shows the framework of the proposed method. The framework consists of two phases, literature Sentiment analysis, and cause analysis. The objective of this study is to introduce an alternative way of evaluating public sentiment and preferences for high-rise residential in Malaysia based on online reviews through text mining techniques. Phase one starts with the extraction of public reviews from online property forums and then identifies the polarity of the review whether it is positive, negative, or neutral. Meanwhile, phase two is to identify the criteria behind the polarity result in the previous phase through Term Frequency Inverse Document Frequency (TF-IDF) analysis.

Phase one: Sentiment Analysis

This phase starts with the extraction of public reviews for multiple high-rise residences located in Selangor and Kuala Lumpur, Malaysia. The process was carried out by using RapidMiner software through web mining features. RapidMiner is a data science software platform that provides features such as data preparation, text mining, machine learning, deep learning, and predictive analytics. Phase one continues with the process of cleaning and preparing opinion text for sentiment classification is known as pre-processing. The raw data requires some initial pre-processing before the implementation of sentiment analysis to avoid incorrect and misleading results. The pre-processing task performs various activities such as removing reviews consisting of unnecessary words and symbols (such as ?, $, #, @, &), tokenizing (breaking a stream of text into words, and phrases), transforming cases, filtering tokens, filters, and stop words (such as "a", "an", "the" do not provide any meaning to the text) (Haddi, Liu, & Shi, 2013; Pradha, Halgamuge, & Tran Quoc Vinh, 2019).

Each project commonly consists of multiple reviews and a single review might have multiple sentences on the same objects and a single sentence may also contain multiple opinions. Therefore, to provide a more transparent sentiment classification result, this study performs sentiment analysis at the sentence level. For this purpose, the extracted reviews have to be rearranged in sentence format. If a sentence consists of homogeneous feelings or emotions, it may be ideal to calculate the sentiment score because it only has to be decided whether the sentence belongs to positive or negative polarity. However, if a sentence has a heterogeneous opinion based on a different object such as '*location is super nice, but the price is not relevant.* This type of review is required to be divided into two sentences.

The sentiment of each review in this study was analyzed using an open-source model namely VADER (Valence Aware Dictionary for Sentiment Reasoning) developed by Hutto and Gilbert (2014). The unique characteristics of VADER are that, in addition to a large set of words, it also considers punctuations, capitalization, degree modifiers, contrastive conjunction (but), and negations. Vader has been utilized in past.

In each review, sentences that contain a similar attribute were concatenated and analyzed using VADER to produce the sentiment score. The most positive and negative scores for each attribute are 1 and -1 respectively.

Phase two: Cause Analysis

To identify the cause of positive and negative reviews from the previous phase, the reviews are analyzed based on the important analysis of word concepts through the TF-IDF method. Reviews are divided into two data sets where the first data set consists of positive reviews and the second data set consists of negative reviews. If a sentence includes both positive and negative words, it can be classified simultaneously into both the positive and negative review data sets. The TF-IDF method is applied to interpret the determinants of the positive and negative opinions. TF-IDF is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus and is used as a weighting factor in searches for information retrieval, text mining, and user modeling. In TF-IDF, if a word has a high numerical score in a specific comment, the word may be recognized as important in that review.

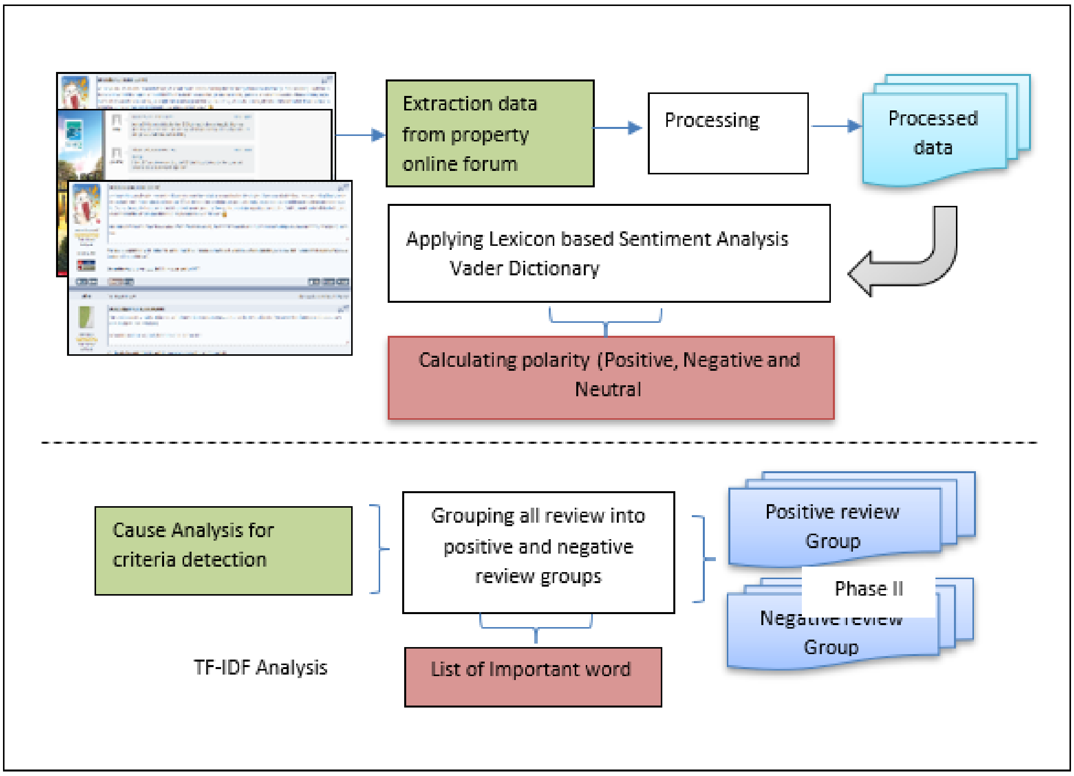

Figure 1. Proposed Framework

VII.EXPERIMENT

In this section, this study experimented with the proposed model above for analyzing the sentiment of public online reviews. The experimental data set was crawled from an online properties forum in Malaysia using RapidMiner software. The data set contains the textual comment for a specific house project. High rise residential project was selected because it's been placed as the highest unsold unit with 50.9% in Malaysia. In total, 5340 reviews within the year 2016 until 2020 covering five high-rise residential projects located in West Malaysia. In general, online opinion text contains noise and unwanted parts that are not significant for the analysis process. Such noise and uninformative text include HTML tags, scripts, and advertisements (Zin, Mustapha, Murad, & Sharef, 2017). As a result, 2631 reviews were used for the next process.

Table 2. Number of reviews

Sources	No extracted reviews	Clean reviews
Online Forum	5340	2631

Vader lexicon for the sentiment dictionary was used to classify the sentiment of the reviews. VADER was developed by (Hutto & Gilbert, 2014) especially for microblog-like contexts such as online reviews. Hutto & Gilbert further claimed that VADER performed well on the social media style of text, it does not require training data, can be generalized to multiple domains and the algorithm calculation is fast enough to be applied using real-time data. Figure 2 shows the numbers of positive, negative, and neutral reviews derived by the sentiment analysis. A total of 1552 reviews were found to be positive, 674 reviews were found to be negative and 405 reviews were found to be neutral.

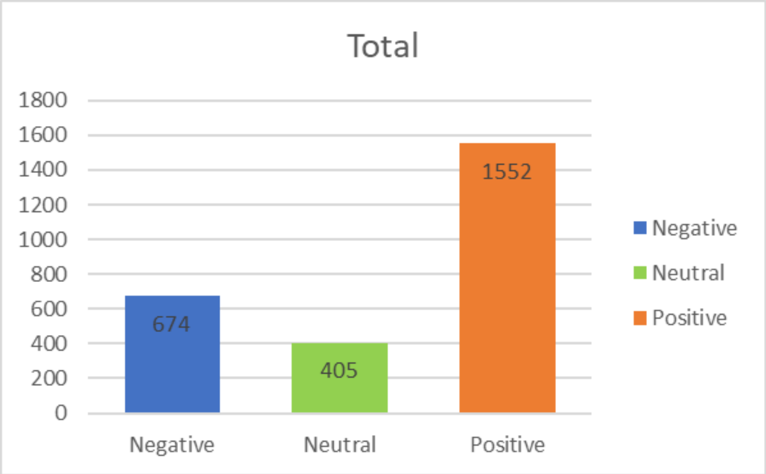

Figure. 2. Result of Positive, Negative, and Neutral Sentiment for Malaysia high-rise Residential Projects.

To further evaluate the determinant of positive, and negative polarity results, the cause analysis was performed through TF-IDF. All the reviews were divided into two datasets based on their polarity where the first dataset consists of positive reviews, and the second dataset consists of negative reviews.

Table 3. Result of TF-IDF Analysis in the Positive, and Negative Groups.

No	Positive		Negative	
	Word	Score	Word	Score
1	location	15.84	price	12.43
2	park	14.45	developer	12.37
3	View	13.96	location	9.95
4	developer	13.82	park	9.32
5	price	13.19	mall	8.73
6	facade	12.68	area	8.00
7	area	12.61	place	7.48
8	traffic	12.53	management	7.39
9	highway	9.20	highway	7.39
10	facility	8.47	density	6.9

Table 2 shows the result of the TF-IDF analysis for the residential. In the positive comment group, the ‘location’ criterion has been mentioned frequently as important, and accordingly, the ‘location’ could be considered the main determinant of the positive opinions of the high-rise residential. This can imply that most people were fewer complaints about the location criterion of the residential projects in their reviews. Followed by ‘park’, ‘view’, ‘developer’, ‘price’, ‘façade’, ‘area’, and ‘traffic’. Meanwhile, ‘Price’ has been mentioned frequently in the negative group, where also can be considered as a determinant of the negative opinions. This result indicates that most people are not satisfied and hold a negative opinion toward price criteria. Followed by ‘developer’, ‘location’, ‘park’, ‘mall’, ‘area’, ‘place’, ‘management’, ‘highway’, and ‘density’. These are the flaw of the high-rise residential projects in Malaysia that developers or government could concentrate on to effectively fulfil the market need. From the result, some criteria have been mentioned in both groups such as ‘location’. However, there was a difference in numerical scores between the positive and negative comment group where the numerical score for ‘location’ was higher in the positive group. This could be a greater number of positive opinions on ‘location’ mentioned by the public towards high-rise residential projects compare to the negative opinion. To summarize, 14 criteria can be considered as the most preferred criteria discussed in the online review among the public for high-rise residential in Malaysia.

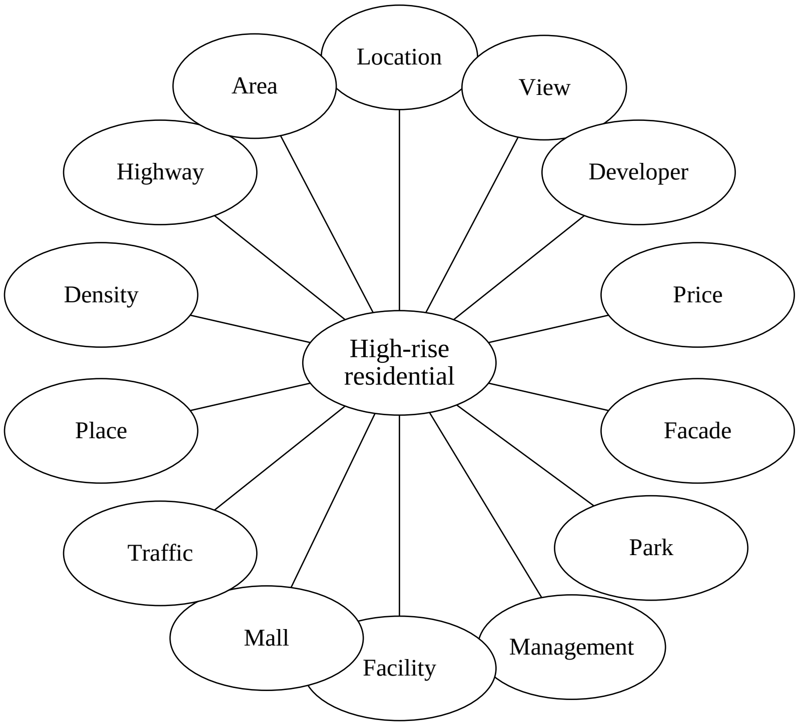

Figure. 3. High-rise residential preference criteria based on online reviews

VIII.CONCLUSION

This study focuses on introducing a new approach to analyzing online property public reviews for evaluation of public sentiment as well as preference criteria towards high-rise residential projects in Malaysia. Such analysis can help developers/governments understand the sentiment and preferences of high-rise residential perceived by the public and can reveal potential high-rise residential projects problems. To demonstrate the effectiveness of the proposed approach, multiple high-rise residential projects have been deployed. 2631 online reviews from online property forums from the year 2016 until 2020 were analyzed. Based on the sentiment analysis of the dataset, the result shows the domination of positive sentiment among the public at 58.98%, followed by negative sentiment at 25.61% and 15.3% of neutral sentiment. Based on the positive and negative polarity results, the ‘location’ criterion was identified as the most important word in positive reviews and followed by park’, ‘view’, ‘developer’, ‘price’, ‘façade’, ‘area’, and ‘traffic’. Meanwhile, the ‘price’ criterion was the most important word in negative reviews. Followed by ‘developer’, ‘location’, ‘park’, ‘mall’, ‘area’, ‘place’, ‘management’, ‘highway’, and ‘density’. Interestingly, some criteria have been mentioned in both review groups such as location, developer, park, price, and area. However, there was a difference in numerical scores between the positive and negative comment group where the numerical score for ‘location’ was higher in the positive group. This could be a greater number of positive opinions on ‘location’ mentioned by the public towards high-rise residential projects compare to the negative opinions. Findings show the developer's weaknesses and strengths in high-rise projects and how developers can improve certain areas.

This, in turn, leads to higher sales. Since, most of the previous studies were based on methodologies such as survey, questionnaire, and interview which is time and cost-consuming, this study has introduced more property-related dynamic and rich data is in line with the development of Information Technology (IT). These property-related online data generated by the public could reflect better information on public high-rise residential. The proposed approach is expected to be an alternative way to replace the traditional method such as a questionnaire survey used by developers and other property stakeholders to improve the Malaysian property industry.

IX.ACKNOWLEDGEMENT

This research was supported in part by the Ministry of Higher Education (MoHE) of Malaysia through Fundamental Research Grant Scheme (FRGS/1/2022/TK01/UUM/02/1). Our sincere thanks are also acknowledged to RMC UUM and UUM for the monetary and other assistance which propelled us towards the finishing line. We also like to express our utmost gratitude to all parties, directly or indirectly, for completing the study.

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