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THE EFFECT OF SECURITY IN THE GREEN BUILDING PRICE PREDICTION MODEL: A COMPARISON BETWEEN MULTIPLE LINEAR REGRESSION AND MACHINE LEARNING APPROACHES

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Abstract

Green building (GB) and building security are two pivotal factors that significantly influence the valuation of property prices. Nevertheless, the research on these determinants was very limited and no empirical study was done to prove the reliability of the factors as price determinants for green building. Hence, this study examines the factors by using two distinct approaches, namely the Multiple Regression Model (MRL) and Machine Learning (ML) to fill the existing empirical gap. With MRL as the conventional approach and ML as an advanced technique, the results were compared to provide maximum effectiveness in analysing the factors included. The data analysis was conducted based on a real GB dataset collected, which comprises 240 green building transactions in the city area of Kuala Lumpur, Malaysia. Prior to MLR modelling, an ANOVA test was conducted to test the statistical significance of all the independent variables (IVs) used in this study, while ML used the algorithm consisting of random forest, decision tree, linear regressor, ridge and lasso. The results indicate that building security has a strong and statistically significant impact on the price of green buildings in the MLR model. However, when it comes to enhancing prediction accuracy using the Random Forest and Decision Tree algorithms in ML models, building security has a relatively minimal influence. These results highlight a substantial difference between the outcomes of the two approaches. Specifically, the machine learning model did not demonstrate a significant relationship between green building attributes and price prediction, whereas the multiple regression model suggests otherwise.

Keywords: Green Building, Machine Learning Model, Multiple Linear Regression, Security of Building

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INTRODUCTION

Sustainable Development Goal (SDG) is currently discussed worldwide as one of the important future roadmaps. Current research also includes this agenda as it is stipulated in the United Nations (UN) agenda, which has been put in place until 2030. Green building (GB) has been recently discussed as one of the initiatives to share the aspiration advocated by the UN. GB is expected to reduce the development of negative impact on human health and environment by enhancing building life cycle development (Bungau et al., 2022). GB provides a conducive living and working environment to allow people to benefit from healthier atmosphere and freedom from unnecessary waste and pollution (Bungau et al., 2022; Ismail et al., 2015). This initiative has also been considered by the Malaysian government, as it is in line with the green technologies in GB through the National Green Technology Policy.

Apart from GB, building security is considered important in housing, building and property industries (Olanrewaju et al., 2018). Free from threat and danger is the main concern behind a building's security, which involve many aspects such as the building structure, monitoring, and maintenances. In this research, building security is associated with social aspects such as the feeling of safety for life, natural surveillance, and social integration (Candas et al., 2015). Therefore, security and GB are closely inter-related for the development of sustainable building solutions. A number of factors have been identified to give some impacts on the building or property prices (Abdullah et al., 2018; Atilola et al., 2019; Portnov et al., 2018; Božić et al., 2013). However, until recently, much of the research from the literature provides less explanation on the contribution of building security to the GB transaction prices. A recent study by Azian (2020) highlighted that by emphasizing building safety, one is able to improve its security measures, such as access control systems, surveillance cameras, and security personnel as this helps provide a safe environment as well as act as one of the attractive elements to families and individuals which can drive up property demand and prices. The study, however, only discussed the theory in general, and no empirical evidence was provided. Hence, a more systematic approach is needed to identify the way building security influences the GB price through rigorous methods of predictor models. This paper presents the effect of security in the green building price prediction model by using two different approaches namely Multiple Linear Regression (MRL) and Machine Learning (ML). Comparing MRL and ML serves as a benchmarking exercise. It helps establish whether the added complexity and computational resources required by ML techniques result in significantly improved predictive accuracy compared to simpler model like MRL. Additionally, as this study uses real data cases, it is important to conduct an intensive data modelling with different approaches. This study empirically utilizes the MLR and ML techniques via multiple algorithms.

LITERATURE REVIEW

Green Building (GB)

Green Real Estate (GreenRE), Green Performance Assessment System (Green PASS), Green Awarding Evaluation Scheme (*Skim Penilaian Penarafan Hijau* JKR (PH JKR)) and Green Building Index (GBI) are the available green rating tools in Malaysia (Shafiei et al., 2017; Ghaffarianhoseini et al., 2013; Zian et al., 2019; Shi & Liu, 2019; MGBC, 2019). Table 1 lists the summary of these rating tools.

Table 1: Characteristics of Malaysian Green Rating Tools

Name of rating tools	**GBI**	**PH JKR**	**Green PASS**	**GreenRE**
Years Introduced	**2009**	**2012**	**2012**	**2013**
Criteria	Energy efficiency Indoor Environmental Quality (IEQ) Sustainable site planning and management Material and resources Water efficiency Innovation	Sustainable site planning & management Energy efficiency Indoor environmental quality (IEQ) Material & resources management Water efficiency Innovation	*Building Construction*: Site Material Energy Water Waste *Building Operation*: Indoor environmental quality (prerequisite) 80% satisfaction of occupants Energy	*Energy Related Requirements:* Energy efficiency *Other Green Requirements:* Water efficiency Environmental protection Indoor environmental quality Other green features Carbon emission of development
Developers	PAM and ACEM (Professional Associations)	JKR (Government-Driven)	CIDB (Government-Driven)	REHDA (Professional Associations)

Source: Shafiei et al. (2017)

The criteria and developers for the four (4) rating tools, namely, 1) GBI, 2) PH JKR, 3) Green PASS and 4) GreenRE have been respectively introduced in 2009, 2012, 2012 and 2013 as indicated in the Table 1. These rating tools used the conventional similar criteria worldwide such as BREEM and LEED (Shafiei et al., 2017). Based on the rating tools and literature study, the conceptual framework of the GB price determinants can be presented in Figure 1. GBI Certification is categorized as an environmental characteristic, while security is a neighbourhood characteristic.

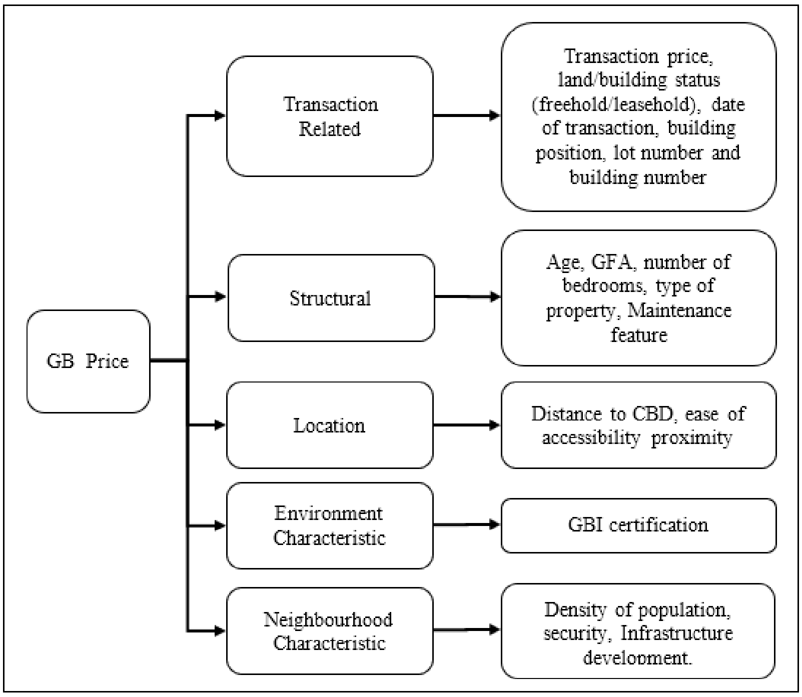

Figure 1: Conceptual Framework

The literature focuses on a multitude of factors contributing to the green building price. The rapidly progressing research discovers building security is one of the significant factors that contribute to green building prices (Jang et al., 2018). While green building practices focus on sustainability, energy efficiency, and eco-friendly materials, integrating robust security measures can add substantial costs (Hoon Lgeh et al., 2021). This includes expenses related to access control systems, surveillance technologies, and physical barriers (Azian et al., 2020). However, investment in security is essential as it not only protects the occupants, assets, and sensitive data but also enhances the overall value of the green building (Suriansyah et al., 2020). By providing a safe and secure environment, green buildings become more attractive to potential tenants, investors, and occupants, potentially commanding higher lease rates and resale values, thereby offsetting the initial security investment and contributing to the long-term sustainability of the building.

MLR and ML for Property Valuation

MLR has been recognized as an established approach in predicting the price of properties (Mao & Yao, 2020; Ping, 2020; Thuraiya et al., 2020; Wu et al., 2020;

Shahirah et al., 2021). The research conducted by Raja Zakariah and Md Termizi (2019), used MLR to analyze the determinants of house prices in Malaysia, while Abdul Rahman et al. (2021) argued that the MLR was used to analyze the housing prices specifically at the Kuala Lumpur in Malaysia. Compared to MLR, ML has been well known and widely used globally (Varma et al., 2018; Park & Kwon Bae, 2015; Chen et al., 2017; Čeh et al., 2018; Huang, 2019), but it is considered new in Malaysia (Daradi et al., 2018). The ML models which are commonly used in property valuation are Linear Regression (Borde et al., 2017; Dimopoulos et al., 2018; Wezel & Potharst, 2005), Decision Tree (Thuraiya et al., 2022; Huang, 2019), Random Forest (Huang, 2019; Wang & Wu, 2018), Ridge (Madhuri et al., 2019; Choi et al., 2019), and Lasso (Madhuri, Anuradha & Pujitha, 2019; Jin & Lee, 2020). According to Choi et al. (2019) and Jin and Lee (2020), the Ridge and Lasso models have been modified with more intelligent techniques such as fuzzy and autoregressive. The utilization of both MLR and ML in property valuation is not yet in existence in the current literature but can be found in other kinds of prediction problems, such as in Golbaz et al. (2019) and Niu et al. (2019). Furthermore, the use of ML for GB is also considered as a new area of research.

RESEARCH METHODOLOGY

This study applied two different approaches in analysing the factors contributed to the green building prices namely the MRL and ML. These distinct types of approaches might come out with different results since MRL were considered as conventional approaches, while ML were more to computer generated with less biased. The variation of results was determined based on the prediction value discussed in the findings.

Multiple Linear Regression (MLR)

Figure 2 presents the MLR implementation of this research. Initial data were collected from the Valuation and Property Service Department (JPPH). The data consist of the property valuation records for GB condominium located at the district of Kuala Lumpur in 2022. Based on Figure 1, 17 variables were used. The dataset consists of 240 records with GB as shown in Table 2.

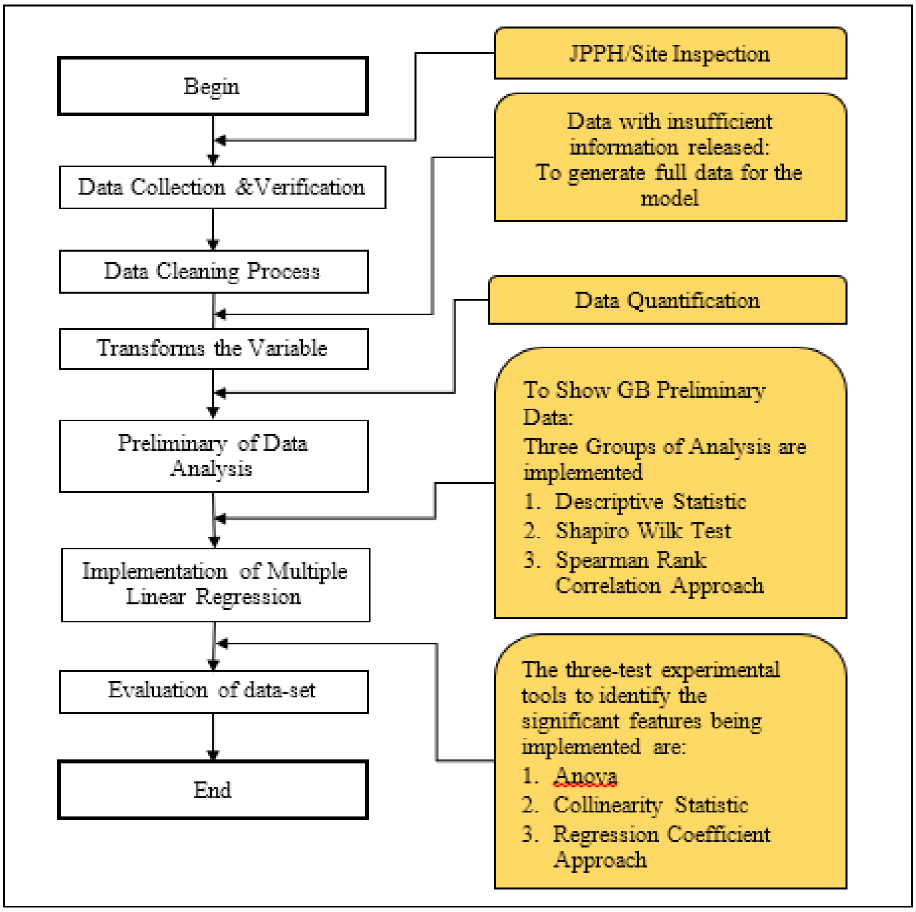

Figure 2: MLP Steps

Table 2: Data Collections and Cleaning

Data	**Data Removed**	**Data left**
Available data in 2018 from the JPPH		1858
Remove another residential category property	122	1736
Remove Transaction from Developer	70	1666
Remove Non-GB	1426	240
GB		240

Table 3 presents the descriptive statistics of the transaction price with an average price of RM1,589,152.87. The distribution was skewed to the right at value 4.03 which implied that most transaction prices were at the lower prices.

Table 3: Summary of Descriptive Statistic of Transaction Price

Measures	**Values**
Mean	1,589,152.87
Std. Deviation	1,661,053.37
Skewness	4.03
Minimum	2098.96
Maximum	11,280,000.00

Machine Learning Models

In this study, different ML models were tested on the GB dataset based on different feature selection groups. Five (5) ML algorithms were used namely Linear Regression, Decision Tree Regressor, Random Forest Regressor, Ridge and Lasso algorithms. In addition, each model in each feature selection group was also evaluated according to different training and validation splitting approaches namely basic split and cross-validation. Figure 3 presents the flowchart of the ML models evaluations.

Python programming language was used to implement the models, run in the Anaconda Jupyter Notebook platform. The computer has Intel i7 7th Generation processor and 16GB RAM.

The Hyper-Parameters tuning is a technique to automate the parameters' configuraton of each ML model. This is an effective technique provided by Python to be used by inexpert data scientists (Masrom et al., 2019), Hyper-Parameters tuning optimized the best configurations of the machine learning. In this study, the researcher utilized the hyper-parameters tuning provided by Python.

Two types of training and validation splitting approaches have been used for the machine learning models. On the other hand, Figure 4 presents the distribution of dataset from the original numbers into the training and validating sets.

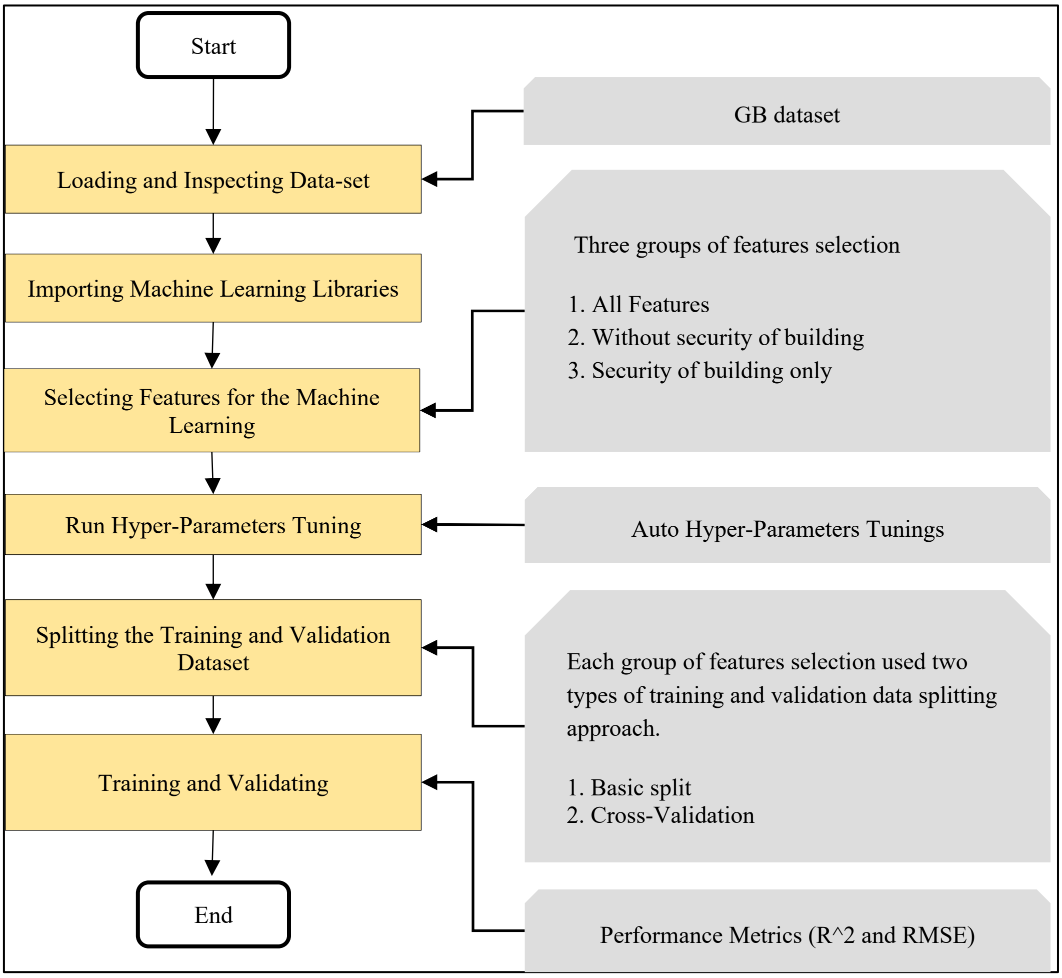

Figure 3: The Steps for Implementing Machine Learning Models

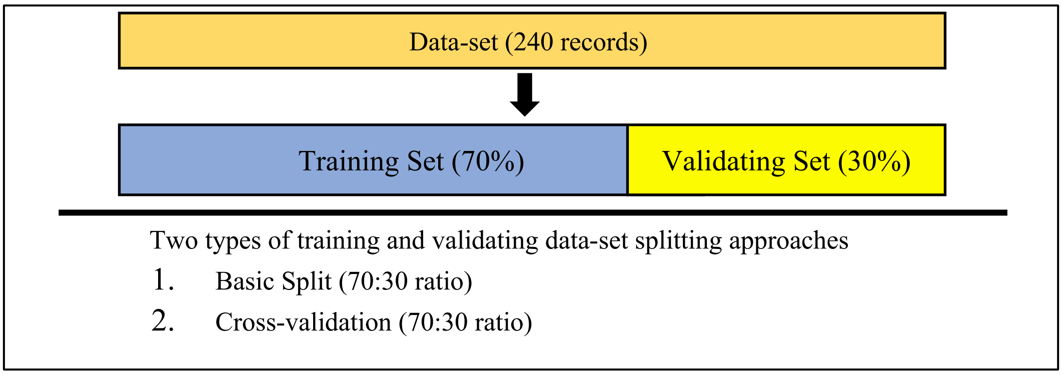

Figure 4: Splitting the Training and Validation Datasets

The Basic Split approach performs one time used on the dataset for training and validation while the Cross-Validation implements a comprehensive crossing from different training and validating folding. Below are some of the basic procedures of Cross-Validation training approach:

1. Split the dataset into 2 parts.
2. Set the 70% of the dataset as training dataset.
3. Set the balance 30% as validating dataset.
4. Train the model with the training dataset.
5. Evaluate the model with the validating set.
6. Repeat steps 1 to 5 for a different set of data folding.

The visualization process of data splitting in fivefold Cross-Validation is shown in Figure 5.

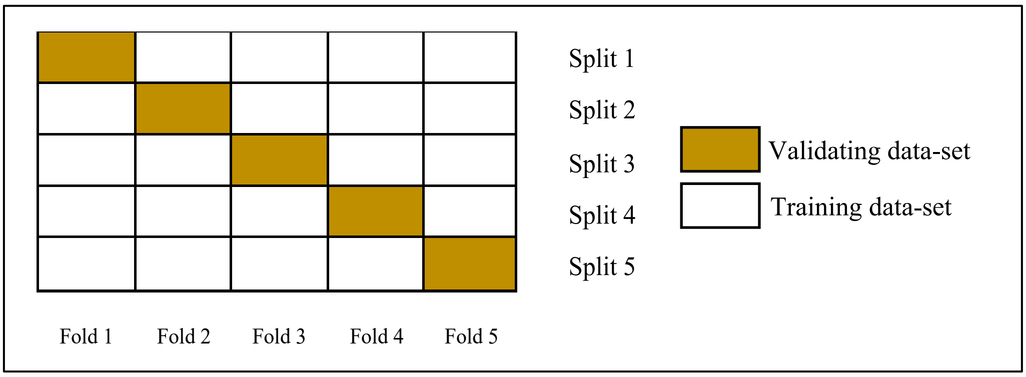

Figure 5: Data Splitting in Five-Fold Cross-Validation Approach

The Cross-Validation number of folding used in this research has been set to five. Hence, it involved five datasets crossing along five iterations of training and validating. The average accuracy scores from the five iterations were taken for the purpose of comparative studies with respect to other algorithms.

RESULTS AND DISCUSSION

Results of MLR

Prior to MLR modeling, an ANOVA test was conducted to test the statistical significance of all the independent variables (IVs) used in this study. Table 4 tabulates the variance ANOVA of the GB dataset. It shows that all the IVs that were selected for the model have contributed 83.40% of the total variation in the DV (transaction prices). This value is quite high and good enough for the Multiple Linear Regression Model (Shalizi, 2021). The model fitness value is 114.744 at a significant p-value of less than 0.05 (0.000). Table 5 lists the variables that have tolerance to the transaction price from the collinearity statistics.

Table 4: ANOVA Table

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	549715548267383.750	10	54971554826738.375	114.744	0.000
Residual	109708947536789.640	229	479078373523.099		
Total	659424495804173.400	239			

*R^2 = 0.834

Table 5: Collinearity Statistics

Independent variables	Collinearity Statistics	
	Tolerance	VIF
Main Floor Area	0.461	2.171
Security of Building	0.129	7.755
Mukim – Kuala Lumpur	0.519	1.926
GBC - Gold	0.246	4.060
Tenure	0.443	2.257
Mukim - Petaling	0.436	2.296
Building Facade	0.466	2.146
Age of Building	0.353	2.831
Level Property Unit	0.779	1.284
GBC - Silver	0.531	1.884

Based on collinearity results, only 10 out of the 17 independent variables (IVs) present a significant relationship to the transaction price. The tolerance values were more than 0.10 to show that there was no multicollinearity problem in the dataset from the 10 listed variables in Table 5 and this was supported by VIF values less than 10. Therefore, these 10 variables were used in the MLR. The results are shown in Table 6.

Table 6: MLR Regression Coefficient

Model	Unstandardized Coefficients		Standardized Coefficients	t	p-value
	B	Std. Error	Beta		
(Constant)	-3223583.573	559809.921		-5.758	.000
Main Floor Area	5231.404	714.924	0.291	7.317	.000
Security of Building	-5138054.835	297945.798	-1.294	-17.245	.000
Mukim – Kuala Lumpur	1591963.798	219454.339	0.271	7.254	.000
GBC - Gold	-3898139.627	272201.193	-0.778	-14.321	.000
Tenure	5756105.972	429946.991	0.542	13.388	.000
Mukim - Petaling	-5806613.752	474014.069	-0.500	-12.250	.000
Building Facade	-4691198.063	419210.387	-0.442	-11.191	.000
Age of Building	475338.798	81308.937	0.265	5.846	.000
Level Property Unit	18023.874	4983.677	0.110	3.617	.000
GBC - Silver	1789518.271	270956.317	0.244	6.604	.000

The MLR results revealed that all the 10 variables contributed some degree of information in determining the DV (transaction price). Some variables with low standardized coefficients (less than 0.5) are *Main Floor Area, Mukim Kuala Lumpur, Age of Building* and *GBC-Silver.* Moderate contributions came from *GBC-Gold, Tenure, Mukim-Petaling* and *Building Façade.* The result shows that the *security of building* made the largest contribution to the MLR when compared to other features. The results of coefficients can be elucidated as follows: The "B value" of approximately -5,138,054.835 signifies that a one-unit increase in building security, measured in accordance with the specific criteria employed in the study, is associated with an anticipated decrease of approximately 5,138,054.835 units in the same currency or measurement scale used for building prices: this is assuming that all other factors remain constant. Meanwhile, the "beta value" of approximately -1.924, a standardized coefficient, conveys that a one-standard-deviation rise in building security corresponds to an expected reduction in building price by 1.924 standard deviations. This standardization facilitates the assessment of the relative significance of security compared to other factors within the model. In practical terms, these coefficients imply that augmenting security in a building tends to substantially diminish its price, and this relationship persists even after standardizing the variables for more meaningful comparison.

Results of Machine Learning Models

The results of ML models are divided into three:

i. Group 1: Used all factors from the Table 5
ii. Group 2: Used all factors from the Table 5 exclude security of building
iii. Group 3: Only used security of building

Table 7 presents the results of machine learning models with all the IVs in Group 1 features selection.

Table 7: Accuracy Results of The Five Machine Learning Algorithms with All Features (Group 1)

No	Algorithm	Split		Cross-Validation	
		R^2	RMSE	R^2	RMSE
1	Random Forest Regressor	0.962	393892.1	0.663	1010579.0
2	Decision Tree Regressor	0.894	664294.1	0.721	918429.4
3	Linear Regressor	0.885	504882.2	0.480	1254698.0
4	Ridge Regressor	0.796	921761.2	0.445	1296588.0
5	Lasso Regressor	0.781	954258.9	0.413	1332991.0

Table 7 depicts that all the five algorithms that used split training approach have produced better results than the cross-validation mainly from the Random Forest Regressor. The highest R^2 value was generated by the Random Forest Regressor (0.962) with the lowest error value. Meanwhile, Ridge and Lasso have lower R ^ 2 value respectively compared to the other three algorithms as well as to the ANOVA result. These results, however, do not directly show the effectiveness of building security in the ML model. Furthermore, in Table 8, the results of each model with the feature selection without the security of the building are listed.

Table 8: Accuracy Result of the Five Machine Learning Algorithms with Features Selection exclude Security of Building (Group 2)

No	Algorithms	Split		Cross-Validation	
		R^2	RMSE	R^2	RMSE
1	Random Forest Regressor	0.963	389249.3	0.629	1059404.0
2	Decision Tree Regressor	0.905	627070.4	0.363	1389184.0
3	Linear Regressor	0.848	580528.2	0.317	1438139.0
4	Ridge	0.731	1058462.0	0.307	1448546.0
5	Lasso	0.715	1090277.0	0.255	1502699.0

Similar to the group features selection 1 (Table 7), Random Forest Regressor algorithm outperformed others in split approach. However, the exlusion of security of building did not extremely produce different accuracy result from the Random Forest. Meanwhile, the performance of Decision Tree

Regressor has increased without the security of building but not in the rest three algorithms. The security of building is identified as the most significant determinator from the MLR but it shows less impact in most of ML models in the group of features selection 2. However, to use the security of buiding alone in the ML models has drastically dropped the performances of each algorithm. This phenomenon can be observed in Table 9.

Table 9: Accuracy of Result from The Five Machine Learning Algorithms with security of building only(Group 3)

No	Algorithm	Split		Cross-Validation	
		R^2	RMSE	R^2	RMSE
1	Random Forest Regressor	0.215	1808990.0	0.084	1666258.0
2	Decision Tree Regressor	0.242	1777426.0	0.107	1644604.0
3	Linear Regressor	0.076	1434889.0	0.107	1644604.0
4	Ridge	0.237	1783934.0	0.108	1643834.0
5	Lasso	0.242	1777430.0	0.107	1644604.0

The results indicate that the security of the building itself does not exert a significant influence on the performance of the ML models. Across all algorithms, the accuracy results are notably of low accuracy, with values falling below 0.5, and the Linear Regressor demonstrating the lowest accuracy at 0.076.

Results Comparison (MRL VS ML)

The unexpected negative relationship between building security and price in the MLR model prompts the need for a more in-depth analysis. While the conventional approach would suggest that enhanced security features should positively influence building prices, the researcher's initial findings suggest otherwise. This intriguing result underscores the complexity of factors influencing property valuation and highlights the importance of exploring this relationship from a different perspective. To gain deeper insights into these results, the variables were tested with ML and tested via multiple algorithms and still did not show any significance of the security of the buildings as a green building price determinant. In all, this study tends to highlight that via the MRL approach, the prices of green buildings correspond to the security of buildings but remain insignificant when tested via ML.

CONCLUSION

In summary, this study aims to assess the impact of building security on green building price prediction using both ML and MLR models. The findings revealed a noteworthy disparity between the two approaches. While the ML model did not demonstrate a significant influence of green building attributes on price prediction, the MLR model indicated otherwise. These contrasting results underscore the importance of selecting an appropriate modeling technique for a given research context, as different methods may yield diverse conclusions. Furthermore, the results emphasize the necessity for further investigation and validation to gain a comprehensive understanding of the complex relationship among green building features, security, and property prices. Such insights are invaluable for policymakers, investors, and stakeholders in the real estate sector for those seeking to make informed decisions about sustainable building practices and security investments.

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