Impact of Security on Rental Price of Residential Properties: Evidence from South Africa

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Abstract. The property market plays a vital role in the economy through the provision of constructed space for productive activities and employment opportunities. Evidence gleaned from the literature suggests that the level of security within an area affects property prices. In the current study, the distance between a property and the police station was used as a proxy variable for measuring the perceived level of security. The data on rental prices of residential properties and its attributes were retrieved from a reliable property source (www.property24.com). A Neural network model was used for evaluating the impact of the presence of a police station on rental prices of residential properties within Cape Town, South Africa. Experimental results showed that the developed model is 77.27% accurate when used to predict the rental prices of residential properties. Floor area, number of bathroom, number of bedroom and proximity of a police station have the most significant impact on the rental price of residential properties. Greater efforts are needed to provide insights into the effect of sustainability on rental prices of residential properties. This information would serve a justification for embedding sustainability into residential construction projects.

Keywords: Crime, neural network, police station, rental price, residential properties

1. Introduction
An accurate estimate of the price of a residential property is important. Research has shown that the price of a residential property is affected by several variables. For instance, the presence of “Servants’ Quarter” had the most important effect on the residential properties rental premium in Lagos, Nigeria [1]. As expected, the inclusion of “Servants’ Quarter” into the designs of new residential developments in Lagos would increase the expected returns for investors. An understanding of the factors, i.e. variables, affecting the price of a residential property is vital for all stakeholders.

The effect of crime on the price of residential properties has been the focus of extensive research. Despite the variance in the techniques used in these previous studies, the findings show that the perceived level of crime has a negative effect on its price. For example, Klimova and Lee [2] reported that the perceived level of crime reduces the price of properties. Similarly, the crime rate affects the demand for residential properties within a neighbourhood [3,4]. It is evident that an inverse relationship exists between the perceived level of crime and the value of properties [5,6]. Hence, the implementation of crime prevention strategies would lead to an increase in the price of properties within an area.

The presence of police within a locality reduces crime. Andresen and Lau [7] found that police foot and vehicle patrol reduces the crime rate within a neighbourhood. Gibbon [4] also, states that homeowners are usually willing to pay to reduce the crime risk exposure of their properties. However, little is known about the impact of the presence of a police station on the rental prices of residential properties in South Africa. The current study seeks to address this gap in the literature by developing a model for predicting the rental price of residential properties. The developed model captures the effects of the proximity of a police station on the rental value of residential properties.
Several factors affect the value of residential properties. These factors have been grouped into three categories, namely neighbourhood, locational and structural [8]. These influences are either on the positive or negative end. Characteristics like the number of bedrooms, bathroom and floor size [9,10], locational characteristics [9,11], low housing [12] and Railway presence [13] are among variables determining residential rental prices. However, a negative effect in crime is recorded if security presence is far from a neighbourhood. Table 1 below summarizes some determinants of residential property value from literature.

| S/N | Determinants                                      | References                  |
|-----|--------------------------------------------------|-----------------------------|
| 1   | Age of building                                  | [1,14–22]                  |
| 2   | Floor Area                                       | [9,14–16,18–20,22,23]      |
| 3   | Number of bedrooms                               | [1,16,18,21–25]            |
| 4   | Proximity of railway station                     | [11,13,16,20,21]           |
| 5   | Garage (parking)                                 | [19,21–23]                 |
| 6   | Number of bathrooms                              | [1,16,17,19]               |
| 7   | Swimming pool                                    | [16,21,25]                 |
| 8   | Level of security in the area                    | [23,26,27]                 |
| 9   | Number of parking space                          | [1,19,28]                  |
| 10  | Heating                                          | [1,19,28]                  |
| 11  | Garden                                           | [16,23]                    |
| 12  | Number of lifts                                  | [16,28]                    |
| 13  | Balcony                                          | [16,23]                    |
| 14  | Proximity of the business district               | [14,27]                    |
| 15  | Sea view                                         | [1] [14]                   |
| 16  | Urban green areas                                | [15]                       |
| 17  | Jacuzzi                                          | [25]                       |
| 18  | Traffic noise                                    | [23]                       |
| 19  | Security fence                                   | [1]                        |
| 20  | Number of toilets                                | [1]                        |

2. Research Methodology

2.1. Data
The study examined the effect of the perceived level of security (i.e. proximity to a police station) on the rental price of residential properties in South Africa. In this study, the data, i.e. rental prices of residential properties and its attributes, were retrieved from a reliable source (www.property24.com). It has been found that listing prices of residential properties tend to provide realistic estimates of its value [27] when compared to transaction data. The extracted data includes information on 14 independent variables and rental prices of residential properties. The independent variables include the number of bedrooms, number of bathrooms, parking type, number of parking spaces, number of dining rooms, availability of balcony, availability of swimming pool, floor area, availability of furniture, availability of value-added services, availability of garden and proximity of police station.

The predicted variable is the monthly rental price of residential properties. These prices have been classified into five groups, namely group A (40,001 – 50,000 South African Rands), B (30,001 – 40,000 South African Rands), C (20,001 – 30,000 South African Rands), D (10,001 – 20,000 South African Rands) and F (1 – 10,000 South African Rands). Table 2 provides details of the variables included in the developed prediction model.
Table 2. Model Variables

| Variable | Name     | Description                          | Definition                        |
|----------|----------|--------------------------------------|-----------------------------------|
| Independent | BA      | Balcony                              | Numeric values of 0, 1, 2, 3…     |
|           | BT      | Bathroom                             | Decimal Value 0.5, Numeric Values 1, 2, 3… |
|           | BE      | Bedroom                              | Decimal Value 0.5, Numeric Values 1, 2, 3… |
|           | D       | Dining                               | Numeric values of 0, 1, 2…         |
|           | FL      | Floor area (m²)                      | Numeric Values of 0,1,2,3…         |
|           | FU      | Furnished                            | Classified into Response: yes or No |
|           | G       | Garden                               | Binary Values of 0 and 1           |
|           | K       | Kitchen                              | Numeric values of 0, 1, 2…         |
|           | L       | Lounge                               | Numeric values of 0, 1, 2, 3…      |
|           | PA      | Parking                              | Classified into Response: No, Covered or uncovered |
|           | PO      | Police Station (Km)                  | Numeric Values of 0,1,2,3…         |
| Output/   | R       | Monthly rental value (in South African Rands) | Groups A (40,001 – 50,000), B (30,001 – 40,000), C (20,001 – 30,000), D (10,001 – 20,000) and F (1 – 10,000). |
| Dependent |         |                                      |                                   |

2.2. Neural network Algorithm- An overview

Neural network (NN) is a nature-inspired modelling technique. NN model is inspired by the human brain. The NN model is made up of interconnected neurons whose functioning is similar to the human brain. Over the years, several techniques have been used for modelling and forecasting of the value of properties. The technique used in previous research includes, NN [1], regression [29] and Hedonic Pricing Model [1,27] techniques have been compared in previous studies. For example, Abidoye and Chan [1] found that NN generates a more accurate prediction of property values when compared to regression. The ability of the NN to capture nonlinearity present in real-world data has been attributed to this finding. The predictive performance of the NN model is also the main reason for its application in this study.

The neural network model applied in this study is a three-layer feedforward model. The neurons in the NN model are calibrated during the learning phase. The final forecast computed by the model is mainly dependent on the initial weights of the neurons. To reduce the variations in the final forecast from the NN model due to randomization, an ensemble of NNs was applied in this study. The final prediction from each NN model was averaged following the suggestion of Friedman, Hastie and Tibshirani [30]. The architecture of the NN model is 14-H-1. The input layer has 14 neurons (i.e. 14 independent variables). The number of nodes in the hidden layer (H) is the only parameter of the neural network (NN) model that was tuned using the grid search algorithm. The output layer (neuron) of the NN model is the rental value.

The predictive model was developed using the R-programming (R Core Team, 2015) and rminer package. The grid search algorithm was used to identify the optimal parameter for the NN model. A grid search is simple to implement and parallelization is trial [31]. It is an algorithm used to identify optimal parameters for machine learning models [32]. Similar to the study of Wilson [33], the collected data set was group into two i.e. training and test data. First, this approach was used to validate the developed model. Second, this division ensured that the overfitting was avoided. The NN model was estimated by capturing the relationship between the 14 independent variables and rental value. Zhang, Patuwo, and Hu [34] mentioned that the ratio for training and test data set in previous studies include 90:10; 80:20 and 70:30, respectively. In this study, the collected data were classified based on the 70:30 ratios (i.e. 207 instances were used for training and 88 instances were used for model validation.
3. Results

3.1. Predictive Performance of the developed NN model
NN can be used for two main types of machine learning tasks namely, classification and regression. Classification refers to when the model is used for prediction of grouping [35]. In contrast, regression refers to when the model is used for prediction of numbers [36]. A confusion matrix is used to summarize the prediction results generated by a classification model. It contains information about the actual and predicted classification [37]. In the present study, the collected data was fitted to a NN model. The predictive performance of the classification model ranges between 0% and 100% [38]. Typically, a value close to 100% indicates that the developed model can correctly predict previously unseen data (i.e. test dataset).

The validation results of the NN model are summarized and presented in Table 3. On the overall, the predictive performance of the developed model is 77.27%. This result shows that the NN model can predict the rental price of residential properties. However, it must be noted that the accuracy of groups A, B, C, and E are low. The low accuracy for these groups could be attributed to the small size of the dataset within these groups [39].

| Observed | Predicted | Accuracy |
|----------|-----------|----------|
| A        | 0 0 1 0 0 | 0.00%    |
| B        | 0 0 2 0 0 | 0.00%    |
| C        | 0 0 7 8 0 | 46.67%   |
| D        | 0 0 2 59 0| 96.72%   |
| E        | 0 0 0 7 2 | 22.22%   |
| Overall  | 77.27%    |          |

3.2. Sensitivity Analysis
One of the limitations of machine learning models, such as NN, is the lack of coefficients. The absence of coefficients makes it difficult to interpret the NN model when compared to regression models. Neural network models are term as “black box” modelling technique due to this limitation. In recent years, there have been several advancements in the field of machine learning, such as sensitivity analysis. Sensitivity analysis is a method used for visualizing the impact of independent variables on the predicted variable in black box models [40].

In this study, a sensitivity analysis was used to assess the impact of the 14 independent variables on the rental price of residential properties. The relative importance of each independent variable is presented in Figure 1. The figure shows that floor area, number of bathrooms, number of bedrooms and proximity to police station have the most significant impact on the rental price of residential properties.
4. Discussion of findings
As earlier discussed in the literature review, the factors affecting the rental price of residential properties tend to be location-specific. The results of this study have been presented in the preceding subsections. It is evident that the impact of the independent variables on the rental prices of residential properties varies. It is evident that each independent variable has varying impact on the rental prices of residential properties (see Figure 1). The findings of the study revealed that floor area, the number of bathrooms, the number of bedrooms, and proximity of police station have the most significant impact on residential rental prices.

Floor area is one attribute that influences residential rental value. Floor area or Number of floors gives a description of the usable space within a property. Floor size is an attribute that influences the rental prices of properties [8,10,41]. In other locations, floor number or storey number determines the value of residential properties [1,42]. This difference is due to the different taste of prospective homeowners. Irrespective, [8] described that floor area is the most important attribute of a building that influences the rental price.

Bathroom and conveniences are essential features that provide comfort to occupants of buildings. The findings of this study agree with those found in previous studies[10,43] which shows that the presence of bathrooms has a positive effect on the value of properties. This is because the number of bathrooms has a significant effect on the residential house [44]. However, regions of very high population density like Hong Kong will prefer more floor space than bathroom number [45]. Irrespective, the bathroom is essential for all property type worldwide.

A bedroom is one of the features that define a residential property. Abidoye and Chan [1] opine that the number of bedrooms increases the residential rental price. Around the world, bedroom significantly influences residential rental prices[9,18,46–49]. Surprisingly, this contradicts the opinion
of Abdullahi et al. [50,51]. This is attributed to the difference in density of geographical location [52] (Location, therefore, is key.

Social amenities have a positive impact on rental properties. A police station is described as a social facility. The perception of safety, fear of crime has an influence on property value[2,53]. Police presence affects property crime [7]. This provides a sense of security for house owners and intending buyers. Studies supports that police presence influence residential property value [4,26,54]. This shows a relationship exists between crime, housing price and, police presence.

Neural Network model can produce reliable estimates of the rental values of residential properties. These results support the findings of [1,40] and others alike, all of which reported that the NN technique has a reliable predictive ability that can address the non-linearity of property values and property attributes. It justifies that the result of NN use in this study is viable.

5. Conclusion
The study addressed the impact of security on rental property price in South Africa using Neural Network. The predictive accuracy of the developed model suggests that the neural network model can produce reliable estimates of the rental values of residential properties. In addition, it was discovered that floor area, bathroom number, number of Bedroom and police station have a significant effect on residential rental value. The findings imply that in Cape Town, South Africa, residential rental prices are determined by these factors. Police or security presence will ward off or reduce property crime. This increases the price of a residence in a neighbourhood. This study contributes to the body of existing knowledge in property economics. It adds to current knowledge on the impact of attributes of residential properties on its rental value. Accessible housing and adequate securities have been described as some vital goals of the United Nations for sustainable development, hence this study provides insight on security as it relates to housing. This is also useful for informing housing decision and policymakers. However, it must be reiterated that the availability of data remains a challenge to researchers in the fields of construction economics and property economics. The geographical scope of the study was limited to Cape Town, South Africa as well. Further work needs to be done to establish the influence of proximity to green areas (such as parks) on the rental value of residential properties. In addition, future studies could be conducted to determine the effectiveness of using a neural network model for forecasting of rental values of commercial properties.

6. References
[1] Abidoye R B and Chan A P C 2017 Modelling property values in Nigeria using artificial neural network J. Prop. Res. 34 36–53
[2] Klimova A and Lee A D 2014 Does a Nearby Murder Affect Housing Prices and Rents? The Case of Sydney Econ. Rec. 90 16–40
[3] Thaler R 1978 A note on the value of crime control: Evidence from the property market J. Urban Econ. 5 137–45
[4] Gibbons S 2004 The Costs of Urban Property Crime Econ. J. 114 F441–63
[5] Pope D G and Pope J C 2012 Crime and property values: Evidence from the 1990s crime drop Reg. Sci. Urban Econ. 42 177–88
[6] Linden L and Rockoff J E 2008 Estimates of the Impact of Crime Risk on Property Values from Megan’s Laws Am. Econ. Rev. 98 1103–27
[7] Andresen M A and Lau K C Y 2014 An evaluation of police foot patrol in Lower Lonsdale, British Columbia Police Pract. Res. 15 476–89
[8] Chau K W and Chin T L 2002 A Critical Review of Literature on the Hedonic Price Model
[9] Fan G-Z, Ong S E and Koh H C 2006 Determinants of House Price: A Decision Tree Approach Urban Stud. 43 2301–15
[10] Zietz J, Zietz E N and Sirmans G S 2008 Determinants of House Prices: A Quantile Regression Approach J. Real Estate Financ. Econ. 37 317–33
[11] Kampamba J and Cloete C E 2015 Forecasting office rentals in Gaborone in the short and long term Sustain. Dev. 1
[12] Du Preez M and Sale M 2013 The Impact of Social Housing Developments on Nearby Property Prices: a Nelson Mandela Bay Case Study *South African J. Econ.* 81 451–66

[13] Boshoff D G B 2017 The influence of rapid rail systems on office values: A case study on South Africa *Pacific Rim Prop. Res. J.* 23 267–302

[14] Mok H M K, Chan P P K and Cho Y 1995 A Hedonic Price Model for Private Properties in Hong Kong *J. Real Estate Financ. Econ.* 10 37–48

[15] Tyrväinen L and Miettinen A 2000 Property Prices and Urban Forest Amenities *J. Environ. Econ. Manage.* 39 205–23

[16] Lam K C, Yu C Y and Lam K Y 2008 An Artificial Neural Network and Entropy Model for Residential Property Price Forecasting in Hong Kong *J. Prop. Res.* 25 321–42

[17] Steven P and Albert F 2009 Neural Network Hedonic Pricing Models in Mass Real Estate Appraisal *J. Real Estate Res.* 31 147–64

[18] Selim S 2008 Life Satisfaction and Happiness in Turkey *Soc. Indic. Res.* 88 531–62

[19] Jozef Z, Alan L and Jian G 2011 A Comparison of Regression and Artificial Intelligence Methods in a Mass Appraisal Context *J. Real Estate Res.* 33 349–87

[20] Mimis A, Rovolis A and Stamou M 2013 Property valuation with artificial neural network: the case of Athens *J. Prop. Res.* 30 128–43

[21] Simons R 2015 Modeling the Effects of Refinery Emissions on Residential Property Values *J. Real Estate Res.* 37 321–42

[22] Mccluskey W J, McCord M, Davis P T, Haran M and McIlhatton D 2013 Prediction accuracy in mass appraisal: a comparison of modern approaches *J. Prop. Res.* 30 239–65

[23] Yacim J, Research D B-J of R E and 2018 undefined Impact of Artificial Neural Networks Training Algorithms on Accurate Prediction of Property Values aresjournals.org

[24] Li H, Li V and Skitmore M 1997 Comparative study of analytical rental model and statistical models for predicting house rental levels *Build. Environ.* 32 389–95

[25] Kaidou D, Moore W and Charles-Soverall W 2014 Neighborhood Features and the Rental Price of Villas and Cottages in Barbados *J. Hosp. Tour. Res.* 38 528–45

[26] Basu S and Thibodeau T G 1998 Analysis of Spatial Autocorrelation in House Prices *J. Real Estate Financ. Econ.* 17 61–85

[27] Abidoye R B and Chan A P C 2018 Hedonic Valuation of Real Estate Properties in Nigeria, Hedonic Valuation of Properties in Nigeria *J. African Real Estate Res.* 3 122–40

[28] Ozalp A Y and Akinci H 2017 The use of hedonic pricing method to determine the parameters affecting residential real estate prices *Arab. J. Geosci.* 10 535

[29] Zambrano-Monserrate M A 2016 Formación de los precios de alquiler de viviendas en Machala (Ecuador): análisis mediante el método de precios hedónicos *Cuad. Econ.* 39 12–22

[30] Friedman J, Hastie T and Tibshirani R 2008 Sparse inverse covariance estimation with the graphical lasso *Biostatistics* 9 432–41

[31] Bergstra J and Bengio Y 2012 Random Search for Hyper-Parameter Optimization *J. Mach. Learn. Res.* 13 281–305

[32] Qolomany B, Maabreh M, Al-Fuqaha A, Gupta A and Benhaddou D 2017 Parameters optimization of deep learning models using Particle swarm optimization 2017 13th *International Wireless Communications and Mobile Computing Conference (IWCMC)* (IEEE) pp 1285–90

[33] Wilson I D, Paris S D, Ware J A and Jenkins D H 2002 Residential Property Price Time Series Forecasting with Neural Networks *Applications and Innovations in Intelligent Systems IX* (London: Springer London) pp 17–28

[34] Zhang G, Eddy B P and Y. Hu M 1998 Forecasting with artificial neural networks: The state of the art *Int. J. Forecast.* 14 35–62

[35] Bost R, Popa R A, Tu S and Goldwasser S 2015 Machine Learning Classification over Encrypted Data *NDSS’15* (San Diego, CA, USA: Internet Society) pp 1–14

[36] Uysal I and Guvenir H A 1998 The knowledge engineering review 1998 Uschold *Knowl. Eng. Rev.* 14 1–59

[37] Santra A K and Christy C J 2012 Genetic Algorithm and Confusion Matrix for Document
Clustering IJCSI Int. J. Comput. Sci. Issues 9 322–8

[38] Cortez P 2015 A tutorial on using the rminer R package for data mining tasks (Universidade do Minho. Escola de Engenharia (EEng))

[39] Yaïci W, Longo M, Entchev E, Foiadelli F, Yaïci W, Longo M, Entchev E and Foiadelli F 2017 Simulation Study on the Effect of Reduced Inputs of Artificial Neural Networks on the Predictive Performance of the Solar Energy System Sustainability 9 1382

[40] Cortez P and Embrechts M J 2013 Using sensitivity analysis and visualization techniques to open black box data mining models Inf. Sci. (Ny). 225 1–17

[41] Kain J F and Quigley J M 1970 Measuring the Value of Housing Quality J. Am. Stat. Assoc. 65 532–48

[42] Cebula R J 2009 The Hedonic Pricing Model Applied to the Housing Market of the City of Savannah and Its Savannah Historic Landmark District Rev. Reg. Stud. 39 9–22

[43] Hughes D and Lowe S 2007 The private rented housing market: regulation or deregulation? (Ashgate)

[44] Musa U, Zahari W and Yusoff W 2015 The Influence of Housing Components on Prices of Residential Houses: A Review of Literature Ninth Malaysian Technical Universities Conference on Engineering and Technology 2015 (MUCET 2015) vol 12 p 12

[45] Leung K M and Yiu C Y 2019 Rent determinants of sub-divided units in Hong Kong J. Hous. Built Environ. 34 133–51

[46] Mbachu J I C and Lenono N 2005 Factors influencing market values of residential properties Queensland University of Technology Research Week International Conference, QUT Research Week 2005 ed A. C. Sidewell (Brisbane)

[47] Oloke O C, Simon F R and Adesulu A F 2013 An Examination of the Factors Affecting Residential Property Values in Magodo Neighbourhood, Lagos State Int. J. Econ. Manag. Soc. Sci. 2 639–64

[48] Wickramaarachchi N 2016 Determinants of rental value for residential properties: A land owner’s perspective for boarding homes Built-Environment Sri Lanka 12 10–22

[49] Sanga S A 2017 The Impact of Traditional House-type on Rental Values in Kinondoni Municipality Dar es Salaam Tanzania vol 12

[50] Abdullahi A, Usman H and Ibrahim I 2018 Determining house price for mass appraisal using multiple regression analysis modeling in Kaduna North, Nigeria ATBU J. Environ. Technol. 11 26–40

[51] Liman H S, Sipan I, Olatunji I A and Afrane E 2015 Hedonic House, modelling of determinants of price in Minna, Nigeria. International Conferences And, Emerging Issues in Economics In ASIA On (Kuala Lumpur.) pp 1–11

[52] Sirmans G S, MacDonald L, Macpherson D A and Zietz E N 2006 The Value of Housing Characteristics: A Meta Analysis J. Real Estate Financ. Econ. 33 215–40

[53] Gilderbloom J I, Riggs W W and Meares W L 2015 Does walkability matter? An examination of walkability’s impact on housing values, foreclosures and crime Cities 42 13–24

[54] Vetter D M, Beltrão K I and Massena R M R 2013 A Service of zbw Leibniz-Informationszentrum Wirtschaft Leibniz Information Centre for Economics The Impact of the Sense of Security from Crime on Residential Property Values in Brazilian Metropolitan Areas (Washington DC)