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GEOGRAPHICAL BIG DATA ANALYSIS OF HOUSE PRICE IN SHENZHEN FOR ADAPTATION IN MALAYSIA

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Abstract

This paper will analyze "Understanding Housing Prices Using Geographical Big Data: A Case Study in Shenzhen" by Jiang et al. (2022) and explain how the methods used in this paper can form an evidence-based understanding of house prices in Malaysia. Understanding the relationship between housing prices and geographic big data trends is critical to developing successful housing policies and urban development strategies. The increased demand for housing has raised concerns about housing price discrepancies, which affect quality of life and the economy. Previous studies have analyzed the price of housing costs also related to geographic and environmental factors, resulting in price differences in each location. However, the complex network of cities makes it difficult to use proximity to the city center to explain urban housing costs. Geographical statistics, exploratory geographic data analysis and other methods have been used to measure geographic autocorrelation with housing prices to improve housing price models. Research by Jiang et al., this is used as the main reference in evaluating big geographic data to predict and analyze real estate prices. Commercial development, transportation, infrastructure, location, education, environment, and level of use affect real estate prices. The geographic distribution of house price data is examined using Moran's I and geographic tracers, while XGBoost lists the factors that influence house prices. This study is important to help Malaysian property developers by using this strategy in determining house prices and suitable residential locations.

Keywords: Housing Prices, Geographical Data, Big Data, Shenzhen, Malaysia.

INTRODUCTION

This paper will analyse a study from the article namely "**Understanding Housing Prices Using Geographic Big Data: A Case Study in Shenzhen**" (Jiang et al. 2022) and finally explain how the methods that been used in this paper can shape evidence-based for understanding housing prices in Malaysia by understanding the relationship between housing prices and geographical big data trends is crucial for developing successful housing policies and strategies for urban development.

The rising demand for housing has resulted in a growing apprehension over the disparity in housing prices, which is interconnected with individuals' quality of life and the advancement of the national economy (Jeanty et al., 2010). Researchers from several disciplines have

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undertaken thorough investigations into house prices to comprehend the aspects that have effect on them. The cost of housing in urban areas is significantly influenced by the geographical position and the surrounding environment, resulting in variations in home prices across various locales (Hu et al., 2019; Cao et al., 2019; Shen & Karimi, 2017; Gurran & Bramley, 2017; Rahadi et al. 2015). In 1960, W. Alonso introduced the bid rent function, which states that the rent for urban dwelling is a function that negatively correlates with the distance from the city center to the periphery (Alonso, 1960). Nevertheless, the intricate and varied nature of urban networks poses a challenge in using proximity to the city center as a reliable model for explaining urban housing pricing. To enhance the accuracy and rationality of the housing price model, researchers have examined and measured the geographic autocorrelation of housing prices via the use of spatial statistics, exploratory spatial data analysis, and other methodologies.

This Jiang et al.'s research presents a framework for predicting and assessing the geographical distribution of home prices using geographic big data. Variables are created to measure the elements that influence home costs, including commercial development, transportation, infrastructure, location, education, environment, and people' consumption levels. The Moran's I tool, and geographic detector are used to investigate the geographical distribution of housing price data, while XGBoost is employed to examine the ranking of variables that influence home prices. The approach offers potential guidance for urban rejuvenation and the identification of high-end residential areas by real estate developers in Malaysia, enabling the development of houses at reasonable prices.

Analyzing Home Price Trends Using Big Data Analytics (BDA) In Jiang et al.'s Analysis

1. Geographic Big Data:

Large datasets containing geographical information are known as "geographic big data." This type of data typically comes from open geospatial databases, satellite images, and remote sensing. To analyze housing prices, geographic big data is essential since it gives spatial context and allows one to look at how different geographical elements relate to home prices.

2. Historial Pricing System:

To define, the hedonic pricing model is a type of economic model that estimates the impact of several factors on a good's price. Specifically, it considers the impact of both internal and external variables on home values. The hedonic pricing model is useful because it provides a framework for investigating and measuring how various characteristics affect home values.

3. Autocorrelation in Space:

Spatial autocorrelation refers to the extent to which the values of a variable are associated in space. It determines if there is a clustering of similar values or whether they are dispersed throughout several locations. Hence, by examining the geographical arrangement of housing prices, spatial autocorrelation may be used to identify patterns and enhance understanding of price variations across various regions.

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4. Remote Sensing:

In remote sensing, information about the surface of the Earth is gathered from afar, typically by means of satellites or other airborne platforms. The study's Landsat8 photos are a type of remote sensing data used to record vegetation and water indices for the purpose of analyzing house prices.

5. Global Moran index

One statistical tool for gauging the degree to which values in geographical datasets cluster or disperse is the Global Moran Index, which measures spatial autocorrelation. The Global Moran Index is useful for analyzing property prices since it shows where areas with high or low prices tend to be concentrated.

6. Geodetector

Geodetector is a technique for spatial analysis that measures the dispersion of a dependent variable by comparing it to the dispersion of its independent variables. Geodetector is used by analyzing the extent to which housing prices vary between administrative regions, which helps us better comprehend spatial differentiation.

7. Model by XGBoost:

Machine learning algorithm XGBoost constructs prediction models by combining ensemble learning with gradient boosting. In this case, the use of XGBoost to evaluate the relevance of features, which allows us to see how various variables affect the cost of housing in cities.

8. Regression using a Random Forest:

As an ensemble learning technique, Random Forest builds several decision trees and then combines their predictions. The nonlinear relationship between related factors and home prices can be modeled using Random Forest Regression.

9. Regression using Support Vector Machines (SVMs):

Classification and regression are two applications of support vector machines (SVMs), which are supervised learning algorithms. The complicated nonlinear relationship between the built environment and home prices is captured by applying SVM Regression.

10. Using GWR (Geographically Weighted Regression):

The generalized weighted relationship (GWR) is a spatial regression method that permits the relationship between variables to differ across space. The spatial heterogeneity of housing prices is considered when using GWR to model different regions individually.

11. Associated Factor Construction

The housing market is complex, with several macroeconomic and microeconomic elements exerting influence on property prices. The proximity to the city center may be used as a criterion for assessing the location factor. Residents are influenced by neighborhood factors and the significance of adjacent amenities. House prices are influenced by several factors

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including neighborhood characteristics, commercial development, transit options, infrastructure quality, education standards, environmental conditions, and financial stability. Future research should focus on investigating the specific factors that influence property values in different communities, including variables like the age of properties and architectural characteristics. Enhancing the analysis of house prices involves using more particular environmental factors via the use of big data, resulting in more precise models. A more thorough understanding of the factors that influence urban housing prices may be obtained by including other data sources, such as extensive data on residential characteristics.

Case Study in Malaysia and The Problems that is Faced in Jiang et al.'s Analysis

The geographical placement of residential properties in Malaysia substantially influences their market worth and the way of life they provide, irrespective of the ownership structure. The proximity of homes to city centres, toll highways, and convenient access to employment opportunities, food shops, and medical facilities may enhance inhabitants' overall quality of life. Customers prioritize a strategic position close to major thoroughfares, public transportation, parking facilities, and essential public establishments like banks and supermarkets when making a purchase. Homebuyers prefer residential locations that include schools, significant retail enterprises, supermarkets, conveniently accessible public transit, and proximity to green spaces and recreational facilities (Farahnadiah et al., 2021). Before construction, housing developers should thoroughly assess the accessibility requirements of residents and ensure the provision of necessary facilities. Effective marketing strategies and government collaboration may stimulate interest among prospective homebuyers. Crucially, ensuring that the housing prices are reasonable and within reach is paramount.

Urban regions exhibit elevated real estate values, differences in housing quality, levies on houses and gates, population movement, and increased construction density (Malek et al., 2017). A study conducted in Johor Bahru in 2015 revealed that exorbitant property prices provide the most significant barrier to the availability of affordable homes. Due to the exorbitant costs, the Bumiputera community in Johor Bahru needs to maintain and possess property. Although there has been a significant decrease of 15% in housing prices, premier sites in Johor Bahru City still maintain high expenses. A double-storey terraced property in Johor Bahru has been sold for over RM300,000. The exorbitant housing expenses provide a significant challenge for Bumiputeras with low to moderate incomes to generate revenue. This might be because the current house market prices surpass the buyer's salary. Ismail et al. (2015) argue that the increase in house prices obstructs the ability of Bumiputera individuals to get loans. For example, the House Price Index in Kuala Lumpur, the country's capital, exhibited a steady upward trend in 2019 (Saripah & Khairos, 2019). Consequently, the increasing costs have posed challenges for the populace in Malaysia in terms of property ownership.

Insufficient finances resulting from exorbitant household bills hinder the acquisition of a home. Even families in remote areas with a middle-class income spend money. The escalation of living costs influences household expenditures (Junaidi et al., 2020). Therefore, maintaining a steady job may expedite obtaining a bank loan and enhance the ability to own property. To enhance the affordability of a property, it is advisable to consider variables such as buying

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power, income stability, and repayment capacity. Revise housing legislation to enhance the welfare of low-income individuals by enhancing the quality, affordability, and features of buildings, design, and facilities. Government intervention in pricing and strategic urban planning may also contribute to the desired outcome. Private developers can make contributions towards the provision of affordable homes. Indeed, high-quality, affordable housing in convenient locations and at reasonable rates creates an improved living environment. Housing-related concerns, such as overcrowding, insufficient parking, exorbitant transportation expenses, and widespread pollution, intensify the burden on those seeking to purchase a house. These problems hinder the ability of individuals in low and moderate-income brackets to acquire property (Yusof, 2019). Additional housing issues include the limited accessibility of reasonably priced and high-quality affordable housing and the psychological, social, environmental, and cultural consequences. Rowley and Ong (2012) argue that while examining housing affordability, it is essential to consider factors such as the dimensions of the dwelling, its standard, surrounding area, geographical position, and household makeup. According to research conducted in 2016, it was shown that 19% of middle-income Malaysians expressed dissatisfaction with the quality of housing. Property ownership is the primary source of stress (Baqutayan, 2016).

Hence, stakeholders have a crucial responsibility in formulating spatial dimensions by set standards, guaranteeing a gratifying living experience for inhabitants, and enhancing the attractiveness of the intended design for prospective house purchasers. The study by Jiang et al. (2022) on utilizing extensive data analysis to determine house prices should be replicated. This will enable the developer and the Malaysian Government to assess different parameters of big data and integrate all relevant information to ensure that the house prices are suitable and affordable. Therefore, there are many learning benefits from the study of Jiang et al. (2022) which can be researched so that the aspect of houses with reasonable prices can be used as a reference for house prices in Malaysia. The benefits of learning understanding include:

1. Heterogeneity in Space:

The research concluded that there is a large amount of spatial heterogeneity in housing prices. The difficulty lies in gaining a knowledge of the various elements that contribute to this difference and finding solutions to them. These aspects include infrastructure, transportation, location, education, environment, and consumption levels (Jiang et al. 2022).

The first echelon of housing costs is commonly found in Futian, Nanshan, and Luohu, which are also home too high-paying businesses and upscale shopping areas. As a result, there is a surge in demand for homes in the vicinity, driving up prices. Longgang and Guangming, on the other hand, are outlying neighborhoods that are important to the city's essential industries and so have a varied effect on housing costs. A spatial aggregation phenomenon was found in Shenzhen home prices by spatial autocorrelation analysis. House prices did not follow a normal distribution but rather followed a continuous surface that could be fitted with a function. This points to a spatial pattern, not chance, suggesting that nearby areas have comparable housing pricing features (Jiang et al. 2022).

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2. Accuracy of the Data and Attention to Detail

The accuracy of the model is strongly dependent on the quality of the data that is input. There are limits in medium-resolution photography that could potentially impair the precision of the model, even though Landsat8 pictures were used to analyze environmental parameters. For improving accuracy, future study should investigate the possibility of incorporating more detailed data, such as data on the attributes of houses and pictures taken at street level.

The research by Jiang et al. (2022) suggested using zonal nonlinear feature models to deal with geographical heterogeneity. These models are only as good as the input data, which must be precise and detailed. To illustrate the point, the analysis that comes out of employing inaccurate or incomplete geographic and environmental data in the model could lead to home price variances that do not reflect reality. To simulate various environmental variables, this study made use of these photographs. The medium resolution of satellite imagery may not be enough for a thorough examination, particularly in densely populated urban regions with complex features, even though the data it provides is invaluable. An improved depiction of the neighborhood around the homes might be possible with higher-resolution data, like aerial photos or data collected at street level. External factors affecting home costs, such as infrastructure and the natural environment, were the primary focus of the analysis. However, the community's internal factors, such as the house's construction date and structural features, were not considered. The dynamics of home prices may be misunderstood if this is not included.

3. The complexity of the model and the sensitivity of its parameters:

The XGBoost model, which is sensitive to characteristics such as the learning rate and the maximum tree depth, requires careful adjustment to achieve optimal performance (Hancock & Khoshgoftaar 2022). Because of this sensitivity, it is difficult to achieve the appropriate balance, which may influence the accuracy of the model.

There is a compromise between bias and variation introduced by a more complicated model. Overfitting happens when a model fits the training data too closely and doesn't generalize well to new, unseen data; this happens when the model is too complicated, even though it may reflect complex relationships in the data. For a model to be applicable to a wide range of housing market scenarios, finding the sweet spot is essential. Complex models, such as ensemble approaches, may trade off performance for interpretability. The more complicated the model, the more difficult it is to understand the connections between the contributing components and home prices. Maintaining a model's interpretability while also meeting the demand for precise forecasts is an ongoing problem.

4. Consideration of Limited elements

Although the research in Jiang et al. (2022) looked at a few micro-influencing elements, such as education, transportation, and infrastructure, it notes that additional structural considerations, such as the age of houses and how they were built, were not considered. The problem is to develop a model that is all-encompassing and considers all the variables that are

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pertinent. In conclusion, the limitations that were found highlight the difficulty of conducting an analysis of home prices. It is necessary to take a multidimensional approach to address these issues. This includes the incorporation of more granular data, the refinement of modeling methodologies, and the consideration of a wider variety of affecting factors to improve the accuracy and application of the findings.

(III)

Like in many other parts of the world, conventional linear models of housing costs fail to adequately describe the dispersion of urban housing costs in Malaysia. The complex dynamics of the real estate market cannot be fully captured by the widely used traditional statistical tools and manual survey data for evaluating home prices. A more thorough comprehension of the relationship between housing prices and geographical big data trends is crucial for developing successful housing policies and strategies for urban development.

Findings and Solutions Application

Insights gained from the research findings in Jiang et al. (2022) can be used to the Malaysian context to shape evidence-based housing policies, which can bring considerable advantages. We may use the recognized factors that affect housing prices—such as education, transportation, consumption, location, infrastructure, and environmental concerns—to inform the development of sophisticated policies that address the specific problems faced by each city.

The regional big data patterns uncovered by the study can play a significant role in the formulation of policies that are unique to each city (Wen et al. 2014). For instance, programs to improve educational facilities and resources in underserved areas may be launched if it was understood that educational characteristics significantly impact housing prices. Targeted urban planning is possible when transportation and infrastructure factors are considered in relation to the effect on home prices (Gurran & Bramley 2017). Rising home prices and better city growth are possible outcomes of well-planned investments in transportation and other infrastructure (Li & Huang 2020).

According to Jiang et al.'s study, there should be individualized approaches to zoning and spatial planning due to the high level of geographical variation. To ensure regulations are tailored to the requirements and difficulties of each place, zoning models in Malaysia should consider the distinct features and dynamics of various regions. This would be beneficial for the cities around the country. To make data-driven decisions, the study stresses the significance of using XGBoost and other advanced analytics and machine learning algorithms to glean useful information from geographical large data. Decisions are more accurate and applicable when these data-driven approaches are used in the policymaking process.

Acknowledging the limits of classic linear models allows policymakers to move towards more advanced techniques that take into consideration the nonlinear interactions present in housing markets, so overcoming the constraints of old models. With this change, the intricacies of home price determination can be more accurately depicted. A road map for proactive problem-solving has been laid out, addressing issues such as regional heterogeneity, data accuracy, and model

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complexity. Government officials can put their money into investigating more precise environmental indices, implementing machine learning models after thoroughly assessing their complexity, and enhancing the accuracy of data. The results highlight the importance of a joint effort between the public and commercial sectors (Jiang et al. 2022). A comprehensive grasp of housing market dynamics can be achieved by involving communities, urban planners, and real estate developers in the policymaking process. Ultimately, the results of this study have the potential to greatly aid Malaysia in formulating strong, evidence-based housing policies. Sustainable urban growth, affordable housing, and resilient cities that can adapt to people's changing needs can all be achieved if policymakers incorporate insights from geographical big data into their deliberations.

Ethical Consideration

Data Privacy and Consent: It is crucial to pay close attention to data privacy while employing geographic big data analytics for housing policy. It is critical to get informed consent from people who contribute to the data and to ensure that personal information utilized in the research is anonymized (Floridi & Taddeo, 2016).

Fair and Transparent Algorithms: Because of ethical concerns, it is essential that algorithmic decision-making be open and transparent. To prevent data biases from being reinforced, policymakers should utilize explainable algorithms (Diakopoulos, 2016). It is only fair that communities get an equal share of the advantages that come from spatial big data analytics. To avoid further societal inequality, policymakers should implement targeted actions (Kitchin & McArdle, 2016).

Theoretical Consideration

Improvements to Urban Theory: By supplying empirical proof for preexisting theoretical frameworks, geographical big data analytics permits improvements to urban theory. The incorporation of XGBoost and other machine learning methods provides a more nuanced comprehension of the nonlinear correlations impacting real estate markets. A shift away from global housing theories and toward localized models is required considering the realization of spatial variability. Housing dynamics may differ greatly from one area to another, and policymakers should accept this reality and reject cookie-cutter solutions. Advancements in theory necessitate teamwork across disciplines, which is why interdisciplinary approaches are so important. To fully grasp the intricate relationship between geography and housing dynamics, it is necessary to combine knowledge from data science, economics, and urban planning (Desouza & Flanery, 2013).

Society Consideration

Policymakers shouldn't have monopoly authority over geographical big data analytics; communities should be actively involved and empowered as well. By incorporating communities into data gathering and making the findings easily accessible, citizens are given the power to actively engage in housing policy decision-making processes (Bryson & Andres, 2018). Urban development policies that are led by data analytics should make every effort to

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lessen the likelihood of displacement. Preventing negative impacts on vulnerable groups through inclusive urban development demands proactive measures (Rossi et al., 2020). Data and analytics accessibility is a social concern, as is the digital divide. The digital divide is real, and policymakers should do everything they can to close it so that everyone can benefit from data-driven insights (Robinson et al., 2015).

CONCLUSION

That paper presents a housing price analysis framework using geographic big data and hedonic price models. It explores the spatial distribution of housing prices and develops zonal nonlinear feature models for regression analysis. That study finds significant variations in housing prices across different districts in Shenzhen, with a spatial aggregation phenomenon. That study also examines the relationship between housing prices and micro-influencing factors, such as infrastructure, transportation, location, education, environment, and consumption levels. The zonal nonlinear feature model outperforms other regression models in explaining the housing price distribution in Shenzhen. However, future research should be considered and implemented in Malaysia, taking all the elements of big data analysis by relating the quality of home ownership to affordable house prices and improving the accuracy of the model using more data.

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