TOWARDS PROPERTY VALUATION ACCURACY: A COMPARISON OF HEDONIC PRICING MODEL AND ARTIFICIAL NEURAL NETWORK

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CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

Signed
ABIDOYE Rotimi Boluwatife

DEDICATION

This thesis is dedicated to God Almighty, Jesus Christ and the Holy Spirit for granting me life and the grace to complete this study. Secondly, to my parents Late Prince M. A. Abidoye and Mrs. J. F. Abidoye for their prayers and support towards my education from the cradle. To my lovely wife, Mrs. Funmilayo Adenike Abidoye and my lovely son, Master Oluwaloni Abidoye for their support and sacrifice throughout my PhD study.

ABSTRACT

The need for accurate property valuation in any country cannot be underestimated due to the significant relationship between the real estate industry and the national economy. Investment decisions relating to the acquisition or disposal of real estate assets are largely dependent on valuation estimates. Inaccuracies in property valuation is a global problem which have been of interest to all stakeholders, and Nigeria is no exception. A possible explanation for this might be the valuation techniques currently adopted, with the hedonic pricing model (HPM) being an example. As evidenced in previous literature, the HPM approach has gained wide acceptance among real estate researchers, despite its shortcomings.

There is an obvious need to seek innovative approaches to improve the quality of property valuation estimates. To address the shortcomings of the HPM approach in property valuation, the current study sets out to develop prediction models for property valuation in Nigeria. Two modeling techniques, i.e. HPM and artificial neural network (ANN), were applied in this study. The predictive accuracy of the developed models served as a basis for comparison. The research objectives are to; assess the current property valuation practice in the Lagos metropolis; identify and generate a list of attributes that influence residential property values in the Lagos metropolis property market; develop a hedonic pricing model for the Lagos metropolis residential property market; develop an artificial neural network model for the Lagos metropolis residential property market; evaluate the predictive accuracy of HPM and the ANN model developed for the Lagos metropolis residential property market; and assess the Nigerian valuers' receptiveness to the application of artificial intelligence (AI) techniques in property valuation.

The data used for this study were sourced from registered real estate firms operating in the Lagos metropolis, Nigeria. The information collected includes the awareness and adoption of various valuation methods, residential property value determinants and the receptiveness of valuers to AI techniques in property valuation, and they were gathered via the administration of online-based questionnaires to the valuers. The data were analyzed using the mean score (MS) ranking technique and the chi-square test. In addition, the sale transactions information of residential properties situated in the Lagos Island property market were collected. These were fitted into HPM and the ANN model developed for the Lagos metropolis property market.

The present research found that the valuers are aware of and adopt the traditional valuation methods, especially the comparable, investment and cost methods in practice. Whereas there is a little awareness and non-adoption of the advanced valuation methods. This suggests that there is a need for a paradigm shift towards more accurate and reliable property valuation approaches. The analysis of the property value determinants reveals that the structural attributes are the most significant to property value formation in the Lagos metropolis. This set of attributes were used for the modeling of the property values in the study area.

In order to facilitate a justifiable comparison, the HPM and the ANN models were developed with the same data set. This data set was divided into two parts; for the training and the testing of the developed models. The HPM approach generated a coefficient of determination (r^2) value of 0.77, but this did not translate into the prediction of accurate property values because of the high mean absolute percentage error (MAPE) value of 38.23% recorded. This is coupled with high mean absolute error (MAE) and root mean squared error (RMSE) values recorded as well. The ANN model produced an r^2 value of 0.81 and a MAPE value of 15.94%. These values together with lower MAE and RMSE values are more encouraging when compared with these of the HPM approach. This indicates that the ANN model is a better substitute to the HPM approach in property valuation. Also, a large percentage of the ANN predicted property values generated prediction errors which are within acceptable international standards, when compared with the HPM outputs. The investigation into the receptiveness of Nigerian valuers to AI valuation techniques shows that the majority of the valuers are willing to acquire the competence in the application of the AI techniques in property valuation. When other requirements of developing a robust property valuation model are met, coupled with this high level of willingness of the valuers, the prevalence of property valuation inaccuracy in the Nigerian context could be reduced remarkably.

Overall, the Nigerian property valuation practice is still at a traditional level. Also, structural attributes of properties were found to be the most important attributes affecting its value. The developed ANN model provides a tool which can be used for property valuation. In addition, the findings provide evidence which justifies the need to adopt advanced modeling techniques (such as AI technique) in the property valuation research and practice.

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Chapters of this thesis have been fully, or partially, published in the following publications:

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Abidoye, R. B. & Chan, A. P. C. (2016). Critical determinants of residential property value: Professionals' perspective. *Journal of Facilities Management*, 14 (3), pp. 283 - 300.

Abidoye R. B. & Chan, A. P. C. (2016). A survey of property valuation approaches in Nigeria. *Property Management*, 34 (5), pp. 364 – 380.

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LIST OF ABBREVIATIONS

AI	Artificial intelligence
ANN	Artificial neural network
ANR	Additive nonparametric regression
AR	Additive regression
ARIMA	Autoregressive integrated moving average
ARMA	Autoregressive moving average
BP	Backpropagation
BQ	Boys’ quarters
CBD	Central business district
CBN	Central Bank of Nigeria
CBR	Case-based reasoning
CPI	Consumer price index
COV	Coefficient of variation
CSA	Comparable sales analysis
EFInA	Enhancing Financial Innovation and Access
ES	Expert system
ESVARBON	Estate Surveyors and Valuers Registration Board of Nigeria
FLS	Fuzzy logic system
GDP	Gross domestic product
GIS	Geographic information system
GWR	Geographical weight regression
HPM	Hedonic pricing model
IVSC	International Valuation Standards Council
JLL	Jones Lang LaSalle
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MBR	Memory-based reasoning
MCPD	Mandatory continuing professional development
ME	Mean error
MLP	Multilayer perceptron
MRA	Multiple regression analysis
MS	Mean score
MSE	Mean squared error
MTR	Mass transit railway (MTR)
NBS	National Bureau of Statistics
NIESV	Nigerian Institution of Estate Surveyors and Valuers

OECD	Organisation for Economic Co-operation and Development
OMV	Open market value
RA	Research Assistants
RBFNN	Radial basis function neural network
RI	Relative importance
RICS	Royal Institution of Chartered Surveyors
RMSE	Root mean square error
SAPOA	South African Property Owners Association
SPSS	Statistical Package for Social Sciences
SVM	Support vector machine
VGC	Victoria Garden City
VIF	Variance inflation factor
WEKA	Waikato Environment for Knowledge Analysis
YP	Years’ purchase

CHAPTER 1 INTRODUCTION

1.1 INTRODUCTION

This chapter describes the purpose of this research by presenting the background of the research, the research problem, the research aim and objectives and the research approach adopted. It also presents the significance and the scope of this study. The chapter also outlined the structure of the thesis so as to enable easier navigation through the remaining chapters of the thesis.

1.2 BACKGROUND OF THE RESEARCH

Real estate property is an investment opportunity which has an edge against inflation. Also, most of the human activities take place in real estate properties such as for living, working, leisure, and so on (Smith and Zaibert, 2001). Due to the importance and the advantages of real estate properties, a significant number of investors are attracted to it for long-term gains. This has resulted in the total value of the world's wealth been estimated at US$250.1 trillion in 2015 (Credit Suisse, 2015), in which more than half of this value is embedded in real estate assets (Giacomini et al., 2015). According to Organisation for Economic Co-operation and Development (OECD) (2016), the real estate industry contributed 11.55%, 11.97%, 12.13% and 6.03% to the gross domestic product (GDP) of the UK (2015), the US (2014), Australia (2015) and China (2015), respectively, during these periods[1]. Nigeria is a developing nation which the researcher has a high affinity for, and it is the focus of this research. However, the real estate sector contributed 8.64% to the Nigerian GDP in 2016Q2 (National Bureau of Statistics, 2016b).

A principal factor considered during the process of investment decisions on real estate property is property valuation estimates (Newell and Seabrook, 2006). Empirical evidence from previous research has shown that property prices are positively related to the volume of investments in construction works (Zheng et al., 2012). Furthermore, the volume of the activities in the real estate industry and the construction sector influences the pace of economic development (Pietroforte et al., 2000; Akinbogun et al., 2014; Chiang et al., 2015). Thus, it can be inferred that the accuracy of property valuation estimates has a significant impact on the economy of a nation.

Real estate investors (such as private individuals, mortgagors, mortgagees, financial institutions, corporate investors and government authorities, among others) rely heavily on real estate professionals' opinions of value to make economic, investment and financial decisions (Taffese, 2007; Adegoke et al., 2013). Thus, a misleading figure can bring about a negative profit margin or even bankruptcy. For instance, if there is a

[1] Author's calculations.

large negative disparity in the valuation figure and the value the subject property eventually commands when sold, when there is a mortgage foreclosure or when there is a takeover. Therefore, estimating the value of real estate properties in an objective and accurate manner is important to real estate stakeholders and the economy of a nation at large (Yalpir, 2014).

1.3 RESEARCH PROBLEM

In estimating the value of a property, valuers usually adopt some valuation methods which include comparable, investment, profit, contractor's and residual methods, which are termed as "traditional methods" (Pagourtzi et al., 2003). Previous studies (Adair et al., 1996b; Crosby, 2000; Babawale and Ajayi, 2011; Owusu-Ansah, 2012) have pointed out the inadequacies of the traditional valuation methods in producing objective, reliable and accurate property values (Zurada et al., 2006).

Property valuation inaccuracy is a global problem which has attracted the attention of scholars all over the world (Parker, 1998; Crosby, 2000; Babawale, 2013b). Webb (1994) and Mallinson and French (2000) posited that property valuation inaccuracy could be inevitable due to the peculiar characteristics of real estate assets. However, a margin of error of between ± 0 and 10% is generally acceptable (Hutchinson et al., 1996; Brown et al., 1998). Studies have shown that the inaccuracies observed within the Nigerian context are beyond the acceptable global standard (Ajibola, 2010; Babawale and Ajayi, 2011; Adegoke et al., 2013). For instance, Ogunba (2004) found that property valuation inaccuracy errors generated in Nigeria are between 22 and 67%. The primary reason for this level of inaccuracies has been linked to the application of inappropriate valuation approaches (Aluko, 2007; Babawale and Ajayi, 2011).

Adegoke et al. (2013) found that the inability of the Nigerian valuers to provide accurate valuation estimates has led to the loss of confidence among valuation report end-users in the professionals and the profession. Also, Babawale and Alabi (2013) reported that there is a high level of inaccuracies in the mortgage valuations carried out by the Nigerian valuers. This has resulted in various stakeholders' doubt of the credibility and reliability of valuation estimates reported by the Nigerian valuers. The study of Adegoke (2016) also confirmed this; that the inaccuracies in the property valuations reported by the Nigerian valuers have reduced their integrity, eroded their credibility and exposed them to professional negligence liabilities.

Recently, there has been renewed interest targeted at improving the reliability and accuracy of property valuation estimates. Previous researches have established that real estate professionals practicing in Nigeria are conversant with the traditional methods of valuation (Bello and Bello, 2009; Babawale, 2012; Abidoye and Chan, 2016c). However, the use of the advanced valuation methods has been limited. Considering the globalization being experienced in different property markets around the world, there is a need to shift from the traditional methods towards advanced approaches so as to achieve a sustainable property valuation practice (Wiltshaw, 1995; Gilbertson and Preston, 2005).

The quest for robust and reliable property valuation methods by researchers has led to the development of a number of valuation approaches. The Hedonic Pricing Model (HPM) is one of such methods, which has been widely adopted in the real estate research domain (Bender et al., 2000; Babawale et al., 2012) across the world (Adair et al., 1996b; Tse and Love, 2000; Ge, 2009). HPM is an analytic technique which is designed for valuing utility bearing capacity goods (Selim, 2008), based on the regression of the independent variables of the subject under consideration against its dependent variable (Limsombunchai et al., 2004). In Nigeria, especially in the Lagos metropolis property market, scholars have used HPM to model property values in different submarkets in the state (Olayiwola et al., 2005; Aluko, 2011; Babawale et al., 2012; Oloke et al., 2013; Famuyiwa and Babawale, 2014, amongst others). There are several drawbacks of the HPM approach which include, but are not limited to: (1) selecting the best functional form (Lin and Mohan, 2011), (2) inability to handle outliers (Selim, 2008), and (3) the issue of multicollinearity of variables and heteroscedasticity (Limsombunchai et al., 2004), amongst others. These shortcomings affect the quality of property valuation estimates computed with the HPM approach.

In order to address the shortcomings of the HPM approach, new modeling techniques (such as artificial neural network {ANN}) have been applied in property valuation research (Do and Grudnitski, 1992; Evans et al., 1992; Tay and Ho, 1992; Bagnoli and Smith, 1998; Amri and Tularam, 2012). ANN is a type of artificial intelligence (AI) modeling techniques designed to function like the biological neural network to handle the complex relationship which exists between the input and output of the subject under consideration (Mora-Esperanza, 2004). It has a learning ability and process commands by the interplay of the network neurons which mimics the human brain neurons (Taffese, 2006).

The ANN technique has been applied successfully and produced excellent results in diverse disciplines, including health and medicine (Zhang and Berardi, 1998), accounting and finance (Tam and Kiang, 1992), engineering and manufacturing (Dvir et al., 2006), marketing (Thieme et al., 2000) and general application (Chang, 2005), for prediction, pattern recognition, classification, nonlinear mapping, and so on (Paliwal and Kumar, 2009).

In the real estate industry, researchers have applied ANN in property valuation and it has produced excellent results. Some instances of the application of ANN in property valuation are presented in Table 1.1.

Table 1.1: Applications of ANN in property valuation in different countries

Author(s)	Countries
Borst (1991)	United States
Do and Grudnitski (1992)	United States
Evans et al. (1992)	United Kingdom
Tay and Ho (1992)	Singapore
Rossini (1997)	Australia
Cechin et al. (2000)	Brazil
Limsombunchai et al. (2004)	New Zealand
Lam et al. (2008)	Hong Kong
Selim (2009)	Turkey
McCluskey et al. (2013)	United Kingdom

Abidoye and Chan (2016b) found that in almost all the ANN studies (property valuation related), the outstanding performance of ANN in terms of predictive accuracy in property valuation is affirmed when compared with the HPM approach. The excellent performance of the ANN technique over other advanced models: additive nonparametric regression (ANR), expert system (ES) and fuzzy logic system (FLS) approach, has also been established (see, for example, Pagourtzi et al., 2007; Lin and Mohan, 2011; Amri and Tularam, 2012).

The property valuation practice in Nigeria, especially in the Lagos metropolis, being the most active property market in Nigeria (Oni, 2010), has been dominated by the adoption of traditional methods of valuation and the HPM approach. Such practice has made valuation inaccuracy unavoidable in property valuation reports which real estate valuers produce to meet the demand of their clients for state-of-the-art services in the twenty-first century (Gilbertson and Preston, 2005). The situation in Nigeria of date is that there has not been any concerted effort to examine the efficacy of applying advanced valuation approaches in the property market, which could produce reliable and accurate property valuation estimates.

Against this background, this research aims to apply the ANN technique to the Lagos metropolis property market in Nigeria, and to investigate if the ANN technique can actually outperform the widely adopted HPM in terms of their ability to accurately predict property values. The results of this research will be useful to real estate scholars and valuers in Nigeria, and beneficial to both the local and foreign real estate stakeholders interacting in the Nigerian property market.

1.4 AIM AND OBJECTIVES

The aim of this study is to investigate the predictive accuracy of HPM and ANN in property valuation, in a bid to improve the accuracy of property valuation estimates in the Lagos metropolis property market in Nigeria.

In order to achieve this aim, the following objectives are pursued:

(i) to assess the current property valuation practice in the Lagos metropolis;

(ii) to identify and generate a list of attributes that influence residential property values in the Lagos metropolis property market;

(iii) to develop a hedonic pricing model for the Lagos metropolis residential property market;

(iv) to develop an artificial neural network model for the Lagos metropolis residential property market;

(v) to evaluate the predictive accuracy of HPM and the ANN model developed for the Lagos metropolis residential property market; and

(vi) to assess the Nigerian valuers' receptiveness to the application of the AI techniques in property valuation.

Figure 1.1 shows the framework of achieving the objectives of the present research and the expected results of each objective.

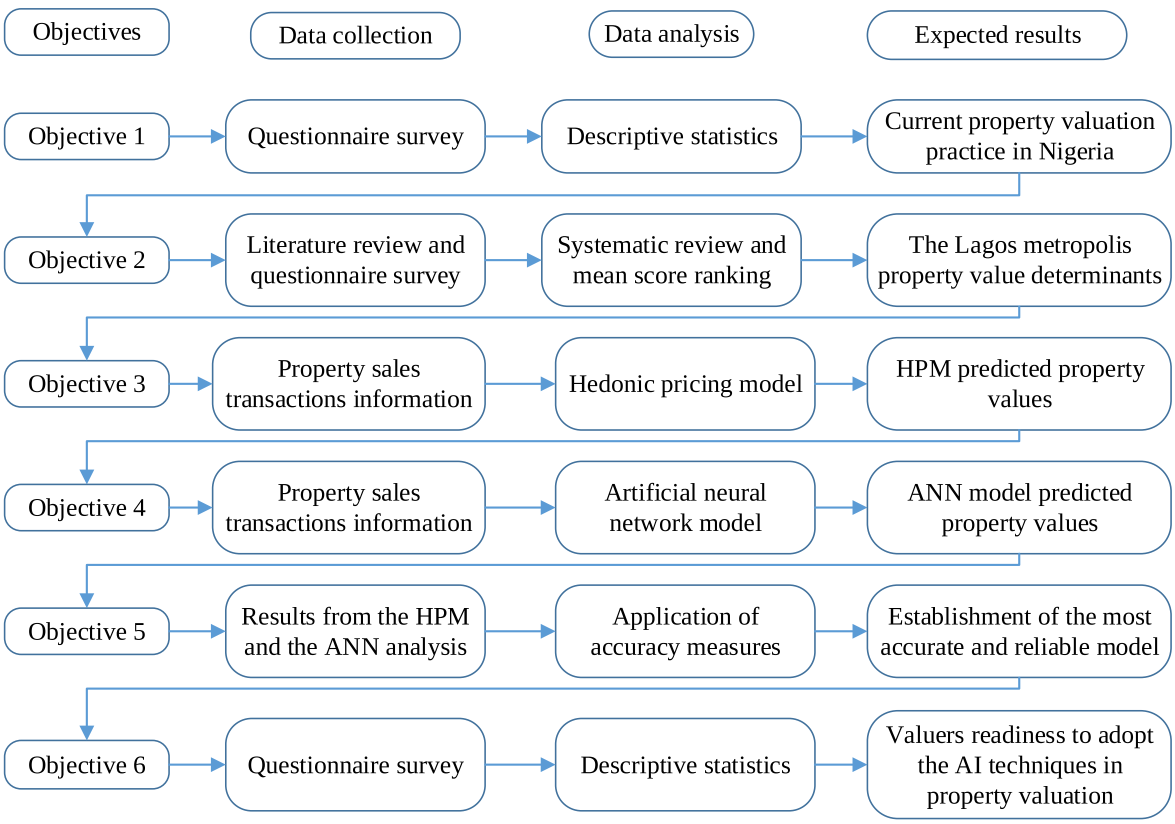

Figure 1.1: Flowchart of overall objectives of the research

1.5 RESEARCH APPROACH

The data used in this study were collected from both primary and secondary sources. A literature review was conducted to extract information related to the research topic from journals articles, conference proceedings, PhD theses, books and reports of organizations sourced from various search engines and databases. Also, questionnaire surveys were conducted to collect information from real estate professionals practicing in the study area on the valuation approaches adopted in practice, variables which influence property values and the willingness to adopt the AI techniques in property valuation.

Historical sales transactions data were retrieved from registered real estate firms operating within the Lagos metropolis. The firms were contacted for historical information/data from their databanks. The collated data were used for the development of both the ANN model and HPM. The Statistical Package for Social Sciences (SPSS) version 20.0 was used for the HPM analysis and for the descriptive statistical analysis of the questionnaires. On the other hand, the R programming software and the Rminer package were employed for the construction of the ANN model.

A key objective of this research is to establish the predictive accuracy of HPM and the

ANN model for the Lagos metropolis property market. Therefore, the mean absolute percentage error (MAPE), the mean absolute error (MAE), the root mean square error (RMSE) and the coefficient of determination (r^2) accuracy measure techniques were used to evaluate the predictive accuracy performance of both models. In addition, the percentage of property values that were predicted by the developed models and that had percentage errors within the acceptable global margin of error was also established for the evaluation of the models. Figure 1.2 shows the research approach flowchart for this study, while the detailed research methodology is provided in Chapter 4.

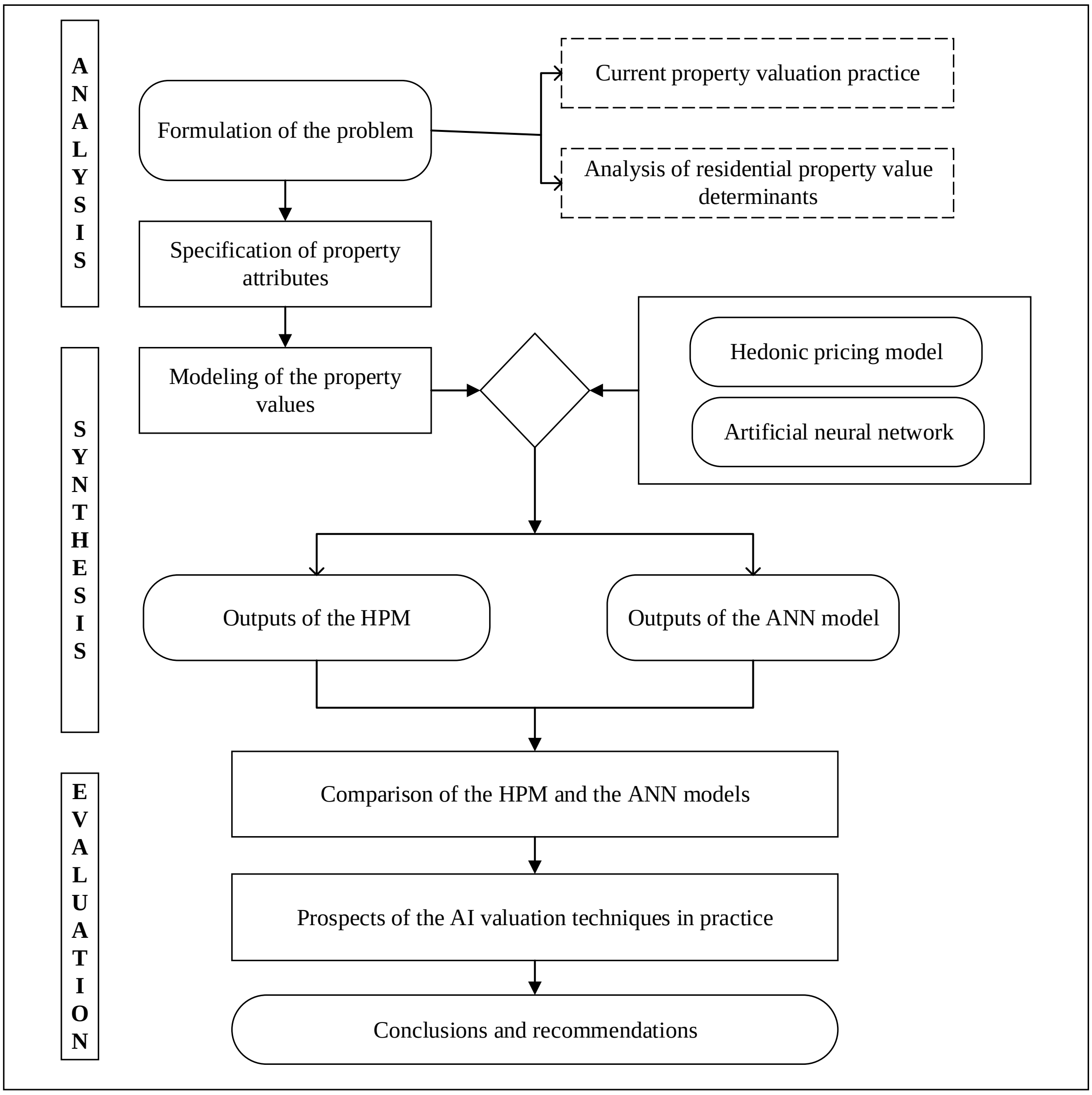

Figure 1.2: Decision-making flowchart
Adapted from: Aragonés-Beltrán et al. (2010)

1.6 SIGNIFICANCE OF THE STUDY

This research focuses on the development of an accurate and reliable model for property valuation. Studies have shown that there is a strong relationship between the property market and economic growth, especially in developing countries (Giang and Pheng, 2011). As discussed in Section 1.2, it is evident that property valuation estimate is a major factor that influences investment decisions of relevant real estate stakeholders. Thus, it is important to have a model that can be used as a decision support tool to facilitate accurate estimation of property values. The present research makes the following contributions to knowledge and the real estate practice in Nigeria and beyond.

First, evidence abounds in the literature that shows that inaccurate property valuation is a problem in the Nigerian property market (Babawale and Alabi, 2013). This inaccuracy could be explained in part by the subjectivity associated with traditional approaches and the lack of property transactions databank. To address this problem, the current research explores the efficacy of using ANN as a model for predicting property values. This study provides a comprehensive review of the literature on property valuation. In addition, it offers deep insight into the factors that influence property values in the context of Nigeria. The findings present a case why the application of ANN in property value prediction can be instrumental in leading to a shift in the property valuation practice, especially in Nigeria. This provides the justification for the adoption of advanced modeling techniques (such as ANN) in property valuation both in practice and research. This would increase the relevance and competitiveness of Nigerian valuers, both locally and in the international property market.

Second, the literature shows that the determinants of property value vary across different countries and locations. Theoretically, the present study attempts to develop models that can adequately capture the interaction between property value and its determinants. This information provided by the models developed in this research are useful to researchers and practitioners. This will help identify attributes that should be incorporated in new property development to maximize return on investments. Also, the determinants can be used for the development of property valuation models in other developing countries.

Finally, the origin of the global financial crisis which occurred between 2007 and 2009, has been traced to the real estate industry (Jiang et al., 2013). The economic crisis may be due to the inefficient and the inaccurate property valuation approaches adopted. Thus, it is necessary to develop a reliable model for property value estimation to support decision-making relating to the mortgage sector. The ANN model developed in this research provides reliable and accurate predictions of property values. It can serve as a learning tool for stakeholders involved in mortgage financing, property development financing, real estate portfolio management and to financial service providers. This would facilitate sustainable growth of the property market and the economy of Nigeria.

1.7 SCOPE OF THE STUDY

The property market is a localized market (Glindro et al., 2008), and as such, a study of this nature must be adaptable and significant to a particular geographical location (Famuyiwa and Babawale, 2014). Bearing this in mind, this research focuses on the Lagos metropolis property market, which is the most vibrant property market in Nigeria (Dugeri, 2011). The sophistication of the stakeholders in this property market has made the Lagos metropolis to be a peculiar city in Nigeria (Oni, 2010). The metropolis houses the head offices of about 95% of Nigeria's commercial banks, and most multinational companies operating in the country (Babawale and Oyalowo, 2011; Central Bank of Nigeria, 2015). Also, more than half of the registered real estate firms in Nigeria have their head offices in the Lagos metropolis (Ibiyemi and Tella, 2013).

The rich financial and commercial activities that take place in the Lagos metropolis have led to high demand for the valuation of real estate properties for different purposes by diverse real estate investors. However, this research is restricted to the estimation of capital values of residential properties in the metropolis and focuses on measuring and comparing the predictive accuracy of the ANN model and HPM valuation techniques in the Lagos metropolis property market.

1.8 STRUCTURE OF THE THESIS

This research is organized and presented in ten chapters described as follows:

Chapter 1 introduces this research by stating the research problem and the aim and objectives of this study. It briefly describes the research approach adopted for the present research, the significance, as well as the scope of this study. And, finally, it presents the outline structure of this thesis. Chapter 2 reviews the literature and explains the concept of property value, property valuation and property value determinants. It further reviews various valuation methods, modeling techniques and property valuation accuracy. Finally, it presents a brief detail of the Nigerian property market.

Chapter 3 reviews the two modeling techniques under consideration in this research, namely HPM and ANN. The chapter reviews the literature on ANN, as well as HPM in terms of their nature, structure, operations, pros and cons and their applications in the property valuation domain. The remaining part of the chapter presents literature on studies which compared the predictive accuracy performance of both models in different property markets around the world. Chapter 4 presents the research methodology adopted for this research. The research design, the research methods, the data collection process and the data analysis tools adopted are explained in detail in this chapter.

Chapter 5 presents the empirical evidence of the current property valuation practice in the Lagos metropolis, which reveals the property valuation methods prevalent in the Lagos metropolis. The empirical evaluation of the residential property value determinants in the Lagos metropolis is also reported in Chapter 5.

Chapter 6 presents the results of HPM developed for the Lagos metropolis property market from the collected data in the study area. Chapter 7 is structured similarly to Chapter 6, by presenting the outputs of the ANN model developed for the Lagos metropolis property market using the same data set.

Chapter 8 discusses the evaluation of the outputs of both the ANN model and HPM. The predictive accuracy of both models is compared and evaluated. Chapter 9 presents the response of the Nigerian valuers as regards their willingness to embrace the AI valuation techniques in practice.

Chapter 10 concludes the thesis by firstly restating the research objectives and summarizing the research findings. It also provides the research's contributions to knowledge and proffers some recommendations. The limitations of this study and finally, the direction of future research are presented in this chapter.

The overall structure of this thesis is presented in Figure ***1***.

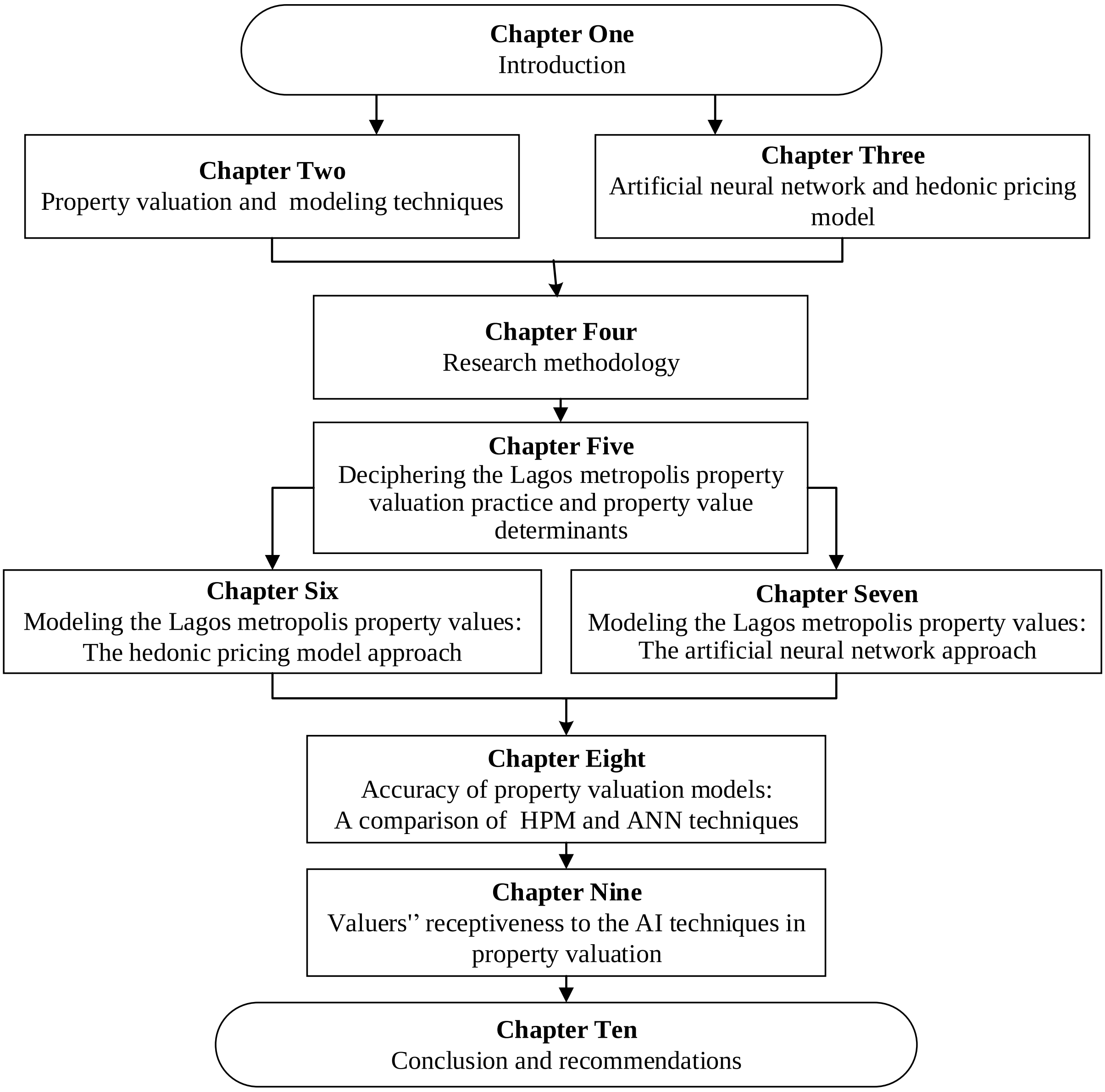

Figure 1.3: Overall flowchart of this thesis

1.9 CHAPTER SUMMARY

This chapter presents the background of the PhD study, the research problem, the aim and objectives of this research and the research approach adopted. It also highlights the significance and the scope of this study. The next chapter presents a review of property valuation, property value determinants, property valuation methods, modeling techniques, and property valuation accuracy. The review will present an insight into the body of knowledge on these issues related to this research.

CHAPTER 2 PROPERTY VALUATION, METHODS AND MODELING TECHNIQUES

2.1 INTRODUCTION

The previous chapter presents the introduction to this study by describing the research problem, the research aim and objectives, the scope of this study, a brief research approach and the significance of this study. This chapter, provides a review of important areas of this research retrieved from articles sourced from online databases and search engines which include Springer, Science Direct, ProQuest, Taylor & Francis and Google Scholar. It explains the property valuation process by presenting different views about the process. The various factors that determine the value of a real estate property are evaluated and a theoretical framework was developed. Property valuation methods and modeling techniques found in the literature (namely traditional methods and advanced methods) are discussed and evaluated. The issue of property valuation inaccuracy, which is an international issue, as well as the Nigerian property market, are discussed.

2.2 PROPERTY VALUATION

Real estate property is a form of long-term investment in which stakeholders invest in so as to recoup capital or regular flow of income at a future date (Shapiro et al., 2012). Generally, a rational investor would occasionally or regularly request to know the value of his/her investment at every point in time, for the purpose ranging from sales and purchase of interest, letting or leasing of property, development feasibility and viability appraisal, alternative use, financial reporting and secured lending, amongst other purposes (Scarrett and Osborn, 2014). The characteristics of the property market which include imperfection, heterogeneous, complex legal interest, complicated land-related laws and regulations have made the services of a real estate professional unavoidable by a rational real estate investor (Shapiro et al., 2012). The services of real estate professionals are essentially needed amongst others to estimate the monetary value of an interest in land and landed properties (Pagourtzi et al., 2003).

Authors have ascribed different meanings to the word ‘property valuation’. Czernkowski (1990) defines property valuation as the process of transforming some given set of data which include age, size, location and proximity to services into a single output (value). That is, property valuation is patterned to an extent to follow a set of rules (heuristics) with a combination of facts to infer new facts (conclusions) to achieve the desired output (valuation figure). In another context, French and Byrne (1996) posit that property valuation is the estimation of the worth of an interest in a property, through the application of valuation approaches which is a reflection of the subject property characteristics and the circumstances surrounding the exchange of the interest in the open market. Millington (2000, p. 4) describes valuation as:

> The art, or science, of estimating the value for a specific purpose of a particular interest in property at a particular moment in time, taking into account all the features of the property and also considering all the underlying economic factors of the market, including the range of alternative investments.

Thus, property valuation is the processing of the property related characteristics, as well as the subject property market information in estimating the value which the interest in a real estate property could be exchanged in an open market. In the following subsections, property value and property valuation process are discussed.

2.2.1 The Concept of Property Value

According to Webster Online Dictionary (2015), value is "the property or aggregate properties of a thing which it is rendered useful or desirable, or the degree of such property or sum of properties; worth; excellence; utility; importance". The word 'value' has been commonly used interchangeably with other related concepts - 'price' and 'worth'. However, the distinction amongst them, according to French (2004), is that:

a. value can be referred to as market value, an estimation of the probable price that a property can be exchanged for when sold in the open market;
b. price is the actual amount a property is sold in the open market; and
c. worth is a subjective perception of an individual as to the capital sum or stream of income s/he is prepared to accept (seller/landlord) or pay (buyer/tenant), for the exchange of an interest in a land or a landed property.

In a perfect property market, the price of a property is a function of the value the buyer and the seller place on it at any given time, and sometimes, the price may also reflect the interest of a third party, for instance, tax authority, other stakeholders in the property market, the agents and the general submarket condition (Daly et al., 2003).

In an effort to present a generally acceptable meaning of the open market value (OMV), Royal Institution of Chartered Surveyors (RICS) (1991, p. SAVP 2:1)[2] practice statement describes OMV as “an opinion of the best price at which the sale of an interest in property would have been completed unconditionally for cash consideration on the date of valuation”, assuming some stated conditions are met. Furthermore, the International Valuation Standards Council (IVSC) revised the definition of market value and it was adopted and presented in the Red Book of Royal Institution of Chartered Surveyors (RICS) (2012, p. 12) as:

> the estimated amount for which an asset or liability should exchange on the valuation date between a willing buyer and a willing seller in an arm’s length transaction after proper marketing and where the parties had each acted knowledgeably, prudently and without compulsion.

This suggests that market value is the value achieved by both buyers and sellers when

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[2] SAVP means Statements of Asset Valuation Practice and Guidance Notes

the interest in a land or landed property is exchanged in a transparent process.

2.2.2 Property Valuation Process

The main purpose of embarking on a valuation exercise is to estimate an accurate property value, buttressed with movements in the property market by analysing the implicit market behaviour to arrive at the probable property value (Lawson, 2008). Property valuation process involves systematic procedures which the valuer observes in estimating the property value. The process involves the application of both mathematical calculation and the valuers' market opinion formed by market experience, and this has made property valuation to be referred to both as an 'art' and a 'science' (Kummerow, 2003; Azmi et al., 2013).

Appraisal Institute (2013) describes the property valuation process as involving problem identification, the collection of relevant market and subject property data, verification and analysis and the communication of the value opinion to the client. Appraisal Institute (2013) developed a framework for property valuation process which involves eight steps to be followed in a valuation exercise. The process starts with the identification of the problem and ends with the reporting of defined value to the client as shown in Figure 2.1.

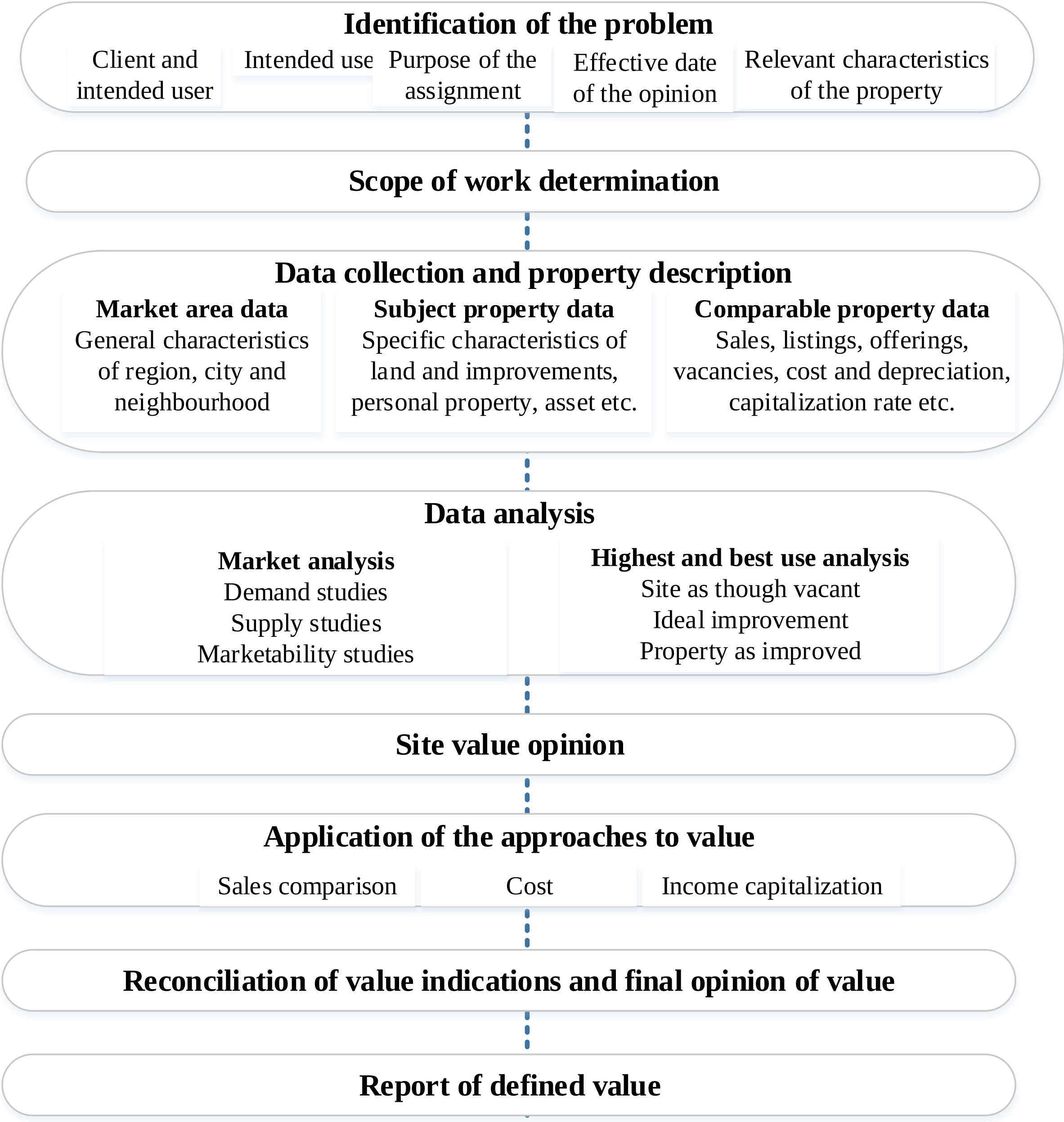

Figure 2.1: Property valuation process

Adopted from: Appraisal Institute (2013, p. 8)

The steps in the valuation process presented in Figure 2.1 can be summarized into three distinct phases: i) data, ii) analysis, and iii) valuation, and every stage's accuracy and reliability are determined by the quality of the previous stage (Tretton, 2007). This suggests that in executing a valuation instruction, the first step is to gather information about the subject property and from the local property market under consideration. This information is analyzed, and this stage is where the real estate professional's experience and skills are applied to deduce facts from the gathered data, as well as apply the most appropriate valuation approach. In the final stage, the valuer pronounces the opinion of the value of the property to the client in the form of a formal written report.

2.3 PROPERTY VALUE DETERMINANTS

Globally, the values of real estate properties are determined by different attributes due to economic, cultural, legal and financial structural peculiarities of each country (Jenkins, 2000; Olayiwola et al., 2005). Scholars (Jenkins, 2000; Li et al., 2011) have emphasized that location is a critical factor that influences property value. This is quite obvious in the real estate practice when property buyers or tenants inform the real estate professionals the areas/locations in which they prefer to live or invest in when engaging their services.

Undoubtedly, a property market is a localized market (Ajide and Alabi, 2010; Galbraith, 2013). An earlier study of Dale-Johnson (1982) also posits that in conducting property price analysis, market segmentation should be considered. This has necessitated the wide use of the case study research approach in property valuation studies in different countries around the world. This could be attributed to the peculiarity of each economy, as well as the delineation of property markets into submarkets in a particular location. The theoretical framework and literature review of property value determinants are presented in the following subsections.

2.3.1 Property Value Determinants: Theoretical Framework

Studies conducted in different property markets around the world have shown that the value of a property is determined by some sets of variables which have been categorized into groups (Tse and Love, 2000; Kauko, 2003; Oloke et al., 2013; Famuyiwa and Babawale, 2014). The classification of these variables as theorized by Chin and Chau (2002) are the locational, the structural and the neighbourhood factors. A further analysis of Chin and Chau (2002) showed that most of the structural attributes contribute positively to property value with the only exception of the age of the property. Whereas some of the locational attributes and neighbourhood attributes impact property value positively, others negatively affect property values.

Wong et al. (2002) classified property attributes into three classes: location attributes (access to social and economic facilities); structural traits (floor area, floor height etc.), and neighbourhood characteristics (neighbourhood quality). Also, property value determinants were grouped into three categories in the study of Wen et al. (2005). The categorization corroborates with those in the literature which are the structural, the neighbourhood and the locational attributes. Property value has been established to be a function of some set of attributes in the real estate domain and those attributes are inherent attributes, neighbourhood characteristics, accessibility and environmental quality (Choy et al., 2007).

Pozo (2009), however, noted that the independent variables that influence property values are explained by the structural, the neighbourhood and the locational factors. Ajide and Alabi (2010) argued that property value determinants are classified into three groups, namely the structural traits, the neighbourhood characteristics and the locational traits. Likewise, Babawale et al. (2012) asserted that property values are determined by attributes which are categorized into three classifications which include the location attributes, the structural and the neighbourhood attributes.

The residential location theory centers on the principle that utility is a function of accessibility to the central business district (CBD) (Wilkinson and Archer, 1973). However, in analyzing residential property location, accessibility is considered not only to the CBD but in relation to other social activities like schools, public transport and recreational center, among others (Jenkins, 2000). Residential locational attributes are variables which relate to access to both social and economic facilities (Mok et al., 1995). The social and economic facilities that surround a property influence its value, probably because accessibility to these facilities would determine the travel time and the cost to access them, which home seekers would likely consider when making sound real estate decisions.

Property structural attributes are property specific and have been established to be highly significant in property value formation and are hence, widely adopted in property value analysis studies (Wilhelmsson, 2000). Palmquist (1984) found that structural attributes have the high contributory power to property values in the US. Wen et al. (2005) also reported that structural characteristics contribute 60% to property values formation.

Neighbourhood classification consists of attributes which are regarded as public services provided within a neighbourhood which residents make use of. The significance of neighbourhood attributes in property value formation cannot be underestimated, as Linneman (1980) reported that neighbourhood characteristics explains between 15 and 50% of property value and explains as much as 100%, where the properties in the neighbourhood are similar in terms of structural characteristics.

Based on the broad classified of property value determinants in the literature, a framework of the property value determinants in the Lagos metropolis property market was constructed. To this end, a systematic review of studies focused on the Lagos metropolis was conducted. This was conducted in three phases: i) the search of online databases and search engines, ii) the use of selection criteria to filter search results, and iii) the review of selected published studies. Based on the results of the systematic review, a framework of the property market was developed as presented in Figure 2.2. This framework depicts what is obtainable in the Lagos metropolis property market.

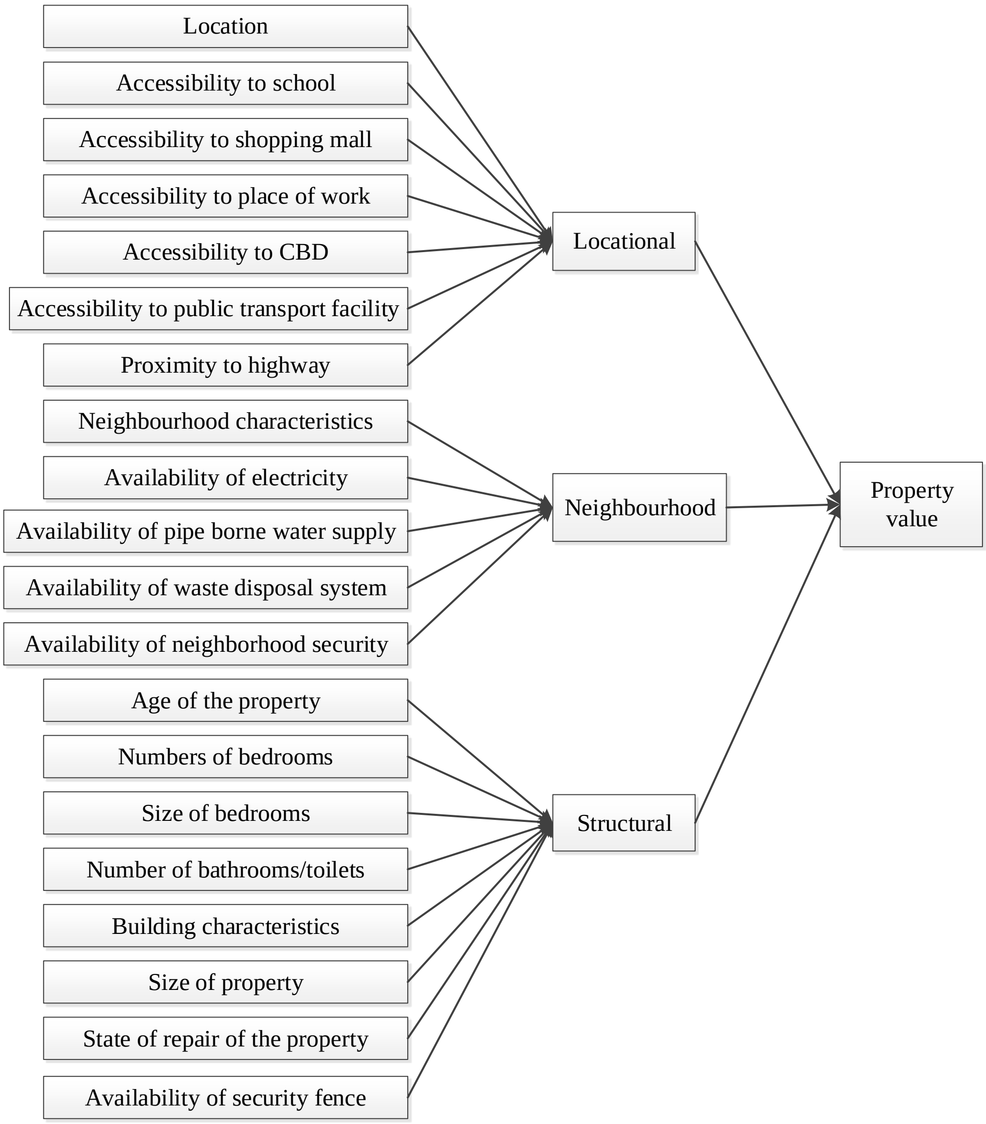

Figure 2.2: Framework of property value determinants in the Lagos metropolis

Source: Abidoye and Chan (2016a, p. 286)

2.3.2 Property Value Determinants: Review of the Literature

The significance attached to real estate properties by different stakeholders has warranted a number of studies conducted in different economies of the world, to investigate the variables that influence property values and the dynamics of property values in these property markets.

The early study of Ball (1973) reviewed studies conducted between 1965 and 1973 in the US and the UK which examined the determinants of property values in these property markets. Locational attributes in terms of distance to social facilities/activities such as CBD and place of work appeared to be more significant in determining property value in these studies. Ball (1973) further added that property values in cities are influenced by the geographical setting and historical evolution of the submarket, the income level of the residents, the level of transportation technological advancement available, the extent of the concentration of activities at CBD, and the willingness of the residents to travel to CBD and also to take up houses in the submarket.

Sirmans et al. (2005) reviewed 125 studies that adopted the HPM approach in measuring the influence of property characteristics on property values in the US. The authors extracted the variables which appeared often in literature in terms of their number of appearances, the number of positive impacts, the negative impact and the number of times not significant to property value determination. The analysis shows that the age of a property is the most frequently used variable and expectedly, its negative impact on property values was recorded in 63 instances out of the 78 appearances. The property square feet, the garage space, the number of bathrooms and the number bedrooms were positive in almost all of their appearances.

Using Hong Kong as a study area, Tse (2002) examined the influence of property characteristics on property value. The study used data collected from six housing estates which witness a high number of transactions. Accessibility to mass transit railway (MTR) station was found to be highly significant to property value formation in Hong Kong, probably because most of the low and middle-income earners depend on it for transportation in the city. In addition, the presence of a sea view, the availability of clubhouse and the high floor level were found to positively influence property values. Expectedly, the age of a property contributes negatively to property values. Conclusively, the study discovered that the availability of more than two bathrooms in a property negatively influences property values, as an increase in the number of bathrooms results in smaller bedroom size, due to the high price/sqft of properties in Hong Kong. This suggests that home buyers prefer to have more space than more bathrooms in Hong Kong.

Mbachu and Lenono (2005) examined the factors that influence residential property values in South Africa. The authors surveyed the opinion of professional members of the South African Property Owners Association (SAPOA) in Johannesburg, as regards the significant attributes which determine property values. It was reported that the property location, the market conditions, the microeconomic and macroeconomic dynamics and the building features are the most significant variables that affect residential property market values.

Wen et al. (2005) constructed HPM equation for the Hangzhou's property market in China. The authors employed 18 independent variables but found that 14 of those 18 variables significantly influence property values. These variables include the floor area, the distance to West Lake, the distance to CBD, the inner environment, the traffic condition, the decoration degree, the garage, the environment, the housing story, the entertainment facility, the community management, the transaction time, the attic and the proximity to the university. Others which include the age of property were found to adversely influence property values.

The prices of residential properties in Hong Kong was modelled by Choy et al. (2007) adopting the HPM approach. The authors collected 749 sales and purchase transactions data from residential apartments in Taikoo Shing housing estate in Hong Kong. It was found that almost all the variables considered are statistically significant and produced all expected signs. However, the author concluded that when an apartment is located on an ‘unlucky number’ floor, it negatively affect its values, whereas an apartment situated on a ‘lucky number’ floor enjoys a premium in terms of higher value. The explanation for this is that in the Chinese culture, “luck” is attributed to some numbers such an 8 (Bourassa and Peng, 1999; Chau et al., 2001), so a premium is added to the value of apartments situated on floor 8, 18, 28, and so on.

The property market and structure of Malaga, one of the most active cities in Spain was explored by Pozo (2009). The author selected structural and location variables for the study and retrieved data from the database of real estate companies, Municipal Census Office and the IT Department in Malaga. The study reported that the floor area of the property, the private parking space, the natural light, the number of bathrooms, the proximity to the coast and the location of the property significantly influence property values in Spain.

Anim-Odame et al. (2009) measured the determinants of property value. The authors collated 2,950 property transactions data from five different districts in Ghana which were consummated between 1992 and 2005. The number of bedrooms, the number of stories, the quality of landscaping, the property size and type, the security of tenure, the plot size and the location were established to be significant determinants of property values.

Messah and Kigige (2011) examined the determinants of property value in Meru, Kenya. The study found that the income of real estate investor is the most highly significant property value determinant which contributes 70% to property value formation, while demand for properties contributes 20%. Surprisingly, the location of a property is not significant to property value formation in Kenya, as it contributed about 3% to property values.

The relationship between property value and some major property components was studied by Boye (2012). The author used a few variables (the gross area of the property, the plot size, the number of apartment units and the number of parking space) for the study. All these variables fit well into the model by producing a high r^2 in all the models developed and further analysis revealed that they are all significant determinants of property value in Ghana.

The study of Sanjari (2012) in Iran, reported that only eight out of the 16 variables used to construct the hedonic model were found to be significant in property value formation. These variables include the gross floor area, the distance from CBD, the stone façade, the floor level, the land area, the distance to the park and the parking facilities.

Adegoke (2014) researched into the critical factors which determine the values of residential properties in Ibadan metropolis, Nigeria. The study examined the factors which affect different classes of property (tenement, bungalow and detached house), but generally, the number of living rooms, the number of bedrooms, the existence of burglary alarm in a property and the number of toilets are the most important determinants of property values.

The determinants of the prices of flats in the city of Paris, France, was examined by Baltagi et al. (2015). A rich data of 156,896 sales transactions of flats sold between 1990 and 2003 was used for the study. The authors reported that the number of bathrooms, the maid's room, the availability of garage and the balcony are the most significant property attributes. One extra unit of these variables contributes €293/m^2, €254/m^2, €326/m^2 and €385/m^2, respectively, to the price of a flat.

Studies carried out in the Lagos metropolis property market were reviewed alongside these conducted in other property markets of the world. A total of 20 attributes were found to be significant in those studies as shown in Table 2.1. From the Lagos metropolis studies, it is clear that the availability of neighbourhood security significantly influences property value in the metropolis, at the same time, the accessibility to the place of work, the number of bedrooms and the number of toilets/bathrooms appeared more often too. In contrast, in the international property markets, the emphasis is placed on the size of a property in property value formation. On a category basis, structural variables appeared often as property value determinants in other international real estate markets, except for property location under the locational category. This cross-national analysis reveals that different set of variables influence property values in Lagos, Nigeria, compared with other parts of the world. These disparities could be explained by the peculiarities of different property markets which is shaped by the characteristics of the stakeholders in terms of their preferences, purchasing power and culture, amongst other factors.

Table 2.1: Property attributes from the Lagos literature and the international literature

	The Lagos metropolis studies								Selected international literature									
Property attributes	Olayiwola et al. (2005)	Bello and Bello (2007)	Ajide and Kareem (2010)	Babawale and Johnson (2012)	Babawale et al. (2012)	Oloke et al. (2013)	Famuyiwa and Babawale (2014)	No. of variable occurrence	Mbachu and Lenono (2005)	Choy et al. (2007)	Ge and Du (2007)	Selim (2008)	Zietz et al. (2008)	Pozo (2009)	Anim-Odame et al. (2009)	Sanjari (2012)	Baltagi et al. (2015)	No. of variable occurrence
Locational attributes																		
Location		✓						1	✓		✓			✓	✓			4
Accessibility to place of work	✓	✓	✓					3										0
Accessibility to CBD	✓							1								✓		1
Accessibility to public transport facility	✓		✓					2	✓	✓								2
Proximity to highway						✓		1										0
Accessibility to school				✓				1										0
Accessibility to shopping mall				✓				1										0

Table 2.1: Continuation

Neighbourhood attributes																		
Neighbourhood characteristics	✓					✓		2										0
Availability of neighbourhood security		✓	✓	✓	✓	✓	✓	6	✓									1
Availability of electricity		✓					✓	2										0
Availability of pipe borne water supply			✓		✓			2				✓						1
Availability of waste disposal system			✓				✓	2	✓									1
Structural attributes																		
State of repair of the property		✓						1										0
Size of property				✓				1		✓	✓	✓	✓	✓	✓	✓		7
Age of the property		✓						1										0
Numbers of bedrooms				✓	✓	✓		3	✓		✓	✓			✓			4
Number of bathrooms/toilets			✓	✓	✓			3					✓	✓			✓	3
Building characteristics				✓				1	✓			✓	✓				✓	4
Availability of security fence					✓			1	✓									1
Size of bedrooms					✓	✓		2	✓									1

Source: Abidoye and Chan (2016a, pp. 287-288)

2.4 VALUATION METHODS AND MODELING TECHNIQUES

Several methods and modeling techniques have been used in property valuation research and practice. These methods and techniques can be found in the literature (Özkan et al., 2007). The appropriate valuation approach to be adopted in property valuation depends on the amount of information available, the use and type of the subject property and the purpose of the valuation exercise (Vos and Have, 1996). Although there is no best method or modeling approach applicable to all property valuation problems (Tse, 1997; Pagourtzi et al., 2007), the differences in stakeholder's perception on the acceptability of a particular approach and real estate properties (goods) suggest the application of different methods of valuation to meet the present need (French and Byrne, 1996; Yacim and Boshoff, 2014). The cultural experience, the socio-economic and also the profile and exposure of the real estate professionals practicing in a country would determine the methods of valuation which would be adopted for property valuation in the nation (Pagourtzi et al., 2003; Tao, 2010).

2.4.1 Valuation Methods

Pagourtzi et al. (2003) present a classification of property valuation methods adopted in practice and theory. This classification includes traditional valuation methods which basically rely on the direct comparison from which the valuer draws a conclusion on the value of the subject property (Yacim and Boshoff, 2014). According to Pagourtzi et al. (2003, p. 386), the traditional property valuation methods include;

i. Comparable method

ii. Investment/income method

iii. Profit/accounts method

iv. Residual/development method

v. Cost/contractor's method

Others are the advanced valuation methods. The details of the advanced methods which are occasionally referred to as modeling techniques are presented in Section 2.4.2. This classification has been established and accepted in the real estate research domain (see, for instance, Özkan et al., 2007; Tao, 2010; Babawale and Oyalowo, 2011).

Among the traditional methods, the comparable (market sales), the investment (income) and the cost (contractor's) methods are the principal and most popular approaches in the property valuation domain (Jenkins, 2000). This is due to their simplicity in the application in the valuation of residential properties (French, 2004). Residential properties, amongst other types of properties, are the main consumer of land in urban areas (Olayiwola et al., 2005), and attracts the highest demand by urban dwellers. Thus, these three methods have been widely explored in the literature, unlike the profit and the residual methods.

The comparable method is the most widely adopted valuation method amongst valuers in different property markets around the world (Bonissone and Cheetham, 1998; Jenkins, 2000; Kauko, 2002). In applying this method, the valuer identifies comparable properties exchanged in the open market and then makes some adjustments to reflect the difference(s) in the attributes of the properties in arriving at a value opinion.

The process of employing the comparable method of valuation is presented by Mackmin (2008, p. 44) as:

1. Select comparable properties in the same property market;
2. Retrieve, confirm and analyze comparable sale prices extracted;
3. Adjust the sale prices based on the established differences in the comparable and subject property; and
4. Pronouncement of the opinion of OMV of the appraised property.

Appraisal Institute (1994) argued that the comparable valuation method is an appropriate and sufficient approach, but due diligence must be observed when adopting it. The performance of this method is also subject to the availability of historical sales databank (American Institute of Real Estate Appraisers, 1987). However, Jenkins (2000) argued that the comparable (grid) approach is subjective and the apportionment of the points seem arbitrary which gives room for the inaccuracy of opinions of values.

On the investment method of valuation, which is usually adopted for the valuation of income generating properties such as residential and commercial properties, Baum and Crosby (1995) provided an approach to the adoption of the method in estimating the capital value of a property as shown below:

	Rent
Less	Outgoings
	Net income
Multiply by	Capitalization factor
	Capital value

In the same vein, Millington (2000) presented an outline for the mathematics of the cost method of valuation as presented below:

	Cost of site
Plus	Cost of the building
Less	Depreciated allowance
And	Obsolescence allowance
	Value of the existing property

Dotzour (1990) tested the reliability and precision ability of the cost method and the comparable method using 320 samples of appraisals collected from 33 states in the US. The author found that the comparable method is more reliable than the cost approach because on the average, an absolute error of 5.98% and 9.78%, respectively, were recorded. The study concludes that the cost method can be used as a check for the comparable method because it estimates the 'top end' ranges of valuation figure. The findings of Dotzour (1990) is consistent with the argument of Ratcliff (1972) that the cost method is unproductive, unrealistic and subjective.

Despite the simplicity attributed to the application of these traditional methods, they are marred with imprecision and inaccuracy (Zurada et al., 2006). This is because these methods are subjective in nature and their output is dependent on the skills and experience of the valuer (Paris, 2008). The application of all the traditional valuation approaches, particularly the comparable method, requires the valuers' adoption of heuristics and industry experience in arriving at property values (Kauko, 2002). This subjective nature of these methods has rendered them inappropriate in this information technology age (McGreal et al., 1998; Gilbertson and Preston, 2005; Grover, 2016).

2.4.2 Modeling Techniques

Modeling techniques (advanced property valuation methods) are models that mimic the thought process of the stakeholders in the property market, as well as the subject property market in arriving/producing valuation figures (Pagourtzi et al., 2003). Some alternative approaches have been developed by scholars to replace the traditional valuation approaches that are entrenched with limitations such as imprecision and high subjectivity as mentioned earlier. These advanced approaches are mostly mathematical models and they include ANN, HPM, spatial analysis, FLS and Autoregressive

Integrated Moving Average (ARIMA) (Pagourtzi et al., 2003).

To date, computer-aided advanced valuation methods are often used instead of the traditional methods in the property valuation practice (Özkan et al., 2007). Rossini (1999) indicated that in some cases, the advanced approaches may produce on average more accurate property valuation estimates than the traditional valuation methods. In addition, the traditional methods do not emulate the thought process of the real estate market players like the advanced methods (Bagnoli and Smith, 1998). Although these advanced methods of valuation usually require the use of a large number of historical property transaction data in their application (Pacharavanich et al., 2000), they have proven to produce, with speed, reliable and accurate valuation figures (Waziri, 2010). These approaches are discussed below:

The application of geographic information system (GIS) has been widely discussed in the property valuation literature (Wyatt, 1996; McCluskey et al., 1997; Wyatt, 1997). The valuation technique which is incorporated with GIS in modeling property prices is the spatial analysis technique. Spatial analysis helps in detecting the omitted property neighbourhood factors that are important for the analysis. This approach has been used to examine and measure the effect of location on property values (Pagourtzi et al., 2003). The inefficiency and misrepresentation of property variables common to

HPM are been addressed by the application of the spatial analysis technique (Yacim and Boshoff, 2014).

According to Anselin (1998), the process of adopting the spatial analysis in property valuation involves four steps, and they are model specification, model estimation, diagnosis and model prediction. Anselin (1998) further claimed that the spatial analysis technique can be useful in property value modeling to forecast accurate property values in locations where there is no information on property attributes.

Can and Megbolugbe (1997) applied the spatial analysis technique in Miami, Florida. It was demonstrated in the study with the use of a few property variables which surround a property. The study concludes that the spatial analysis approach would produce accurate valuation outputs even when variables are not available or omitted.

Cellmer (2011) integrated spatial analysis with geographical weight regression (GWR) to evaluate the impact of noise on property values. The author found that traffic noise significantly influences property values and established the usability of spatial analysis to measure the effect of environmental externalities in a particular location. An overview of the spatial analysis process is presented by Wyatt (1996) as shown in Figure 2.3.

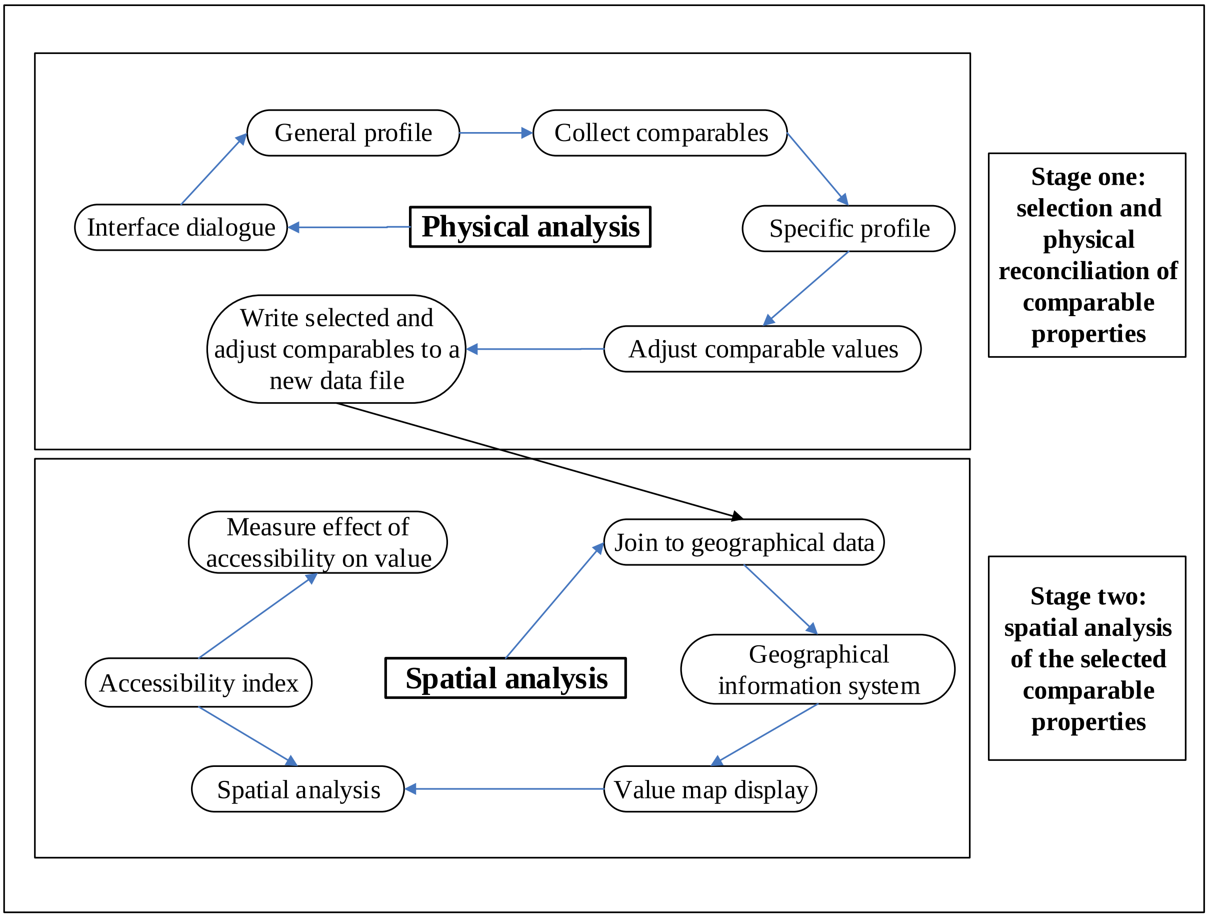

Figure 2.3: An overview of spatial analysis operation

Adopted from: Wyatt (1996, p. 75)

Despite the applicability of this technique (i.e. spatial analysis) in property value modeling, the limitations of this approach include non-continuity, the number and distribution of observations, non-homogeneity and the influence of non-spatial factors, relatively high price spread and changes in prices over time (Cellmer, 2014, p. 58).

The vagueness and ambiguity that is associated with property price analysis may render property price modeling estimates unreliable (González and Formoso, 2006). The FLS technique is a property valuation approach that has been designed to handle this vagueness - ambiguous, inaccurate market data in property price modeling. Zadeh (1965) introduced FLS technique and argued that the fuzzy set of an element in a group is characterized by a membership function.

The principle of FLS is based on the translation of vague property information into meaningful numeric value, by following some defined set of rules in the application. These rules are expressed as “if”, “or” and “then” to produce the output. A typical example is “if a property is big and has high floors, then the value is high”. The FLS technique has been widely employed in the different fields of studies for decision-making. See McNeill and Freiberger (1994) and Mardani et al. (2015) for the review of the application of FLS. According to Pagourtzi et al. (2003), the process of operating a knowledge-based FLS consists of four elements, namely fuzzification, knowledge base, processing and defuzzification as shown in Figure 2.4.

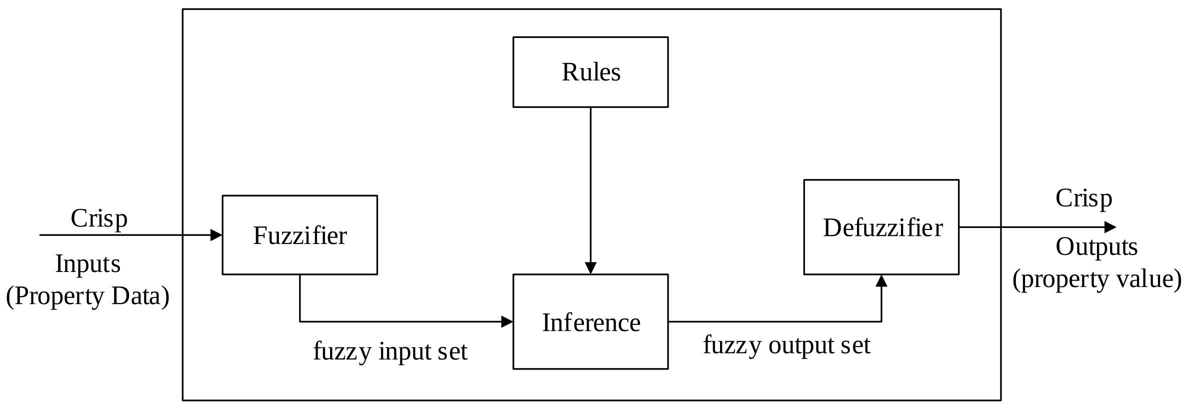

Figure 2.4: A fuzzy logic system

Adopted from: Mendel (1995, p. 347)

The first demonstration of the application of FLS in property valuation was the study of Dilmore (1993), and it was adopted to assess the impact of distance on property values. Bagnoli and Smith (1998) applied FLS on income-generating properties in order to measure the contributory power of property attributes on property values. The price of properties in Turkey was also forecasted using the FLS technique by Kuşan et al. (2010). The superiority of FLS over HPM has been established in the literature. For example, González and Formoso (2006) and Yalpir and Özkan (2011) documented the predictive accuracy of FLS over HPM.

Property transactions data that are used for market analysis are sometimes in a time series form. When this is the case and the observations have a statistical dependent relationship, Box-Jenkins also known as ARIMA technique is usually applied (Tse, 1997). The autoregressive moving average (ARMA) models which are applicable to stationary data, is being transformed to handle non-stationary data set by differencing the data, and this modification is the ARIMA model (Pagourtzi et al., 2003). This technique was developed by Box and Jenkins (1976). Since then, the model has been applied in property value forecasting. Tse (1997) applied the ARIMA technique in property value forecasting in Hong Kong. In the US, Crawford and Fratantoni (2003) also applied the ARIMA model in property value forecasting and found that the model is good for out-of-sample property value forecasting.

The HPM approach is suitable for property market research (Kauko, 2003; Selim, 2008; Babawale et al., 2012), and has been widely adopted in real estate research (Bender et al., 2000; Jenkins, 2000). The HPM principle is premised on multiple regression analysis (MRA) (Jenkins, 2000; Kauko, 2002). The origin of this technique could be traced to the novel study of Haas (1922a) that employed the regression analysis to predict farmland prices in Minnesota, United States. Since then, the model has been adopted in different property markets around the world, both in theory and in practice (Schwartz, 1995; McCluskey et al., 1997). This technique is explained in detail in the next chapter.

The ANN technique is a contemporary property value modeling technique which was developed to handle the limitations of HPM (Tay and Ho, 1992; Bagnoli and Smith, 1998; Amri and Tularam, 2012). ANN is a type of AI which is designed to function like the human brain (Mora-Esperanza, 2004). It has a learning ability and process commands by the interplay of the network neurons that mimics the human brain neurons (Taffese, 2006). In the real estate industry, researchers have applied ANN in property valuation, for instance, Borst (1991), Evans et al. (1992), Wilson et al. (2002), Lam et al. (2008) and Kauko et al. (2002), amongst others. In all these cases, their results affirm the outstanding performance of ANN in terms of its predictive accuracy in property valuation. A detailed review of the ANN technique is presented in the next chapter.

When the impressive performance of the advanced techniques are compared with the traditional methods, all of the advanced valuation techniques are not without their own pros and cons (Lam et al., 2008). This is because none of the various advanced models fits into all modeling and real-life property valuation situations (Tse, 1997). Table 2.2 shows the applications of the advanced techniques in different real estate markets around the world, as well as their strengths and weaknesses (Abidoye and Chan, 2016c, p. 367).

Table 2.2: Applications of advanced valuation techniques

Valuation techniques	Authors	Country	Strengths	Weaknesses
Autoregressive integrated moving average (ARIMA)	McGough and Tsolacos (1995) Tse (1997) Crawford and Fratantoni (2003)	United Kingdom Hong Kong United States	Helps in tracking real estate price cycle directions, its reliance on autocorrelation gives accurate results	Can only handle time-series data, short-term forecasting model
Artificial neural network (ANN)	Borst (1991) Tay and Ho (1992) Lam et al. (2008)	United States Singapore Hong Kong	User friendly and easy to use, deals with nonlinear relationship in data, adaptability and generalization ability, higher precision	'Black box' nature, hidden internal structure, data hungry
Hedonic pricing model (HPM)	Adair et al. (1996b) Tse and Love (2000) Babawale et al. (2012)	Northern Ireland Hong Kong Nigeria	Versatile approach, can handle many variables, objective, gives contributory power of each variable, good indicator of value	Multicollinearity, heteroscedasticity, functional form misspecification, cannot handle nonlinear variable relationship and outlier data
Fuzzy logic system	d'Amato and Siniak (2009) Hui et al. (2009) Kuşan et al. (2010)	Belarus Hong Kong Turkey	Ability to cope with vagueness nature of property variables, more realistic approach	Difficulty in determining fuzzy set and fuzzy rules
Spatial analysis	Basu and Thibodeau (1998) Cho et al. (2008) Li et al. (2011)	United States United States Hong Kong	Applicable where there is inadequate information on property variable, produces fair value estimates of local variables	Non-continuity, the influence of non-spatial factors, non-homogeneity and changes in prices over time can affect estimates

Source: Abidoye and Chan (2016c, p. 367)

2.5 PROPERTY VALUATION ACCURACY

Property valuation accuracy has received widespread attention by real estate researchers in different property markets around the world - the US, UK, Australia, and so on. Waldy (1997) defines valuation accuracy as the measure of the closeness or divergence of valuation estimates to the market value of a subject property. Waldy (1997) argued that valuation variation/variance is the difference in the values arrived at by different valuers when a subject property is being appraised and should not be mistaken for valuation accuracy. The position of Crosby (2000) substantiates the argument of Waldy (1997), but adding that valuation bias occurs when there is a consistent overvaluation or undervaluation of a subject property, in relation to the sales price (target).

The issue of valuation inaccuracy could lead to the bankruptcy of real estate investors and stakeholders rely largely on the opinion of value communicated by real estate professionals to make real estate investment decisions (Taffese, 2007). When this happens, it could lead to the questioning of the relevance, as well as the credibility of valuers. At the same time, it could reduce the confidence stakeholders have in the profession (Adegoke et al., 2013), and this will, in turn, affect the performance of the property market and impliedly the economy of the nation at large, due to the relevance of real estate to the economic development of a nation (Chiang et al., 2015).

In a more stable property market, those variations in property valuation estimates may be within a lesser range, but in an unstable market, the reverse may be true (Shapiro et al., 2012). Valuation inaccuracy may be unavoidable in property valuation because different valuers interpret the property market and property value determinants differently, but there is an acceptable range of variations in estimates (Shapiro et al., 2012).

Hager and Lord (1985) posited that the range of acceptance for property valuation inaccuracy should be about 5% more or less of the average value of the subject property. Similarly, Mackmin (1985) suggested that valuation estimates produced by valuers would be acceptable if it is within ± 5% range of the property value. Furthermore, Hutchinson et al. (1996) argued that a valuation estimate within 5 to 10% range is acceptable, only when it is above 10% that the estimate can be subjected to contention. This argument is supported by Brown et al. (1998) that mentioned that a valuation figure beyond 10% could be attributed to a valuer's negligence in property value estimation. The following subsections discuss property valuation accuracy studies, both within the international context and the Nigerian context, and also present a brief description of the Nigerian property market.

2.5.1 The International Property Valuation Accuracy Studies

In the UK, Hager and Lord (1985) were the first to investigate valuation accuracy in property valuation. The study involved ten valuers who were asked to appraise two properties. The ten valuers were not certainly familiar with the subject property market but possess property valuation experience. The average variation in the value estimates for property A was ±10.34%, while that of property B was ±16.94%, both which are wider than the ±5% range which was expected by the authors. Hager and Lord (1985) argued that valuers' in-depth knowledge of the submarket of the property to be appraised would reduce valuation inaccuracy in property valuation.

The reliability of commercial property valuation was assessed by Cole et al. (1986), using the sales conducted between 1978 and 1984 as data for the study. The authors mentioned the causes of property valuation inaccuracy to include the terms of sale, the buyer and the sellers' motivations, the capital improvement carried out since the last valuation, the sales date, the change in discount or capitalization rate, the date of the last valuation and the closing cost. The study found the margin of error to be between 5.9 and 9.5%, without outliers and with outliers, respectively. The authors concluded that 9.5% margin is acceptable in property valuation considering the exigencies of time.

Webb (1994) also admitted that valuation inaccuracy is unavoidable in the US property market, but argues that the faulty valuation processes may not be responsible for that, rather it could be attributed to limited information available to the valuers at the time of valuation. Webb (1994) further posit that since valuation inaccuracy is unavoidable during the real estate life cycle, investors and stakeholders should make provision for it when making real estate investment decisions.

Newell and Kishore (1998) examined the accuracy of commercial valuations in Australia using data of valuation conducted between 1987 and 1996. Comparing the results of the study to what was obtained in the US and the UK, the authors found that the range of valuation inaccuracy experienced in Australia is lesser. This is in tangent with the findings of Parker (1998, p. 16) that mentioned that "Australian valuation estimates are a good proxy for market prices", but further advocate for efforts to ensure that valuation estimates fall within the 5% range of the market value.

The uncertainty being experienced in property valuation was discussed by Mallinson and French (2000) who posited that uncertainty in property valuation is unavoidable, and hence proposed a method of measuring and recording valuation uncertainty. According to Mallinson and French (2000, p. 28), a valuer must report some variables after a valuation exercise in order to convey the uncertainties associated with the estimates. These items are listed below and depicted in Figure 2.5.

1. the single valuation estimate [V];
2. the range of most likely observations [V1 - V2];
3. the probability of the most likely observation [P3];
4. the range of higher probability [Za - Zz];
5. the range of 100% probability [Va - Vz];
6. the skewness of probabilities [Va-V1, V2-Vz].

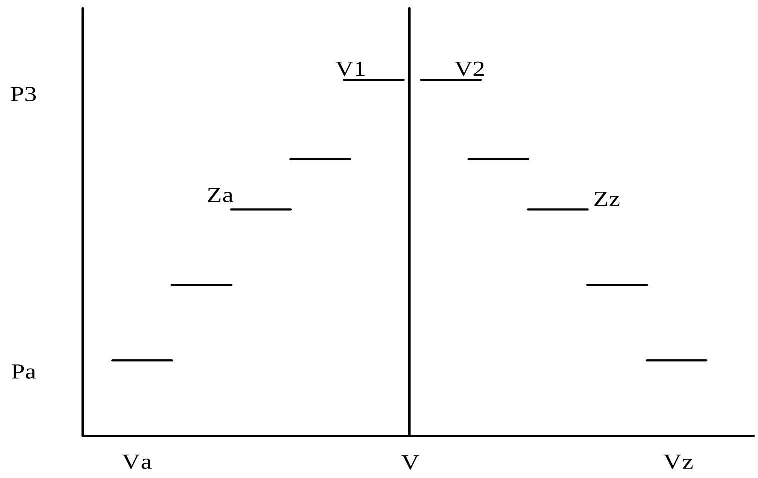

Figure 2.5: Uncertainty valuation report
Adopted from: Mallinson and French (2000, p. 28)

2.5.2 The Nigerian Property Valuation Accuracy Studies

Despite Nigeria being the biggest economy in Africa (The World Bank, 2017), its property market and valuation practice are still at a developing stage (Babawale and Ajayi, 2011; Abidoye and Chan, 2016c), that is, the property market has not yet matured (Dugeri, 2011). Therefore, research in this area has been of interest to Nigerian real estate scholars.

The study of Ogunba and Ajayi (1998) carried out in the Lagos metropolis revealed that the valuation estimates produce by valuers in the metropolis are not a good representation of actual property values. This was established by the findings of the study which discovered a prevalent margin of error ranging between 33.43 and 36.47% in the study area.

The valuation variations in five south-western states in Nigeria was investigated by Ogunba (2004). The valuers' estimates of 11 residential properties were compared with the actual selling price of these properties in order to establish what variations in value that occurred. The author found that there was a wide variation between the valuers' figures and the actual selling price of these properties in all the states, which range between 22.73 and 67.91%.

Ogunba (2004) attributed valuation inaccuracy to the non-uniformity in the mode of making provision for outgoings by valuers in property valuation exercise, inconsistency in the yield used by valuers in property valuation and the defective mode of estimating rental value. The study concluded that valuers' higher educational and professional qualification, vast years of valuation practice experience and being specialized in valuation practice are the factors that could improve valuation accuracy.

This conclusion is similar to the position of Shapiro et al. (2012) that argued that the accuracy of a valuation estimate is largely dependent on the understanding and knowledge of the valuer of the price movement in the subject property market, as well as the expertise of the valuer to measure the impact on property values.

Ajibola (2010) also examined the Lagos metropolis and found a similar result to the existing Nigerian literature. However, the lack of market data, the influence of clients on valuers and the adoption of traditional methods of valuation were attributed to the prevalence of valuation inaccuracy in the Lagos metropolis property market.

Babawale and Ajayi (2011) also examined the variance in residential property valuation in the Lagos metropolis. Although most of the sampled valuers are in support of the industry standard of ± 10% deviation, only 55% of the valuations examined in the study fall within this range. The authors conclude that "*residential property valuation in Lagos metropolis exhibits inaccuracy below industry's acceptable minimum standards*" (Babawale and Ajayi, 2011, p. 222).

Other contributions to this debate in Nigeria include causes of valuation inaccuracy in the Lagos metropolis (Otegbulu and Babawale, 2011; Ayedun et al., 2012; Babawale and Omirin, 2012), the perception and expectations of valuation report end-users on valuation accuracy (Adegoke et al., 2013; Babawale, 2013b), and the role of estate surveyors and valuers' training and exposure on property valuation accuracy (Ayedun et al., 2014). Other areas include point estimate and acceptable margin of error in valuation reporting (Aluko et al., 2004) and the effect of valuation inaccuracy on mortgage financing in Nigeria (Babawale and Alabi, 2013).

2.5.3 The Nigerian Property Market

The evolution and growth of the Nigerian property market are not well documented in the literature. Dugeri (2011) attributed this to the lack of interest by international property investors when compared with the European and Asian property markets. Another plausible reason could be linked to the lack of a centralized databank for the storage of property transactions information (Aluko, 2007). The emergence of big data analysis has led to improvements in practice related to property valuation, investment analysis and portfolio management, among other aspects, of the real estate practice (Du et al., 2014). However, Ogunba and Ajayi (2007) acknowledged that the reverse is the case in property markets of developing countries, with Nigeria as an example.

Nigeria is made up 36 states and a Federal Capital Territory - Abuja (The World Bank, 2014). The Nigerian property market can be categorized into primary (characterized with high rental and capital values) and secondary markets (characterized by low rental and capital values), with the primary markets being the most active (Olaleye, 2008). The primary markets are the Lagos, the Abuja and the Port Harcourt property markets and these three markets account for about 60% of the real estate transactions completed in Nigeria (Olaleye, 2008). The Lagos metropolis is the most active property market in Nigeria due to the high number of sophisticated real estate stakeholders that interact in the metropolis (Oni, 2010). Also, a large percentage of the multinational companies operating in Nigeria are domiciled in Lagos and over 90% of the commercial banks and financial companies operating in Nigeria have their head offices in Lagos (Central Bank of Nigeria, 2015). This is because the Lagos metropolis is the commercial nerve center of Nigeria (Aluko, 2007). This corroborates why more than 50% of the Nigerian registered real estate professionals practice in the Lagos metropolis property market (Ibiyemi and Tella, 2013).

Dugeri (2011) evaluated the maturity of the Nigerian property market based on five parameters which include the openness of the market, the property profession, capital liquidity, the state of information and the market transparency. The study discovered that the Nigerian property market is characterized by immature real estate professional practice which is evident with a scanty number of registered professionals practicing in different submarkets in Nigeria (with the exception of the primary markets), and with an increasing number of charlatans intruding on the professional practice (Akinbogun et al., 2014). Also, its mortgage system is not robust enough to cater for the demand of every eligible Nigerian (Enhancing Financial Innovation and Access (EFInA), 2014). The Nigerian property market is not transparent because real estate professionals do not provide the correct property transactions information in a bid to protect their clients and real estate market research is limited in Nigeria because there is a paucity of data which are needed for research endeavour (Dugeri, 2011).

Dugeri (2011) concluded that the property market is still in its infancy stage. This conforms to the findings of Akinbogun et al. (2014) that the lack of proper land registration system, inefficient planning system and constraints in access to housing finance are the plausible reasons for the immature state of the Nigerian property market. These findings could be substantiated with the position of Jones Lang LaSalle (JLL) (2016) that reported that the Nigerian property market can be categorized as a “low transparent” real estate market. This is in comparison with South Africa which is “highly transparent”, and Botswana, Zambia and Kenya that are classified as “transparent” property markets in the Sub-Saharan African region. However, it should be noted that the Nigerian property market has the potential to grow and mature into the one of the most advanced within the African continent, but there is a need to address several pertinent issues (see Dugeri, 2011; Akinbogun et al., 2014), so that the property market can grow in a sustainable manner.

2.6 CHAPTER SUMMARY

Property value and property valuation are reviewed in this chapter. Property value is differentiated from ‘price’ and ‘worth’ which are widely used interchangeably. The process of conducting a valuation exercise is elaborated and the stages involved are summarized into data collection, data analysis and pronouncement of the opinion of value.

The framework of property value determinants for the Lagos metropolis is developed based on the existing literature – neighbourhood, structural and locational factors. It is established that different sets of attributes affect property value in different property markets around the world due to the difference in the socio-economic, financial and legal peculiarities of the economies.

The traditional and advanced valuation methods employed in property valuation are evaluated. It was established that the traditional methods have some drawbacks in terms of inaccuracy and inefficiency and thus, the development of the advanced methods to address the shortcomings of the traditional methods. Despite the shortcomings of the advanced methods, they have been established in different property markets of the world to have produced reliable and accurate valuation estimates. Therefore, their applicability in other developing economies should be explored, which is what the present study is set out to achieve.

Valuation inaccuracy has been in the international debate for a while and the Nigerian property market is not an exception. Generally, a valuation inaccuracy error of ± 5 to 10% closeness to the property value has been established to be of minimum industry standards. The studies conducted in the Lagos metropolis, Nigeria, have shown that valuation inaccuracy is predominant in the property market, with ranges obtained in studies beyond industry standards and makes the valuations conducted in the metropolis not to be a good proxy for property values.

The application of inappropriate (traditional) valuation methods has been attributed to valuation inaccuracy. Therefore, the following chapter discusses in detail the applications of HPM and ANN in property valuation. These two approaches were selected amongst other modeling techniques due to their peculiarities as elaborated in Chapter 1, and their review is aimed at establishing the trend in the literature and establish the need to compare the predictive accuracy of both models in property valuation in the Nigerian property market.

CHAPTER 3 ARTIFICIAL NEURAL NETWORK AND HEDONIC PRICING MODEL

3.1 INTRODUCTION

The preceding chapter presents a review of property valuation, its process, various valuation methods and modeling techniques adopted in the property valuation domain. It also discusses property valuation inaccuracy which has remained an issue of debate amongst professionals and academics on the global scene. All of these provides a background for the main issues which this research centers on. Previous studies which aimed at applying modeling techniques in property valuation have shown that nonlinear modeling approaches are more accurate and reliable when compared with linear approaches. Therefore, the HPM approach which has been widely adopted in the real estate research and the novel ANN technique are reviewed in this chapter. This is to offer insights into both techniques and a foundation for this study.

In this chapter, the background of both techniques is presented, contemporary issues which arise in their applications in property valuation, as well as their pros and cons in property valuation are also discussed. In addition, the application of both techniques in the real estate research domain is examined so as to draw inferences and establish trends from previous studies. Due to the fact that no model fits all (Pagourtzi et al., 2007), a review of studies that have compared the predictive accuracy of ANN and

HPM is conducted to establish the extent to which ANN is superior to the HPM approach in property valuation application.

The application of both ANN and HPM techniques in the Nigerian real estate research domain is also reviewed. This is done so as to gain further insights into the current state of knowledge and identify the gaps which exist in the literature.

3.2 THE ARTIFICIAL NEURAL NETWORK MODEL[3]

In the literature, several modeling techniques have been applied to solve problems in different academic disciplines. Frew and Jud (2003) asserted that the emergence of nonlinear modeling techniques addresses the shortcomings of traditional models in the area of efficiency. Also, the value estimates arrived at by the application of the traditional valuation approaches are not generally acceptable and lack a 'certification process' (Taffese, 2006, p. 710). This could be attributed to the fact that 'real world' problems have nonlinear behaviours.

Mora-Esperanza (2004, p. 257) describes ANN as a "computer system whose microprocessors, rather than laid out in series as in traditional computers, are connected in parallel, forming layers and making multiple connections, imitating the

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[3] This section has been published in **Abidoye R. B.** and Chan, A. P. C. (2017). Artificial neural network in property valuation: Application framework and research trend. *Property Management*, 35(5), (**In Press,** DOI: https://doi.org/10.1108/PM-06-2016-0027).

way the neuronal network is organized in the brain". Taffese (2006), in another context, describes ANN as an interaction between processing elements in a network which ultimately presents the global behaviour of the network by interpreting the relationship between the elements' parameters and processing elements.

The ANN technique has been applied in the different subject areas for prediction, pattern recognition, classification, process control, nonlinear mapping and data analysis (Paliwal and Kumar, 2009). Its outstanding predictive accuracy has been established in wide range fields as presented in Table 3.1.

Table 3.1: The applications of ANN techniques in different domains

Domains	Studies
Health and medicine	Razi and Athappilly (2005); Subasi and Erçelebi (2005); Behrman et al. (2007); Chien et al. (2007); Wesolowski and Suchacz (2012)
Engineering	Yesilnacar and Topal (2005); Dvir et al. (2006); Pendharkar (2006); Maliki et al. (2011); Yuan and Guangchen (2011)
Marketing	Thieme et al. (2000); Gan et al. (2005); Chiang et al. (2006)
Stock market	Fernandez-Rodrıguez et al. (2000); Enke and Thawornwong (2005); Eriki and Udegbunam (2013)
Tourism demand	Law and Au (1999); Uysal and El Roubi (1999); Burger et al. (2001)
Environment management	Al-Alawi and Al-Hinai (1998); Mohandes et al. (1998); Chukwu and Nwachukwu (2012)
General application	Curry et al. (2002); Sharda and Delen (2006); Xuefeng et al. (2006); Nikolopoulos et al. (2007); Nasr et al. (2012)

ANN has proven to be an appropriate technique for prediction. This is corroborated by the comprehensive review of its applications in different disciplines conducted by

Paliwal and Kumar (2009). The review shows that ANN outperformed other advanced techniques in 56 out of the 96 articles reviewed. It ranked equally with others in 23 out of 96 articles, and it is only in 17 instances out of 96 that other techniques outperformed ANN. All these suggest that ANN is an advanced technique that has been tested in many instances to be a good predictive analytical tool.

The ANN technique is suitable for property price modeling because the model mimics humans, and hence the output produced by it could be a proxy for the estimation of a real estate valuer (Borst, 1991). The 'pattern recognition' feature of the ANN model makes it suitable for property valuation because real estate properties possess attributes which define the nature of a property. ANN 'learns' from the information of the properties to identify the pattern to produce the outputs (property values) (Tay and Ho, 1992).

3.2.1 Background and Theory of Artificial Neural Network

The origin of the neural network technique could be traced to McCulloch and Pitts (1943) who attempted to model the human brain neuron by demonstrating that the neural network can work out arithmetic logical functions. According to Zhang et al. (1998), the first application of ANN to forecasting was conducted by Hu (1964) that explored the technique for weather forecasting by using Widrow's adaptive linear network. But as at that time, there were no multi-layer network training algorithms, the technique did not receive enough attention. A follow-up study of Rumelhart et al. (1986) introduced the backpropagation (BP) algorithms and since then, the ANN technique has been applied in the various fields of studies.

The operation of ANN is based on the interaction of neurons. Neurons are interconnected and function by receiving commands from the 'Dendrites' (connectors), and after the information has been processed, it is passed to the other neuron by the 'Axons' (connectors) (Mora-Esperanza, 2004). The structure of a neuron is presented in Figure 3.1.

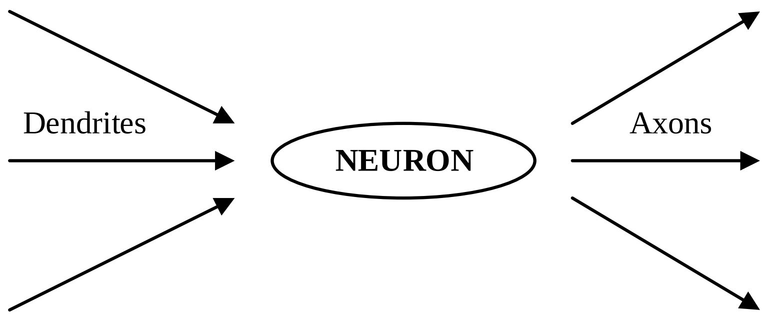

Figure 3.1: The structure of a neuron
Adopted from: Mora-Esperanza (2004, p. 256)

According to Wong et al. (2002), the operation of the neural network, as presented in Figure 3.2, starts with an activation function which integrates the input values. This information is transferred to the hidden layer. The operation in the hidden layer happens in two stages: "1) the weighted summation functions and 2) the transformation functions" (Pagourtzi et al., 2007, p. 53). The weights are transferred through an activation process to the sigmoid transformation function, from where the output is produced. The integration which takes place in the network is more advanced than the polynomial equation which HPM is based on (Mora-Esperanza, 2004).

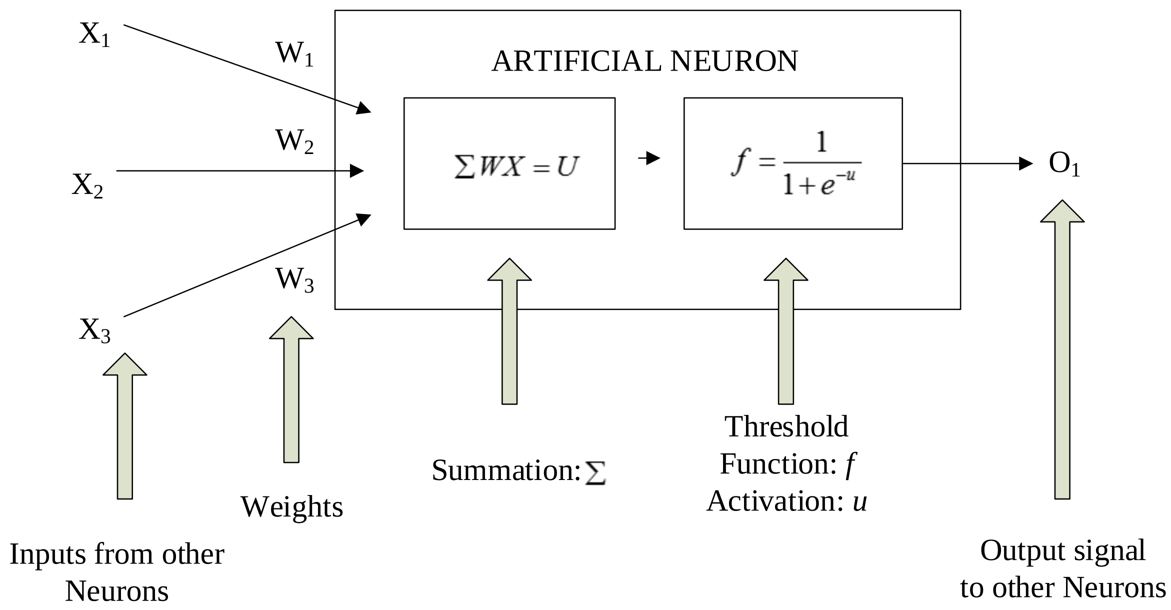

Figure 3.2: The components of a typical processing unit
Adopted from: Wong et al. (2002, p. 190)

Where $X_{1\text{-}3}$ are the input values, $W_{1\text{-}3}$ are the assigned weights of the input values, U is the summation function, while f is the threshold value from which output is determined.

The transfer function "determines the relationship between input and output of a neuron and its network" (Lin and Mohan, 2011, p. 234), by summing the weights of the input signals in generating the network output (Fausett, 1994). There are three basic forms of action or transfer functions, namely threshold functions, piecewise-linear function and sigmoid function (Haykin, 1999). The most widely used is the sigmoid function (Mora-Esperanza, 2004), typically due to being 'advantageous within the context of many paradigms' (Ge, 2004, p. 139) and easy to apply in computer programming (Mora-Esperanza, 2004). The sigmoid function takes continuous values which range from 0 to 1 (Haykin, 1999), using the expression in Equation 3.1 (Morano et al., 2015, p. 26). Figure 3.3 shows a typical sigmoid function graph.

$$f(x) = \frac{1}{1+e^{-kx}} \tag{3.1}$$

Where x is the input and k is the slope of the tangent of the curve at the inflection point.

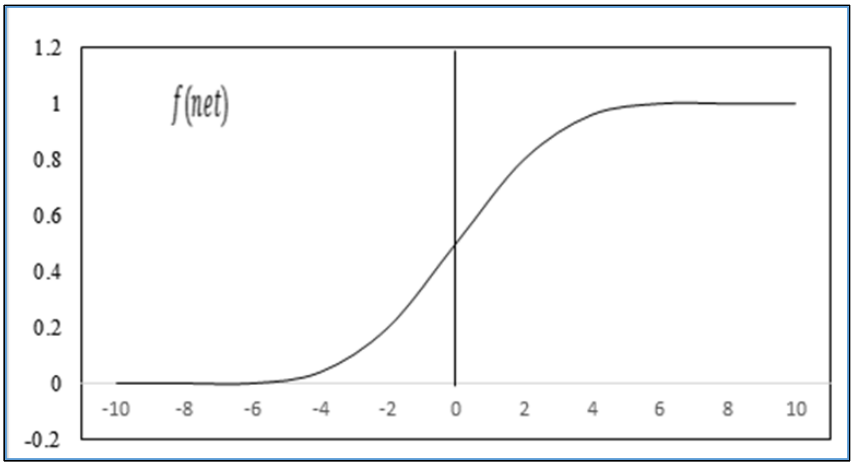

Figure 3.3: Sigmoid function
Adapted from: (Haykin, 1999, p. 13)

3.2.2 Construction of Artificial Neural Network Model

The process of applying the ANN technique to a problem involves some steps. These steps are not a one-off procedure because the steps are iterative until an optimal ANN network is identified. Kaastra and Boyd (1996) documented a detailed process of developing an ANN model which involves eight main steps presented below:

Step 1: The selection of the variables to be included in the model
Step 2: The collection of data from the study area
Step 3: Pre-processing of the collected data
Step 4: Division of the data set for training and testing of the model
Step 5: Neural network paradigm

- Determination of the number of hidden layers
- Determination of the number of hidden neurons
- Determination of the number of output neurons
- Selection of the transfer function

Step 6: Model evaluation criteria and accuracy measure
Step 7: Training of the ANN model
Step 8: Implementation

In applying ANN in property valuation, historical sales transaction data of the property market under consideration are required. The ANN model can then be processed to 'learn' from the input data. This sales transaction data comprises the property attributes (ANN inputs) and property prices (ANN outputs). These parameters can be likened to the independent variables and the dependent variable, respectively, similarly used in the development of HPM. This is probably one of the reasons it is easy to compare the predictive accuracy of both techniques based on the same parameters.

The data set available for the construction of the model is to be divided into two parts. The first is used for 'training'; while the other is used for 'verification and testing' of the model (Wilson et al., 2002). The training data set is utilized for the construction of the model, whereas the testing data set is used for the evaluation of the predictive accuracy of the developed model (Lam et al., 2008). There is no consensus as to the sharing ratio of the data set (Cechin et al., 2000). However, a ratio of 80:20, i.e. for training and testing/validation, respectively, is common in the literature (see Table 3.2).

3.2.3 Network Architecture and ANN Model Development

The construction of artificial neural network is referred to as the 'network architecture' (Zhang et al., 1998). There are generally three types of network architecture which include feedback (recurrent) network, single-layer feedforward network and multi-layer feedforward network (De Castro and Timmis, 2002). Figure 3.4 shows the graphical representation of feedforward or feedback network architecture. In the feedforward architecture, the activation travels in a forward manner i.e. from the input layer to the output layer and the neurons in each layer are connected in a forward direction, but the reverse is the case for feedback architecture (Callan, 1999). BP is a network training method which is adopted to minimize the squared error of the outputs generated by the network (Fausett, 1994). It is simple, stable and can handle complex data set (Elhag, 2002). This could be attributed to why the feedforward-backpropagation ANN paradigm is commonly applied in property valuation (Selim, 2009; McCluskey et al., 2013).

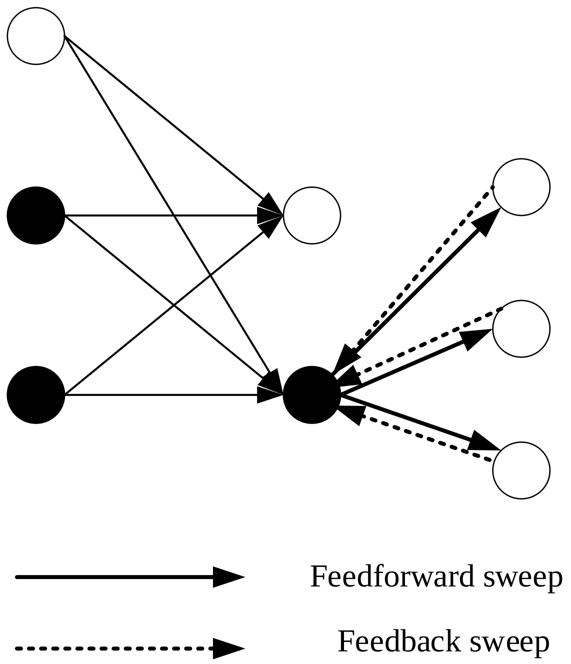

Figure 3.4: Artificial neural network paradigm
Source: Callan (1999, p. 33)

The ANN model consists of three layers, namely the input, the hidden and the output layers (Zhang et al., 1998). At the input layer, input variables which represent property attributes (when the model is used for property price prediction) are fed into the network. The hidden layer is the layer in-between the input and the output layers. The result of the transformation which takes place in the hidden layer is produced at the output layer, which is where the predicted property value is obtained.

Mora-Esperanza (2004) posited that an input variable size of between 10 and 50 is common for the construction of ANN models for property valuation and that the number of the hidden layers can range between half and double the number of input variables. However, Hornik (1991) and Masters (1993) argued that one hidden layer is sufficient for ANN to perform excellently. The output layer usually has just one neuron, which is the predicted property price.

The number of neurons used in the hidden layer of a model could aid the retrieval of an improved result (Borst, 1995), but unfortunately, there is no consensus as to the number of hidden neurons to be included in a model (Cechin et al., 2000). Nevertheless, Ward (1996) presented an expression which can be used in determining the number of neurons in the hidden layer which is presented in Equation 3.2.

$$N_h = \frac{N_{in} + N_{out}}{2} + \sqrt{N_s} \qquad (3.2)$$

Where N_h is the number of neurons of the hidden layer, N_{in} is input layer, N_{out} is output layer and N_s is the number of training samples.

A typical ANN model architecture is presented in Figure 3.5. The architecture depicts a scenario of a model which has six input variables, one hidden layer (with three neurons) and one output layer which represents the market value.

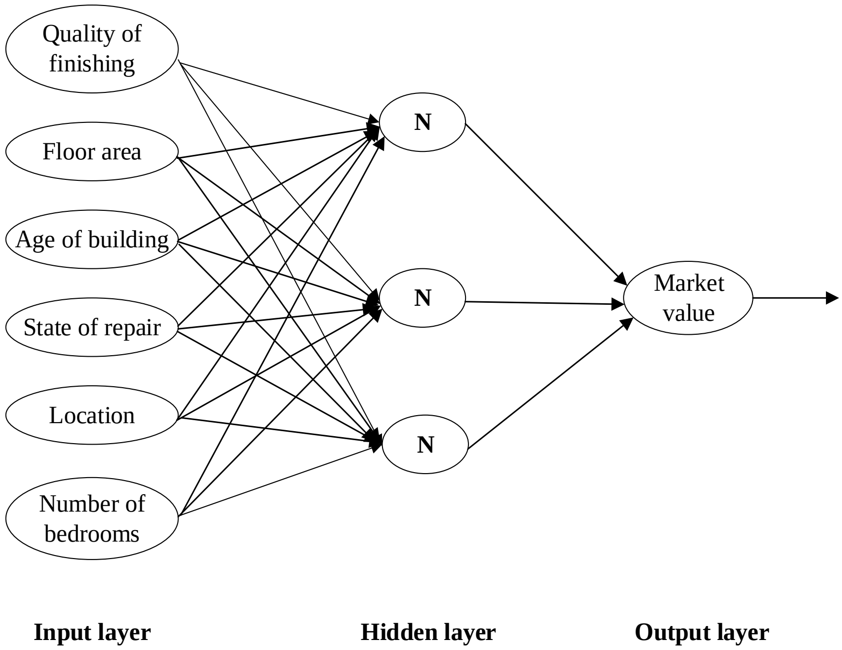

Figure 3.5: A simple ANN model for property valuation
Adapted from: Mora-Esperanza (2004, p. 257) and Taffese (2006, p. 711)

The number of samples needed to construct an ANN model is not established in the literature. However, Rossini (1997, p. 9) mentioned that a 'small data set' is sufficient for the construction of an ANN model. From another view, Mora-Esperanza (2004) posited that the number of samples should be proportional to the number of variable entries. The ANN model does not need more data than usually required by linear models for it to function excellently (Zhang et al., 1998).

The need for the ANN model to 'learn' like the human brain makes its operation to be based on a 'trial and error' process to determine the best optimal ANN model (Limsombunchai et al., 2004; Lin and Mohan, 2011). The reason is that it learns like a new baby from experience when mastering the act of talking or walking.

3.2.4 Strengths and Weaknesses of Artificial Neural Network

The emergence of the ANN technique in the property valuation domain has addressed the technical limitations of the HPM technique (Do and Grudnitski, 1992; Tay and Ho, 1992; Worzala et al., 1995). The ANN modeling technique has proven to be a better alternative to the commonly adopted HPM in property valuation due to its adaptability and generalization capabilities (Taffese, 2006). The model can handle the nonlinear relationship (the complex interaction between demand and supply factors that affects property prices (Ge, 2004)) which exists between property values and property variables (Cechin et al., 2000). It has generalization ability (Xie and Hu, 2007) and is easy to operate when compared with the HPM approach (Borst, 1991). It can also address the 'time variant problem, even under uncertain or erroneous attributes of real estate valuation' (Taffese, 2006, p. 712).

Some other valuation approaches e.g. comparable method and HPM are characterized by subjectivity (Kauko, 2004; Yacim and Boshoff, 2014), whereas the processing of the ANN model does not require human input in its analysis (Tay and Ho, 1992). The ANN technique has been widely accepted in the property valuation domain for its ability to outperform the HPM approach (Borst, 1991; Taffese, 2006) because the technique produces model output with speed and is also simple to operate (Ge, 2004). The ANN model produces estimates (outputs) which are highly precise, handles data set which contains outliers and is also user-friendly (Mora-Esperanza, 2004).

ANN, being an advanced property modeling technique, comes with some drawbacks. Jenkins (2000) presented the limitations of ANN in relation to the traditional approaches and HPM to include the fact that ANN is data hungry because more data are needed for its development, compared to the comparable method which could be applied with as few as two comparable properties.

Other shortcomings of the ANN technique are the inability to understand what happens in the internal structure of the network (Jenkins, 2000), and the problem of determining the actual size and structure to produce the output (Taffese, 2006). McGreal et al. (1998), Limsombunchai et al. (2004) and Lam et al. (2008) opined that the 'black-box' nature of the ANN model and the lack of the interpretation of the produced output are some of the limitations of the modeling technique. However, the operation of HPM is also complex and cannot be easily explained (Mora-Esperanza, 2004).

In essence, the ANN technique is to be used as a tool which the valuer adopts in property valuation exercise and not to be seen as an expert in itself. This has translated into "various countries having included the ANN in their real estate valuation computer system, as a help tool for their valuators" (Mora-Esperanza, 2004, p. 260).

In sum, the continuous development of different neural network software has been handling these shortcomings (McCluskey, 1996). Moreover, ANN's user-friendliness makes it easy to be used by non-computer experts, for instance, other real estate stakeholders (Rossini, 1997; Wong et al., 2002). Also, since the aim of a valuer is to arrive at a reliable and precise estimate which will be a good proxy for property value, the need to fully understand how the output is generated may not be significant, because the main reason for embarking on a valuation exercise is to estimate reliable and acceptable valuation figures (McCluskey, 1996).

Further comments by Jenkins (2000) revealed that towards the end of the 1990s, efforts to reduce the arbitrariness associated with the ANN technique were published. This was confirmed by Borst (1995) that proved that the explainability of the ANN model is possible. This is substantiated in the literature, where studies have applied the ANN technique in the sensitivity analysis of variables included in the model (see Lai, 2011; Tabales et al., 2013; Abidoye and Chan, 2017a, amongst others).

3.2.5 Applications of Artificial Neural Network in Property Valuation

The application of ANN in property valuation can be traced to the early 1990s. Borst (1991) is the first to apply ANN in property valuation. The study presented a description of ANN and examined the predictive accuracy of the ANN technique under four cases using different network architecture. Borst (1991) concluded that the prediction accuracy produced by ANN is reliable and that with more research efforts towards the application of ANN in property valuation, the model will produce outstanding estimates.

After Borst (1991) seminal study, other scholars have applied ANN in property valuation problems. Kathmann (1993) presented an overview of the application of ANN in property valuation and also evaluated the significance of the technique. The author found ANN to be superior to other valuation techniques. In a similar vein, McGreal et al. (1998) applied ANN in predicting property value using 1,026 Belfast property sales data. In an attempt to avoid bias in the data utilized, the authors restricted the data to transactions completed between 1992 and 1993. In order to extend the scope of the study from the mere application, the 1992 and 1993 data were analyzed separately so as to establish if ANN can produce a consistent result over time. The predictive accuracy of ANN was confirmed in the study. The model produced accurate and consistent outputs in both the 1992 and 1993 models. The authors documented the excellent predictive accuracy of the ANN technique but suggested that more effort should be invested in researching into how to make the ANN model perfect.

More property markets around the world have been modeled using ANN. A summary of such studies is presented in Table 3.2, while some others are presented in Section 3.4.2. The information in Table 3.2 depicts that the technique truly possess an outstanding accurate predictive ability as it was established in all the studies

Table 3.2: Studies of ANN applications in property valuation

Authors	Countries	Sample size/ no. of variables	Training: Testing ratio	Summary of findings
Borst (1995)	United States	217/11	90:10	ANN predicted more accurately than HPM
McCluskey (1996)	Ireland	416/9	90:10	ANN produced excellent realistic output
Wilson et al. (2002)	United Kingdom	?	80:20	ANN is a promising forecasting technique
Ge and Runeson (2004)	Hong Kong	?/18	?	ANN is an effective forecasting technique
Mora-Esperanza (2004)	Spain	100/12	85:15	ANN is appropriate for property value forecasting
Lam et al. (2008)	Hong Kong	4143/29	80:20	ANN is a viable property forecasting tool
Tabales et al. (2013)	Spain	10124/6	80:20	ANN is an effective forecasting technique
Ahmed et al. (2014)	Bangladesh	100/40	70:30	ANN is an alternative to HPM
Morano et al. (2015)	Italy	90/7	80:20	ANN predicted excellently
Kutasi and Badics (2016)	Hungary	1,806/52	80:20	ANN produced better results than HPM

Note: ? means value or figure not provided.

3.3 THE HEDONIC PRICING MODEL[4]

Real estate property is a composite good which is made up of a number of unique bundles of attributes that affect its value wherever it is located (Rosen, 1974; Sirmans et al., 2005). The uniqueness of the stakeholders that interact in the property market, as well as the heterogeneous characteristics of real estate properties, could be attributed to the differences in the value ascribed to them by different stakeholders (Chin and Chau, 2002; Sirmans et al., 2005). The inability to separately value those property attributes has led to the development of a model which presents the contributory power of each of those attributes to property value formation, and hence the emergence of the HPM technique.

The HPM approach has been applied in price indexes analysis in different fields, including, but are not limited to, computers (Dulburger, 1989; Nelson et al., 1994; Berndt et al., 1995; Holdway, 2011), healthcare (Berndt et al., 2000; Cutler and Berndt, 2007), home appliances (Silver and Heravi, 2001), automobiles (Triplett, 1969; Ohta and Griliches, 1976; Triplett, 2004), and so on. The background of HPM, its principles, pros and cons and applications in the real estate domain are presented in subsequent

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[4] Part of this section has been published in **Abidoye, R. B.** and Chan, A. P. C. (2017). Critical review of hedonic pricing model application in property price appraisal: A case of Nigeria. *International Journal of Sustainable Built Environment,* 6(1), pp. 250 - 259.

subsections.

3.3.1 Background of the Hedonic Pricing Model

HPM is a popular quantitative analysis technique which has been widely adopted in property appraisal and used at the same time to complement the traditional methods especially the comparable method (Limsombunchai et al., 2004; Taffese, 2006).

The origin of the application of HPM in real estate research dates back to the early 1920s. Although it may be hard to trace the actual origin of HPM, Colwell and Dilmore (1999) argued that the first study that adopted the HPM approach in real estate research is Haas (1922b) who applied HPM to estimate the value of a farmland in Minnesota, United States. Likewise, Bruce and Sundell (1977) mentioned that MRA was applied to farmland appraisal in 1924. These arguments were substantiated by Lentz and Wang (1998) but claimed that there was no proper justification for the model until later years.

Wallace (1926) adopted the regression analysis to predict the farmland in different counties in Iowa, United States. Chin and Chau (2002) argued that Ridker and Henning (1967) are the first authors to apply HPM in residential property appraisal to examine the impact of air quality on property values. Chin and Chau (2002) further asserted that Freeman (1979) gave the much needed theoretical justification for HPM in the real estate research domain.

Authors generally relate the origin of HPM to the study of Court (1939) who developed a hedonic pricing index for the price of automobiles. Court (1939) asserted that the demand for automobiles cannot be explained by a single variable, but the implicit market price of the subject's characteristics, derived by equating the demand and supply for each characteristic in a model are needed for value formation. Court (1939) explained in a semi-log form that these three variables, wheelbase, dry weight and horsepower, would contribute to the price being paid for cars. Thereafter, still in the early days, scholars (see, Muth, 1966; Oates, 1969) adopted HPM to real estate research. However, Lancaster (1966), through "consumer theory" and especially the study of Rosen (1974), presented the theoretical underpinning for the application of HPM in property valuation. Based on the assertions found in Rosen (1974), researchers have been adopting this method in different property markets around the world.

3.3.2 Principles of the Hedonic Pricing Model

The principles of HPM are based on the regression analysis (Lentz and Wang, 1998; Selim, 2009). Regression analysis could be in the form of simple regression or multiple regression. In the case of simple regression, the analysis is geared toward evaluating the relationship between a dependent variable and one independent variable. When the relationship under consideration is between a dependent variable and more than one independent variable, then it is referred to as MRA. MRA is largely employed for property price analysis because the value of a real estate property is dependent on more than one attribute (Chin and Chau, 2002).

One of the essences of MRA is to develop the best-fit representation for the relationship which exists between the dependent variable and the independent variables of the sample data being analyzed (Elhag, 2002). According to Kmenta (1997), simple and multiple regression can be expressed mathematically as shown in Equations 3.3 and 3.4, respectively.

$$\hat{Y}_i = \beta_0 + \beta_1 X_{1i} + \varepsilon_i \tag{3.3}$$

$$\hat{Y}_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots\ldots\ldots\ldots + \beta_k X_{ki} + \varepsilon_i \tag{3.4}$$

Where $\hat{Y}_i$ = predicted value β_0 = regression constant

β_1 = slope of $\hat{Y}$ with variable X_1 when variables X_2, X_3, ….., X_k are held constant

β_2 = slope of $\hat{Y}$ with variable X_2 when variables X_1, X_3, ….., X_k are held constant

β_k = slope of $\hat{Y}_i$ with variable X_k when variables X_1, X_2, …., X_{k-1} are held constant

ε_i = random error in $\hat{Y}$ for observation *i*

$\beta_1, \beta_2, \beta_3$, ………, β_k are referred to as the regression coefficients.

In order to establish if the regression analysis yields a goodness of fit, the r^2 is usually computed. This indicates the proportion of the variability in *Y* which is explained by variation in *X*. The r^2 measures how well the regression line fits the sample data and this value ranges between 0 and 1 ($0 \leq r^2 \leq 1$) (Kmenta, 1997). An r^2 value of 1 depicts a perfect goodness of fit that is the better X is able to explain Y, while a value close to 0 signifies otherwise.

Adjusted r^2 (r^2_{adj}) is computed in order to reflect the number of independent variables (k) and the sample size (n) used for the development of the regression model (Elhag, 2002). The r^2 and r^2_{adj} can be computed using Equations 3.5 and 3.6, respectively.

$$r^2 = \frac{SSR}{SST} \tag{3.5}$$

$$r^2{}_{adj} = 1 - \left(\left(1 - r^2\right) \frac{n-1}{n-k-1} \right) \tag{3.6}$$

Where SSR is the sum of squares regression and SST is the total sum of squares.

The construction of HPM involves a prescribed procedure. However, Verma (2013, p. 146) presented the procedure for developing HPM as follows:

i. compute descriptive statistics of the sample data in terms of mean, standard deviation, skewness, kurtosis and frequency distribution to check the distribution of each variable;
ii. plot the scatter diagram in order to evaluate the linearity of all the independent variables with the dependent variable;
iii. compute the correlation matrix among the independent variables to assess if multicollinearity exists among them. If it exists, then one of the two correlated variables can be deleted or other appropriate multicollinearity treatments can be applied;

iv. develop the regression equation by using the unstandardized regression coefficients;
v. conduct a significance test of the regression coefficients by using the *t*-test;
vi. test the significance of the regression model by using the *F*-test; and
vii. compute the r^2 and adjusted r^2 to establish the percentage variance of the dependent variable explained by all the independent variables in the regression model.

3.3.3 Hedonic Pricing Model Issues

Despite the fact that HPM has been generally accepted in the property valuation domain, some issues are still embedded in its application which includes model specification procedures, independent variable interactions, heteroscedasticity, multicollinearity, outlier data points and nonlinearity (Do and Grudnitski, 1992; Limsombunchai et al., 2004).

Functional form specification is the process of choosing the functional form of the regression equation which best explains the relationship between the dependent variable and the independent variables. There are three general functional forms of an HPM analysis, which includes the linear, log-linear/semi-log and log-log functional forms (Freeman, 1993). There is no consensus in the literature as to the functional form to be chosen in the HPM analysis (Kryvobokov and Wilhelmsson, 2007). Thus, there is little guidance as to choosing the right functional form (Selim, 2008).

Heteroscedasticity, which is the opposite of homoscedasticity, is a well-established issue in terms of the application of HPM (Selim, 2009). Homoscedasticity describes an assumption that for all values of X, the variation around the regression line is constant. When otherwise, heteroscedasticity occurs, that is the variation of errors are different for different values of the independent variables. This can be checked by a visual inspection (the plot of the standardized residuals against the standardized predicted value to identify the changing scatters), White's test, Breusch-Pagan test and Glejser test, among others.

Multicollinearity occurs when two or more explanatory variables are highly correlated in the sample and this violates the classical linear regression model. Sheppard (1997) argued that multicollinearity may be inevitable in hedonic pricing analysis due to the similarity of some property variables. This is also the position of Newel (1982) who argued that multicollinearity is not uncommon in property data. This can be handled with the computation of correlation matrix which displays the correlation coefficient between the explanatory variables. A common method of measuring multicollinearity among independent variables is the variance inflation factor (VIF) approach (details of VIF is presented in Section 4.8.5).

Nonlinearity depicts the situation where the dependent variable does not have a linear relationship with the independent variables. This can be examined through the scattered plots or by conducting Kolmogorov–Smirnov test and Shapiro–Wilk test, amongst other approaches.

3.3.4 Strengths and Weaknesses of Hedonic Pricing Model

Do and Grudnitski (1992) asserted that the HPM technique addresses the deficiencies of the traditional property valuation methods. Also, the HPM approach has the ability to estimate the contributory impact of an independent variable (property attribute) on a dependent variable (property value). “The superiority of the HPM technique is its simplicity and computational advantage” (Lin and Mohan, 2011, p. 226). The regression coefficient is the only variable needed to interpret the structure of HPM, and this makes it a straightforward technique (Chin and Chau, 2002).

Comments on the drawbacks of the HPM technique, according to Taffese (2006), include the issue of multicollinearity and the inclusion of outliers into the model. According to McGreal et al. (1998), HPM is limited in its application in property valuation due to its inability to adequately capture the nonlinearity of real estate data and the subjectivity in identifying the appropriate functional form, whereas the ANN technique maps the best functional form by learning from data provided to the model during training (Do and Grudnitski, 1992; Limsombunchai et al., 2004).

The workability of the HPM technique could be affected by small sample data set (Rossini, 1997). The nonlinearity relationship which exists between property values and property attributes which HPM cannot handle limits its application in property valuation (Taffese, 2006). Worzala et al. (1995) augured that the shortcomings of the HPM approach include subjectivity, inaccuracy, multicollinearity and the lack of ability to handle outliers. All these could result in imprecise valuation estimates.

3.3.5 Applications of Hedonic Pricing Model in Property Valuation

The HPM approach has been widely adopted in the real estate research domain and has been widely adopted to estimate the price effect of various property attributes on property values.

Bruce and Sundell (1977) conducted a review of studies that adopted MRA in real estate appraisal before 1954, during 1954 and 1964 and between 1964 and 1977. The authors asserted that during the study period, the approach has been applied in the appraisal of four classes of real estate properties, namely rural bare land, urban bare land, single-family residences and multiple-family residences. The authors attributed the unpopularity of the approach in these early days to unavailability of computers to handle the mathematical calculations involved.

The study conducted by King (1976) adopted the HPM approach in the estimation of property price utilising data of 683 properties sold or purchased in New Haven, the United States, between 1967 and 1970. The study adopted property characteristics categorised into four groups to validate the Lancaster's demand theory in property pricing. The findings of the study conform to the Lancastrian 'new demand theory' which reveals that households price those property attributes in making sound real estate decisions. Table 3.3 shows a summary of some studies that have adopted HPM in examining the effect of property attributes on property values.

Table 3.3: Hedonic pricing model and property attributes studies

Attributes	Studies
Property size	Wolverton (1997), Tse (2002), Wen et al. (2005), Choy et al. (2007), Pozo (2009), Selim (2008)
Better view	Rodriguez and Sirmans (1994), Benson et al. (1998), Wolverton (1997), Choy et al. (2007)
Balcony	Chau et al. (2004)
Lucky number	Bourassa and Peng (1999), Chau and Ma (1998), Chau et al. (2001),
Age of property	Tse (2002), Choy et al. (2007)
Location	Joslin (2005), Mbachu and Lenono (2005), Pozo (2009), Anim-Odame et al. (2009),
Nearness to transport facilities	Mbachu and Lenono (2005), Choy et al. (2007)
Nearness to shopping centers	Sirpal (1994), Des Rosiers et al. (1996),
Number of bedrooms	Morancho (2003), Ottensmann et al. (2008), Pozo (2009), Canavarro et al. (2010), Selim (2008)
Number of bathrooms	Morancho (2003), Maurer et al. (2004), Ottensmann et al. (2008)
Parking space	Goodman and Thibodeau (1997) Maurer et al. (2004), Wen et al. (2005), Canavarro et al. (2010)
Open space/parks	Bolitzer and Netusil (2000), Irwin (2002), Nicholls and Crompton (2005), Crompton (2005), Voicu and Been (2008)
Place of worship	Do et al. (1994), Carroll et al. (1996), Babawale and Adewunmi (2011)
Airport noise	Levesque (1994), Tomkins et al. (1998), Espey and Lopez (2000)
Landfills/waste site	Bouvier et al. (2000), Seok Lim and Missios (2007), Ready (2010), Owusu et al. (2014)
Power lines	Wolverton and Bottemiller (2003), Sims et al. (2009), Elliott and Han (2013)

An applied review and detailed theoretical development of the HPM approach is presented by Chin and Chau (2002) and Malpezzi (2003), but a meta-analysis of articles that have adopted HPM to measure the marginal contribution of attributes that determine property values was conducted by Sirmans et al. (2005). Table 3.4 shows the summary of HPM studies carried out in some property markets around the world.

The findings of those studies reiterate the fact that different property attributes drive property values in different property markets around the world.

In developing HPM, the aim is usually to model the property market under consideration. However, the essence, at the same time, is to establish the significance and contribution of each independent variable to property values in terms of the effect of the marginal changes in property values. HPM housing studies (Adair et al., 1996b; Tse and Love, 2000; Selim, 2008) have found property attributes to be either positively or negatively significant to property value formation. Chin and Chau (2002) presented a checklist of commonly used property attributes and their expected effect on property values.

Table 3.4: Details of HPM studies in real estate

Authors	Countries	Sample size	Variables used	Summary of findings
Pasha and Butt (1996)	Pakistan	650	A total of 26 variables which consist of property specific attributes and household demographics	Income elasticity of demand for property attributes in Pakistan is relatively low. However, plot size, living space and number of bedroom influence property values in Pakistan
Maurer et al. (2004)	Paris	84,686 (1990:1-1999:12)	Property area, the number of toilets, the number of floors, number of garages, terrace, the number of service rooms, elevator, construction period, garden and occupancy status.	An overview into the real estate cycles of Parisian property market was presented by the identification of specific patterns in historical index sequences, which provides valuable information about property value formation in the property market.
Jim and Chen (2006)	China	652 (2003-2004)	Window orientation, the number of bedrooms, floor area, the number of floors, the number of bathrooms, green space view, distance to new town center, proximity to the woods, traffic noise and water bodies.	Proximity to green space and water bodies were found to influence property values. Whereas, traffic noise and proximity to the woods did not have any impact on property values.
Choy et al. (2007)	Hong Kong	749 (1999:07 – 2000:06)	Ground floor area, age, floor level, garden, sea view, unclear view, nearness to railway station, lucky number floor, unlucky number floor	Almost all the variables significantly influence property. However, lucky floor number is statistically insignificant to property prices in Hong Kong.
Hui et al. (2007)	Hong Kong	3000 (Q3:2000-Q2:2001)	Age, the number of floors, the number of bedrooms and bathrooms, clubhouse, time to CBD, secondary school, sea view, noise level, air quality and greenbelt area.	Apart from distance to CBD and greenbelt area and all other variables are significant to property values.

Langrin (2008)	Jamaica	2,271 (2003:2-2008:3)	Date of sale, postcode, lot size, floor area, year of construction, property type, the number of floors, the number of bedrooms and bathrooms, garage and water tank.	The number of floors, lot size, the number of bathroom, garage and water tank influence property prices. Whereas, the number of the bedroom more than three reduces property values.
Selim (2008)	Turkey	5741 (2004:01 –2004:12)	Forty-six variables which include but not limited to age of the property, the number of rooms, property size, property type and heating system.	The water system, swimming pool, type of property, the number of rooms and property size significantly influence property prices in Turkey.
Cebula (2009)	United States	2,888 (2000-2005)	Twenty-four variables which include a number of bathrooms, fireplaces, number bedrooms, garage, floor area and a pool, amongst others.	Most of the variables are significant including the number of bedrooms and bathrooms, fireplaces, the number of floors, garage car spaces, living space floor area, the presence of a deck, private courtyard, a pool, brick construction, new house, located close to a park and situated on a cul-de-sac.
Canavarro et al. (2010)	Portugal	16,700 (2005-2009)	Eighteen variables which include property type, the number of bedroom and bathroom, air condition, garage, elevator and security, among others.	A different set of variables affects the value of both new and second-hand properties. However, location, area, the number of bathroom and garage are significant to the values of both sets of properties.
Owusu-Ansah (2012)	Ghana	18,652 (2005-2010)	Bedroom, property area, the number of floors, the number of bathrooms, the number of public rooms, garage, fence wall, swimming pool, land registration, year of valuation.	All the variables are significant to property value in Ghana with the exception of property area.

3.4 COMPARISON OF THE PREDICTIVE ACCURACY OF HPM AND ANN

In order to improve the predictions generated from a modeling process, researchers seek to identify and develop techniques with improved predictive accuracy. This has led to some studies comparing the application of HPM and the ANN model in property valuation (McGreal et al., 1998). This has probably been driven by the quest to establish a more reliable and accurate model which is able to produce valuation estimates which are a good proxy for property values. Most of such studies have investigated the predictive accuracy of the widely adopted HPM over the more recent valuation models especially the AI-based techniques. The output produced/yielded by the models under consideration are usually subjected to accuracy measure in order to establish the most accurate model.

There exists a number of model accuracy measures in the literature and they include MAE, RMSE, mean error (ME), mean squared error (MSE), Theil's U, MAPE, r^2 and the adjusted r^2, amongst others. More details about these measures are presented in Chapter 4. The information in Table 3.5 shows the model performance measures adopted in the real estate literature. The analysis reveals that RMSE and MAE are commonly used in comparative studies with a frequency of eight, respectively, out of 18 studies. In addition, r^2 and MAPE were adopted six times, respectively, while others were used either once or twice in the studies reviewed.

Table 3.5: Accuracy measure techniques adopted in ANN and HPM studies

Authors	Forecasting Models	Accuracy measures								
		MSE	ME	RMSE	MAE	MPE	MAPE	Theil's U	R^2	Adj. R^2
Do and Grudnitski (1992)	ANN, MRA and Comparable					X	X			
Tay and Ho (1992)	MRA and ANN					X			X	
Worzala et al. (1995)	MRA, ANN				X					
McCluskey and Borst (1997)	MRA, CSA and ANN									
Rossini (1997)	MRA and ANN				X					
Nguyen and Cripps (2001)	MRA and ANN						X			
Wilson et al. (2002)	ANN			X						
Limsombunchai et al. (2004)	MRA and ANN			X					X	
Pagourtzi et al. (2007)	MRA, ANN, ES and BN						X			
Xie and Hu (2007)	ARIMA, ANN and SVM	X	X							
Guan et al. (2008)	ANN			X	X		X			
Lam et al. (2008)	ANN				X				X	
Peterson and Flanagan (2009)	MRA and ANN			X			X		X	
Selim (2009)	MRA and ANN	X		X	X					
Lin and Mohan (2011)	MRA, ANR and ANN			X	X			X		
Zurada et al. (2011)	MRA, ANN, AR, RBFNN, MBR,			X	X				X	
	SVO-SMO Regr.									
Amri and Tularam (2012)	ANN, HPM and ANFIS									X
McCluskey et al. (2013)	ANN, HPM and GWR			X	X		X		X	X
	Total	**2**	**1**	**8**	**8**	**2**	**6**	**1**	**6**	**2**

Note: CSA - Comparable sales analysis, SVM - Support vector machine, MBR – memory-based reasoning, RBFNN - Radial basis function neural network, AR - additive regression

3.4.1 Comparative Performance of HPM and ANN in Property Valuation

A number of scholars have performed studies in different property markets around the world to establish the superiority of both models in property valuation. The likeness between the ANN technique and other statistical analysis techniques has allowed its comparison with HPM (Brunson et al., 1994). A comprehensive review of comparative studies of the performance of ANN and HPM in property valuation conducted by Mora-Esperanza (2004) shows that on average, ANN produces an error rate of between 5 and10%, while the rate is between 10 and 15% for HPM. It is reasonable to suggest that the ANN technique has proven to be more accurate than the HPM approach in property valuation research.

One of the early efforts to compare the predictive accuracy of ANN and HPM is the study of Do and Grudnitski (1992) who utilized property sales data of California, United States. The study showed that the ANN model produced forecast which was twice better than HPM, in terms of the predictive accuracy of the property values. A further comparison of the novel ANN model with the traditional comparable valuation method produced exceptional accurate results. Do and Grudnitski (1992) posited that the ANN technique has great potential in producing accurate property valuation estimates.

Utilizing 1055 property sales data from the Singapore's property market, Tay and Ho

(1992) examined the predictive performance of ANN and HPM. The same data set was used to develop both models and their outputs were compared to establish the most reliable model. The study found that with the presence or the removal of the outliers, the ANN technique produced more accurate and reliable estimates when compared with HPM.

Thereafter, researchers continued to evaluate the performance of both models. As a result, Worzala et al. (1995) investigated the predictive accuracy of the ANN model and HPM in property valuation by attempting to confirm the veracity of earlier studies, i.e., Borst (1991) and Do and Grudnitski (1992). Three models were constructed in the study; the first utilized the whole 288 sample data, the remaining two were developed using data set similar to the two previous research. This was done in order to allow for justifiable comparison. It was found that ANN produced a slightly different output compared with HPM. However, the authors suggested a note of warning when employing ANN in property valuation, due to much effort not being put into the ANN principles at that time.

Further comments by McGreal et al. (1998) support the position of Worzala et al. (1995) that a cautionary measure should be taken when adopting ANN in property valuation. The position of those authors does not limit the predictive accuracy of the ANN technique because virtually all property valuation techniques require a measure of caution in their application. So advocating for carefulness in ANN technique application is expected.

Recently, studies have been assessing the predictive accuracy of some other modeling techniques in relation to ANN and HPM. Lin and Mohan (2011) assessed the predictive accuracy of ANN, HPM and ANR using 33,342 transaction data of residential properties in Amherst, US. The data was divided into two sets in the ratio of 80:20, which is for the training and testing of the models, respectively. The study found that ANN outperformed HPM and ANR, and concluded that ANN is a good property price prediction tool.

Using a large sample size of about 16,000, Zurada et al. (2011) examined the predictive performance of a total of seven traditional regression and AI-based modeling techniques. These techniques include M5P trees, additive regression, support vector machines using sequential minimal optimization regression (SVM-SMO regression), radial basis function neural network (RBFNN), memory-based reasoning (MBR), HPM and ANN. The AI-based techniques did not produce exceptional forecasts when compared with the nontraditional regression models.

In Australia, Amri and Tularam (2012) conducted a similar assessment by examining

ANN, HPM and FLS predictive ability in property value prediction. The three models were developed using a data set of 7,849 sales data and ten independent variables. The comparative performance shows that the ANN model outperformed the other two techniques. A further analysis which involved the inclusion of social indicators into HPM produced an adjusted r^2 value of 0.42, a value which is still lower than that of the ANN model. In sum, the outstanding predictive accuracy of the ANN technique was proven in relation to HPM and FLS.

Recently, McCluskey et al. (2013) conducted a comparison of the performance of ANN, HPM and GWR, utilizing 2,694 sales data of properties in Northern Ireland. The GWR approach was adopted in the study in order to explore other modeling techniques. The analysis shows that the GWR approach is superior to ANN and HPM in terms of model explanation, but ANN was found to be a reliable technique in terms of predictive accuracy in property valuation.

The results of the comparative studies on both models conducted in different property markets may be mixed, but there is a confirmation of the predictive accuracy of ANN over HPM and some other modeling techniques which have been adopted in the real estate industry. This was confirmed by the review conducted by Abidoye and Chan (2016b) on studies that adopted ANN and HPM in property valuation which reveals that in about 82% of the articles reviewed, the ANN technique outperformed other techniques. In 11% of the cases, the performance of ANN, compared with other valuation approaches, was equal, while only 7% of the reviewed studies reported that the ANN technique did not outperform other valuation techniques. See Table 3.6 for the details of some comparative studies.

Table 3.6: Summary of ANN and HPM comparative studies

Authors	Countries	Sample size/ no. of variables	Summary of findings
Do and Grudnitski (1992)	United States	163/8	ANN better than HPM
Tay and Ho (1992)	Singapore	1055/10	ANN better than HPM
Worzala et al. (1995)	United States	288/8	ANN not totally better than HPM
Lenk et al. (1997)	United States	288/7	ANN did not outperform HPM
Rossini (1997)	Australia	334/12	Superiority of ANN over HPM is inconclusive
Cechin et al. (2000)	Brazil	1600/6	ANN better than HPM
Din et al. (2001)	Switzerland	285/15	ANN is more promising than HPM
Nguyen and Cripps (2001)	United States	3906/6	ANN outperformed HPM
Wong et al. (2002)	Hong Kong	251/12	ANN is an alternative to HPM
Limsombunchai et al. (2004)	New Zealand	200/13	ANN outperformed HPM
Özkan et al. (2007)	Turkey	170/7	ANN outperformed HPM
Pagourtzi et al. (2007)	Greece	141/13	ANN is a better alternative to HPM
Selim (2009)	Turkey	5741/46	ANN is a better alternative to HPM
Peterson and Flanagan (2009)	United States	46467/7	ANN better than HPM
Lai (2011)	Taiwan	2471/9	ANN is a better alternative to HPM
McCluskey et al. (2012)	Northern Ireland	2,694/6	HPM better than ANN
Morano and Tajani (2013)	Italy	85/6	ANN forecast well than HPM
Sampathkumar et al. (2015)	India	204/13	ANN more accurate than HPM

3.5 MODELING THE NIGERIAN REAL ESTATE PROPERTY MARKET

The Nigerian property market has been of interest to domestic real estate scholars and their efforts have been invested in modeling different real estate submarkets in the country (Abidoye and Chan, 2017b). However, more attention has been placed on major urban centers, probably due to the vibrancy of their property markets, especially the Lagos metropolis property market (Oni, 2010).

Of all the advanced valuation modeling techniques, HPM has received more attention by the Nigerian real estate scholars. The first application of the HPM technique in the Nigerian real estate research can be linked to the study of Megbolugbe (1986). Megbolugbe (1986) applied the model to property price analysis in the city of Jos, Nigeria. After this initial application, the next two applications were reported in Megbolugbe (1989) and Megbolugbe (1991). Other early real estate HPM studies in Nigeria include Arimah (1992), Arimah and Adinnu (1995), Arimah (1997) and Akpom (1996).

The HPM approach had not received much attention by Nigerian real estate scholars until 2000 and subsequently, HPM has been adopted in the modeling of different submarkets in Nigeria. For instance, Akure (Bello and Bello, 2008; Olujimi and Bello, 2009), Onitsha (Emo et al., 2013), Ibadan (Adegoke, 2014), Abuja (Oduwole and Eze, 2013), Bauchi (Aliyu et al., 2011; Gambo, 2012) and Lagos (Olorunfemi, 2009; Babawale et al., 2012; Famuyiwa and Babawale, 2014), amongst other submarkets.

The impact of property attributes and externalities on property values has been measured in Nigeria using the HPM approach. Some of those studies examined the impact of closeness to place of worship (Babawale and Adewunmi, 2011; Iroham et al., 2011; Babawale, 2013a), proximity to high voltage power line (Akinjare et al., 2012; Oluwunmi et al., 2012; Abidoye and Oyedeji, 2014), proximity to landfill and waste dump site (Bello and Bello, 2009; Akinjare et al., 2011) and impact of the availability of Jacuzzi bathtub on property value (Otegbulu and Johnson, 2011), amongst others. Abidoye and Chan (2017b) presented a review of the application of the HPM approach in the Nigerian property market.

The AI techniques that have been adopted in the international real estate research domain have not been embraced in Nigeria. Therefore, its origin and application in the Nigerian real estate domain may not be easily articulated, probably due to the scanty literature. Igbinosa (2011) applied the ANN technique to the Nigerian property market domain in prioritizing the property value determinants. The data used for the analysis were collated from the Lagos metropolis and Benin city property markets. Those are two different real estate submarkets which possess totally different market characteristics. Therefore, the results of the study may not be generalized for either of the markets.

Musa et al. (2013) developed an ANN hybrid model which combines the ANN and the case-based reasoning (CBR) technique in property valuation. The study found the ANN-CBR system to be a good valuation technique which produces a more accurate result than the individual ANN or CBR techniques. However, the data used for the study was collected in Benin city and from just one real estate firm. Hence, the model may not be generalized to the whole city and let alone the Lagos metropolis property market, which is the focus of this research.

All these points to the fact that there has not been any deliberate effort to effectively model the Lagos metropolis property market exclusively using ANN or to efficiently assess its predictive accuracy in property valuation in Nigeria's most active and vibrant property market. This gap is to be filled by this study focusing mainly on modeling the Lagos metropolis property market using the ANN technique and comparing its output with that of the HPM approach, so as to establish a model that can be adopted for accurate and reliable property value estimation.

3.6 CHAPTER SUMMARY

This chapter presents the background and the application of both ANN and HPM in property valuation. The HPM approach has been in the real estate research domain since the early 1970s and subsequently, the technique has caught the attention of scholars in virtually every property market around the world. Conversely, the ANN technique came to light in the early 1990s, to address most of the shortcomings of HPM due to its ability to adequately capture nonlinear characteristics in real estate data and its predictive accuracy strength.

The issues that are common in their application were examined and possible ways of overcoming them were reviewed. It was discovered that the shortcomings attributed to the ANN technique in real estate application has been continually addressed by researchers through the development of software programs and this has aided its rapid popularity amongst real estate researchers.

The ANN technique was found to have outperformed the HPM approach in property valuation by producing accurate and reliable estimates in different property markets, though a few studies have reported otherwise. This predictive accuracy has been established in other domains where both approaches have been applied. This finding indicates that the choice of the ANN technique for the case study area is an appropriate attempt.

The Nigerian property market was modeled with HPM first in 1986 and since then it has been widely employed in modeling different submarkets within the country. Whereas, ANN which has received so much attention in the international real estate research has not been embraced in the Nigerian real estate research domain.

Due to the need for real estate professionals to report reliable and accurate valuation estimates, this study will experiment the application of ANN in the Lagos metropolis property market. The next chapter presents the research methodology adopted for this research. A detailed discussion of the various research methods, research approach and data collection methods is presented in the next chapter.

CHAPTER 4 RESEARCH METHODOLOGY

4.1 INTRODUCTION

The previous two chapters have discussed the background of this research and also provided a comprehensive literature review of the issues related to this research topic. Chapter 2 and 3 present the current state of knowledge in the area of property valuation and various valuation methods. Despite the importance of ANN, there remains a paucity of evidence of its application in property values estimation in Nigeria. To address this gap, a comparative analysis of the predictive accuracy of HPM and ANN model was carried out in this research.

To achieve the aim of the present research, six objectives were delineated at the outset. This chapter provides an explanation of the research methods adopted in addressing each of the objectives of this research, as well as the different statistical analyses conducted in the course of the current research. It also describes the research framework for the study, the different types of data and the process of data collection.

4.2 RESEARCH DESIGN

The research design describes a plan which integrates the different parts of a study (e.g. data collection, variables measurement and data analysis) so as to address the research objectives (Sekaran and Bougie, 2013). The essence of developing a research design for a study is to provide a systematic approach to answering the research questions of the study and this could be achieved by adopting quantitative, qualitative or multi-method designs (Saunders et al., 2012). The present research has two main objectives: 1) to identify the current property valuation practice prevalent in the Lagos metropolis, Nigeria, and 2) to develop and compare the predictive accuracy of HPM and ANN model in property valuation in the Lagos metropolis property market.

The nature of this research warrants the collection of data from a group of people and data from a large area, and therefore the quantitative research approach was adopted (Easterbrook et al., 2008). Quantitative data that relates to the property market, property valuation practice and the value of properties within the Lagos metropolis property market were collected from registered real estate firms operating in the Lagos metropolis. A registered real estate firm is a firm that is accredited by both The Nigerian Institution of Estate Surveyors and Valuers (NIESV) and the Estate Surveyors and Valuers Registration Board of Nigeria (ESVARBON). These professional bodies are backed up by the Laws of the Federal Republic of Nigeria (Decree No. 24 of 1975, now CAP III of 1990) to regulate the real estate professionals and real estate practice, respectively, in Nigeria (Abidoye and Chan, 2016c).

In the literature, there are a number of research methods which have been adopted by scholars, i.e. “the general plan of how the researcher will go about answering the research question(s)” (Saunders et al., 2012, p. 680). Alavi and Carlson (1992) identified 18 research strategies and found that experiment, survey research, literature survey, case study, modeling, archival research, grounded theory, action research and ethnography are more popular in built environment related studies (Laryea and Leiringer, 2012). Hence, in order to achieve the aim and objectives of this research as detailed in Chapter 1, survey research and modeling approach were adopted. This is in addition to the literature (review) survey conducted to complement the survey research and the modeling approach.

The survey research approach is suitable for addressing the research objectives of this research because it is appropriate to answer the “what; where; how much and how many questions” (Saunders et al., 2012, p. 176), that pertain to this research topic. The modeling approach was adopted because it can handle the complexity of real-world problems (Bertrand and Fransoo, 2002), with property valuation as an example. However, the literature review was conducted so as to assess the current state of knowledge of the topics under investigation in the present research, and to also evaluate the existing range of literature (Mulrow, 1994).

4.3 RESEARCH FRAMEWORK OF THE STUDY

The first step of this research entailed an assessment of the current property valuation practice in the study area. This was conducted so as to ascertain the extent to which real estate valuers practicing in the study area are aware of and utilize various valuation methods identified in the literature, particularly the advanced approaches that have proven to be reliable and accurate in property valuation. The essence of this investigation was to identify any gap(s), which this research intends to fill.

In the next stage, the property attributes that influence property values in the study area were identified through a literature review and an empirical study. The literature review was conducted in parallel with other property markets around the world, so as to establish any correlation or difference in the set of attributes that homebuyers consider when making real estate decisions in different property markets around the world. The significance of each property attribute was established under each category factors: locational, neighbourhood and structural. The property attributes that are peculiar to the study area were fitted in the ANN model and HPM.

Residential property sales transactions data were retrieved from registered real estate firms operating in the Lagos metropolis property market. The collected data were used to develop HPM and the ANN model reported in the current research. Previous studies have suggested that property valuation models should be market specific (Goodman and Thibodeau, 1998; Famuyiwa and Babawale, 2014). Therefore, HPM and the ANN model were constructed for the Lagos metropolis property market. The models represent constructs which could be adopted for the valuation of residential properties in the study area.

The predictive accuracy of both models was evaluated using measures of accuracy which have been successfully used in previous studies. The accuracy measures were used to compare the predictive value (i.e. outputs from the developed models) and the actual property values in the test data set. This was used to establish the model which can accurately and reliably predict property values in the Lagos metropolis property market. Lastly, the receptiveness of valuers practicing in Nigeria, as regards the adoption of advanced valuation techniques in property valuation was investigated. This was done to establish the willingness to embrace these approaches in property valuation in Nigeria. Figure 4.1 shows the framework of the process followed in conducting this research.

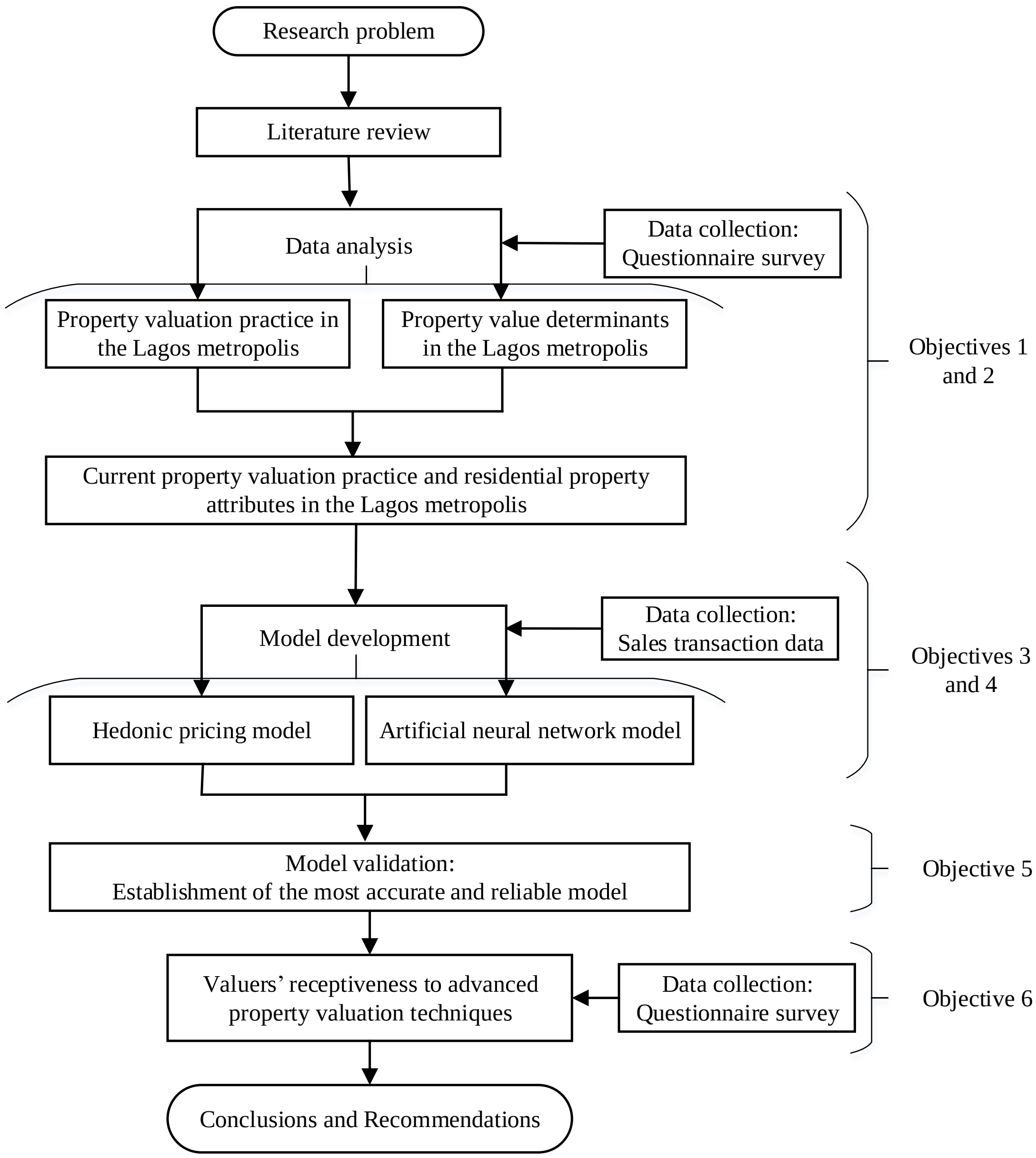

Figure 4.1: Framework of this research

4.4 DATA COLLECTION

4.4.1 Data Collection for the Questionnaire Surveys

The adoption of a questionnaire in survey research is usually utilized to examine the perception or opinion of people about the subject under study and it can be administered face-to-face, by post, over the telephone, by email or over the internet, the latter which is the trending approach (Hoxley, 2008). This approach was adopted in the present research to capture the opinion of real estate valuers on the research questions under investigation.

Before the questionnaire surveys of this research were conducted, the questionnaires were subjected to a thorough review and refining by a group of real estate experts as opined by Gillham (2000). As a result, pilot questionnaires which contained variables and attributes retrieved from the literature were administered to five registered real estate professionals that are experienced in property valuation and have a solid knowledge of the Lagos metropolis property market, as suggested by scholars (Hager and Lord, 1985; Shapiro et al., 2012; Mooya, 2015). The valuers were asked to assess the appropriateness and suitability of the developed questionnaires. The feedback received from those experienced professionals showed that the instrument adequately captured information relevant to the Nigerian context. Hence, the questionnaires were suitable for administration to the target respondents (see Appendix 1 and 3).

The targeted respondents for the questionnaire surveys were professional members of NIESV. The sampled valuers were contacted via their email addresses, which were retrieved from the 2014 edition of the membership directory of NIESV (see Nigerian Institution of Estate Surveyors and Valuers, 2014). Conversely, the survey instruments were administered to the respondents via an online platform - SurveyMonkey (www.SurveyMonkey.com). The collection of data through the use of an online-based platform ensures reliability because it affords a wider coverage of the respondents and, at the same time, gather data which are less susceptible to error (Dix and Anderson, 2000).

In addition to the online questionnaires, Microsoft Word version of the structured questionnaires was designed and attached to the email message which also contained the online link to the SurveyMonkey questionnaires. This Microsoft Word version was purposely designed in order to cater for respondents that may not have access to a stable internet service, and thus allowing them to partake in the online survey. The respondents were invited to fill in the Word version offline and return it to the researcher's email address. This approach is similar to those used in previous studies, for instance, Mooya (2015) and Ameyaw and Chan (2015), amongst others.

4.4.2 Data Collection for Property Value Modeling

The data used for the construction of HPM and the ANN model were residential property sales and purchase transactions concluded in the Lagos metropolis property market. The collected data for this study covered a long time between 2010 and 2016. This is due to the fact that property transactions are not well documented in Nigeria

(Babawale and Ajayi, 2011; Dugeri, 2011). As various property submarkets in a nation are not the same (Fletcher et al., 2000), this necessitates market segmentation in property market analysis research (Dale-Johnson, 1982). Hence, the data of residential properties in affluent areas of the Lagos metropolis (Lagos Island) which include the Lekki Peninsula Scheme 1, Ikoyi, Victoria Island, Victoria Garden City (VGC) and gated estates along the Lekki - Epe Expressway corridor were collected (see Figure 4.2 for the map showing the area under consideration).

Using data retrieved from the whole city of Lagos may produce misleading and unreliable models (see Jenkins, 2000). Moreover, the data was restricted to this particular geographical area, in order to control the variations in household income, resident characteristics and other exogenous factors that could influence property values (Wolverton, 1997). The study area where the data was collected is a neighbourhood that has common characteristics in terms of income, population density, property finishes, access to infrastructure, and so on. The choice of this submarket was due to two reasons: (1) a high number of completed transactions, and (2) the number of registered real estate professionals involved in the market. Hence, there is a high likelihood that sales data would be recorded (Iroham et al., 2014).

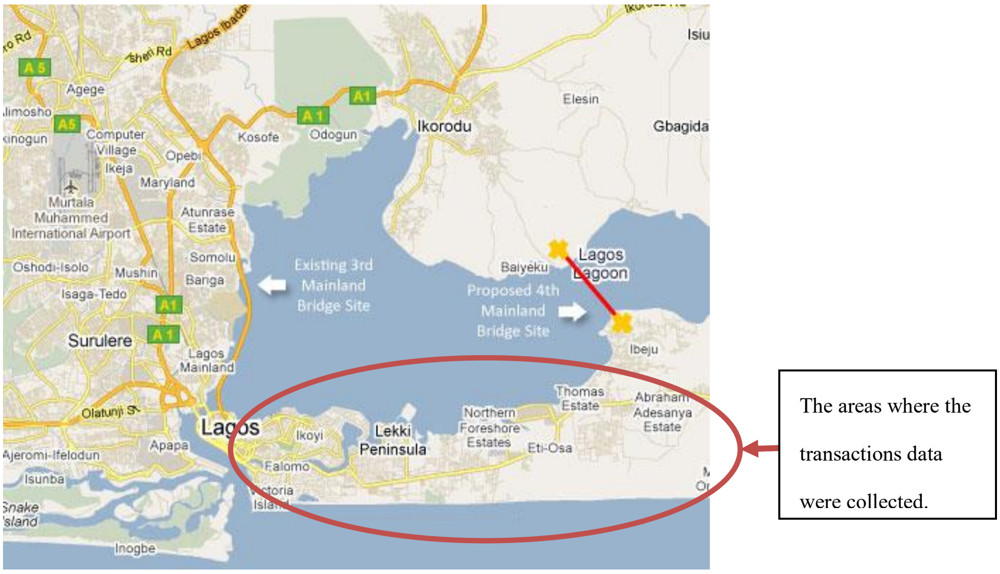

Figure 4.2: Map of Lagos showing the study area for data collection

Source: http://www.lgtnigeria.com/topic_page.php?id=87&page=1

Due to the lack of a property sales databank in the Lagos metropolis, Nigeria (Ajibola, 2010; Adegoke et al., 2013; Oduwole and Eze, 2013), unlike in developed nations such as Singapore, Japan, Hong Kong, and so on (Hofmann, 2003), the researcher and two trained Research Assistants (RA) retrieved the transaction data from registered estate surveying and valuation firms operating in the Lagos metropolis property market.

According to the 2014 edition of the membership directory of NIESV, there are 313 registered real estate firms in the Lagos metropolis. Out of the 313, about 145 are situated in the Lagos Island (the area where the properties sales data collected are situated), while the rest are located in other parts of the metropolis. The 145 Lagos Island firms are initially contacted to check on their willingness to participate in the study. Thereafter, some other firms located outside Lagos Island were contacted as well in order to retrieve as large a number of samples as possible.

Landis (1998) contended that property transactions data collection involves the process of collecting the details of exchanged properties which include the selling price, the selling date, the number of bedrooms, the property size and the number of toilets, amongst other property attributes. Landis (1998) further elaborated that property transactions data may not be readily available because of the confidential nature of property market transactions. This approach to data collection is not uncommon in previous studies. Castle and Joseph (1998), McGreal et al. (1998), Bourassa et al. (2006), Choy et al. (2007) and Owusu-Ansah (2012), amongst others, adopted a similar approach.

The RAs were trained on the data collection process. This was done to ensure that the required data were collected in an appropriate manner from the real estate firms (see Appendix 2 for a sample of the letter of introduction to the firms and the data collection sheet). The first part of the data collection sheet includes information about the name, the address and the contact phone number of the firms under consideration. The main part consists of the list of attributes which influence property values as identified from the literature, with the researchers' judgement and the valuers' opinions on the property attributes which are peculiar to the Lagos metropolis property market.

It should be noted that due to the limitation of a complete property attributes databank in Nigeria, and the importance of the structural property attributes to property value formation (Palmquist, 1984; Wen et al., 2005), the property attributes retrieved from real estate firms are structural attributes. At the end of the data collection period, which lasted for four months, all the collected data were collated and pre-processed. The processing entails the removal of entries with incomplete details. The valid data were eventually used for the development of the HPM and ANN models.

As mentioned earlier, the transaction data which the author collected were those completed between 2010 and 2016. However, the effect of inflation on the prices recorded during the transaction periods may have rendered the data inconsistent. To this end, a price deflator was applied to the retrieved property prices in order to factor in the effect of inflation on the property prices. The Consumer Price Index (CPI) for Nigeria, for the period under consideration, was collected from the Central Bank of Nigeria (CBN) and the National Bureau of Statistics (NBS). More details on the collected data are presented in Chapter 6 and 7.

4.5 RESEARCH METHODS

In order to achieve the objectives of this research as presented in Chapter 1, certain research methods were adopted in accomplishing each of them. Table 4.1 shows the corresponding research method(s) and data analysis techniques used to achieve each objective. It is worth mentioning that this chapter only provides an outline of the methodologies adopted in this research and more details of the research method used in achieving each objective is presented alongside the analysis of each objective in subsequent chapters.

Table 4.1: Research methods adopted for this research

		Research methods			Data analysis			
Research Objectives		Literature review	Questionnaire Survey	Transaction data	MS ranking technique	Hedonic pricing model	Artificial neural network	Model validation
1	To assess the current property valuation practice in the Lagos metropolis	✓	✓		✓			
2	To identify and generate a list of attributes which influence residential property values in the Lagos metropolis property market	✓	✓		✓			
3	To develop a Hedonic pricing model for the Lagos metropolis residential property market	✓		✓		✓		
4	To develop an artificial neural network model for the Lagos metropolis residential property market	✓		✓			✓	
5	To evaluate the predictive accuracy of HPM and ANN models developed for the Lagos metropolis residential properties	✓		✓				✓
6	To assess Nigerian valuers' receptiveness to the application of the AI techniques in property valuation	✓	✓		✓			

4.5.1 Literature Review

This research started with a systematic literature review. This review ensured that the current state of knowledge is established and the gap(s) in the literature are identified (Mayer, 2009). This research method can be said to be the backbone of this research because, in order to accomplish the objectives of this research, references are made to the literature that focuses on the major issues that are related to the research topic. Thus, references are made to previous studies in every part of this thesis in cases where there is a need to justify assertions, actions and to make comparisons (Denscombe, 2014). The comprehensive literature reviewed in this study was presented in Chapters 2 and 3. The adoption of other research methods used in this research to achieve the research objectives is presented in the next section.

Articles reviewed in this study were sourced from online databases and search engines such as Scopus, EBSCOhost, Springer, Science Direct, ProQuest, Taylor & Francis and Google Scholar. These articles include journal papers, books, PhD theses, conference proceedings and online reports published by organizations.

4.6 ADDRESSING THE RESEARCH OBJECTIVES

4.6.1 Addressing Research Objective 1: Questionnaire Survey

The questionnaire used to address objective 1 was designed to have four sections (see

Appendix 1). In the first part, the valuers were asked to provide information about their demographic characteristics in terms of educational qualifications, professional status, years of industry cognitive experience and area of specialization, amongst other information. The second section contained details about the real estate firm, where the respondent is working. In the third section, the various valuation approaches identified from the literature as being applicable in property valuation were presented to the valuers. The professionals were requested to indicate if they are aware or not of both the traditional and the advanced valuation methods. In addition to the response to the awareness of the valuation methods, the valuers were also asked to signify how often they used those sets of valuation approaches in practice.

Descriptive statistics in terms of the frequency distribution and chi-square test were used for the analysis of the collected data for this purpose. The appropriate reliability and statistical significance tests were conducted and their details are presented in Section 4.7. The findings of objective 1 are reported in Chapter 5.

4.6.2 Addressing Research Objective 2: Questionnaire Survey

For objective 2, the questionnaire instrument was structured to collect information from real estate professionals practicing in the study area on their opinions on the determinants of residential property values in the Lagos metropolis property market.

A single questionnaire was designed to collect data used for the achievement of objectives 1 and 2, indicating that the respondents' information and details of the valuers' firm provided in section one and two, respectively, in the questionnaire, represent the characteristics of the valuers and firms that provided information for objective 2. However, the various attributes that influence residential property values in the case study area that were identified from the literature, were presented to the valuers in the fourth section of the questionnaire (see Appendix 1).

Adopting a five-point Likert scale, the respondents were asked to rank the importance of each property attribute in property value formation. The scale of 1 to 5, representing highly insignificant to highly significant, was adopted. That is, a valuer is expected to tick 1 if the subject property attribute's contribution is highly insignificant to property values, tick 3 if the effect of the attribute on property value is neutral, and select 5 if the impact of the attribute is highly significant to property value formation. The reliability of the collected data was estimated using the Cronbach's alpha, and the mean score (MS) ranking technique was adopted for the analysis of the collected data. Further details on these analysis techniques are presented in Section 4.7, while the results of this survey are documented in Chapter 5.

4.6.3 Addressing Research Objective 3: Hedonic Pricing Modeling

The HPM analysis reveals the association between independent variables and the dependent variable in terms of the contributory power of each independent variable to the formation of the dependent variable (Wen et al., 2005). The HPM approach was used to achieve objective 3. The necessary tests were conducted on the collected data before been feed into the regression model. The variables' coefficients generated from the analysis were used to estimate the property values of the holdout samples. The accuracy of the predicted property values was evaluated by comparing it with the actual property values of the holdout samples. This was done to establish the predictive accuracy of the HPM approach in property valuation. A detailed explanation of the application of HPM is described in Chapter 3, while the detailed reporting of its actual adoption in this research is presented in Chapter 6.

4.6.4 Addressing Research Objective 4: Artificial Neural Network Modeling

The ANN model is a novel analysis technique which is gaining rapid popularity among researchers (Adhikari and Agrawal, 2013), including real estate researchers and professionals. An ANN model was developed in order to achieve research objective 4. Data of sales and purchases transactions completed in the Lagos metropolis property market were fitted into the ANN model. The validity of the trained model was tested with the holdout sample so as to establish the predictive accuracy of the ANN technique in property valuation. The detailed process of the application of the ANN model is presented in Chapter 3, while the actual application of ANN in this research is presented in Chapter 7.

4.6.5 Addressing Research Objective 5: Validation of the Developed Models

In order to establish the predictive accuracy of HPM and the ANN model developed in this research, the predictive accuracy of both models was measured using r^2, MAPE, MAE and RMSE. Model validation is an essential part of model development because the generalization of an inaccurate and non-validated model could lead to inaccurate estimates (Nordstrom, 2012). Each of the models was validated with the holdout sample data and the predicted values were compared with the actual property values so as to establish the model which predicts property values accurately (Wen, 2014). In addition to the accuracy measures adopted for model validation, the percentage of predicted property values that had prediction error rates that fell within the acceptable industry standards was established. This was done to establish the predictive accuracy of the ANN technique in comparison with the HPM approach in predicting property values in the Lagos metropolis property market. A more detailed description of predictive accuracy measures adopted is presented in Section 4.7, while the model validation analysis is presented in Chapter 8.

4.6.6 Addressing Research Objective 6: Questionnaire Survey

There is a relationship between research and the practice of any profession (Hemsley-Brown and Sharp, 2003). Therefore, the readiness of the Nigerian valuers to adopt the AI valuation techniques in property valuation was assessed. A questionnaire survey was conducted on the Nigerian valuers through an online platform (see Appendix 3 for a sample of the questionnaire). The questionnaire was divided into five parts. The first section of the questionnaire is about the valuers' demographic information. Section two included questions which center on their knowledge of AI techniques, while the third part contained questions on the reason for the low awareness and application of the techniques. The fourth section contained factors that could enhance the adoption of the AI techniques, and the last section center on the benefits and prospects of adopting the AI valuation techniques. The response of the respondents was received on a five-point Likert scale with options that range from 1 to 5, representing from 'strongly dissatisfied' to 'strongly satisfied', respectively. The reliability of the collected data was estimated and the MS ranking technique and chi-square were adopted for the analysis of the collected data. The results of this survey are presented in Chapter 9.

4.7 MODEL ACCURACY PERFORMANCE MEASUREMENT

Model performance measures are approaches used to evaluate the predictive accuracy of a model. The metrics found in the literature include MAE, RMSE, ME, MAPE, r^2, adjusted r^2, and so on (Hyndman and Koehler, 2006; McCluskey et al., 2013). However, there is no generally acceptable indicator, but the RMSE has been widely adopted in the literature (Wilson et al., 2002; Zurada et al., 2011; McCluskey et al., 2013), and the closer a RMSE and MAE values to 0, the better the model (Lin and Mohan, 2011). Contrarily, Makridakis et al. (1998) argued that MAPE is widely used in the literature. The MAPE measure quantifies the error of prediction in terms of percentage (Zurada et al., 2011).

The r^2 is usually adopted to interpret the relationship between the independent variable(s) and the dependent variable (Sincich, 1996b). Therefore, the adoption of other measures of accuracy which can establish estimation errors is necessary. In this study r^2, MAPE, MAE and RMSE accuracy measures were adopted, based on their suitability for the topic under investigation based on the existing literature (see Table 3.5 for the commonly used accuracy measures in the literature). The expressions for the calculation of the accuracy measures found in the literature (Limsombunchai et al., 2004; Lin and Mohan, 2011; Zurada et al., 2011) are presented in Equations 4.1 to 4.7.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\mathrm{P_i} - \hat{\mathrm{P}}_\mathrm{i}\right)^2} \tag{4.1}$$

$$r^2 = 1 - \frac{\sum_{i=1}^{n}\left(P_i - \hat{P}_i\right)^2}{\sum_{i=1}^{n}\left(P_i - \overline{P}\right)^2} \tag{4.2}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}\left(P_i - \hat{P}_i\right) \tag{4.3}$$

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(P_i - \hat{P}_i\right)^2 \tag{4.4}$$

$$\text{ME} = \max_{i \in n}\left(P_i - \hat{P}_i\right) \tag{4.5}$$

$$\text{MAPE} = \frac{\sum_{i=1}^{n}\left(\frac{P_i - \hat{P}_i}{\hat{P}_i}\right)}{n} \tag{4.6}$$

$$\text{Theil's U} = \sqrt{\frac{\sum_t\left(P_i - \hat{P}_i\right)^2}{\sum_i\left(P_i\right)^2}} \tag{4.7}$$

Where P_i is the actual property value, $\hat{P}_i$ is estimated/predicted property value from the model, $\overline{P}$ is the sample mean of the property values, and n is the number of observations.

4.8 DESCRIPTIVE STATISTICS AND OTHER ANALYSIS TOOLS ADOPTED

Some descriptive statistics and analysis tools were employed in addressing the research objectives of this study. In analyzing the collected data and making inferential conclusions from the questionnaire surveys, the statistical analysis tools employed are namely, Cronbach's alpha, MS, the coefficient of variation (COV) and chi-square. The SPSS software version 20.0 (SPSS Inc., Chicago, USA) was used in performing these statistical analyses. The SPSS software was also used for the development of HPM using MRA. Microsoft Excel (Microsoft, USA) was utilized for data coding before being entered into the SPSS software for analysis and for some calculations.

For the development of the ANN model, R programming software (R CoreTeam, 2016) and the Rminer package (Cortez, 2010) were adopted in this research. R programming software is freely available for download from http://www.r-project.org/. "R is more flexible and extensible by design, thus integration of statistics, programming and graphics are more natural" when compared with other software, for instance, Waikato Environment for Knowledge Analysis (WEKA) (Cortez, 2010, p. 572). This software has been adopted in previous ANN studies and has produced excellent results; see, for instance, Cortez et al. (2009) (food processing), Lisboa and Taktak (2006) (medicine) and Hu et al. (2005) (civil engineering), among other studies.

4.8.1 Cronbach's Alpha

In establishing the reliability of the questionnaire surveys conducted in this research, Cronbach's alpha was estimated. This test measures the extent of the internal consistency amongst all the respondents of a survey (Tavakol and Dennick, 2011). Cronbach's alpha value ranges between 0 and 1; however, Nunnally and Bernstein (1978) posited that a value between 0.50 and 0.60 signifies a reliable consistency amongst the subjects, while Hair et al. (2010) put the value at 0.70 and above. According to Reinhardt (1996), the Cronbach's alpha value can be computed using the mathematical expression presented in Equation 4.8.

$$\alpha = \frac{k}{(k-1)}\left[1-\left(\frac{\sum_{k}^{\sigma^2}}{\sigma_T^2}\right)\right] \tag{4.8}$$

Where K is the number of items in the test, $\sum_{k}^{\sigma^2}$ is the sum of the k item score variances and σ_T^2 is the variance of the total test scores.

4.8.2 Mean Score Ranking

The MS ranking technique is usually used to evaluate the importance and significance of variables under consideration in a survey research and it is widely employed in the literature (Adair et al., 1996a). In this research, MS was adopted in objectives 1, 2 and 6 to evaluate the valuers' responses to the knowledge and application of valuation methods, evaluate the significance of each property attribute which contributes to property value formation and to evaluate the respondents' receptiveness to the AI valuation techniques. The MS ranking is estimated using the formula in Equation 4.9 as obtainable in Ameyaw and Chan (2015).

$$MS = \frac{5n_5 + 4n_4 + 3n_3 + 2n_2 + 1n_1}{N} \tag{4.9}$$

Where *n* is the score given by valuers based on a five-point scale of 1 to 5 and *N* is the number of valuers that rated a variable.

As such, a variable with MS of 4.00 and above is adjudged as highly significant, those with MS of values ranging between 3.50 and 3.99 as significant, variables with MS of 3.00 to 3.49 as slightly significant, while variables with less than 3.00 were regarded as insignificant.

4.8.3 Coefficient of Variation

In addition to the MS ranking, another analysis conducted is COV. The COV analysis is the measure of the standard deviation as a percentage of the mean (Sørensen, 2002). The COV of each property attribute was estimated in this research to express the relative variability of valuers' responses of each property attribute on property value (Elhag and Boussabaine, 1998). According to Elhag et al. (2005), a low COV value signifies a relatively high agreement amongst the respondents and vice-versa. The COV can be computed using the formula in Equation 4.10.

$$\text{COV} = \frac{S}{\overline{X}} \times 100\% \qquad (4.10)$$

Where S is the standard deviation and $\overline{X}$ represents the sample mean.

4.8.4 Chi-Square

In analyzing the property valuation practice in the study area (objective 1), and the willingness of the Nigerian valuers to adopt the AI techniques, the chi-square (χ^2) test was conducted. This was performed in order to establish the statistical relationship and independence amongst the research variables (Verma, 2013). That is, the significant statistical relationship between valuers' demographic characteristics and their awareness and the questions under investigation. According to Verma (2013), χ^2 can be computed using the mathematical expression presented in Equation 4.11.

$$\chi^2 = \sum_{i=1}^{n} \frac{\left(f_o - f_e\right)^2}{f_e} \tag{4.11}$$

Where f_o and f_e are the observed and expected frequencies for each of the possible outcome.

4.8.5 Variance Inflation Factor

The VIF test was conducted to identify correlated property attributes used in developing a robust HPM in achieving objective 3. A VIF value is usually greater or equal to 1, and this connotes little or no presence of multicollinearity among the variables, whereas a VIF value of above 10 indicates a high level of multicollinearity (Berenson et al., 2012). According to Elhag (2002), VIF can be estimated using the expression in Equation 4.12.

$$VIF = \frac{1}{1 - R_i^2} \tag{4.12}$$

Where R_i^2 is the coefficient of determination of the regression of i^{th} independent variable and all other independent variables.

4.9 CHAPTER SUMMARY

This chapter provides a discussion of the philosophical assumptions that underlie the current research. Based on the description of various research approaches, this chapter shows the reasons for the suitability of literature review, survey and modeling for this research. The literature review (which is presented in Chapters 2 and 3) provides information on the current state of knowledge related to the research topic. While the other research methods were employed in achieving objectives 1 to 6. The research methods and data analysis tools are explained and discussed. Predictive accuracy evaluation of HPM and the ANN model was carried out so as to address objective 5.

Due to the lack of a real estate transactions databank in Nigeria, a detailed description of the data collection process is provided. The various statistical analyses conducted in this research are also discussed and are used mainly in this research in analyzing the data collected for the questionnaire surveys. This chapter shows that this research is built on robust research methods and methodology. Based on these, the evidence provided and discussed in the subsequent chapters of the thesis are valid.

CHAPTER 5 DECIPHERING THE LAGOS METROPOLIS PROPERTY VALUATION PRACTICE[5] AND PROPERTY VALUE DETERMINANTS[6]

5.1 INTRODUCTION

The previous chapter has presented the research methodology adopted in this research. It describes the various research methods adopted for the present research, the analytical framework of this research, the research design and the descriptive statistical analysis performed. It also describes the process of data collection and how each of the research objectives was achieved. This chapter presents the findings of research objectives 1 and 2 and those of research objectives 3 -6 will be discussed in Chapters 6 to 9. These two objectives provide an overview of the Lagos metropolis property market in terms of the prevalent property valuation practice and the determinants of residential property values.

5.2 DATA COLLECTION AND ANALYSIS METHODS

5.2.1 Data Collection

In the literature, it has been pointed out that quantitative research methods are adequate for addressing problems which involve a large population and a widespread of

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[5] This chapter has been published in **Abidoye, R. B.** and Chan, A. P. C. (2016). A survey of property valuation approaches in Nigeria. *Property Management,* 34 (5,) 364-382.

[6] This chapter has been published in **Abidoye, R. B.** and Chan, A. P. C. (2016). Critical determinants of residential property value: Professionals' perspective. *Journal of Facilities Management,* 14 (3), 283-300.

participants over a geographical area (Easterbrook et al., 2008). In addition, those methods ensure that comparative data analysis and generalization of results could be inferred from research findings (Phua, 2013). Therefore, this study adopted quantitative research methods to collect and analyse data from valuers practicing in the Lagos metropolis.

The data was collected with the use of an online-based questionnaire. Mooya (2015) adopted the same research method to investigate the real estate education and professional practice in South Africa. The questions in the questionnaire were structured into four parts. The first part was designed to obtain demographic information about the professionals, while the second part was about the information of valuers' firm. The third part presented various property valuation methods that have been established in the literature (see, for instance, Pagourtzi et al., 2003; Lorenz and Lützkendorf, 2008; Yacim and Boshoff, 2014), and the respondents were instructed to indicate their level of awareness of those methods. This third section also contained questions designed to capture how often the professionals employ those methods in practice, that is, they were asked to indicate if they use them always, regularly, occasionally, or not at all. This was aimed at achieving research objective 1 of this research. The content of the fourth section aimed at achieving research objective 2.

The questions in the fourth section were designed based on a comprehensive list of residential property value determinants in Lagos generated from previous studies conducted in the study area. Those research articles were sourced from various online databases and search engines. In the light of the findings of the reviewed studies, a total of 20 attributes were identified as attributes that influence residential property values in the Lagos metropolis property market. The respondents were asked to rate the level of significance of the identified attributes based on a five-point Likert scale, with options ranging from 1 to 5, where 1 signifies highly insignificant, 2 - insignificant, 3 - indifferent, 4 - significant and 5 - highly significant. The respondents of this study were professional members of NIESV.

The 2014 membership directory of NIESV (Nigerian Institution of Estate Surveyors and Valuers, 2014) shows that 548 valuers are domiciled in the Lagos metropolis. However, a total 350 of those valuers have their email addresses documented in the directory. Eventually, the questionnaire was sent to the email addresses of 150 stratified randomly sampled valuers practicing in the Lagos metropolis property market. A professional valuer is an individual that has attained the prescribed minimum educational qualification, cognitive professional experience and expertise as set by NIESV and ESVARBON.

The sample size was carefully selected by considering the sample size obtainable in previous studies. For example, 50 professionals were sampled by Finlay and Tyler (1991), Kennedy (1998) surveyed 100 professionals, Bello and Bello (2009) elicited information from 107 experts, while Ibiyemi and Tella (2013) examined 110 valuers. The respondents were expected to respond to the survey within three months, with a reminder sent to them at the end of the second month.

At the end of the cut-off date, a total of 60 responses were received, representing 40% response rate, out of which five of the responses were incomplete. In sum, a total of 55 responses were valid for analysis. This response rate exceeds the acceptable margin of 30% as posited by Akintoye and Fitzgerald (2000). It is assumed that the busy nature of the study area may have been responsible for the average response rate. The situation in the Lagos metropolis is that most valuers spend much of their time on the road due to the jostle and bustle in the megacity.

The SPSS software version 20.0 was employed in the data analysis and the data were presented using descriptive statistics in terms of percentiles. This approach was also adopted in Boyd (1995), Waziri (2013) and Mooya (2015). In addition, the chi-square test was conducted in order to prove the statistical relationship between the research variables, namely the relationship between valuers' level of education, years of experience and their awareness of these valuation methods.

5.2.2 Reliability Test

When measuring the internal consistency of the data used for this study, the Cronbach's alpha test was performed to establish the reliability and internal consistency of the collected data. The purview of the Cronbach's alpha value lies between 0 and 1. Conversely, a Cronbach's alpha value of above 0.70 depicts a valid reliability (Hair et al., 2010). For research objective 1, the Cronbach's alpha value of 0.74 was achieved. For research objective 2, a Cronbach's alpha value of 0.843 was recorded. These values are above the acceptable threshold of 0.70, which shows that there is internal consistency amongst the respondents. This means that from the collected data, valid conclusions can be made.

Regarding the Cronbach's alpha of the collected data for objective 2, the information in Table 5.1 shows the Cronbach's alpha when each variable is deleted. According to Oyedele (2013), the Cronbach's alpha if an item is deleted measures the significance of each variable to the overall Cronbach's alpha. This indicates that the value of a variable which is equal to or less than the overall Cronbach's alpha value (0.843) suggests a significant contribution, whereas a value higher than the overall Cronbach's alpha value signifies insignificant contribution. Following this rule, it was revealed that all the attributes have values less than 0.843, and hence they were all retained in the analysis.

Table 5.1: Reliability analysis of the variables

Overall Cronbach's alpha reliability = 0.843	
Property attributes	Cronbach's alpha if item deleted
Locational attributes	
Location	0.838
Accessibility to place of work	0.822
Accessibility to CBD	0.828
Accessibility to public transport facility	0.838
Proximity to highway	0.835
Accessibility to School	0.840
Accessibility to shopping mall	0.832
Neighbourhood attributes	
Neighbourhood characteristics	0.836
Availability of neighbourhood security	0.831
Availability of electricity	0.829
Availability of pipe borne water supply	0.827
Availability of waste disposal system	0.833
Structural attributes	
State of repair of the property	0.841
Size of property	0.839
Age of the property	0.837
Numbers of bedrooms	0.838
Number of bathrooms/toilets	0.839
Building characteristics	0.824
Availability of security fence	0.835
Size of bedrooms	0.822

5.2.3 The Study Area

The Lagos metropolis property market was chosen as the study area for this research. This choice stems from the fact that the Lagos metropolis property market is the most vibrant and has highest average property value in Nigeria (Dugeri, 2011). This translates into the high sophistication of the players and stakeholders in the property market (Oni, 2010). The United Nations has adjudged Lagos as a megacity, the most populous city in West Africa, and projected that the city could be the third largest in the world after Tokyo and Bombay (Lagos State Government, 2015).

About 95% of commercial banks and 90% of insurance companies operating in Nigeria have their head offices situated in the Lagos metropolis and also, most multinational companies in the Nigeria operate in the Lagos metropolis (Babawale and Oyalowo, 2011; Central Bank of Nigeria, 2015). This class of real estate stakeholders constitutes the biggest proportion of valuation report end-users (Gilbertson and Preston, 2005). This implies that the findings of this research would be beneficial to all the real estate stakeholders in Nigeria and beyond.

5.2.4 The Valuers' Profile

The profile of the respondents in a survey research determines the reliability of the information elicited from the survey. The profile of the respondents for this study is presented in Table 5.2. The lowest academic qualification required to become a member of NIESV is a high school degree, although this membership route is very unpopular, because of the lengthy membership route. Since anyone who aspires to become a professional in a field would acquire a higher education, it is expected that none of the professionals possesses a high school degree as the highest educational qualification. About 32.73% of the respondents possess Higher National Diploma which is the minimum higher educational qualification required to become a professional member of NIESV. A total of 21.82% of the professionals have acquired a Bachelor of Science degree, while about half (45.45%) of the respondents have acquired a Postgraduate degree and Masters of Science degree, which implies that the professionals are developing themselves academically. None of the valuers possesses a PhD degree, probably because of the general notion that a PhD degree is only necessary for individuals that want to build an academic or research career.

In terms of years of professional experience which suggests good knowledge and understanding of the property market, a total of 61.81% of the professionals have been practicing in the industry for between 6 and15 years. Also, 32.73% of the respondents can be said to be new in the real estate practice, because they possess less than five years of real estate industry experience. The remaining 5.46% possess over 15 years of experience. Since the majority of the professionals have between 6 and 15 years of working experience, it may be reasonable to assume that most of them are of the middle-aged class, and thus are expected to be well informed of the current developments in the real estate profession globally, because of the likelihood of an affinity for the trending information technology.

Table 5.2: Estate surveyors and valuers' profile

Variables	Frequency (n)	Percentage (%)
Educational qualifications		
High school	0	0.00
Associate degree/Higher National Diploma	18	32.73
Bachelor of Science	12	21.82
Postgraduate/Masters of Science	25	45.45
PhD	0	0.00
Total	**55**	**100.00**
Years of industry experience		
0-5 years	18	32.73
6-10 years	24	43.63
11-15 years	10	18.18
16-20 years	2	3.64
Above 20 years	1	1.82
Total	**55**	**100.00**
Area of specialization		
Valuation	14	25.45
Property management	15	27.27
Agency	3	5.46
Property investment consulting	2	3.64
General practice	21	38.18
Total	**55**	**100.00**

The area of specialization of the valuers indicates their specialization at the time of this survey. It is worth to note that it is common for real estate professionals to switch from one area of the profession to another, or even be involved in general practice, making them experienced in all the areas. As such, Mooya (2015) posited that the experience real estate professionals gather from general practice, property management, agency, investment analysis, valuation, and so on, is essential and helpful to the valuation practice. About 38.18% of the respondents that specialize in the general practice area of the profession indicate that those proportions are conversant with property valuation practice. Their knowledge of the Lagos metropolis property market is noteworthy for this study, coupled with 25.45% of the professionals that major in property valuation. However, 27.27% of the valuers are into property management, while the remaining three and two valuers specialize in real estate agency and property investment consulting, respectively.

5.3 THE LAGOS METROPOLIS PROPERTY VALUATION PRACTICE

The research findings and the discussions of the outcomes of addressing research objective 1, which aimed at assessing the property valuation practice in the Lagos metropolis in terms of the level of awareness and usage of valuation methods by valuers, are presented in subsequent subsections.

5.3.1 Level of Awareness of the Valuation Methods

The valuers' level of awareness of the various valuation methods which forms part of the fulcrum of this study was examined and presented in Table 5.3. The response shows that the professionals are very much aware of the traditional valuation methods. This is deduced from the information that reveals that all the respondents (100%) are aware of investment, comparable and cost valuation methods, while 98.18% and 94.54% of the valuers are aware of the profit and the residual methods, respectively. This conforms to the findings of Bello and Bello (2009) and also corroborates the position of some researchers (Bagnoli and Smith, 1998; McGreal et al., 1998; Yacim and Boshoff, 2014) that the traditional methods of valuation are simple in approach, because they are dependent on the availability of market information and the valuers' subjective judgement, and thus are generally common amongst real estate professionals.

Table 5.3: Awareness of traditional valuation methods

Valuation methods	Aware		Not aware	
	Frequency (n)	Percentage (%)	Frequency (n)	Percentage (%)
Investment method	55	100.00	0	0.00
Comparable method	55	100.00	0	0.00
Cost method	55	100.00	0	0.00
Profit method	54	98.18	1	1.82
Residual method	52	94.54	3	5.46

The information in Table 5.4 shows the relationship between the valuers' educational level, their level of experience and their awareness of the valuation methods. For the traditional methods, the valuers' level of educational qualifications has a significant statistical relationship with the investment, the comparable and the cost methods of valuation with a ρ-value of 0.000 in the three instances. This indicates that the awareness of these three property valuation methods could be attributed to valuers' educational qualifications. For the profit and residual methods, their ρ-values of 0.161

and 0.867, respectively, which are greater than 0.05 depicts a non-statistical significant relationship between valuers' level of education and awareness of both valuation methods.

In the same vein, the valuers' awareness of the investment, the comparable and the cost approaches could be attributed to their years of professional experience. This is because, for the three methods, a ρ-value of 0.000 was recorded for each. However, valuers' level of professional experience does not have a statistically significant relationship with their level of awareness of profit and residual methods, as in the case of educational qualifications. This suggests that the more a graduate valuer continues to acquire cognitive professional experience, the more s/he acquires more skills in the application of the three most widely adopted traditional methods of valuation.

Table 5.4: Chi-square test for awareness of traditional methods and valuers' education and experience

Valuation methods	χ^2 value	Degree of freedom (df)	ρ -value
Educational level			
Investment method	0.000[a]	4	0.000[a]
Comparable method	0.000[a]	4	0.000[a]
Cost method	0.000[a]	4	0.000[a]
Profit method	3.650	4	0.161
Residual method	0.296	4	0.867
Level of professional experience			
Investment method	0.000[a]	4	0.000[a]
Comparable method	0.000[a]	4	0.000[a]
Cost method	0.000[a]	4	0.000[a]
Profit method	1.316	4	0.859
Residual method	5.391	4	0.249

Note: [a] – No statistics are computed because the method is a constant.

On the other hand, the professionals are not generally aware of any of the advanced valuation methods as shown in Table 5.5. There is some level of awareness of the HPM method (32.73%) in this category, and this may be attributed to the fact that HPM is popular and widely used in the housing market research as posited by researchers (Adair et al., 1996b; Bender et al., 2000; Tse and Love, 2000; Kauko, 2003). Comparatively, the moderate level of awareness indicted for HPM by the valuers could be substantiated by the adoption of the HPM approach in the property market research in Nigeria by researchers (see Aluko, 2011; Babawale et al., 2012; Famuyiwa and Babawale, 2014, amongst others).

Table 5.5: Awareness of advanced valuation methods

Valuation methods	Aware		Not aware	
	Frequency (n)	Percentage (%)	Frequency (n)	Percentage (%)
Hedonic pricing method	18	32.73	37	67.27
Spatial analysis method	6	10.91	49	89.09
Autoregressive integrated moving average	5	9.09	50	90.91
Artificial neural networks	4	7.27	51	92.73
Fuzzy logic system	2	3.64	53	96.36

For the other advanced methods, the level of awareness has not improved considerably after the study of Bello and Bello (2009), despite the findings of Babawale and Oyalowo (2011) where 100%, 90.70% and 80.40% of the valuers sampled indicated a willingness to acquire more training on ANN, ARIMA and FLS, respectively. This enthusiasm has not materialized to date, as 92.73%, 90.91% and 96.36% of the professionals surveyed in the present study are not aware of these aforementioned methods, respectively. In addition, 89.09% are not aware of the spatial analysis method. These results suggest that the property valuation practice in the metropolis has not transformed over time. It seems the professionals have not developed themselves by acquiring the know-how to apply the advanced property valuation techniques.

The information in Table 5.6 shows that the valuers' educational achievements do not have a statistically significant relationship with their awareness of all the advanced valuation approaches. This is because the ρ-values for each of the methods are greater than 0.05. Also, their levels of professional experience do not translate into the awareness of the advanced valuation approaches, with all the methods having a ρ-value of greater than 0.05. This depicts that with most of the valuers possessing years of experience of between six and 15 years, they have not become familiar with the advanced valuation methods. It is, therefore, reasonable to suggest that the professionals are not updated in terms of the paradigm shift going on in the property valuation domain around the world.

Table 5.6: Chi-square test for awareness of advanced methods and valuers' education and experience

Valuation methods	χ^2 value	Degree of freedom (df)	ρ -value
Educational Level			
Hedonic pricing method	1.505	4	0.471
Spatial analysis method	3.680	4	0.159
Autoregressive integrated moving average	1.444	4	0.486
Artificial neural network	3.694	4	0.158
Fuzzy logic system	0.651	4	0.722
Level of professional experience			
Hedonic pricing method	4.419	4	0.352
Spatial analysis method	1.811	4	0.770
Autoregressive integrated moving average	1.198	4	0.878
Artificial neural networks	2.071	4	0.723
Fuzzy logic system	1.967	4	0.742

Note: [a] – No statistics are computed because the method is a constant.

5.3.2 Level of Usage of the Valuation Methods

It may be misleading to conclude that the level of awareness of these valuation methods would automatically translate into their level of usage. Moreover, the level of usage would reveal the most adopted approach in practice. Thus, the frequency of use of the valuation methods is presented in this section.

The response of the professionals shown in Table 5.7 depicts that many (63.64%) of the valuers always employ the comparable method in property valuation practice. This conforms to the case in other property markets around the world, where the comparable method is the most widely applied method amongst the traditional approaches (Pagourtzi et al., 2003; Yacim and Boshoff, 2014). The investment and the cost methods are used regularly as 54.55% of the valuers indicated this for both methods. This agrees with the findings of Babawale (2012) that valuers widely adopt these three methods in practice. The profit and residual methods are the least adopted, because 60% and 70.90%, respectively, employ these approaches occasionally. This finding is similar to that of Bello and Bello (2009). This is probably because the purpose for which most valuation reports are requested and the types of properties being valued in the metropolis cannot be appraised with these valuation methods.

The property valuation method to be adopted for a valuation exercise is largely dependent on the property type (Yacim and Boshoff, 2014), consequently, the less adoption of these two methods is in line with what is obtainable in South Africa according to Mooya (2015). This similarity may be attributed to the fact that both countries are on the same continent - Africa.

Table 5.7: Adoption of traditional valuation methods

Valuation methods	Always		Regularly		Occasionally		Not at all	
	n	%	n	%	n	%	n	%
Investment method	17	30.90	30	54.55	8	14.55	0	0.00
Comparable method	35	63.64	19	34.54	1	1.82	0	0.00
Cost method	14	25.45	30	54.55	11	20.00	0	0.00
Profit method	6	10.91	11	20.00	33	60.00	5	9.09
Residual method	3	5.46	10	18.18	39	70.90	3	5.46

On the use of the advanced methods, it is obvious that the professionals do not always adopt any of the advanced methods in practice, as shown in Table 5.8. A minuscule proportion of the professionals do use these approaches regularly and occasionally, while a larger percentage (more than 90% in almost all the cases) do not use these approaches at all. In this category, it is only the HPM approach that is used occasionally and regularly by 18.20 and 7.30% valuers, respectively. The low adoption of these advanced methods may be ascribed to the fact that most of the professionals are not aware of these advanced methods and even the few who are aware lack the proficiency to apply them in practice.

This seems to be the true picture of the professionals, as the findings of Waziri (2013) in a related profession, the construction industry in Nigeria, indicated that construction industry experts do not employ the AI techniques in cost estimation. Mooya (2015) reported the same for real estate valuers in South Africa. It appears that built environment professionals in this continental region are not embracing the advanced approaches in practice.

Table 5.8: Adoption of advanced valuation methods

Valuation methods	Always		Regularly		Occasionally		Not at all	
	n	%	n	%	n	%	n	%
Hedonic pricing method	0	0.00	4	7.27	10	18.18	41	74.55
Spatial analysis method	0	0.00	2	3.64	1	1.82	52	94.54
Autoregressive integrated moving average	0	0.00	1	1.82	2	3.64	52	94.54
Artificial neural networks	0	0.00	2	3.64	0	0.00	53	96.36
Fuzzy logic system	0	0.00	2	3.64	0	0.00	53	96.36

It can be summarised that after the studies of Bello and Bello (2009) and Babawale and Oyalowo (2011), there has not been a substantial transformation in the property valuation practice in Nigeria when compared with what is obtainable in other parts of the world. The valuers still adopt traditional valuation methods in practice. It seems the professionals are not being educated about these methods because with about 67.27% possessing at least a Bachelor of Science degree, it means they had not been introduced to these methods in the classroom and neither has the regulatory professional bodies organized professional development workshops or conferences centered on these advanced trends in property valuation.

5.4 PROPERTY VALUE DETERMINANTS

Real estate property serves as consumption (owner-occupier) and investment (investors) goods to its holder (Chin and Chau, 2002). Real estate property is complex in nature, that is, it is made up of many unique sets of characteristics that influence its value (Rosen, 1974; Sirmans et al., 2005). The impacts of property attributes on property values are perceived differently by the different stakeholders due to the heterogeneous nature of real estate properties (Shapiro et al., 2012). A real estate professional is often sought to appraise the value of an interest in a property and in so doing, what the valuer analyses during this exercise are the bundles of characteristics of the subject property (Appraisal Institute, 1994). The present investigation, therefore, aims to evaluate the valuers' judgement on the level of significance of property value determinants in the Lagos metropolis property market in Nigeria.

5.5 THE LAGOS METROPOLIS PROPERTY VALUE DETERMINANTS

The outcomes of addressing research objective 2 which is aimed at identifying the property value determinants are presented in the following subsections.

5.5.1 Analysis of Attributes' Significance

The level of significance (i.e. MS), COV, the category ranking, the overall ranking and the criticality of each property attribute are presented in the second to the sixth columns in Table 5.9. The COV of each attribute was calculated. The COV of the attributes ranges between 8.85% (location) and 31.63% (accessibility to school). These variations are low, which suggests a high agreement among the valuers as regards the significance of those property attributes.

As evident in Table 5.9, the MS values of the attributes ranges between 4.92 and 3.13. The MS values of six out of the 20 attributes are considered to be highly significant, 11 are significant, while the remaining three are slightly significant to property value formation, whereas none of the attributes is insignificant. Property size and neighbourhood security had the same MS value of 4.06. Also, accessibility to CBD and building characteristics recorded MS values of 3.75, respectively. This suggests that when appraising a property, the same value is placed on those pairs of attributes.

Table 5.9: Ranking of property value determinants

Property attributes	Mean score	COV	Category ranking	Overall ranking	Criticality
Locational attributes					
Location	4.92	8.85	1	1	H. significant
Accessibility to place of work	3.79	25.78	2	9	Significant
Accessibility to CBD	3.75	21.04	3	10	Significant
Accessibility to public transport facility	3.62	19.86	4	13	Significant
Proximity to highway	3.56	25.14	5	15	Significant
Accessibility to school	3.15	31.63	6	17	S. significant
Accessibility to shopping mall	3.13	27.55	7	18	S. significant
Neighbourhood attributes					
Neighbourhood characteristics	4.31	15.61	1	2	H. significant
Availability of neighbourhood security	4.06	20.36	2	4	H. significant
Availability of electricity	3.81	22.69	3	8	Significant
Availability of pipe borne water supply	3.65	24.76	4	12	Significant
Availability of waste disposal system	3.38	27.53	5	16	S. significant
Structural attributes					
State of repair of the property	4.23	16.62	1	3	H. significant
Size of property	4.06	22.87	2	4	H. significant
Age of the property	4.00	15.65	3	5	H. significant
Numbers of bedrooms	3.98	13.61	4	6	Significant
Number of bathrooms/toilets	3.90	18.47	5	7	Significant
Building characteristics	3.75	21.04	6	10	Significant
Availability of security fence	3.73	27.12	7	11	Significant
Size of bedrooms	3.60	22.87	8	14	Significant

Note: H. significance is highly significant and S. significance is slightly significant.

5.5.2 Ranking of the Locational Attributes

The highest and lowest ranked attributes in the overall variable list (location and accessibility to a shopping mall) are in the locational category. Property location has been investigated widely in the literature. This attribute was ranked as the most highly significant attribute by the valuers, both in the locational category, as well as in the overall category with an MS of 4.92. The early study of Wilkinson and Archer (1973) posit that location is an important variable that influences property values. Authors have reported that location is highly significant in property value formation (for example, Cheshire and Sheppard, 1998; McCluskey et al., 2000; Han et al., 2002; Kauko, 2003; Joslin, 2005; Ge and Du, 2007). In the Lagos metropolis, a property located in the high-income neighbourhood, such as Ikeja GRA, Banana Island, Ikoyi and Lekki Peninsular, among others, would command a high value than those located in the low-income areas of Mushin, Oshodi, Iyana-Ipaja, and so on.

The next two significant attributes in this category are accessibility to the place of work and accessibility to CBD, with MS values of 3.79 and 3.75, respectively. They are ranked as the ninth and tenth attributes, respectively, in the overall variable list. Their position in the locational category could be justified, probably due to the fact that the Lagos metropolis is the commercial nerve center of Nigeria, where a high number of commercial and industrial activities takes place. Hence, when making residential decisions, a home buyer or tenant would consider the distance from their place to work and CBD to their house.

5.5.3 Ranking of the Neighbourhood Attributes

This classification consists of attributes that are regarded as public services provided within a residential neighbourhood. The significance of neighbourhood attributes in property value formation cannot be underestimated, as Linneman (1980) reported that neighbourhood characteristics account for between 15 and 50% of property values, and explains as much as 100%, where the properties in the neighbourhood are similar in terms of structural characteristics.

In this investigation, neighbourhood characteristics attribute was ranked as the highest in this category, and, at the same time, second in the overall list of the attributes. This shows its significance to property value determination because it recorded an MS value of 4.31. The study of Cheshire and Sheppard (1998) found that the characteristics of a neighbourhood where a property is located influence its value. Home seekers would be willing to pay for a property located in a neighbourhood characterized by good features. Han et al. (2002) reported that a property in a neighbourhood with good characteristics commands a high value. Also, Kauko (2003) established that this attribute is a significant property value determinant. This is what is obtainable in Lagos because a neighbourhood with good characteristics, such as Ikeja GRA, Banana Island, Lekki Peninsular Phase 1 and VGC are provided with good facilities (good roads, properties with modern designs, properties finished with modern materials, properties with an ocean view, a neighbourhood with a large composition of high-income earners) and attract a higher property value. This corroborates the study of Iroham et al. (2014) conducted in the Lagos metropolis, Nigeria.

Gallimore et al. (1996) remarked that home seekers would be willing to pay for an apartment in a neighbourhood which is free of crime, kidnapping and other forms of social vices. Also, Clark and Herrin (2000) reported that murder rate in a neighbourhood has an adverse effect on property values. This was also noted by Amenyah and Fletcher (2013) who reported that residents prefer to live in a neighbourhood that has no history of theft, kidnapping and robbery cases. Hence, it is understandable that the attribute was ranked as highly significant by the valuers with an MS value of 4.06. This suggests that home seekers place more value on the security of their lives and properties, in other words, a property in a safe neighbourhood would command a high property value. In the Lagos metropolis, properties located in areas that are perceived to be free of crime, either because it is a gated neighbourhood with a corporate-regulated security or close to a police station, would be highly sought after. This is also the case in the Ibadan metropolis, Nigeria, where Adegoke (2014) found that the availability of burglar alarm is significant to property values.

5.5.4 Ranking of the Structural Attributes

Property structural attributes (Table 5.9) have been established to be highly significant in property value formation and are, thus, widely adopted in property value analysis studies (Wilhelmsson, 2000). Palmquist (1984) found that structural attributes have the highest contributory power to property values in the US. Wen et al. (2005) also reported that structural characteristics contribute 60% to property values. From the valuers' point of view in the Lagos metropolis, in the overall attributes category, structural attributes occupy the third to the seventh positions, confirming the literature.

In this category, the state of repair of a property is the most important structural variable and indeed highly significant with an MS value of 4.23. This attribute, describing the aesthetics and the finishes of a property, influences the value place on a property, suggesting that a property that is well maintained would command a high value. A property in a poor state would thus require a degree of money to repair or replace some of its components. This would be factored into the overall value which would result in a lower value. This is also the case in South Africa, as reported by Mbachu and Lenono (2005), where aesthetic design in terms of design and finishes was ranked as significant by real estate valuers.

The taste, needs and the preference of different home seekers would influence the size of property they may be willing to pay for. Also, the size of a property would determine the value they would place on such a property (Owusu-Ansah, 2012), with the implication that big households would, all things being equal, create a demand for a large property and would be willing to pay for such. Out of the 20 most frequent property attributes used in related studies reviewed by Sirmans et al. (2005), property size positively influenced property values 42 times out of the 52 instances. This indicates that the bigger a property, the higher the price the property would command. The case is not different in the Lagos metropolis and the influence of the size of a property is confirmed with an MS value of 4.06 recorded by the variable.

According to Chin and Chau (2002), the expected sign of the age of a property on property value is negative. This means that the value of a property decreases as the age increases (in a case where the property is not being maintained). This attribute, being ranked as highly significant to property value in the Lagos metropolis, is justifiable because a home seeker would make provisions in terms of a premium on the amount to offer, considering the age of the property. It is expected that as a property gets older, wear and tear of its components begins to set in, which would warrant some level of repair, replacement or refurbishment as the case may be. This suggests that a new property would command a higher value when compared with an older property.

5.6 SUMMARY OF RESEARCH FINDINGS

The questionnaire findings of the current property valuation practice in the Lagos metropolis reveal that the majority of the professionals are aware of and familiar with the traditional valuation methods, especially comparable, cost and investment methods. In contrast, the valuers are not much aware of the advanced methods of valuation, although with an exception of the HPM method, which is being adopted in real estate research in the study area. It was also found that valuers' level of education, as well as years of professional experience, do not have a statistically significant relationship with their awareness of the advanced valuation methods. And for the traditional methods, a statistically significant relationship only exists for the investment, the comparable and the cost methods.

In terms of the frequency of use of all the valuation approaches, the valuers always and regularly make use of the traditional valuation methods (comparable, cost and investment methods). Their little awareness of the advanced approaches results in their low adoption in practice. All these indicate that the property valuation practice in Nigeria is still in its infancy, and so there is the need to introduce the AI valuation techniques in property valuation in the Lagos metropolis, which could generate more accurate and reliable property valuation estimates as obtainable in other property markets around the world.

As regards the property value determinants in the Lagos metropolis, the most highly significant attributes are in this order: the location of a property, the neighbourhood characteristics, the state of repair of a property, the size of a property, the availability of neighbourhood security and the age of a property. The location of a property was the highest ranked significant variable, which conforms to the existing literature. The

Lagos metropolis property market has been proven to be the most vibrant property market in Nigeria, and hence when making financial and economic investment decisions in the metropolis, real estate stakeholders ought to consider those sets of highly significant attributes. In addition, the list of property value determinants peculiar to the property market is one of the main requirements for the modeling of property values in Lagos, which is demonstrated in this research.

5.7 CHAPTER SUMMARY

The studies reported in this chapter are questionnaire surveys pertained to the Lagos metropolis property market. The current property valuation practice prevalent in the Lagos metropolis was investigated, and the findings reveal that the adoption of the traditional valuation methods is predominant among the valuers. At the same time, it was found that property structural attributes significantly influence residential property values in the metropolis, when compared with locational and neighbourhood attributes. Property location, neighbourhood characteristics, property state of repair, property size, availability of neighbourhood security and age of property were eventually found to be the most highly significant attributes that influence residential property values in the Lagos metropolis. A list of property attributes generated is used for the empirical modeling of the Lagos metropolis property values adopting the HPM approach and evaluating the predictive accuracy of the approach. This is presented in the next chapter.

CHAPTER 6 MODELING THE LAGOS METROPOLIS PROPERTY VALUES: THE HPM APPROACH

6.1 INTRODUCTION

In Chapter 5, the current property valuation practice in the Lagos metropolis, as well as the evaluation of the residential property values determinants in the Lagos metropolis are reported. It was found that the valuation practice is still at the traditional level. With the advocacy that advanced property valuation methods could provide more reliable and accurate estimates, this may warrant a shift towards advanced property valuation methods. Property structural attributes were established to be highly significant to property values in the Lagos metropolis. However, those attributes are needed for the development of property value models. The HPM approach was used in modeling residential property values of the Lagos metropolis. The study documented in this chapter evaluates the predictive accuracy of the HPM approach to generate accurate and reliable property valuation estimates, which would be a good representation of the market value.

6.2 HEDONIC PRICING MODEL IN NIGERIA

In measuring the impact of various property attributes on property values in Nigeria, scholars have adopted the HPM approach to examine the effect of the nearness to a university (Babalola et al., 2013), the neighbourhood security (Olujimi and Bello, 2009;

Adegoke, 2014), the electricity supply (Bello and Bello, 2008; Famuyiwa and Babawale, 2014), the number of bedrooms (Oduwole and Eze, 2013), the number of bathrooms and toilets (Babawale et al., 2012), the pipe-borne water (Babawale et al., 2012) and the property size (Oduwole and Eze, 2013), among other attributes, on property values.

Previous studies that have adopted HPM in real estate in Nigeria have only established the explanatory relationship of property attributes and property values. To date, no effort has been invested to substantiate the suitability of the HPM approach to produce accurate and reliable property valuation estimates which can be a good proxy for property values. There is a need to bridge the gap between 'explaining' and 'predicting' modeling, as this would provide the "reality check to the relevance" (Shmueli, 2010, p. 292) of HPM in property valuation. This study, therefore, aims to establish the predictive accuracy of the HPM approach for property valuation to produce accurate and reliable property valuation figures.

6.3 DATA COLLECTION AND METHODS

6.3.1 The Data[7]

Transactions (i.e. sales and purchases) data were collected from registered real estate

[7] The same data set used for this study was used for the development of the ANN model. Thus, the details of data collection process are not presented in Chapter 7.

firms domiciled in the Lagos metropolis property market. Due to the unavailability of a centralized sales transactions databank in Nigeria (Adegoke et al., 2013), the data collection process was limited to those firms which provided access to the information on completed transactions relating to residential properties. Therefore, structural attributes of residential properties were the major independent variables selected for this study. This is not uncommon in similar studies such as Do and Grudnitski (1992), Owusu-Ansah (2012) and Thanasi (2016), amongst others, where data sets of structural attributes were used to model property prices.

The only neighbourhood variable added is the sea view, as the study area is surrounded by water bodies (see Figure 4.2), and it was easy for the real estate professionals to provide such information regarding the properties included in this study. In the same vein, the location of a property was included in order to distinguish the location of each data entry. The list of the 11 independent variables and one dependent variable considered in this study are presented in Table 6.1, alongside their mean, standard deviation, minimum and maximum values.

Table 6.1: Descriptive statistics of the variables

Variables	Mean	Standard deviation	Minimum	Maximum
Dependent				
Price	149,769,541.60	199,367,090.90	14,500,000.00	1,182,844,000.00
Independent				
Bedrooms	3.49	1.26	1	10
Toilets	4.28	1.37	1	7
Bathrooms	3.38	1.25	1	7
Property type	3.87	1.45	1	6
Boys' quarters	1.08	1.36	0	8
Parking	3.27	2.45	0	20
Age	3.30	4.97	0	42
Floors	2.83	2.19	1	16
Security fence	0.98	0.14	0	1
Sea view	0.05	0.22	0	1
Location	3.36	1.70	1	5

Sample size = 321. US$1 = ₦282.5 (Source: Central Bank of Nigeria, as at 30/06/2016)

The information was collected from high-income neighbourhoods in the Lagos Island property market (i.e. Ikoyi, Victoria Island, VGC, Lekki Peninsula Phase 1 and other high-income neighbourhoods on the Lekki – Epe corridor (between Lekki Peninsula Phase 1 and Abraham Adesanya Estate)) and properties in the study area command higher values, when compared with other locations in the Lagos metropolis (Famuyiwa and Babawale, 2014).

It was intended to retrieve information of completed sale transactions as far back as possible, in order to retrieve a sizable sample data. Unfortunately, the firms do not maintain a property sales databank. However, the author managed to collect transactions completed between 2010 and 2016. At the end of the data collection exercise which lasted for four months (March 2016 - June 2016), data on 370 completed transactions were retrieved. The data were pre-processed. After the cleaning process which aimed at excluding entries with missing/incomplete records, 321 observations remained and were subjected to analysis. The definition and measurement of the property variables included in this study are shown in Table 6.2.

Table 6.2: Definition, measurement and frequencies of the variables

Variables	Definition	Measurement	Frequencies of the variables
Price	Sale price of property	Naira (₦), Nigerian currency	Most of the properties were sold for between ₦14,500,000.00 - ₦200,000,000.00
Bedrooms	Number of bedrooms	Numeric (0,1,2,3…)	Most of the properties have between 3-5
Toilets	Number of toilets	Numeric (0,1,2,3…)	Most of the properties have between 4-6
Bathrooms	Number of bathrooms	Numeric (0,1,2,3…)	Most of the properties have between 3-5
Property type*	Construction style of the property	Numeric (1,2…6)	Study area is characterized by flats and detached houses
Boys' quarters	Number of BQ rooms	Numeric (0,1,2,3…)	Most of the properties have at least 1
Parking	Number of parking lots	Numeric (0,1,2,3…)	Most of the properties have at least 2 lots
Age	Property age	Numeric (0,1,2,3…)	Most of the properties were relatively new. 37.1% are 1year old
Floors	Number of floors	Numeric (0,1,2,3…...)	52.6% of the properties are on 2 floors
Security fence	Availability of security fence	1 if available, and 0 otherwise	98.1% have security fencing
Sea view	Presence of sea view	1 if available, and 0 otherwise	94.7% do not face the sea or lagoon
Location	Location of the property	The neighbourhood situated	This is spread over the areas

Note: * Property type includes: duplex, detached house, semi-detached house, terrace, flat and others.

BQ means Boy's quarters which is called servants' quarters in some environment.

Location describes the geographical position of each property included in this study.

The frequency distributions of the collected data show that about 57% of the properties were sold for less than ₦100,000,000, while only 15 properties were sold for above ₦500,000,000 (see Appendix 4). It can be said that most of the properties were either three-, four- or five-bedroom properties, with the properties having a corresponding number of bathrooms. Most of the properties had about four, five and above five toilets, suggesting that most properties had extra toilets when compared with the number of bathrooms in a property. The extra toilet facility could be for guest use. It is worth noting that this feature is highly priced in the Lagos metropolis property market.

Flat, detached and terrace buildings are common in the study area (see Appendix 4). One servants' quarters (usually referred to as boys' quarters [BQ] in the Nigerian environment) is attached to about half (44.2%) of the properties. Although some properties do not have BQ, those are probably one bedroom properties. In those cases, the occupants may not need their domestic staff to live with them in the property. The properties used for this study have at least one parking lot for the use of the occupants. Twenty-one of the properties were recently constructed and sold at the time of data collection. Also, most of the properties were either constructed between one to three years ago, suggesting that properties in the study area are relatively new.

More than half (52.6%) of the properties are on 2 floors, 13.7% have 3 floors, while some (10.6%) are on one floor. Almost all (98.1%) the properties included in this study have security fences erected around their perimeter boundaries. On the other hand, most of the properties do not have sea view (94.7%). In terms of the location of the properties, about a quarter are located in Ikoyi, 16.5% are located in Lekki Peninsula Phase 1, while about half (46.7%) are located in other areas such as Northern Foreshore, Nicon Town, Oniru Estate and Chevy View Estate, amongst other high-income neighbourhoods, in the study area.

It should be noted that the 'location of property' variable was included to describe the geographical position of the property. The actual address of each property used in this study could not be retrieved from the real estate firms. This is not uncommon in the literature (for instance Selim, 2009; Kontrimas and Verikas, 2011; Tabales et al., 2013).

The composite CPI that is available from the National Bureau of Statistics (see National Bureau of Statistics, 2016a) was used to deflate the current property prices to constant prices. This adjustment ensured that the effect of inflation on property values was removed. The process for adjusting the values can be mathematically expressed as presented in Equation 6.1. This formula was adopted from McCluskey et al. (2012).

$$\text{Current property price} = \text{Base year price} \times \frac{\text{Current CPI}}{\text{Base year CPI}} \tag{6.1}$$

6.4 MODEL SPECIFICATIONS

The selection of the variables to be included in the model started with the testing for multicollinearity between the independent variables by estimating their partial correlation coefficients. In addition, the VIF test was conducted.

The multicollinearity test reveals a high correlation between the number of toilets and the number of bathrooms in a property. The correlation coefficient of the number of bathrooms and the number of toilets was 0.965 which was the highest amongst the variables. This corroborates the statistics in Table 6.3 which shows that their VIF values are higher than the acceptable value of 10, as well as their tolerance values which are also higher than 0.10 (Berenson et al., 2012). Consequently, the number of toilets variable was removed from the list of independent variables and a reanalysis of the data produced an acceptable VIF value of 8.400 and tolerance value of 0.119 for the number of bathrooms' variable, which was subsequently retained.

The plausible explanation for the multicollinearity that existed between those two variables could be due to the fact that most of the bathrooms in the properties used for this study have in-built toilets (en-suite). This may be responsible for the number of bathrooms in a property to be almost the same as the number of toilets, and in most cases, the number of toilets is the number of bathrooms plus one toilet (usually guests' toilet). The need for guest toilets could be attributed to the fact that the residents in the study area value privacy and convenience (Otegbulu and Johnson, 2011). Although the correlated variable (the number of toilets) was removed, it should be noted that the presence of multicollinearity is irrelevant when adopting HPM for prediction, thus it will not affect the predictive performance of the developed model (Nguyen and Cripps, 2001).

Table 6.3: Variance inflation factor test

Variables	Collinearity Statistics[a]			
	All the variables		Retained variables	
	Tolerance	VIF	Tolerance	VIF
Bedrooms	0.158	6.334	0.161	6.210
Property type	0.367	2.728	0.367	2.727
Boy's quarters	0.439	2.279	0.446	2.243
Parking	0.449	2.228	0.457	2.190
Age	0.684	1.463	0.686	1.458
Floors	0.724	1.381	0.730	1.370
Security fence	0.839	1.192	0.844	1.185
Sea view	0.931	1.075	0.930	1.075
Location	0.608	1.644	0.642	1.559
Bathrooms	0.049	20.405	0.119	8.400
Toilets	0.062	16.009	Removed	Removed

Note: a. is Dependent variable: Price of property

A linear relationship between property price (dependent variable) and the independent variables was established. The scatter plot approach was adopted so as to visualize the association between the variables. The scatter plots (see Appendix 5) show that there is a linear relationship between property price and the independent variables. The relationship recorder here does not violate model assumptions (Janssen et al., 2001), and is common in real estate related studies (McGreal et al., 1998; Din et al., 2001; Limsombunchai et al., 2004).

The Glejser test was performed to check for heteroscedasticity (see Table 6.4). This was performed following three basic steps. (1) conducting a regression analysis and saving the residuals; (2) the absolute value of the residuals were then regressed on the possible sources of heteroscedasticity, which in this case were the independent variables; and (3) a significant coefficient of each variable indicates heteroscedasticity. This analysis shows that there is no presence of heteroscedasticity among the variables because the significant coefficients of all independent variables are greater than 0.05 (Gujarati and Porter, 2009).

Table 6.4: Glejser test for heteroscedasticity

Variables	t	Sig.	Explanation
(Constant)	1.652	.100	No heteroscedasticity
Number of bedrooms	-.869	.385	No heteroscedasticity
Number of bathrooms	1.066	.288	No heteroscedasticity
Type of property	1.074	.284	No heteroscedasticity
Number of BQ rooms	-1.033	.303	No heteroscedasticity
Number of parking space	5.355	.420	No heteroscedasticity
Age of property	-.483	.630	No heteroscedasticity
Number of floors	-1.687	.093	No heteroscedasticity
Presence of security fence	-.838	.403	No heteroscedasticity
Presence of sea view	.658	.511	No heteroscedasticity
Location of property	-4.903	.372	No heteroscedasticity

In order to establish the predictive accuracy of the HPM approach, the data set was divided into two parts, for training and testing of the model. The training set was 80% (256) of the data set and was used to generate the HPM coefficients, while the remaining 20% (65) holdout samples were used for the testing of the model. The accuracy of the model was tested based on its r^2, MAPE, MAE, RMSE and ultimately, the percentage of the predicted values that are close to the actual property values. In this study, the linear functional form was adopted. This is because it can be easily computed and also relatively easy to interpret (Lin and Mohan, 2011). The linear functional form has also been frequently adopted in previous studies and this could be attributed to the ease of the interpretation of the parameters (Morancho, 2003), which is noteworthy for a study of this nature. The data were analyzed using the SPSS software, version 20.0.

6.5 RESULTS AND DISCUSSION

6.5.1 Empirical Results

The result of the HPM analysis is presented in Table 6.5. The model produced an adjusted r^2 value of 0.76 and an r^2 value of 0.77, which indicates that the variables included in the model explain 77% variations in the prices of properties in the study area. Most of the variables produced expected contributive signs to property values, while the rest produced unexpected signs. For instance, expectedly, the age of a property had a negative sign which is consistent with the literature (see for instance Hui et al., 2007), suggesting that an old property will usually command a lower value when compared with new ones.

The effect of the number of bathrooms and the presence of a security fence in a property were negative. In terms of the number of bathrooms in a property, some previous studies such as Ottensmann et al. (2008) and Pozo (2009), among others, reported that this variable would positively influence property values. Whereas, Tse (2002) and Kutasi and Badics (2016) found that the number of bathrooms in an apartment could negatively affect the price of properties in Hong Kong and Hungary, respectively. Those diverse findings could be attributed to the localized nature of the property market. Therefore, it could be safe to conclude that in the study area, home buyers do not place more importance on the number of bathrooms in a property, but they value privacy in some other forms in terms of the master's bedroom being en-suite and there being a visitors' toilet in a property.

Table 6.5: Results of the regression analysis

Independent variables	Coefficient	t-ratio	p-value
Bedrooms	8664822.596	.738	.461
Bathrooms	-20051336.870	-1.448	.149
Property type	8076944.769	1.144	.254
Boys' quarters	102816020.589	15.151	.000
Parking	9526774.351	2.615	.009
Age	-1635743.326	-1.068	.286
Floors	4539570.089	1.455	.147
Security fence	-10789691.840	-0.229	.819
Sea view	154767562.522	4.832	.000
Location	-26885403.503	-6.176	.000
Constant	98778305.063	1.396	.164

R^2= 0.766, Adj R^2= 0.757, F-ratio= 80.381, n=256

In the same vein, Lynch and Rasmussen (2001), Owusu-Ansah (2012) and Adegoke (2014), among other studies, found that higher security measures (low crime rate) in a neighbourhood would significantly increase the value of a property, whereas this study found that the presence of a security fence (high-security measure) in a property would negatively influence its price. This finding may be attributed to the fact that most of the residential neighbourhoods sampled usually have a general neighbourhood organized security personnel, in addition to each house's security guards. So the presence of a security fence in those neighbourhoods may not be regarded as a security measure for real estate investors in the study area.

Of all the ten explanatory variables, the presence of a sea view and the number of BQ rooms in a property are the most highly significant variables which influence property value. Both variables had the highest coefficients which contribute to the value formation of properties in the study area. In a similar previous study of Mok et al. (1995), it was found that a property that has a sea view will command a higher value. The positive influence of the BQ room on the price of properties was also reported in the study of Basu and Thibodeau (1998).

6.5.2 Model Performance

As stated earlier, in an attempt to achieve the objectives of this study, the performance of the model developed was tested using the MAPE, the MAE and the RMSE accuracy measures. These approaches are commonly adopted in the literature (McCluskey et al., 2013). The results shown in Table 6.6 reveals an MAE value of ₦61,408,856 and an RMSE value of ₦103,370.573. In addition, an MAPE value of 38.23% was recorded which depicts that the prediction produced an average error of 38%, which may not be acceptable by a rational real estate stakeholder. This suggests that there is some level of inaccuracies in the HPM predictions, despite the satisfactory r^2 value of 0.77.

This confirms that the performance of a model could not be evaluated entirely by adopting the r^2 value (Willmott, 1981). These findings of the present study corroborate the position of Ogunba and Ajayi (1998) and Babawale and Ajayi (2011) that reported that the level of property valuation inaccuracy prevalent in the Nigerian valuation practice is unacceptable based on international standards.

Table 6.6: Predictive accuracy of the HPM approach

Measure of accuracy	Hedonic pricing model
r^2	.77
MAPE (%)	38.23
MAE	61,408,856.10
RMSE	103,370.573.40

Hager and Lord (1985) and Hutchinson et al. (1996), among others scholars, posited that a property valuation margin of error of between ± 5 and 10% of the actual property value is acceptable and that any error beyond this could be attributed to the valuers' negligence. The HPM coefficients generated from the analysis was used to predict the holdout samples in order to establish the predictive accuracy of the HPM approach. The result of the predictions was categorized so as to establish the percentage of the samples that fell within the acceptable margin and those which were otherwise.

The information in Table 6.7 shows that only 26.67% of the predicted property prices had an error margin of between ± 0 and 10%, while 13.33% of the predicted prices had an error margin of between ± 11 and 19%. In addition, a whopping 60% predictions produced an error of above ± 20%. This indicates that in two out of three HPM predictions, an error rate of above ± 20% could be generated and the chance of producing accurate estimates with lesser errors is slim.

Table 6.7: Valuation accuracy of the HPM prediction

Accuracy range	Frequency (n)	Percentage (%)
± 0-10%	8	26.67
± 11-19%	4	13.33
Above ± 20%	18	60.00

These findings seem unsatisfactory, suggesting that the adoption of the HPM approach for property valuation would not produce accurate and reliable valuation figures which can be a good proxy for market value. One of the implications of this is that it would continually deepen the loss of the confidence which property valuation end-users have in the real estate profession and professionals. Property valuation inaccuracy could be minimal in stable (developed) property markets (Shapiro et al., 2012). This has been substantiated in the study of Cole et al. (1986), Newell and Kishore (1998) and Parker (1998), among others. Therefore, it is highly imperative that research endeavour is directed at investigating and addressing the factors mitigating against the estimation of accurate valuation figures, especially in developing economies, with Nigeria as an example. If property valuation inaccuracy is reduced to an acceptable standard, this would result in achieving a sustainable property valuation practice.

6.6 CHAPTER SUMMARY

This chapter reports the establishment of the predictive accuracy of the HPM approach in property valuation which addressed research objective 3. Residential properties sales transactions data fitted into the model were collected in the Lagos metropolis. The data included 11 independent variables (property attributes) and one dependent variable (property values). The HPM model was solely developed to evaluate the accuracy performance of the HPM approach, and thus the developed HPM coefficients were used to predict the property values of the holdout data sample. This accuracy was assessed based on the accuracy measures generally adopted in the literature. The evaluation shows that the HPM approach is not a good valuation method that could produce accurate and reliable property values. This could be attributed to its inability to handle the nonlinearity relationship that exists between property values and property attributes (Lin and Mohan, 2011), its inability to handle outliers (Selim, 2008) and inaccuracy (Lam et al., 2008), among other shortcomings. This necessitated the adoption of other nonlinear valuation techniques such as ANN which could produce better accurate valuation estimates than HPM. The application of the ANN technique in property valuation using the Lagos metropolis as a representative case is presented in the next chapter.

CHAPTER 7 MODELING THE LAGOS METROPOLIS PROPERTY VALUES: THE ANN MODEL APPROACH[8]

7.1 INTRODUCTION

The application of the HPM approach in property valuation was reported in Chapter 6. The predictive accuracy of the HPM approach was established and found to be undesirable for predicting accurate and reliable property valuation estimates. Given the prevalence of valuation inaccuracy in the Lagos metropolis, it is not desirable to continually rely on the HPM approach to produce accurate property values, and thus the need to adopt a more robust advanced valuation method. The ANN technique which has been proven to be a reliable technique was applied in the property valuation of the Lagos metropolis residential properties. This exploration is reported in this chapter.

7.2 DATA COLLECTION AND METHODS

The data used for the development of the ANN model reported in this study was collected from the Lagos metropolis property markets. This data set was the same used for the construction of the HPM (see Section 6.3.1 in Chapter 6). This was done so as to facilitate a justifiable comparison of the performance of both models. So the data

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[8] This chapter has been published in **Abidoye R. B.** and Chan, A. P. C. (2017). Modeling property values in Nigeria using artificial neural network. *Journal of Property Research*, 34(1), pp. 36 - 53.

collection details and process presented in Section 6.3.1 for the HPM study will not be repeated here. The process followed in developing the ANN model is presented in the next section.

7.3 MODEL SPECIFICATIONS

The ANN model was developed using a three-layer feedforward network. Mora-Esperanza (2004) suggest that the number of hidden layers in an ANN model can range between half and double the number of the input variables. However, the use of one hidden layer is considered adequate for handling complex real-life prediction for ANN models (Masters, 1993; McCluskey et al., 2012). There is no agreement in the literature as regards the number of hidden neurons an ANN model should have (Cechin et al., 2000). However, in the present study, the number of neurons in the hidden layer was automatically determined by the R programming software, by optimizing the network architecture that best fit the data during the grid search, using the default parameters in terms of learning rate, stopping criteria and weight decay.

The development of an ANN model is based on a trial and error experimentation to attain the best model (Limsombunchai et al., 2004). The iteration process is usually performed in order to construct the best ANN model that fits the data. After the iteration, an ANN architecture of 11-5-1 (11 input variables, 1 hidden layer (with 5 neurons) and 1 output) generated by the software was found to be the best network in this study. Figure 7.1 shows the topology of the ANN architecture generated in this study.

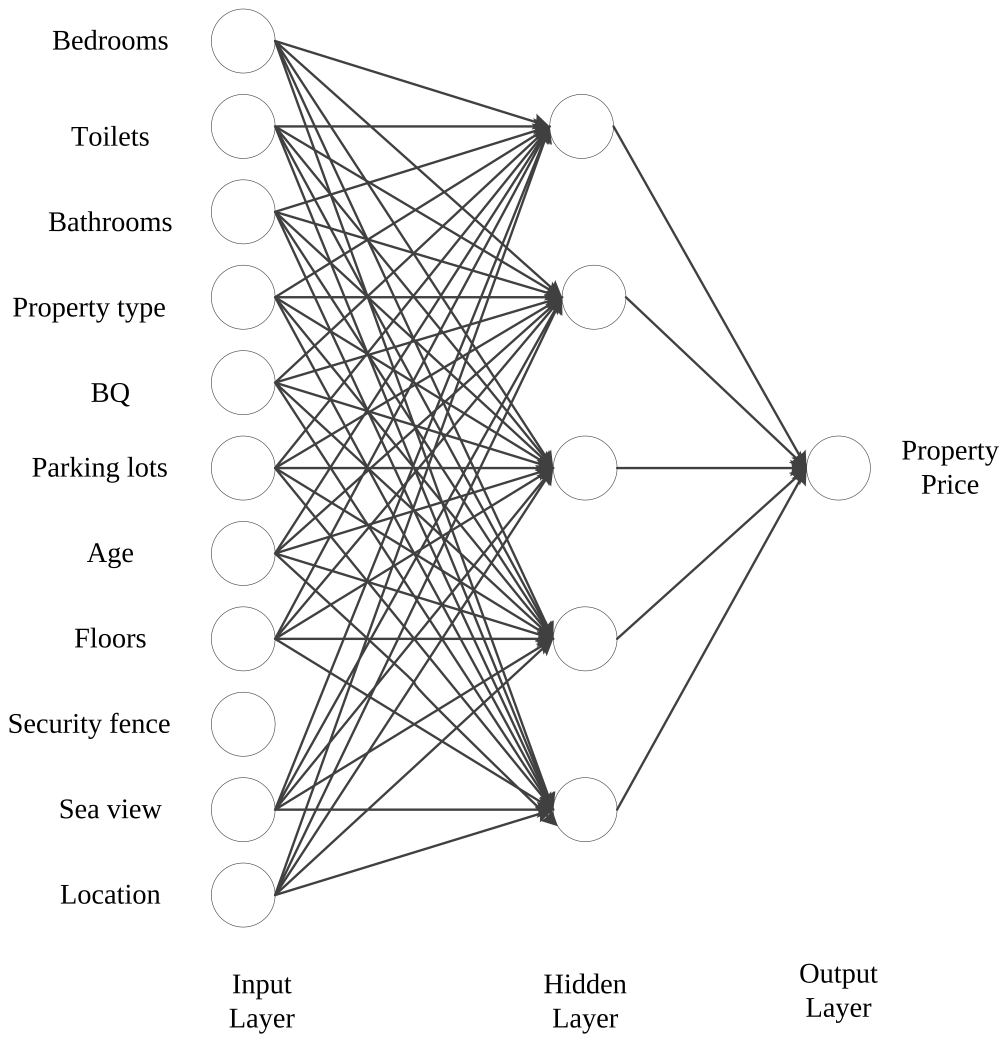

Figure 7.1: The ANN architecture
Source: Abidoye and Chan (2017a)

As mentioned, the ANN model presented in the present study was developed using the R programming software (R CoreTeam, 2016) and the Rminer package (Cortez, 2010). The R custom codes (see Appendix 7) were used in implementing the development of the ANN model in this study, by using the multilayer perceptron (MLP) package in R. The BP learning algorithm which is widely adopted in the literature (Mimis et al., 2013) was adopted in this study. BP is based on MLP which ensures that the neurons in the models are arranged in interconnected layers (input, hidden and output).

In developing the ANN model, the available data set was divided into two sets, i.e. for training and testing of the model (Wilson et al., 2002). The training data set was used to develop the model by determining the arc weights, while testing entails the evaluating of the predictive and generalization ability of the developed model (Lam et al., 2008). There is little or no guidance in the literature on the division ratio for the data for the training and testing of the model (Cechin et al., 2000). Ratio 90:10, 80:20 and 70:30 for training and testing, respectively, have been widely adopted in the literature because the model testing can be performed with a small data set (Zhang et al., 1998). This suggests that the analyst's discretion is required in determining the ratio based on what is obtainable in the literature.

For this study, the collected data were randomly divided into two parts using a ratio of 80% and 20%, respectively, for the model training and testing. This amounted to 256 samples for training and 65 holdout samples for the testing of the predictive accuracy of the ANN model. In estimating the error rate of this model, a cross-validation was used and the standard approach is a 10-fold cross-validation (Witten and Frank, 2005). Through this, the model average all the ten error estimates generated, in order to arrive at an unbiased and minimum error measure (Murat and Ceylan, 2006). In this study, a 10-fold cross-validation was used as obtainable in previous studies (see for instance Zurada et al., 2011; McCluskey et al., 2012). Table 7.1 shows the details of the ANN model developed.

Table 7.1: Details of the ANN model

Parameters	Details
Network architecture	Three-layer (11-5-1)
Algorithm	Backpropagation
Training and testing ratio	80:20
Dataset	321
Validation	10-fold cross-validation

7.4 RESULTS AND DISCUSSION

7.4.1 Model Performance

The developed ANN model generated an r^2 value of 0.81. This connotes that the model explains 81% of the variance in the property values. The r^2 value ranges between 0 and 1, and a value close to 1 shows perfect performance (Limsombunchai et al., 2004). Hence, the ANN model can be said to have performed satisfactorily in this regard. The MAPE value of the model is 15.94%, the MAE value is ₦28,492,514, while the RMSE is ₦41,814,564 (see Table 7.2). According to Lin and Mohan (2011), an MAE value of a model that tends towards 0 depicts a goodness of fit; a low RMSE value connotes a superlative model (Limsombunchai et al., 2004); and the MAPE measures the error of prediction in terms of percentage (Zurada et al., 2011). The MAE and RMSE figures recorded here suggest that the outputs of the ANN model are encouraging, considering the mean property price of the properties used for this study is ₦149,796,541. Also, the MAPE value (15.94%) recorded in this study seems promising when compared with the high property valuation inaccuracy of as high as about 67.91% being experienced in the Nigerian property market as reported by Ogunba (2004).

Table 7.2: Predictive accuracy of the ANN model

Accuracy measures	ANN model
r^2	0.81
MAPE (%)	15.94
MAE	28,492,514
RMSE	41,814,564

The validation of the developed model was performed on the holdout sample data. Through this, the holdout sample data were predicted using the ANN model developed with the training samples. Those predicted estimates were compared with the expected property values so as to establish if there is any difference between the actual property values and predicted values. Figure 7.2 shows the plot of the relationship between the expected property values and the ones predicted by the ANN model. The scatterplot shows that the ANN model produced a good prediction for almost all the holdout samples, with just few which were far from the line of fit. The ANN model can handle data sets that contain outliers and still produce precise outputs (Mora-Esperanza, 2004). This has been proven in previous studies where the ANN model produced a good fit with and without the inclusion of outliers in the data set (see for instance Cole et al., 1986; Tay and Ho, 1992).

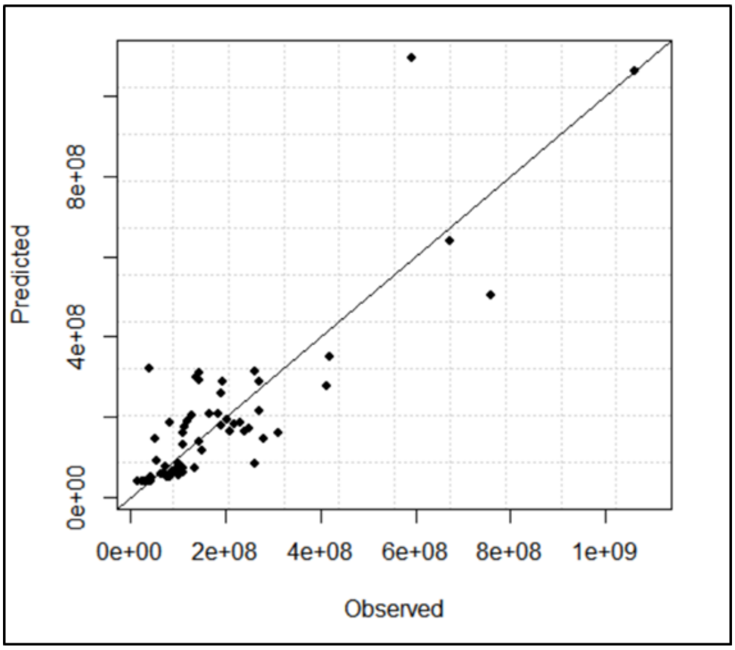

Figure 7.2: Expected property values against predicted property values
Source: Abidoye and Chan (2017a)

Concerning the number of the ANN model predicted property values, 33.33% of the predicted values has a margin of error of between ± 0 and 10%, while 43.33% has an error margin of between ± 11 and 19%. Only 23.33% has an error greater than ± 20% (see Table 7.3). This implies that the tendency of generating a more accurate and reliable property valuation estimate is higher when the ANN technique is adopted.

Table 7.3: Valuation accuracy of the ANN model predictions

Accuracy range	Frequency	Percentage (%)
± 0 - 10%	10	33.33
± 11 - 19%	13	43.33
> ± 20%	7	23.33

The results of this study are similar to the findings of Ge and Runeson (2004), Mimis et al. (2013) and Cechin et al. (2000), among other studies, all of which reported that the ANN technique possesses a reliable predictive accuracy that can address the nonlinearity of property values and property attributes. Whereas, a few studies (for instance, Kontrimas and Verikas, 2011; McCluskey et al., 2012) conclude that the ANN may not be a reliable predictive technique for property valuation.

The inconclusiveness of the findings of previous studies could be attributed to the quality of the data sample used for those studies, as this may have an effect on the ANN output (Lenk et al., 1997). The ANN model should not be seen as a replacement of the valuer in a valuation exercise; it is a tool to achieve the end result (property valuation figure). This is evident in most developed property markets around the world where AI property valuation techniques have been adopted in practice (Mora-Esperanza, 2004; Grover, 2016). Hence, valuers' sound knowledge of the property market under investigation is necessary for property valuation because this may also affect the quality of the ANN predicted estimates (Gilbertson and Preston, 2005).

7.4.2 Relative Importance of the Property Attributes

The output of the ANN model does not contain the coefficients or *t*-values of the property attributes like in the HPM approach; however, its output can establish the relative importance (RI) of the attributes included in the model (McCluskey et al., 2012). Figure 7.3 shows the RI of the 11 attributes used in developing the ANN model. The RI value ranges between 0.0 and 0.5, where a 0.0 value indicates that the attribute has no effect on property value formation, while 0.5 connotes a highly significant contribution to property value estimation.

The most important attribute is the number of BQ in a property, which recorded an RI value of 0.49 out of the 0.50 benchmark (see Figure 7.3), implying a highly significant contribution to the value of properties in the study area. A BQ is an adjoining room normally constructed outside of the main building for the accommodation of domestic and other personal staff. Given that the study area is a high-income residential neighbourhood, it is safe to suggest that home buyers or tenants would first consider the number of BQ rooms available in a property before negotiating further. This property attribute may be uncommon in the real estate literature, probably because in other real estate markets, servants' quarters are within the main building. However, Basu and Thibodeau (1998) found that the presence of servants' quarters has a significant influence on property prices in Dallas, United States.

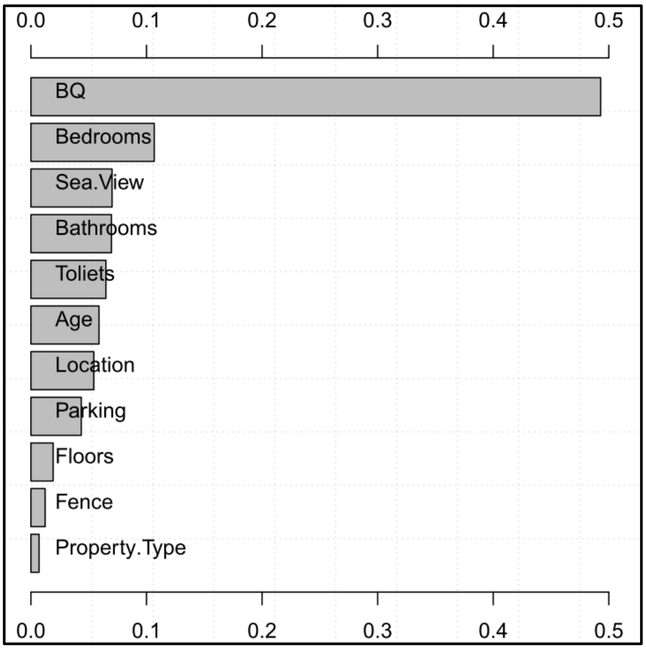

Figure 7.3: The relative importance of the property attributes

Source: Abidoye and Chan (2017a)

The second most important attribute is the number of bedrooms in a property, which translates that the higher the number of bedrooms in a property, the higher the property value. This corroborates the findings in other property markets around the world (Ge and Du, 2007; Selim, 2008). The presence of a sea view in a property was found to be the third most important attribute in the present study. The study area where data were collected for this research is surrounded by the sea and lagoon, which may explain why it is considered a high-income neighbourhood dominated mostly by expatriates and high-income earners. These findings corroborate the studies of Tse (2002); Choy et al. (2007) Hui et al. (2007) and Michael et al. (2002) who reported that the presence of a sea view significantly influences the value of a property. The least important attribute is property type. Generally, the study area is characterized by property types associated with high-income earners such as duplexes, detached houses, terraces, and others. So, it is understandable that property values in this property market are not highly determined by this variable.

7.5 CHAPTER SUMMARY

The findings presented in this chapter emanated from the modeling of property values in the Lagos metropolis using the ANN technique. The model produces encouraging results by predicting property values with a MAPE value which is in the range of what is obtainable in the literature. These results show that the techniques could be applied in property valuation both in developed and developing property markets and still produce excellent results. The technique was also used to conduct a sensitivity analysis of the RI of the variables included in the model. This analysis revealed that the number of BQ rooms in property has the highest significance to property values in the study area. Therefore, real estate developers should accord this variable more importance when developing real estate properties in the study area. The result of the ANN study is compared with that of the HPM approach and is presented in the next chapter. This evaluation will provide an insight into the most accurate and reliable property valuation technique between both models.

CHAPTER 8 A COMPARISON OF THE PREDICTIVE ACCURACY OF HPM AND ANN TECHNIQUES

8.1 INTRODUCTION

The previous chapter reported the predictive performance of the ANN technique in property valuation using the Lagos metropolis as the study area. The predictive accuracy of the ANN technique was found to be encouraging, which corroborates the existing literature. The predictive accuracy of HPM and the ANN model is compared and reported in this chapter. The evaluation is conducted based on the accuracy measures and establishing the number of predicted property values produced by both models which have an error margin that is within the acceptable industry standards. This will indicate the best model which is robust and reliable to produce more accurate property valuation estimates.

8.2 HPM AND ANN MODEL COMPARISON IN PROPERTY VALUATION

In the real estate research domain, several methods have been used to estimate property values (Kummerow, 2003). Those approaches range from traditional to advanced valuation techniques (Pagourtzi et al., 2003). Studies have shown that traditional valuation approaches are unreliable and inaccurate (Crosby, 2000; Zurada et al., 2006). This has led to a shift towards advanced valuation techniques, which tend to be more accurate and reliable when compared with traditional methods (Gilbertson and Preston, 2005). HPM is an advanced valuation method which has been used widely both in theory and in practice (Selim, 2008). However, despite its simplicity and straightforwardness in approach (Chin and Chau, 2002), it cannot effectively capture the nonlinear relationship which exists between property values and property attributes; it is subjective in nature, inaccurate, and so on (Worzala et al., 1995; Limsombunchai et al., 2004; Lin and Mohan, 2011).

In addressing the shortcomings of the HPM approach, the ANN technique, which has produced more accurate, reliable and comfortable predictions estimates, has been adopted in property valuation (Borst, 1995; Mora-Esperanza, 2004). A plausible reason for this is that the ANN technique possesses high precision quality, it can handle the nonlinear relationship between property attributes and property values (Cechin et al., 2000), it can handle data outliers (Mora-Esperanza, 2004), it is not subjective (Tay and Ho, 1992) and user-friendly (Borst, 1991; Ge and Runeson, 2004), amongst others.

Studies (Babawale and Ajayi, 2011; Adegoke et al., 2013) focused on the Nigerian real estate industry have reported that the property valuation inaccuracy predominant in the domain is highly unacceptable based on international standards (Hutchinson et al., 1996; Brown et al., 1998). This could be attributed to the adoption of inappropriate and unreliable property valuation approaches (Aluko, 2007). The HPM approach has been widely applied in the Nigerian property valuation research (Abidoye and Chan, 2017b), and in the property valuation practice (Abidoye and Chan, 2016c). However, the application of the ANN model in property valuation by researchers in such developing countries as Nigeria has been limited (Abidoye and Chan, 2016c). This may be accountable for the prevalence of property valuation inaccuracy observed in both practice and research in Nigeria (Ogunba and Ajayi, 1998). Considering the aforementioned, the present study seeks to evaluate the predictive accuracy of the ANN technique in comparison with the HPM approach in Nigeria.

8.3 DATA COLLECTION AND METHODS

The same data set were used to develop both the ANN model and HPM. This was done so as to enable a common ground for comparison. The results from the ANN model and the HPM predictions serve as the data for this study. Therefore, Section 6.3.1 could be referred to for the details of the data used in developing both models.

A large portion (80%) of the data set was used for the development of both models, while the rest (20%) was used for the testing of the models, as commonly done in previous studies (see Wilson et al., 2002; Lam et al., 2008; Morano et al., 2015, amongst others). The testing of the models was performed so as to establish the predictive accuracy of the models. In doing this, the holdout samples were used to predict the actual property values and any difference between the predicted property values and the actual property values (if any) amounts to an error in estimation. The accuracy measures adopted are RMSE, MAE, MAPE and r^2 as obtainable in previous related studies. (McCluskey et al., 2013).

In addition to the accuracy measures adopted for the evaluation of the accuracy of the developed models, the percentage of the predicted property values that have an error margin which falls within the international acceptable margin of between ± 0 and 10% (see Hutchinson et al., 1996; Brown et al., 1998), and those that fell beyond this margin were established. This is to ascertain how suitable either of the models can satisfy international standards in the property valuation domain.

A visual examination of the predicted property values shows that some were beyond reasonable range, and hence the removal of such properties sales. Consequently, a holdout sample of 30 observations were used for the testing of the models. This is not uncommon in previous studies, see, for instance, Worzala et al. (1995) and McCluskey (1996).

8.4 RESULTS AND DISCUSSION

The evaluation of the developed HPM and ANN model are presented in Table 8.1. On the basis of the r^2 values of the models, ANN produced an r^2 of 0.81. This is higher than that of HPM which is 0.77. Since the r^2 only explains the relationship between the dependent variable and the independent variables and not the quality of the predictions generated by the models (Willmott, 1981), the evaluation of the models based on MAE, RMSE and MAPE is necessary. In the same vein, the ANN model produced MAE and RMSE values lower than that of HPM, because those of the ANN model are closer to 0 when compared with the values of HPM. This depicts that the ANN could predict property values more accurately than HPM.

Table 8.1: Predictive accuracy of HPM and ANN models

Models	r^2	MAE	RMSE	MAPE (%)
HPM	0.77	61,408,856	103,370.573	38.23
ANN	0.81	28,492,514	41,814,564	15.94

On the MAPE values of the models, the ANN model produced a MAPE value of 15.94%. This suggests that the average absolute error which could be recorded in predicting property values using the ANN technique is about 15%. This figure seems above the ± 10% industry standard, a plausible reason could be because the Nigerian property market is not transparent (Akinbogun et al., 2014), which could have some implications on the property valuation estimates (Grover, 2016). However, this figure is in the range of what is obtainable in the literature (see for instance Lewis et al., 1997 (18%); Jenkins et al., 1999 (18%); Pagourtzi et al., 2007 (31.6%); Guan et al., 2008

(17.6%); Kutasi and Badics, 2016 (15.93%), amongst others).

The MAPE value generated from the HPM approach is 38.23%, indicating that the absolute error using HPM could be higher than 30%. And in a few instances, the percentage difference between actual property values and predicted property values was as high as 100% (see Appendix 6). These results show that the ANN model could predict accurately two times better than the HPM approach. This corroborates the findings of Do and Grudnitski (1992, p. 44) that reported that “the ANN’s estimates of residential property values are nearly twice as accurate as those of a multiple regression model”, based on the MAPE values of both models. This also substantiates the findings of Ogunba (2004) that the valuation inaccuracy that is common in Nigeria could be as high as between 22 and 67%, probably due to the adoption of unreliable valuation approaches, yielding valuation inaccuracies that are not within acceptable industry standards (Babawale and Ajayi, 2011).

These results indicate that other nonlinear valuation approaches, specifically ANN, could produce better results than HPM. This is because the prediction error generated with the use of the HPM approach would be unacceptable by any rational real estate investor. This supports the findings of previous studies that reported the better predictive accuracy of the ANN technique compared to the HPM approach (for instance, Do and Grudnitski, 1992; Wong et al., 2002; Peterson and Flanagan, 2009; Lin and Mohan, 2011, amongst others).

The predictive accuracy of both models was also evaluated based on the number of predicted property values which had an absolute error range within the acceptable industry standards. The information in Table 8.2 shows that 26.67% of the predicted values of HPM has an error of between ± 0 and 10%, whereas the ANN model had 33.33% of its predictions within the same range. This same trend was evident for the rest of the accuracy range, with the ANN model having a lower number of predicted values with an error rate of greater than ± 20%, when compared with HPM.

About two-thirds (60%) of the HPM predictions had an error margin of over ± 20%. This could be responsible for the loss of confidence the valuation clients have in the profession and the professionals in Nigeria (Adegoke et al., 2013), because such a high error margin may render a real estate investor/stakeholder to go bankrupt.

Table 8.2: Property valuation accuracy of the HPM and the ANN models prediction

Accuracy range	Hedonic pricing model		Artificial neural network	
	Frequency	Percentage (%)	Frequency	Percentage (%)
± 0 - 10%	8	26.67	10	33.33
± 11 - 19%	4	13.33	13	43.33
> ± 20%	18	60.00	7	23.33

The predicted property values produced by both HPM and the ANN model were plotted against the actual property values as shown in Figure 8.1. This visual evaluation shows that the ANN model predicted property values are much closer to the actual property values when compared with the HPM predicted values. Greater disparities exist between the HPM predictions and the actual property values which suggest that the HPM could not produce reliable and accurate property valuation estimates.

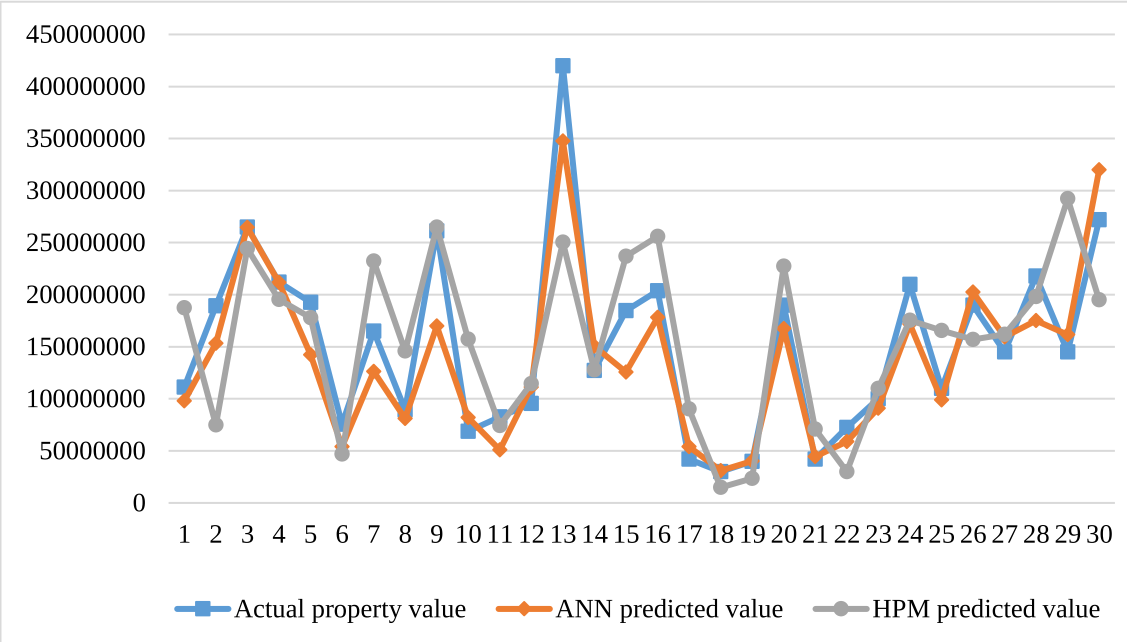

Figure 8.1: Actual property values and the predicted values of HPM and the ANN model

Overall, the results of this study clearly indicate that the ANN model could predict more accurate and reliable property valuation estimates when compared with the HPM approach. These results support the findings established in different property markets around the world that have reported the greater predictive accuracy of the ANN model over the HPM approach in property valuation; for instance, the studies of Nguyen and Cripps (2001) and Lin and Mohan (2011) in the United States, Selim (2009) in Turkey, Morano and Tajani (2013) in Turkey, Wong et al. (2002) in Hong Kong, Limsombunchai et al. (2004) in New Zealand and Amri and Tularam (2012) in Australia, amongst other property markets, around the world.

The present study is an exploration of the ANN technique in a developing nation, Nigeria, whose property market is opaque and immature (Dugeri, 2011; Walters et al., 2011). However, the credibility of the models could be improved by the use of more robust and quality data (Grover, 2016). When such data are in place together with other preconditions for developing a robust property valuation models (see Grover, 2016), as obtainable in most developed nations (Hofmann, 2003), accurate property valuation estimates could be recorded. This would, in turn, reduce the property valuation inaccuracies prevalent in such emerging markets. Subsequently, AI property value modeling techniques could be introduced in the property valuation practice in developing countries as evident in some developed property markets (see Wilkinson and Archer, 1973; Schwartz, 1995; McCluskey et al., 1997; Mora-Esperanza, 2004; Grover, 2016).

8.5 CHAPTER SUMMARY

The predictive accuracy of HPM and the ANN model was evaluated and reported in this chapter to demonstrate the efficacy of both models in property valuation. The predictions of both models were compared using measures of accuracy and the percentage of predicted values with estimation errors that fell within the acceptable industry standards. It is concluded that the ANN model outperformed the HPM approach in terms of predictive accuracy. The ANN model predictions were about two times more accurate than those of the HPM approach, and a higher number of ANN predicted property values had error margins within the admissible industry standards. The accurate predictive performance of ANN over the HPM approach reported in this study corroborates the existing literature. The findings of this study suggest that the ANN technique could produce accurate and reliable valuation figures. Therefore, the receptiveness of the Nigerian valuers to adopt the AI techniques in property valuation was investigated and reported in the next chapter.

CHAPTER 9 VALUERS' RECEPTIVENESS TO AI TECHNIQUES IN PROPERTY VALUATION[9]

9.1 INTRODUCTION

The previous chapter reported that the ANN technique outperformed the HPM approach in property valuation. Since the ANN technique has proven to be a good property valuation method, there is a need to establish the receptiveness of the Nigerian valuers who are the providers of property valuation services, to acquire the know-how of the AI valuation techniques and to eventually adopt them in practice. This exploration which would determine the future direction of the Nigerian property valuation practice, is presented in this chapter.

9.2 DATA COLLECTION AND METHODS

The main focus of this study is to evaluate valuers' willingness to embrace the AI techniques in property valuation in Nigeria. Quantitative research approach which allows the coverage of a wider spectrum of respondents being studied (Dix and Anderson, 2000) is adopted in this study. A questionnaire survey is a form of quantitative research approach that is usually adopted to measure the perception of

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[9] This chapter has been published in **Abidoye R. B.** and Chan, A. P. C. (2017). Valuers' receptiveness to the application of artificial intelligence in property valuation. *Pacific Rim Property Research Journal,* 23(2), pp. 175 - 193.

respondents in respect of the subject matter under study. It can be administered to the respondents by face-to-face, by post, over the telephone, by email or over the internet (Hoxley, 2008). Online questionnaire approach was used in this study to capture the opinion of real estate valuers on the research topic under investigation. As opined by Gillham (2000) and Mooya (2015), the survey instrument was validated by a group of real estate experts that have good knowledge of the Nigerian property market before the administration of the questionnaire to the respondents. After this exercise, the valuers commented that the instrument was adequately designed to capture the objectives of the study, hence the questionnaire was administered to the respondents.

9.2.1 Questionnaire Administration

The SurveyMonkey platform was utilized to design the online questionnaire. This approach is not uncommon in similar studies (see, for instance, Poon et al., 2011; Worzala et al., 2013; Mooya, 2015). The questionnaire was segmented into five parts. The first section centered on the characteristics of the respondents. Section Two to Five focused on questions on; the knowledge of the AI valuation techniques, the reasons for low awareness and applications of the AI valuation techniques, the measures which would enhance the adoption of the AI valuation techniques and the benefits, and the prospects of adopting the AI valuation techniques, respectively.

It is worth noting that the AI techniques referred to in this study are HPM, ANN and FLS. These AI techniques have been applied in property valuation both in theory and in practice in some developed countries (see, Schwartz, 1995; McCluskey et al., 1997; Grover, 2016). Responses were ranked on a five-point Likert scale (where 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree and 5 = strongly agree). This scale is common and appropriate for the study of this nature (Allen and Seaman, 2007; Dawes, 2008).

According to the 2014 membership directory of NIESV, there are 1794 registered estate surveyor and valuers in Nigeria. Out of this number, only 1229 have their email recorded in the directory. Consequently, the link to the online questionnaire was sent to 300 randomly selected valuers. The respondents were expected to respond to the survey within a period of two months. Furthermore, a reminder was sent to the respondents within the survey period so as to increase the response rate. At the end of the survey period, 138 responses were received, which represents a response rate of 46%, which is higher than what is obtainable in similar studies that have utilized survey research method (Akintoye and Fitzgerald, 2000). It was worth mentioning that 92 out of the138 responses were properly completed and valid for further analysis.

9.2.2 Data Analysis Method

The collected data were analyzed using the SPSS version 20.0 software. This tool was used to conduct descriptive analyses in terms of percentile distribution and MS. Also, the chi-square test was performed to examine the statistical relationship (if any) which exist between the valuers' profile and the factors which affect the issues under investigation. The MS ranking technique was adopted in ranking the factors included in the survey instrument. This approach has been adopted in previous built environment studies. See, for instance, Frank et al. (2007), Babarinde (2015), Mooya (2015) and Abidoye and Chan (2016c), among others.

9.2.3 The Respondents

Professional members of NIESV practicing in different property markets in Nigeria are the participants of this survey. Those valuers have obtained either a Probationer, Associate or Fellow membership status of NIESV and have acquired some considerable years of professional real estate practice experience. Estate Surveyors and Valuers are real estate professionals that have been empowered by the Laws of the Federal Republic of Nigeria (Decree No. 24 of 1975, now Cap III of 1990) to carry out real estate related services to the public. Therefore, the responses from NIESV members are considered as the most appropriate for the present study.

9.3 RESULTS AND DISCUSSION

9.3.1 Reliability Test

The reliability of the collected data was evaluated in order to ascertain the suitability of the data for the present study. The Cronbach's alpha test was conducted so as to establish the internal consistency amongst the valuers. A Cronbach's alpha value of 0.72 was recorded in this study which signifies a satisfactory reliability and internal consistency because a Cronbach's alpha value that is above 0.70 is satisfactory (Hair et al., 2010).

9.3.2 The Valuers' Profile

It is expected that the characteristics of the valuers in terms of educational qualifications, professional experience, sector of practice and the position held in their firms, among other factors, would have an influence on the subject under consideration. Some of the demographic profiles of the respondents are presented in Table 9.1.

These characteristics include their membership status with NIESV, the number of years of industry experience, the gender and the sector of practice. The statistics presented in Table 9.1 shows that about 76% of the valuers are either Fellow or Associate members of NIESV. This implies that majority of the respondents are committed members of the professional body. Also, Table 9.1 shows that about 63% of the valuers have acquired an industry professional experience ranging between 6 and 20 years, and 17% possess over 20 years of experience. This indicates that the valuers are sufficiently experienced in the real estate practice.

Table 9.1: The valuers' profile

Variables	Frequency (n)	Percentage (%)
Membership status with NIESV		
Fellow	14	15.20
Associate	56	60.90
Probationer	22	23.90
Total	92	100.00
Years of industry experience		
1-5 years	18	19.60
6-10 years	28	30.40
11-15 years	22	23.90
16-20 years	8	8.70
20 years and above	16	17.40
Total	92	100.00
Gender		
Male	78	84.80
Female	14	15.20
Total	92	100.00
Sector of practice		
Private real estate firm	66	71.70
Government parastatal	4	4.30
Financial institution	2	2.20
Education (lecturer)	16	17.40
Oil and gas sector	0	0.00
Built environment consortium	4	4.30
Total	**92**	**100.00**

The gender distribution of the participants indicates that 85% are men, whereas, 15% are female. It fair to interpret that the real estate profession is male-dominated in

Nigeria. In addition, about 72% of the respondents work in a private real estate firm and 17% are lecturers. This high percentage of valuers that are working in organizations where property valuation is either carried out or researched in is noteworthy for the present study.

The information presented in Figure 9.1 shows the highest educational qualification of the valuers. About 22% of the valuers have acquired Bachelor of Science degree, 61% possess a Postgraduate Diploma/Master's degree and 4% of the respondents are Doctor of Philosophy degree holder. This suggests that the valuers are much educated and are expected to be conversant with the global updates in the property valuation practice.

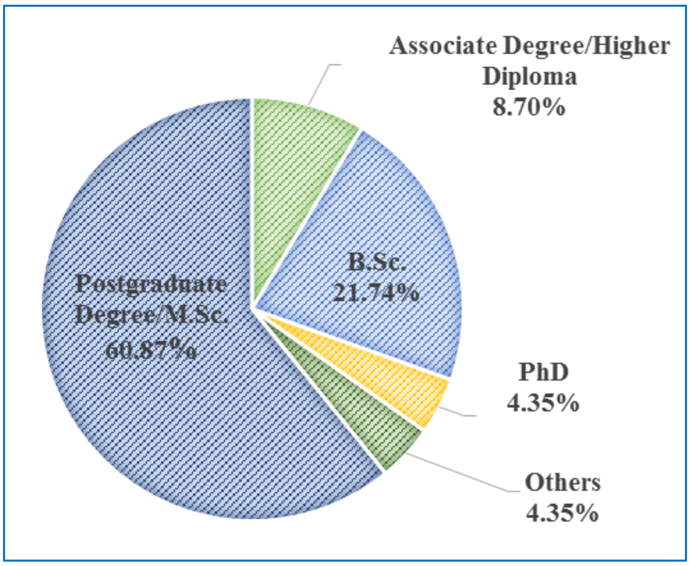


Figure 9.1: Valuers' highest educational qualifications

On the positions held by the valuers in their firms, 44% are principal partners, 15% are managing partners and senior estate surveyors, respectively. This amounts to over 70%

of the valuers occupying top positions in their firms, which assures the validity of the feedback of this survey. Figure 9.2 presents the distribution of the location of higher institutions the valuers attended. It is evident that about 87% of the valuers attended higher institutions located in Nigeria, while meagre 2% have experienced foreign education. Eleven percent of the valuers have a combination of foreign and local educational experience.

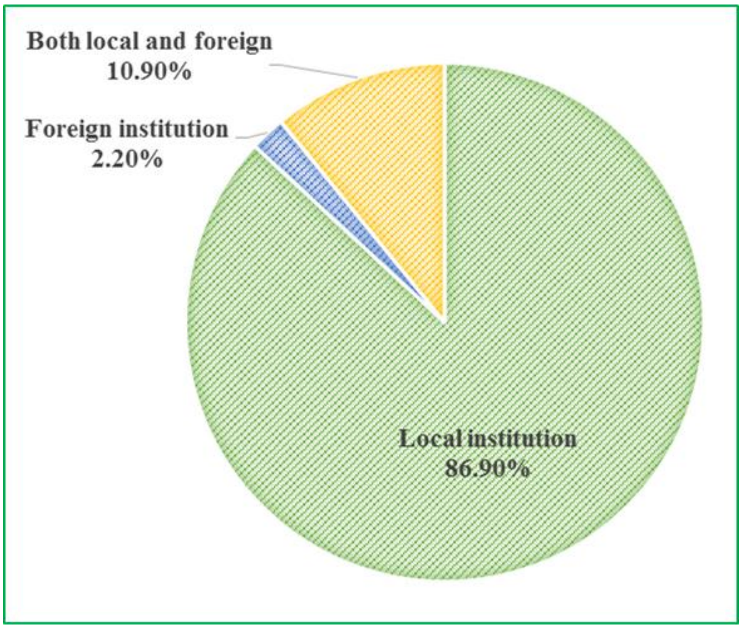


Figure 9.2: Location of an academic institution(s) attended

9.3.3 Knowledge of the AI Valuation Techniques

The questions contained in Table 9.2 was posed to the valuers in order to ascertain their level of awareness of the AI techniques and some other issues relating to the knowledge of the AI techniques. Almost 60% of the valuers either strongly agree or agree to be aware of these techniques, while the rest are either indifferent or disagree on the issue. On the use of the AI techniques in practice, only 13% of the valuers adopt the approaches in practice. The technique referred to here by those valuers could probably be HPM, as Abidoye and Chan (2016c) reported that this is one of the advanced approaches which the valuers operating in the Lagos metropolis (Nigeria) widely adopt. The low usage of these techniques may be connected to the lack of introduction to these techniques during academic training at tertiary educational (i.e. university and polytechnic), as more than half (52%) of the valuers indicated this.

It is expected that the basic rudiments of these techniques are to be taught to students during academic training. However, in a situation where that did not happen, the valuers have to learn on the job by attending workshops, seminars, training and conferences. Unfortunately, about 74% of the valuers have never received any in-house training organized by NIESV or ESVARBON, suggesting that the valuers have not been provided with the opportunity to learn on the job through this avenue. These professional bodies that have been empowered by the Laws of the Federal Republic of Nigeria seem to have failed to sufficiently promote the awareness and adoption of those AI techniques in practice.

Table 9.2: Knowledge of the AI valuation techniques

Questions	Level of agreement (%)					Mean score	Standard deviation
	SA	A	N	D	SD		
Valuers are aware of the AI valuation techniques	13.0	45.7	15.2	10.9	15.2	3.3043	1.2730
Valuers do use the AI valuation techniques in practice	2.2	10.9	28.3	32.6	26.1	2.3043	1.0455
Valuers were introduced to AI valuation techniques while in school (university or polytechnic)	4.2	34.8	8.7	21.7	30.4	2.6087	1.3502
NIESV or ESVARBON do organize conference, MCPD, seminar or workshop where this issue is discussed	6.5	13.0	6.5	41.3	32.6	2.1957	1.2156
The basics of AI valuation techniques are well documented in valuation textbooks and journal articles	10.9	37.0	13.0	17.4	21.7	2.9783	1.3666
Valuers are willing to acquire the know-how of the application of AI techniques in property valuation	56.5	37.0	2.2	2.2	2.2	4.4348	0.8294
Valuers will adopt the AI techniques in practice after acquiring the know-how	41.3	41.3	10.9	2.2	4.3	4.1304	0.9968

Note: SA – Strongly agree, A – Agree, N – Neutral, D – Disagree and SD – Strongly disagree

Putting all the aforementioned together, 93% of the valuers indicated their willingness to acquire the know-how of the application of the AI techniques, while about 82% indicated their readiness to adopt those techniques in practice. This high receptiveness of the valuers should be harnessed by the relevant professional bodies and other real estate stakeholders, as this would expose the valuers to international best property valuation practice.

9.3.4 Reasons for the Low Awareness and Application of the AI Techniques

In order to further investigate the cause(s) of low awareness and application of the AI techniques amongst valuers, responses were sought on questions addressing the issue (see Table 9.3). The factors were ranked in order of their importance to the awareness and application of the AI techniques that are under investigation.

As shown in Table 9.3, the professional bodies (NIESV and ESVARBON) and the educational institutions were ranked as the first and second factors, respectively, with an MS of 3.5870 and 3.5435, respectively. This corroborates the findings reported earlier (see Table 9.2) and implies that it is imperative that these two factors are accorded utmost attention by the concerned real estate stakeholders. The third factor is the individual valuers that have not been proactive enough to be updated about the developments in other property markets around the world.

Table 9.3: Reasons for the level of awareness and applications of the AI valuation techniques

Factors	Level of agreement (%)					Mean score	Standard deviation	Rank
	SA	A	N	D	SD			
NIESV and ESVARBON are responsible for the lack of awareness and adoption of the AI valuation techniques among valuers	26.1	34.8	21.7	6.5	10.9	3.5870	1.2505	1st
The educational institutions (academics) are responsible for the lack of awareness of the AI valuation techniques among valuers	26.1	28.3	26.1	13.0	6.5	3.5435	1.1990	2nd
Real estate professionals are responsible for their own lack of awareness of the AI valuation techniques	13.0	21.7	39.1	21.7	4.3	3.1739	1.0546	3rd
My level of education is responsible for the lack of awareness of the AI valuation techniques	10.9	6.5	26.1	21.7	34.8	2.3696	1.3153	4th
My years of professional experience is responsible for my lack of awareness of the AI valuation techniques	4.3	6.5	23.9	28.3	37.0	2.1304	1.2139	5th

Note: SA – Strongly agree, A – Agree, N – Neutral, D – Disagree and SD – Strongly disagree

9.3.5 Valuers’ Profile and Willingness to Acquire and Adopt AI Techniques

It will be interesting to know if the valuers’ level of education, the year of experience, the sector of practice, or the location of the institution(s) attended have any significant relationship with their willingness to acquire the know-how and adopt the AI valuation techniques. As this would indicate what to focus on in order to achieve the goal of transforming the valuation practice in Nigeria. The results of the chi-square test performed to establish the relationship are presented in Table 9.4.

On the willingness to acquire the know-how of the AI techniques, the year of experience has a strong statistical significance with the acquisition of AI know-how at 5% level of significance. It is safe to suggest that the longer a valuer practice the real estate profession, the greater the desire to be proficient in AI valuation. This substantiates the findings of Mooya (2015) in South Africa who reported that the length of professional experience of a valuer determines their professional competence.

On the other side, the years of experience and the sector where a valuer practices significantly influence their readiness to adopt the AI techniques in practice. This implies that the more a valuer practice this profession, the more the eagerness to adopt the techniques in practice. This is coupled with the sector of practice which is probably in a real estate firm, owing to the fact that most (70%) of the valuers work in private real estate firms.

Table 9.4: Chi-square test for valuers' willingness to acquire and adopt AI knowledge and their profile

Characteristics	χ^2 value	Degree of freedom (df)	ρ -value
Willingness to acquire AI techniques know-how			
Acquire higher educational qualification	5.281[a]	16	0.994[a]
The years of experience	32.229[a]	16	0.009[a]
The sector of practice	11.778[a]	16	0.759[a]
The location of institution(s) attended	10.282	8	0.246
Willingness to adopt AI techniques in practice			
Acquire higher educational qualification	24.539[a]	16	0.078[a]
The years of experience	41.857[a]	16	0.000[a]
The sector of practice	64.305[a]	16	0.000[a]
The location of institution(s) attended	9.926	8	0.270

9.3.6 Enablers of the AI Valuation Techniques Adoption

From the perspective of introducing the AI techniques in practice in Nigeria, all real estate stakeholders have a role to play. Table 9.5 reflect the opinion of valuers on the measure that could enhance the adoption of the AI techniques. Of the five measures presented, a partnership between the Nigerian real estate professional bodies (NIESV and ESVARBON) and international professional bodies such as RICS was ranked first with an MS value of 3.8913. This implies the need for an active and sustainable collaboration between the Nigerian real estate professional bodies and their international counterparts. This partnership has been achieved in some African countries (Ghana, Kenya and South Africa) and has gone beyond mere affiliations, rather the operation of international real estate bodies such as RICS has been extended to those property markets (Royal Institution of Chartered Surveyors (RICS), 2015).

The second factor is the overhauling of the property valuation curriculum of higher institutions of learning where real estate related courses are offered. This still amounts to the need for basic educational training for real estate undergraduates in order to keep them updated with the current trends in the international property valuation practice (Mooya, 2015). The compulsory attendance of training, workshops and conferences organized by NIESV and ESVARBON was ranked as the third factor which could enhance AI valuation adoption in Nigeria. While, the acquisition of higher education was ranked as the least factor in this category, probably because it was established that professional practice would influence the adoption of AI valuation techniques (see Table 9.5).

Table 9.5: Measures to enhance the adoption of AI valuation techniques

Enablers	Level of agreement (%)					Mean score	Standard deviation	Rank
	SA	A	N	D	SD			
NIESV and ESVARBON partnership with other international real estate professional bodies	30.4	45.7	10.9	8.7	4.3	3.8913	1.0737	1st
The overhauling of valuation curriculum by ESVARBON	23.9	50.0	15.2	8.7	2.2	3.8478	0.9600	2nd
Valuers compulsory attendance of seminar, training, workshop and conference organized by ESVARBON and NIESV	21.7	50.0	19.6	2.2	6.5	3.7826	1.0252	3rd
The amendment of the membership code of conduct of NIESV and ESVARBON	19.6	21.7	28.3	19.6	10.9	3.1957	1.2687	4th
Valuers mandatory acquisition of higher academic education	15.2	26.1	10.9	32.6	15.2	2.9348	1.3490	5th

Note: SA – Strongly agree, A – Agree, N – Neutral, D – Disagree and SD – Strongly disagree

9.3.7 Prospects of Adopting AI Valuation Techniques

Scholars have applied successfully and reported outstanding results in the application of the AI techniques under investigation in the present study (see for instance Tay and Ho, 1992; Adair et al., 1996b; Tse and Love, 2000; Hui et al., 2009; Kuşan et al., 2010; McCluskey et al., 2013). Therefore, it is believed that if the AI techniques are employed in the Nigerian property market, it could bring about a paradigm shift from the present state to an international level (Babawale and Oyalowo, 2011). However, in order of importance from the view of the valuers, the adoption of the AI techniques in the Nigerian property market would transform the real estate practice, it would be sustained when implemented and the techniques would produce reliable and accurate valuation estimates that would reduce valuation inaccuracy in the property market (see Table 9.6).

The views of the Nigerian valuers are not estranged with that of Malaysian valuers that are optimistic that computer-aided valuation would transform the Malaysian property valuation practice (Azmi et al., 2013). These benefits should not be underemphasized because the Nigerian property market is still at the developing stage (Dugeri, 2011) and at the same time, it is highly imperative to regain end-users' confidence of valuation reports in Nigeria (Adegoke et al., 2013), in order for Nigerian real estate professionals to remain competitive and respected (Babawale and Ajayi, 2011).

Table 9.6: Benefits of adopting the AI valuation techniques

Factors	Level of agreement (%)					Mean score	Standard deviation	Rank
	SA	A	N	D	SD			
This will add value and transform the Nigerian property valuation practice	23.9	47.8	19.6	4.3	4.3	3.8261	0.9901	1st
The adoption of the AI techniques in the Nigerian property valuation practice will be sustained when implemented	8.7	50.0	39.1	2.2	0.0	3.6522	0.6701	2nd
It will produce reliable estimates that will be acceptable by valuation report end-users and all stakeholders	15.2	41.3	39.1	2.2	2.2	3.6522	0.8446	2nd
The AI valuation techniques can reduce subjective interference in property valuation practice	17.4	34.8	39.1	6.5	2.2	3.5870	0.9276	4th
It will reduce the time involved in carrying out valuation exercise	13.0	41.3	34.8	10.1	0.0	3.5652	0.8555	5th
The AI valuation techniques can replicate human skills	10.9	37.0	32.6	15.2	4.3	3.3478	1.0102	6th
It will reduce the cost involved in carrying out valuation exercise	4.3	39.1	39.1	15.2	2.2	3.2826	0.8558	7th
The AI valuation techniques are more superior to the traditional valuation methods	10.9	17.4	39.1	26.1	6.5	3.0000	1.0690	8th

Note: SA – Strongly agree, A – Agree, N – Neutral, D – Disagree and SD – Strongly disagree

9.4 CHAPTER SUMMARY

The current immature state of the Nigerian real estate practice, in terms of its property valuation practice, motivated the present study. Howbeit, the receptiveness of Nigerian valuers to adopt the AI valuation techniques was investigated. It was revealed that a little bit above half of the valuers are aware of the AI appraisal techniques, but do not adopt them in practice. This is largely due to the little or no continuous professional training and non-inclusion of the AI techniques in the current curriculum of real estate programs at universities and polytechnics. Valuers' length of professional experience and the sector where they work was found to influence their willingness to adopt these AI techniques.

Meaningful collaboration and affiliation with international real estate professional bodies and the overhauling of valuation curriculum at universities and polytechnics would aid the adoption of the techniques across the nation. This will add value to the property valuation practice, in terms of estimating and reporting reliable and accurate valuation estimates that would be a good representation of market value. The subjective interference of valuers in property valuation exercise can be reduced and then lessen the level of valuation inaccuracy prevalent in the property market to the lowest minimum. The next chapter of this thesis concludes the research.

CHAPTER 10 CONCLUSIONS AND RECOMMENDATIONS

10.1 INTRODUCTION

The previous nine chapters of this thesis have presented the different components of the current research. The introduction to the research was presented in Chapter 1. The review of the literature conducted was documented in Chapters 2 and 3, while Chapter 4 contains the information about the research methodology adopted for this research. Chapters 5, 6, 7, 8 and 9 presented the findings from achieving the six objectives of this research. The present chapter is the last chapter of this thesis which concludes this research. This chapter firstly restates the aim and objectives of the research and also presents the summary of the research findings. The significance of the study, as well as the contributions to knowledge, are documented in this chapter. The recommendations, limitations of the study and the future research directions are also presented in this chapter.

10.2 REINTRODUCTION OF THE RESEARCH OBJECTIVES

The aim of the present research is to examine the accuracy and reliability of property value prediction models in the Lagos metropolis property market, by comparatively evaluating the application of HPM and the ANN model in property valuation. In order to achieve this aim, the following objectives were pursued:

i. to assess the current property valuation practice in the Lagos metropolis;

ii. to identify and generate a list of attributes that influence residential property values in the Lagos metropolis property market;
iii. to develop a Hedonic Pricing Model for the Lagos metropolis residential property market;
iv. to develop an Artificial Neural Network model for the Lagos metropolis residential property market;
v. to evaluate the predictive accuracy of the HPM and ANN models developed for the Lagos metropolis residential property; and
vi. to assess Nigerian valuers' receptiveness to the application of the AI techniques in property valuation.

10.3 SUMMARY OF MAJOR FINDINGS

The aim and objectives of this research have been achieved at various stages of the research. A summary of the findings which address each objective are presented in the subsections below:

10.3.1 Research Trend of the Application of ANN in Property Valuation

The ANN technique has been applied in the different disciplines, without the exception of the real estate domain for property price prediction and forecasting. The technique has gained much popularity amongst real estate researchers and professionals and has produced encouraging results in different property markets around the world. However, the trend of its application in this research domain has not been documented in the literature. An effort was made in this research to document the research trend of the application of ANN in the real estate domain.

The analysis of the retrieved articles shows that the first study that applied ANN in property valuation was published in 1991 (see Borst, 1991). Thereafter, the technique received more attention from 2000. A quarter of the articles selected for review emanated from the United States, while the rest were conducted mostly in developed countries. It was also found in most of the instances, the ANN model outperformed other modeling techniques. This established predictive accuracy of the ANN technique makes it a valuable tool for property valuation. These research findings are documented in Abidoye and Chan (2016b).

The application of the ANN technique in property valuation in developing property markets has been limited. This is a major gap in the current knowledge relating to this field. Due to the importance of property valuation, there is a need to consistently seek for ways to improve its accuracy. This information would facilitate improvement in the property valuation practice.

10.3.2 The Research Trend of the Application of HPM in Nigeria

The origin of the HPM approach could be traced to the early 1920s. This early usage and ease of application may be the principal reason for the popularity of the HPM approach in the property price modeling domain. The literature on the application of

HPM is disjointed. Hence, it is difficult to know what has been done and the gaps that need to be addressed. Therefore, a need to highlight the trend and gap(s) of its application in property price appraisal in the Nigerian property market in this research.

It was found that the HPM approach was first introduced into the Nigerian real estate research domain in 1986. Since then, there was a scanty turnout of publications, until 2010 when a considerable number of articles were published annually, suggesting that the approach gained prominence amongst Nigerian real estate researchers in 2010. The highest number of articles were published in 2011. The Lagos metropolis property market and indeed south-western states have been widely used as study areas by the researchers. In addition, real estate practitioners have not been involved in real estate research, whereas academics affiliated to universities have been the highest contributors to real estate research literature in Nigeria. This review shows the gap between theory and practice in the Nigerian real estate domain, and this could be one of the factors responsible for the immature state of the Nigerian property market. This gap must be filled in order to achieve a sustainable real estate practice (Hemsley-Brown and Sharp, 2003). These research findings are documented in Abidoye and Chan (2017b).

10.3.3 The Current Property Valuation Practice in the Lagos Metropolis

A number of methods exist for property valuation. Those methods are used in estimating property values in several countries around the world. Studies conducted in Nigeria have reported that the level valuation inaccuracy being experienced in the property market could be linked to the adoption of inappropriate valuation approaches. The current property valuation practice in Nigeria, in terms of the valuation approaches adopted by valuers, was investigated in this study. It was found that majority of the valuers are aware of and familiar with the traditional valuation methods, especially the comparable, the cost and the investment methods. In contrast, the valuers are not much aware of the advanced valuation approaches, although with an exemption of the HPM approach, which is being adopted by the Nigeria real estate scholars.

On the frequency of use of all the valuation approaches, the valuers always and regularly make use of the traditional valuation methods (comparable, cost and investment methods). The little awareness of the advanced approaches results in their low adoption in practice. Due to the prevalence of traditional valuation approaches in Nigeria, there is the need to improve the accuracy of property valuation estimates which necessitates a paradigm shift towards the application of AI modeling. With the successes recorded in the application of the AI techniques in developed property markets and even in other domains, there is a need for its exploration in Nigeria. Hence, the justification to conduct this research.

10.3.4 Property Value Determinants in the Lagos Metropolis Property Market

Studies have shown that the value attached to a property is dependent on certain factors, which can be categorized into; locational, neighbourhood and structural. The impact of those factors on property values vary from one location to another. A possible explanation for the inconsistency could be attributed to differences in the socio-economic, legal, environmental, cultural peculiarity across countries. Therefore, an attempt was made to gain deep insight into the determinants of property value in the Lagos metropolis property market. A literature review of relevant studies was carried out. This led to the identification of the 20 factors (i.e. determinants) that influence property values in the property market within the study area (i.e. the Lagos metropolis).

In this order, the location of a property, the neighbourhood characteristics, the state of repair of a property, the size of the property, the availability of neighbourhood security and the age of a property are the most significant attributes that determine residential property values in the Lagos metropolis, based on their RI. This process provides the justification for the variables included in the final property values prediction models developed. Therefore, those set of variables was used to develop HPM and ANN model for the Lagos metropolis property market.

10.3.5 Modeling the Lagos Metropolis Residential Property Values: The HPM Approach

A number of HPM previous research have applied the HPM approach in property appraisal in Nigeria. Those studies have largely focused on ‘explanatory’ rather than ‘prediction’. Therefore, the predictive accuracy of the approach was investigated using the Lagos metropolis as the study area. The analysis shows that the HPM approach produced inaccurate property values when the predicted values of the holdout samples were compared with the actual property values. The approach generated high MAPE (38.23%), MAE (₦61,408,856) and RMSE (₦103,370.573) values. These values may partly explain the prevalent level of inaccuracy in property values reported in previous studies.

About 60% of the predicted property values produced an inaccuracy error which is above ± 20% of the actual property values. This demonstrates that the HPM approach may not be able to accurately capture the nonlinear relationship between property value and its determinants. It is also imperative to note that the errors are larger than acceptable industry standards. Therefore, there is a need to explore the use of nonlinear modeling techniques in the property market which could generate more accurate and reliable property valuation estimates.

10.3.6 Modeling the Lagos Metropolis Residential Property Values: The ANN Approach

Studies have shown that the ANN technique has the capability of capturing and producing accurate predictions in real-world problems. The efficacy of using ANN model in property valuation was investigated in the present study. This is largely because a reliable model for predicting property values in Nigeria is lacking. The findings of the present study show that the ANN technique possesses a good accurate predictive ability based on MAPE value of 15.94%, MAE value of ₦28,492,514 and RMSE value of ₦41,814,564 that the model generated. These figures are encouraging as the MAPE value is within the range obtainable in the literature. This implies that the ANN technique is suitable for generating accurate and reliable property valuation estimates.

The RI analysis conducted on the property attributes revealed that the number of BQ rooms in a property is the most important attribute affecting property values. This implies that home buyers would consider this attribute when making real estate decisions. The findings suggest that the ANN technique could be used as a tool by real estate stakeholders, especially, valuers and researchers in property valuation both in the developing and developed countries.

10.3.7 Evaluation of the Predictive Accuracy of the HPM and ANN Models

The predictive accuracy performance of a model could not be conclusive until it is benchmarked against another. This necessitated the comparison of the predictive accuracy of HPM and the ANN model, so as to establish the most accurate and reliable property valuation technique between the two models. The same data set was fitted into both models and this was done in order to enable a fair comparison. It was found that the ANN technique outperformed the HPM approach, in terms of accuracy in predicting property values, by producing a higher r^2 value, lower MAPE, MAE and RMSE values when compared with the HPM approach.

The MAPE values generated by HPM and ANN model are 38.23% and 15.94%, respectively. This shows that the ANN techniques could predict figures which are two times more accurate than the HPM approach. This confirms the predictive accuracy of the ANN model which has also been established in previous studies. In addition, a higher number of the ANN predictions generated prediction errors that are within the acceptable industry standards. The findings demonstrate the efficacy of the ANN technique in property valuation, and if all the preconditions of property value modeling are met, the ANN technique could produce property valuation estimates which would be generally acceptable by all property valuation stakeholders.

10.3.8 Valuers' Receptiveness to the AI Techniques in Property Valuation

In a bid to bridge the gap between theory and practice, the receptiveness of the Nigerian valuers to the application of the AI techniques in property valuation was investigated. This was done so as to ascertain if the valuers, who are the main player in the valuation process (Ogunba, 2004; Shapiro et al., 2012), are actually prepared for the transformation that is much needed in the Nigerian property valuation landscape. The results of the study show that more than half of the valuers are aware of the AI valuation techniques. However, the techniques are not used in practice. Whereas, almost all the valuers are willing to acquire the know-how of and are prepared to adopt these techniques in property valuation.

The low adoption of the AI techniques was attributed to professional bodies responsible for the regulation of real estate practice and tertiary educational institutions in Nigeria, who were not proactive enough to promote their know-how and application. It was found that active collaboration between local professional bodies and similar international organizations on the training and development of members may improve the usage of the AI techniques. The study highlights the need for a paradigm shift in property valuation practice within the Nigerian context.

10.4 SIGNIFICANCE AND CONTRIBUTIONS TO KNOWLEDGE

An effort was made in this research to evaluate the predictive accuracy of HPM and the ANN model in property valuation in Nigeria, towards achieving property valuation accuracy. This investigation is crucial to both the real estate research and practice, considering the significant relationship between the theory and practice of a profession in achieving a sustainable growth (Van de Ven and Johnson, 2006). Therefore, the contributions of this research could be categorized into two folds i.e. theory and practice.

10.4.1 Contributions to Theory

In the research parlance, an effort was made to review and document the trends in the application of the ANN technique in property valuation (see Abidoye and Chan, 2016b). This provides an in-depth insight into the past, present and the future of this research area, which could stimulate more research effort directed towards this topic. In the same vein, a review of the application of the widely adopted HPM approach in the Nigeria property market was also documented. This was done in order to trace the origin of the technique in Nigeria and also to identify research gap(s) (Abidoye and Chan, 2017b). The study reveals that a wide gap exists between the Nigerian real estate scholars and practitioners. When this gap is bridged, it could lead to the transformation of the Nigerian real estate industry.

Previous HPM real estate studies conducted in Nigeria have focused solely on the ‘explanatory’ ability rather than the ‘predictive’ ability of the HPM approach in property value analysis. However, the predictive ability of the HPM approach in property valuation in the Nigerian property market was explored in this study. The study found the HPM approach to be inaccurate and unreliable for property valuation, hence the need for the adoption of a more robust property valuation model.

The ANN valuation technique has gained widespread popularity among real estate scholars and professionals in different property markets around the world. However, the technique has not been embraced by the Nigerian real estate scholars and practitioners. An effort was directed towards investigating its predictive accuracy in property valuation in Nigeria. This study confirms that the ANN technique is an effective property valuation tool that could reduce property valuation inaccuracy. This phase of the present research is reported in Abidoye and Chan (2017a). The comparison of the predictive accuracy of HPM and the ANN technique show that ANN outperformed HPM in terms of accuracy and reliability. This indicated that the ANN is a better alternative to the HPM approach in property valuation.

10.4.2 Contributions to Practice

The estimation of accurate property valuation figures is dependent on the methods adopted by the valuers. In a situation where the valuers cannot provide state-of-the-art services to meet the demand of both the local and the international valuation clients, the growth of the real estate profession in such economy could be endangered. This prompted an investigation into the current property valuation methods adopted in practice in Nigeria (Abidoye and Chan, 2016c). It was found that despite the transformation being experienced in different sectors of the Nigerian economy, the Nigerian property valuation practice is still at the traditional level because the majority of the valuers are not aware of and do not adopt the advanced valuation approaches in practice. This reveals a big challenge, which needs an urgent attention by all the stakeholders in order to ensure a sustainable property valuation practice in Nigeria.

Currently, the Nigerian mortgage system is not robust and not well established (Udechukwu, 2008; Ibem, 2011). Knowing that the financial institutions are the biggest property valuation report end-users (Gilbertson and Preston, 2005), the readiness of the Nigerian valuers to provide impeccable property valuation services to complement the Nigerian mortgage sector in the nearest future cannot be overemphasized. The adoption of the AI techniques would ensure that accurate and reliable estimates are generated so as to reduce the risk that all the stakeholders are exposed to in this system.

The Nigerian economy is an oil-dependent economy. Fluctuations in the prices of crude oil usually create a lot of societal problems and a significant reduction in government's revenues. Thus, it is important for the government to restructure its alternative sources for revenue generation. The AI modeling techniques can be used to facilitate the process of estimating property valuation figures for the purpose of collecting property-related taxes such as the ground rent, the tenement rate, and so on. This has proven to be cost-effective and required less number of valuers to appraise a large number of properties as obtainable in other property markets around the world (see Grover, 2016).

Property attributes that determine property values were evaluated and ranked based on their RI. This information would be of great importance to real estate portfolio managers, as well as real estate developers. This provides them with a list to consider when investing in real estate in the study area. This would ensure profit maximization.

The survey of the willingness of the Nigerian valuers to embrace the adoption of AI techniques in property valuation is significant because this reveals that the valuers are prepared to be agents of transformation as soon as other necessary conditions of property value modeling are in place in Nigeria. This could be capitalized upon by the real estate regulatory bodies to begin the campaign toward the transformation of the property valuation practice in Nigeria.

10.5 RECOMMENDATIONS OF THE STUDY

Continuous improvement is a process which facilitates competitiveness and continued relevance of a person, process, profession, and so on. This research has reported that the valuation practice in Nigeria is still in its infancy. However, in order to meet international standards in terms of property valuation services, a whole lot has to be done to achieve this. Therefore, in the light of the findings from this research, the following recommendations are proposed:

10.5.1 Maintenance of a Robust Property Transactions Databank

Authors (Gilbertson and Preston, 2005; Grover, 2016) have claimed that a robust and quality property transactions databank is a precondition for developing a reliable and accurate property valuation models. However, the opposite is what is obtainable in Nigeria. Therefore, NIESV and ESVARBON should put a plan of action in place to ensure that a robust databank is maintained. This could be achieved by directing real estate firms to henceforth document the records of property transactions they consummate electronically. This can then be collated by a team that would be trained in this regard. Incentives and penalties could be put in place so as to ensure compliance.

NIESV and ESVARBON could evaluate the international best practices of how databanks are maintained in developed property markets and then adopt such to the Nigerian situation. Although a databank maintenance effort was made previously by NIESV, this only generated yields and years' purchase (YP) in the Lagos, the Abuja and the Port-Harcourt property markets (see Nigerian Institution of Estate Surveyors and Valuers, 2013). Hence, the data was not used in this study because it is not useful for developing property valuation models.

10.5.2 Training of Real Estate Valuers

The training of practicing estate surveyors and valuers in the proficiency of the advanced valuation approaches should be accorded an urgent attention by NIESV and ESVARBON. This could be achieved by formulating and implementing massive nationwide campaign strategies to promote the enlightenment, the training and eventual enforcement of the adoption of the advanced valuation methods by professional members. This can be achieved by organizing seminars, mandatory continuing professional development (MCPD), workshops and conferences that will address this issue. Those training should be aimed at exposing valuers to global best practices and should be hands-on, as this would enhance the ability of the valuers to incorporate market research into property valuation practice.

10.5.3 Collaboration between the Real Estate Scholars and Practitioners

It has been established that research is vital for a sustainable professional practice in any discipline (Hemsley-Brown and Sharp, 2003). Therefore, there is a need to close the gap between the real estate academics and professionals in Nigeria. The need to improve the accuracy of property valuation estimates necessitates a paradigm shift towards the application of AI modeling. This collaboration would facilitate improvements in the real estate practice.

10.5.4 Overhauling of Real Estate Curriculum in Higher Institutions of Learning

There is a need to improve the current curriculum used for real estate courses, especially property valuation, at different levels of higher institutions of education in Nigeria. This was vividly established in this research where it was found that most of the valuers were not introduced to advanced property valuation methods while in school. The overhauling should be benchmarked against international standards in order to keep the students updated with the trending international valuation theories and methodologies before they graduate and mature into a professional. This would ensure that real estate graduates can fit in properly into both the local and the international job markets.

10.5.5 Collaboration with International Real Estate Professional Bodies

NIESV should also speedily facilitate the affiliation with RICS, this revolutionary achievement has been achieved in Ghana, Kenya and South Africa (Royal Institution of Chartered Surveyors (RICS), 2015). When this is affiliation replicated in Nigeria, it would: 1) facilitate information transfer, 2) provide a platform for the exposure to global best practices, and 3) facilitate the process of diffusion of innovation in the real estate practice.

10.6 STUDY LIMITATIONS

The questionnaire surveys conducted in this research were limited to the sampling of valuers whose email addresses are documented in the 2014 edition of NIESV's directory. Therefore, valuers whose details are not in the directory or have their incomplete information (no e-mail address) captured in the directory might have been excluded from this research. However, the high profile of the sampled surveyors ensures that meaningful inferences were made from the questionnaire surveys.

To date, in Nigeria, there is no centrally managed property sales and purchases information databank. This current situation warranted the door-to-door collection of property sales and purchases information from real estate firms operating in the Lagos metropolis. This resulted in retrieving 370 sales observations and eventually using 321 complete sales observations to build the property valuation models reported in this research. The relevance of the findings of this research is not undermined by this sample size because the sample size used in this research is within the range used in previous studies. However, if more data becomes available in the future the study could be replicated.

Data used in developing HPM and the ANN model were collected from high-end property market in Lagos, Nigeria. The exploration of the ANN technique in other property markets in Nigeria could generate different results. Also, the use of the ANN technique can be replicated in other developing countries too. Other macroeconomic variables (such as interest rates, GDP and exchange rate, amongst others), locational and neighbourhood attributes that could affect property values, were not included in the models developed in this research.

10.7 FUTURE RESEARCH

With the results of this research, continuing research is necessary so as to improve the desirable performance of the ANN model. This is because of the importance of accurate and reliable property valuation estimates to all real estate stakeholders and the nation at large. Studies in certain fields have shown that the inclusion of macroeconomic variables could improve the quality of predictions. Hence, future research could consider including those in the models. Also, property size variable was not considered in this study, due to the lack of adequate information from the real estate firms. However, should this be available in future, it may and should be included in property price modeling. Future research should consider developing the ANN model with a bigger sample size. This was not possible in this research due to the time and logistics constraints. The applicability of the ANN technique in property valuation in other property markets within Nigeria and also in other developing countries should be explored, as this will ensure a sustainable property valuation practice.

10.8 CHAPTER SUMMARY

This chapter summarizes this research by providing the major research findings, the significance of the research, recommendations of the study, study limitations and the area of future research direction.

APPENDICES

APPENDIX 1

Questionnaire administered to valuers on property valuation methods and property value determinants

THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

DEPARTMENT OF
BUILDING & REAL ESTATE
建築及房地產學系
INTERNATIONAL • COLLABORATIVE • CONSTRUCTION

QUESTIONNAIRE ON

ESTATE SURVEYORS & VALUERS PERSPECTIVE ON THE FACTORS THAT DETERMINES RESIDENTIAL PROPERTY VALUES IN LAGOS METROPOLIS

Dear Sir/Ma,

I am currently undergoing my PhD programme at The Hong Kong Polytechnic University, Hong Kong in the Department of Building and Real Estate and I am conducting a research on the above-mentioned topic.

The aim of the research is to identify the critical factors that determine the value of properties in Lagos metropolis and also the effect of externalities on property values. The result of this study will inform estate surveyors and valuers on the major factors to consider when appraising a property and when giving sound investment advice to their clients in the study area.

I will appreciate it if you will provide answers to the questions below diligently and I assure you that all information provided by you, will be treated with extreme confidentiality.

Thank you

Rotimi. B. Abidoye *M.Sc., ANIVS, RSV*
rotimi.abidoye@
+8523400

Section I: Estate Surveyor's Personal data

(i) Name (optional): ……………………………………………

(ii) Highest educational qualifications

High School { } Asso. Degree/Higher Diploma { } B.Sc. { } Postgraduate/M.Sc. { } PhD { } Others (Please specify): …………………………………..

(iii) Membership status with NIESV (Nigerian Institution of Estate Surveyors and Valuers)

Student Member { } Probationer { } Associate { } Fellow { }

(iv) Membership of other professional body (you can tick more than one)

ESVARBON { } NIM { } RICS { } AFRES { }

FIABCI { }

Others (Please specify): ……………………., ……………………………

(v) Position in your firm

Principal Partner { } Branch Manager { } Senior Estate Surveyor { } Estate Surveyor { } Pupil Surveyor { } Others (Please specify): ……………………

(vi) How long have you been in real estate practice?

0-5years { } 6-10years { } 11-15 years { } 16-20years { }

Above 20 years { }

(vii) Area of practice/specialization?

Valuation { } Property Management { } Agency { } General practice { }

Section II: Firm's data

(i) Name of firm

(Optional): ………………………………………………………

(ii) Age of firm

0-5years { } 6-10years { } 11-15 years { } 16-20 years { }

Above 20 years { }

(iii) Firm's staff strength

0-5 { } 6-10 { } 11 and above { }

(iv) Location of firm within Lagos

Victoria Island / Lagos Island { } Lagos Mainland { }

(v) Number of branches in Nigeria

0-5 { } 6-10{ } Above 11 { }

(vi) Number of oversea branches

0-5 { } 6-10{ } Above 11 { }

Section III: Valuation methods

(i) How many valuation exercise(s) do you carryout averagely per month?

0-5 { } 6-10 { } 11-15 { } 16-20 { } Above 20 { }

Kindly indicate your level of familiarity with each method of valuation for appraisal of residential properties and how often you adopt them in residential property valuation exercise.

S/N	Valuation Methods	Familiarity		Frequency of usage			
		Aware	Not Aware	Always	Regularly	Occasionally	Not at all
1	Investment method						
2	Comparison method						
3	Cost method						
4	Profit method						
5	Residual method						
6	Hedonic pricing method						
7	Spatial analysis method						
8	Autoregressive integrated moving average						
9	Artificial neural network						
10	Fuzzy logic method						
11	Others (Please specify)						

Section IV: Factors that determine residential property values in the Lagos metropolis

Kindly indicate your level of agreement with the factors listed below by ranking them based on the scale; 1- Highly insignificant, 2- Insignificant, 3- Indifferent, 4- Significant, 5- Highly Significant.

S/N	**Property characteristics**	**Scale**				
		1	**2**	**3**	**4**	**5**
1	Location of the property					
2	Accessibility to school					
3	Accessibility to shopping mall					
4	Accessibility to place of work					
5	Accessibility to CBD					
6	Accessibility to public transport facility					
7	Proximity to highway					
8	Neighbourhood characteristics					
9	Availability of electricity					
10	Availability of pipe borne water supply					
11	Availability of waste disposal system					
12	Availability of neighbourhood security					
13	Age of the property					
14	Numbers of bedrooms					
15	Size of bedrooms					
16	Number of bathrooms/toilets					
17	Building characteristics					
18	Size of property					
19	State of repair of the property					
20	Availability of security fence					
21	Others (Please specify)					

End of the questionnaire.

Thank you.

APPENDIX 2

Letter of introduction to registered real estate firms and a sample of the data collection sheet

Date,

Receiver's Address

Dear Sir/Madam,

Towards Property Valuation Accuracy in Nigeria – Residential Properties Sales and Purchases Data Collection

I am a PhD student at Department of Building and Real Estate of the Hong Kong Polytechnic University, Hong Kong. Currently, I am undertaking a research on **Property Valuation Accuracy in Nigeria – Developing an Efficient Valuation Model**. I hereby solicit for your support towards this research by kindly providing me/my research assistant with residential properties sales and purchase information that has been completed in your firm since 2000 to 2015. The data collection form consists of residential property attributes that have been established to influence property value in the Lagos metropolis property market. Hence, I request that you provide the features of each property that has been sold or purchased on behalf of your clients.

The data so collected will be used solely for the development of a hedonic pricing model and an artificial neural network valuation model. These models will be eventually compared in order to establish the most reliable and accurate model. Kindly note that the details of your firm remain anonymous and the information received will be treated with strict confidentiality and used solely for academic research purposes. Your cooperation is highly sorted in order for this research aim to be achieved.

Thank you.

Rotimi Boluwatife ABIDOYE, *M.Sc., ANISV, RSV.*
Mobile Number: +234802951

Ir. Professor Albert P. C. Chan (Chief supervisor).

THE LAGOS METROPOLIS RESIDENTIAL PROPERTIES SALES AND PURCHASES DATA COLLECTION FORM

Name of firm:							**Firm’s contact number**							
Address of firm:														
S/N	**Location**	**No. of bedrooms**	**No. of toilets**	**No. of bathrooms**	**Property size**	**Property type**	**No. of BQ**	**No. of parking space**	**Age of property**	**No. of floors**	**Availability of security fence**	**Year of sale**	**Sea view**	**Price**

APPENDIX 3

Questionnaire on AI property valuation techniques: Valuers' receptiveness and prospects in the Nigerian valuation practice

QUESTIONNAIRE ON
ARTIFICIAL INTELLIGENCE PROPERTY VALUATION: VALUERS' RECEPTIVENESS AND PROSPECTS IN THE NIGERIAN APPRAISAL PRACTICE

Dear Sir/Ma,

I am currently undertaking my PhD programme at The Hong Kong Polytechnic University, Hong Kong, in the Department of Building and Real Estate, and I am conducting a research on the above-mentioned topic.

The aim of this research is to establish valuers' receptive level and the prospects of adopting the Artificial Intelligence (**hedonic pricing model, artificial neural network and fuzzy logic system**) valuation approaches in the Nigerian real estate valuation practice. The result of this study will inform estate surveyors and valuers, real estate professional bodies and other property valuation stakeholders on the possibility of automating the Nigerian property valuation practice.

I will appreciate it if you will provide answers to the questions below diligently and I assure you that all information provided by you, will be treated with extreme confidentiality.

Thank you.

Rotimi. Boluwatife ABIDOYE *M.Sc., ANIVS, RSV*
rotimi.abidoye@
+8523400

Section I: Estate Surveyor's Personal data

(viii)Highest educational qualification

High School { } Associate Degree/Higher Diploma { } B.Sc. { }
Postgraduate/M.Sc. { } PhD { } Others (Please specify): ……………………….

(ix) Sex Male { } Female { }

(x) What is your professional membership status with NIESV?

Fellow { } Associate { } Probationer { } Student { } None { }

(xi) Position in your firm

Principal Partner { } Managing Partner { } Branch Manager { }
Senior Estate Surveyor { } Estate Surveyor { } Pupil Surveyor { }
Others (Please specify): …………………………………………

(xii)How long have you been in real estate practice? 0-5years { } 6-10years { } 11-15 years { } 16-20years { } 20years and above { }

(xiii) Location of academic institution(s) attended

Local Institution { } Foreign { } Both { }

(xiv)Sector of practice

Private real estate firm { } Government parastatal { } Financial institution { } Education (Lecturer) { } Oil and gas sector { } Built environment consortium { } (Please specify): ……………………………………………

Section II: Knowledge of AI appraisal techniques

Kindly indicate your level of agreement with the following statements. **Note**: Artificial Intelligence (AI) valuation approaches for the purpose of this study are **hedonic pricing model, artificial neural network and fuzzy logic system**.

Note: SD - strongly disagree, D - disagree, N- neutral, A- agree and SA - strongly agree

Questions	**Response**				
	SA	**D**	**N**	**A**	**SA**
Are you aware of the AI valuation techniques?					
Do you use the AI valuation techniques in practice?					
Were you introduced to AI valuation techniques while in school (university or polytechnic)?					
Have you ever attended a conference, MCPD, seminar or workshop organized by NIESV or ESVARBON where this issue was discussed?					
Have you read about AI techniques in valuation textbook(s) or journal article(s)?					
Are you willing to acquire the know-how of the application of AI techniques in property valuation?					
Will you be willing to adopt the AI techniques in practice after acquiring the know-how?					

Section III: Reasons for the low awareness and applications of the AI valuation techniques

Kindly indicate your level of agreement with the following statements. Note: SD means strongly disagree, D – disagree, N- neutral, A- agree and SA – strongly agree

Statements	**Response**				
	SD	**D**	**N**	**A**	**SA**
NIESV and ESVARBON are responsible for the lack of awareness and adoption of the AI appraisal approaches amongst valuers					
Educational institutions (academics) are responsible for the lack of awareness of the AI appraisal approaches amongst valuers					
Real estate professionals are responsible for their lack of awareness of the AI appraisal techniques					
My level of education is responsible for the lack of awareness of the AI valuation techniques					
My years of professional experience is responsible for my lack of awareness of the AI valuation techniques					

Section IV: Measures that will enhance the adoption of AI appraisal techniques

Kindly indicate your level of agreement with the following statements on the measures that will enhance the adoption of AI appraisal techniques in the Nigerian appraisal practice.

Note: SD-strongly disagree, D - disagree, N- neutral, A- agree and SA - strongly agree

Statements	**Response**				
	SD	**D**	**N**	**A**	**SA**
The adoption of the AI techniques in Nigeria can be achieved by mandating valuers to acquire higher academic education					
The adoption of the AI techniques in Nigeria can be achieved when valuers are mandated to attend seminars, training, workshops and conferences centered on this topic organized by ESVARBON and NIESV					
The adoption of the AI techniques in Nigeria can be achieved when ESVARBON overhauls the valuation curriculum of universities and polytechnics offering real estate courses					
The adoption of the AI techniques in Nigeria can be achieved when NIESV and ESVARBON amend their membership code of conduct					
The adoption of the AI techniques in Nigeria can be achieved when NIESV and ESVARBON partner with other International real estate professional bodies such as RICS					

Section V: Benefits of adopting AI appraisal techniques

Kindly indicate your level of agreement with the following statements on the benefits of adopting AI appraisal techniques in the Nigerian appraisal practice.

Note: SD-strongly disagree, D - disagree, N- neutral, A- agree and SA - strongly agree

Statements	**Response**				
	SD	**D**	**N**	**A**	**SA**
The adoption of the AI technique in Nigerian valuation practice will be sustained when implemented					
The adoption of AI appraisal techniques will add value and transform the appraisal practice in Nigeria					
The AI appraisal techniques can replicate human skills					
AI appraisal approaches are more superior to the traditional valuation methods					
The AI appraisal techniques can reduce subjective interference in property valuation practice					
The adoption of AI techniques will reduce time involved in carrying out valuation exercise					
The adoption of AI techniques will reduce cost involved in carrying out valuation exercise					
AI techniques will produce reliable estimates that will be acceptable by valuation report end-users and all stakeholders					

End of the questionnaire.

Thank you.

APPENDIX 4

Frequency distributions of the collected data

Frequency distribution of the variables

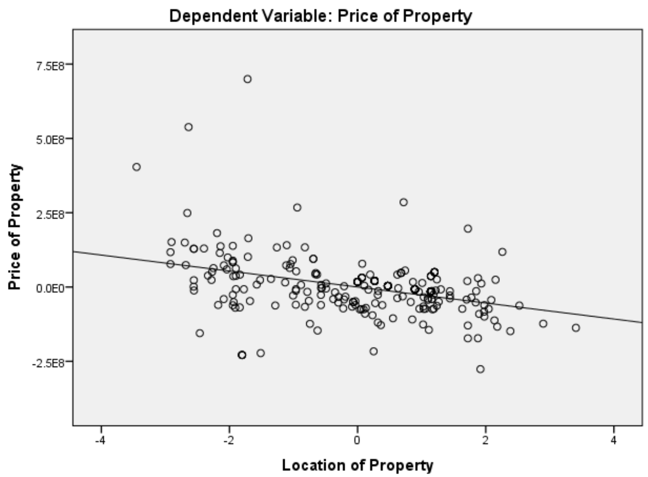
Variables	Frequency	Percentage (%)
Price		
0-50,000,000	111	34.6
50,000,001 – 100,000,000	73	22.7
100,000,001 – 200,000,000	66	20.6
200,000,001 – 500,000,000	56	17.4
Above 500,000,000	15	4.7
Number of bedrooms		
1	29	9.0
2	31	9.7
3	95	29.6
4	94	29.3
5	69	21.5
Above 5	3	0.9
Number of bathrooms		
1	29	9.0
2	50	15.6
3	83	25.9
4	92	28.7
5	64	19.9
Above 5	3	0.9
Number of toilets		
1	19	5.9
2	11	3.4
3	52	16.2
4	84	26.2
5	92	28.7
Above 5	63	19.6
Property type		
Duplex	12	3.7
Detached house	71	22.1
Semi-detached house	36	11.2
Terrace	67	20.9
Flat	98	30.5
Others	37	11.5

Number of BQ		
0	105	32.7
1	142	44.2
2	61	19.0
3	3	0.9
4	1	0.3
5	1	0.3
Above 5	8	2.5
Number of parking lots		
0	3	.9
1	46	14.3
2	121	37.7
3	45	14.0
4	34	10.6
5	28	8.7
Above 5	44	13.7
Age of building		
0	21	6.5
1	119	37.1
2	54	16.8
3	53	16.5
4	14	4.4
5	19	5.9
Above 5	41	12.8
Number of floors		
1	34	10.6
2	169	52.6
3	44	13.7
4	57	17.8
5	1	0.3
Above 5	16	5.0
Availability of security fence		
Yes	315	98.1
No	6	1.9
Availability of sea view		
Yes	17	5.3
No	304	94.7

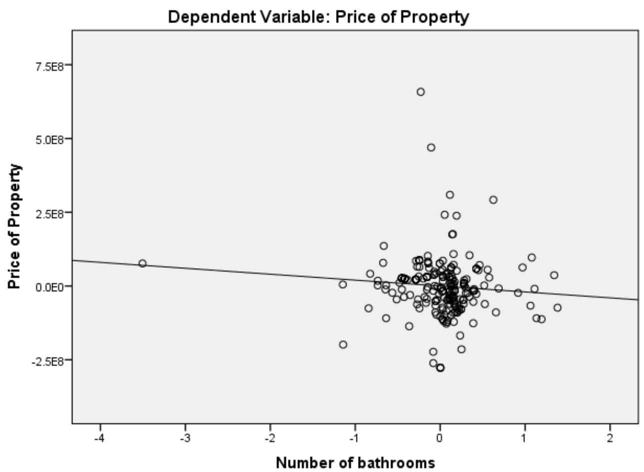
Location of property		
Ikoyi	82	25.5
Victoria Island	28	8.7
Lekki 1	53	16.5
VGC	8	2.5
Others	150	46.7

APPENDIX 5

Scatter plots of linearity test of the HPM

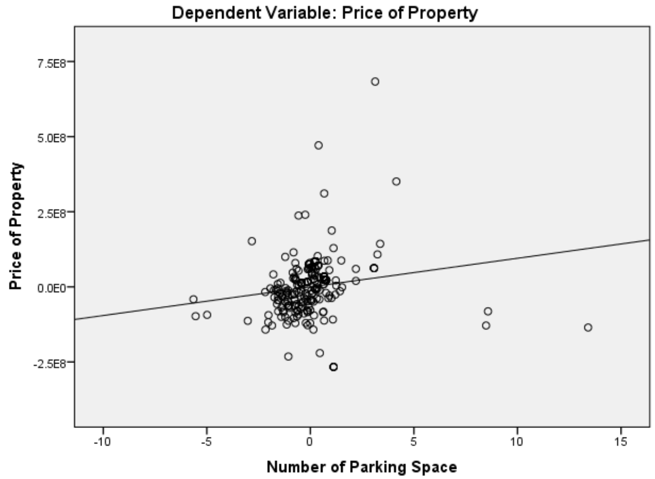

Dependent Variable: Price of Property
7.5E8
5.0E8
2.5E8
0.0E0
-2.5E8
Price of Property
-4
-2
0
2
4
Location of Property


Dependent Variable: Price of Property
7.5E8
5.0E8
2.5E8
0.0E0
-2.5E8
Price of Property
-2
0
2
4
6
Number of Bedrooms


Dependent Variable: Price of Property
7.5E8
5.0E8
2.5E8
0.0E0
-2.5E8
Price of Property
-4
-3
-2
-1
0
1
2
Number of bathrooms


Dependent Variable: Price of Property
7.5E8
5.0E8
2.5E8
0.0E0
-2.5E8
Price of Property
-2
0
2
4
Type of Property


Dependent Variable: Price of Property
Price of Property
Number of BQ rooms
7.5E8
5.0E8
2.5E8
0.0E0
-2.5E8
-5.0E8
-4
-2
0
2
4


Dependent Variable: Price of Property
Price of Property
Number of Parking Space
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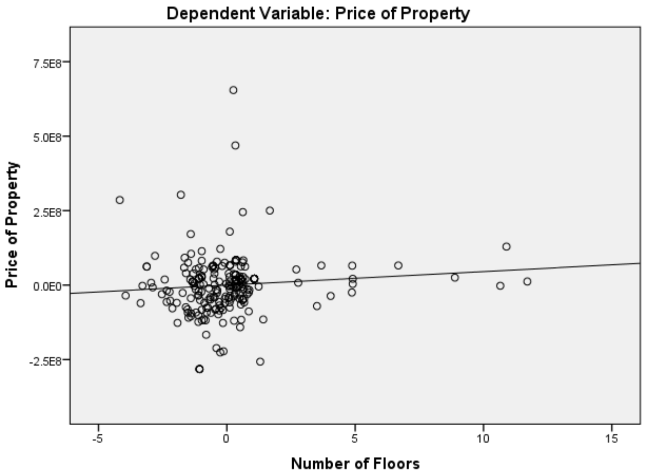
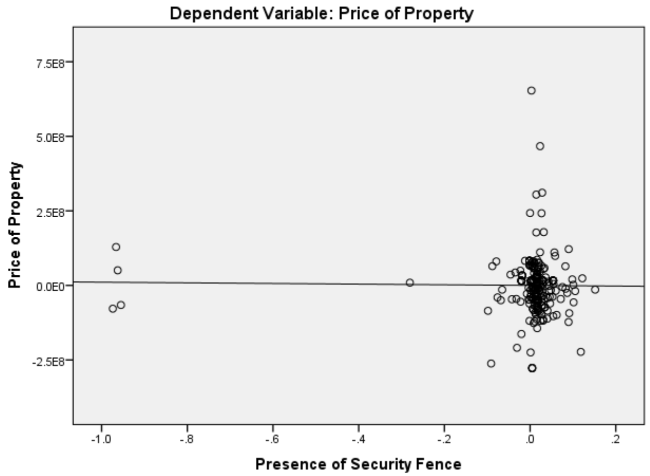
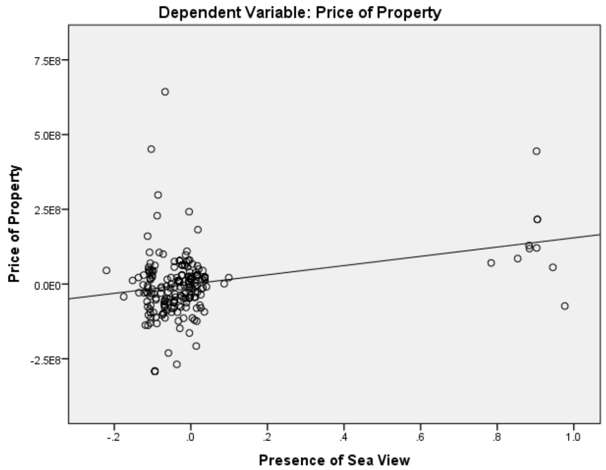
5.0E8
2.5E8
0.0E0
-2.5E8
-10
-5
0
5
10
15


Dependent Variable: Price of Property
Price of Property
Number of Floors
7.5E8
5.0E8
2.5E8
0.0E0
-2.5E8
-5
0
5
10
15


Dependent Variable: Price of Property
Price of Property
Presence of Security Fence
7.5E8
5.0E8
2.5E8
0.0E0
-2.5E8
-1.0
-.8
-.6
-.4
-.2
.0
.2


Dependent Variable: Price of Property
7.5E8
5.0E8
2.5E8
0.0E0
-2.5E8
Price of Property
-20
-10
0
10
20
30
Age of Building


Dependent Variable: Price of Property
7.5E8
5.0E8
2.5E8
0.0E0
-2.5E8
Price of Property
-.2
.0
.2
.4
.6
.8
1.0
Presence of Sea View

APPENDIX 6

Actual property values, ANN predicted property values and HPM predicted property values

HPM and ANN property values predictions				
Actual Property Values	**ANN predicted values**	**HPM predicted values**	**ANN prediction error (%)**	**HPM prediction error (%)**
111090000	97872115	187515677.2	11.90	-68.80
189303750	153268249	74929931.62	19.04	60.42
265025250	264723657.8	244410951.7	0.11	7.78
192556000	142297011	178031793.8	26.10	7.54
75647000	54106903	46897170.54	28.47	38.01
165048000	126230126	232250234.9	23.52	-40.72
89401000	81172837	145774376.6	9.20	-63.06
261326000	170040410	264980670.6	34.93	-1.40
68770000	81958549	157160890.9	-19.18	-128.53
82712500	51038195	74437574.35	38.29	10.00
95437500	111057526	114701420.1	-16.37	-20.18
419925000	347516329	250301576.3	17.24	40.39
127250000	150635901	127798471	-18.38	-0.43
184512500	125580216	236789805	31.94	-28.33
212020200	211778926.2	195528761.4	0.11	7.78
203600000	178111842	256067350.3	12.52	-25.77
42000000	53853180	90139662.12	-28.22	-114.62
30000000	31030426	14826321.51	-3.43	50.58
40000000	40057821	23491144.1	-0.14	41.27
190000000	167423921	227263030.7	11.88	-19.61
42000000	44607030	70904367.27	-6.21	-68.82
72500000	58956057	30117844.6	18.68	58.46
100000000	90933980	109827092	9.07	-9.83
210000000	171751581	175520356.9	18.21	16.42
110000000	98987646	165622515	10.01	-50.57
190000000	202613838	156957692.4	-6.64	17.39
145000000	159363934	161864922.4	-9.91	-11.63
218000000	175146167	198277100.2	19.66	9.05
145000000	161555621	292154224.3	-11.42	-101.49
272000000	319791715	195005613.6	-17.57	28.31
111090000	97872115	187515677.2	11.90	-68.80

APPENDIX 7

R Codes

```
# Load package

library(rminer)


# load data

data2 = read.csv(file.choose(), header=T)

# select inputs:

inputs=1:11 # select from 1 ("location") to 11 ("sea view")

# select outputs: regression task

price = which(names(data2)=="Price")

cat("output class:",class(data2[,price]),"\n")

# fit holdout example:

set.seed(12345)

H=holdout(data2$Price,ratio=0.8,seed=12345)

print("holdout:")

print(summary(H))

# Fit model

R1=fit(Price~.,data2[H$tr,c(inputs,price)], model="mlpe",size = 2, decay = 0, rang =
0.7, maxit = 100)

# get predictions on test set (new data)

P1=predict(R1,data2[H$ts,c(inputs,price)])

# show scatter plot with quality of the predictions:

T1=data2[H$ts,]$Price

e1=mmetric(target1,P1,metric=c("RMSE","R2"))
```

```
error=paste("ANN, holdout: RMSE=",round(e1[1],2),", R2=",round(e1[2],2), sep=" ")
pdf("rf-1.pdf")
mgraph(target1,P1,graph="RSC",Grid=10,main=error)
dev.off()
cat(error,"\n")
### regression examples: y - desired values; x - predictions
y = target1
x = P1
print(mmetric(y,x,"ALL"))
print(mmetric(y,x,"MAE"))
m=mmetric(y,x,c("MAE","RMSE","RAE","RSE","R2"))
print(m)
# Run sensitivity analysis
I=Importance(R1,data2[H$tr,c(inputs,price)])
print(round(I$imp,digits=2))
imax=which.max(I$imp)
L=list(runs=1,sen=t(I$imp),sresponses=I$sresponses) # create a simple mining list
par(mar=c(2.0,2.0,2.0,2.0)) # enlarge PDF margin
mgraph(L,graph="IMP",leg=names(cmath),col="gray",Grid=10,PDF="imp-8")
```

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