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PREDICTING HIGHEST PROFESSIONAL QUALIFICATION APPLYING THE USAGE OF STRATEGIC MANAGEMENT TOOLS AND TECHNIQUES AND YEARS OF PROFESSIONAL EXPERIENCE

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Abstract

Professional service firms employ strategic management (SM) in achieving their long term goals. Estate valuation and surveying firms, a subset of professional firms, are not an outlier in SM practices and strategic management tools and techniques (SMTT) usage. The aim of this paper is to predict the highest professional qualification of Estate Surveyors and Valuers (ESVs) in Southwest Nigeria, applying the degree of usage of strategic management tools and techniques (SMTTs) and years of professional experience. In this context, the highest professional qualification is being a Fellow of the Nigerian Institution of Estate Surveyors and Valuers (FNIESV), a step above being an Associate (ANIESV). The data is from a field survey and data mining models were used. The result showed that professional status (FNIESV or ANIESV) could be classified based on SMTT usage and years of professional experience. Adaptive boosting gave the best classification accuracy, specificity, and other evolution metrics.

Introduction

Dynamic estate surveying and valuation firms (ESVFs) and some other organizations adopt strategic management to chart a clear objective, which is achieved by formulation, implementation, and evaluation of the major actionable, timely, and measurable goals' policies [1]. An audit of a business environment often reveals gaps that should be bridged. This is done by crafting strategies that would help achieve the organization's goals in terms of profitability, viability, and sustainability [2]. Once the assessment is completed, resources are deployed to achieve the stated objectives.

The aim of this paper is to predict the highest professional qualification of Estate Surveyors and Valuers (ESVs) in Southwest Nigeria, using the degree of usage of strategic management tools and techniques (SMTTs) and years of professional experience. In this context, the highest professional qualification is being a Fellow of the Nigerian Institution of Estate Surveyors and Valuers (FNIESV), a step above being an Associate (ANIESV). Besides, SMTTs are collections of business strategies that organizations can use to implement their strategic plans and achieve or maintain a competitive advantage. Researchers have developed some SMTTs, which are somewhat related but distinct to address unique aspects of strategy crafting, formulation, implementation, and evaluation. The choice of the use of SMTTs depends on the nature of the strategy, timeline, organizational strengths and weaknesses, and organizational structure. Several of the most widely used SMTTs are listed but not limited to the following: mission and vision statements, activity-based costing, SWOT analysis, analysis of employee satisfaction, value chain analysis, balanced scorecard, VRIO analysis, mergers, McKinsey 7S Model, market penetration and Porter's 5 Forces. SMTTs are used to implement, track, and evaluate strategy in organizations effectively.

The use of SMTTs in professional service firms is often discussed in terms of specific conditions. There appears to be no general recommendation, but rather, users prescribe the methods that they believe are robust to help achieve objectives. However, some SMTTs cannot be applied by ESVFs because of their peculiarity. For instance, ESVFs may be reluctant to outsource critical roles. Secondly, privatization, as SMTTs may not be adopted since most ESVFs in the study area (SW Nigeria) are privately owned. Lastly, information and technological gaps could present a challenge in adopting SMTTs in some climes.

Literature Review

The dynamic business environment demands that ESVFs be proactive and frequently change to adapt to the industry's needs in real estate appraisal and agency, property valuation, management, and development [3]. The uncertain business terrain leads to increased risk, and strategies are needed to mitigate the risk by designing models that incorporate all the sources of variation of property market values [4]. In valuation, the widely used hedonic models may not be the best choice in strategizing against uncertain business environments [5]; rather, stochastic models are preferred to handle the sources of variation per time. Nevertheless, it should be noted that hedonic models are valuable tools, and it is a strategic tool in achieving organizational goals in ESVFs [6]. Irrespective of the valuation models, certain factors contribute uniquely to real estate value, and adequate strategies are needed to ensure hitch-free valuation processes [7, 8]. Housing quality and location are the two examples of such factors [9-12].

SMTTs have helped in different aspects of valuation process. SMTTs have been used in a study in the Netherlands to manage complexities inherent in commercial property valuation [13]. Similarly, SMTT has been used to forecast the viability of properties for future investment [14]. Particularly, game theory and multi-criteria expert decision systems were applied in property appraisals under uncertain investment scenarios [15, 16]. In the same vein, a value-based strategic planning framework was used as a real estate valuation strategy to respond to competition and ensure ESVFs sustainability [17]. Expansion or diversification has been applied in real estate valuation, appraisal, and price forecasting [18].

The adoption of SMTTs in developing countries has not been adequately reported. This is surprising since the adoption of SMTTs in ESVFs is a function of attitudinal or behavioral disposition [19].

This work employed data mining tools. There has been an explosion in the research on the application of machine learning tools or data mining models. The field of real estate valuation has benefited from such machine learning or data mining methodologies. The complexities in real estate valuation, appraisal, and house price prediction are now cheaply handled by machine learning tools [20]. The complexities could be defined as complex interconnections or nonlinear relationships among the variables that must be accounted for in the valuation process [21]. The valuation process often involves a large amount of data, which limits the accuracy of hedonic models but now, such big data can be handled by data mining models [22]. Traditional valuation models are not fully flexible in reducing the effects of complexities and uncertainties inherent in the valuation process [23]. Data models efficiently classify attributes and improve precision in appraisal and real estate market value prediction. Examples are the use of neural networks and genetic algorithms in real estate valuation [24-26]. Boosted regression tree was applied in [27]. Worryingly, developing countries have not fully subscribed to the use of advanced computational methods. Hence, traditional methods of property valuation are still in use in those countries.

Materials and Methods

The summary of all the methods and tools used to obtain the results are stated.

Nature of data: A field survey.

Time of survey: The survey was carried out between February and April 2020.

Target population: ESVFs in the six (6) states of the southwest geopolitical region in Nigeria.

Sampling frame: The sampling frame is ESVFs in the six (6) states of the southwest geopolitical region, Nigeria.

Sampling method: Purposive sampling because the samples were restricted to ESVFs. Simple random sampling was used to select respondents within each organization. In the case of sole proprietorships, only the owners were selected.

Instrument of data collection: Self-administered questionnaire.

Sample size used in data analysis: 263.

Target variable: The target variable is the highest professional qualification (HPQ), which is a Fellowship of the Nigerian Institution of Estate Surveyors and Valuers (FNIESV) and Associate Nigerian Institution of Estate Surveyors and Valuers (ANIESV).

Independent variable: Two independent variables were used. The first is SMTT’s usage, where the respondents were asked to choose as many as possible. Sixty-six (66) SMTTs were made available. The second is the number of years of professional experience (YOE). The options of responses are: (i) less than 5 years, (ii) between 6 and 10 years, (iii) between 11 and 15 years, (iv) between 16 and 20 years, (v) between 21 and 25 years and (vi) above 25 years.

Nature of variables: The target variable (HPQ) is categorical (0 and 1), while the first independent variable (SMTT's usage) is continuous. The second independent variable (YOE) is categorical (0, 1, 2, 3, 4, and 5). Less than 5 years were coded as zero (0) while above 25 years were coded as five (5).

Data analysis tools: SPSS 24 and Orange software. The former was used for the statistical analysis while the latter was used for data mining.

Data mining model: Classification.

Result

Statistical analysis

Descriptive statistics showed that 62 (23.6%) of the respondents are FNIESV, while 201 (76.4%) are ANIESV. 13 (4.9%) of the respondents have never used any of the sixty-six (66) SMTTs. The mean and modal SMTTs usages are 13 and 5, respectively. It was also obtained that 92% of the respondents have used between zero (0) and twenty-five (25) SMTTs.

Descriptive summary of the years of professional experience showed 15 (5.7%) of the respondents have less than 5 years of professional experience; 44 (16.7%) have between 6 and 10 years; 33 (12.5%) have between 11 and 15 years; 44 (16.7%) have between 16 and 20 years; 41 (15.6%) have between 21 and 25 years; while 86 (32.7) have above 25 years of professional experience working as ESV in Southwest Nigeria.

The SMTTs usage was factored out based on HPQ, and the result is presented in Table 1 where the FNIESV has more SMTT usage than ANIESV. This is expected since strategic management is a high level management responsibility. Hence, the respondents in fellow category are most likely to be in top management positions.

Table 1. SMTTs usage based on HPQ

Statistic	FNIESV	ANIESV
Mean (standard error)	13.45 (1.23)	12.46 (0.728)
Median	11	11
Huber's M-estimator	11.73	10.77
Tukey's biweight	11.33	10.22
Hampel's M-estimator	12.13	10.77
Andrews' wave	11.27	10.20
Variance	93.858	106.639
Standard deviation	9.688	10.327

Box plots showing the factoring of SMTTs based on HPQ are presented in Figure 1, where it could be seen that extreme observations for ANIESV were reported. Also, most observations are skewed towards the median for the fellow category while the associate category appears to be purely centered, the outliers notwithstanding.

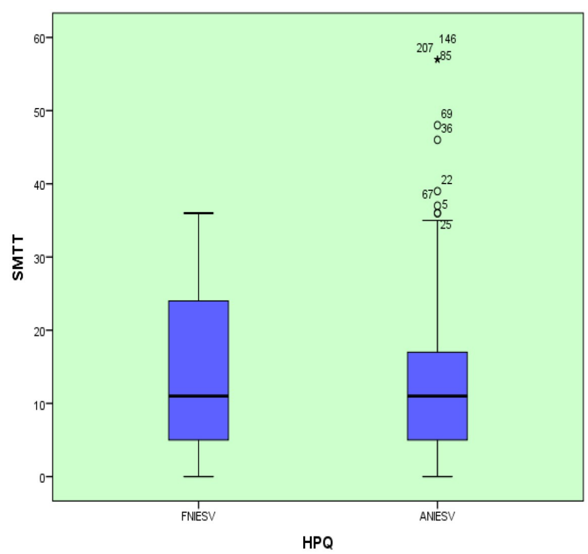

Figure 1. Plot of SMTTs usage based on HPQ.

The YOE usage was factored out based on HPQ, and the result is presented in Table 2 where the FNIESV has more SMTT years of professional experience than ANIESV. This is expected since strategic management is a high-level management responsibility, and consequently, it takes several years to gather sufficient experience to be at the top management level.

Table 2. YOE based on HPQ

Statistic	FNIESV	ANIESV
Mean (standard error)	4.44 (0.099)	2.79 (0.118)
Median	5	3
Huber's M-estimator	n/a	2.80
Tukey's biweight	n/a	2.79
Hampel's M-estimator	n/a	2.79
Andrews' wave	n/a	2.79
Variance	0.611	2.776
Standard deviation	0.781	1.666

n/a: not available. Some M-estimators cannot be computed because of the highly-centralized distribution around the median

Box plots showing the factoring of YOE based on HPQ are presented in Figure 2, where it could be seen that observations for FNISV were highly skewed towards five (5). This indicates that those in the fellow category have a higher number of years of experience than those in the associate category.

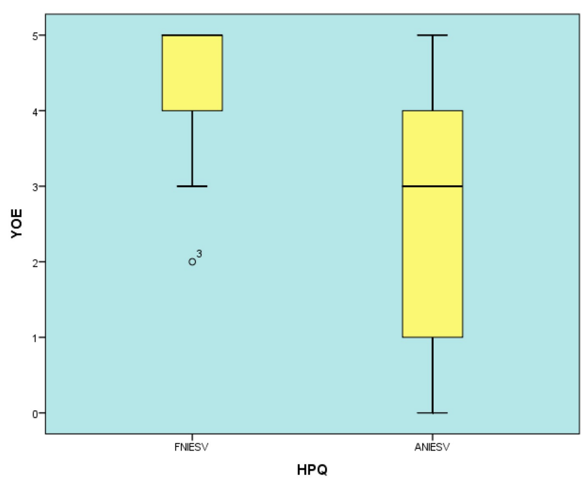

Figure 2. Plot of YOE usage based on HPQ.

The independent samples test, as presented in Table 3, showed that there is no mean difference in SMTTs usage between FNIESV and ANIESV. Nonsignificance was the outcome of the *t*-test for both instances of equal variance assumed and otherwise.

Table 3. The *t*-test summary of SMTTs usage based on HPQ

Test	Statistics	*p*-value
Levene's test for equality of variances	$F = 0.755$	0.386
Equal value assumed	$t = 0.672$	0.502
Equal value not assumed	$t = 0.695$	0.488

Data mining

Using the information described in the materials and methods section, firstly, it was obtained that the four best performing models based on area under curve (AUC) are shown in Figure 3.

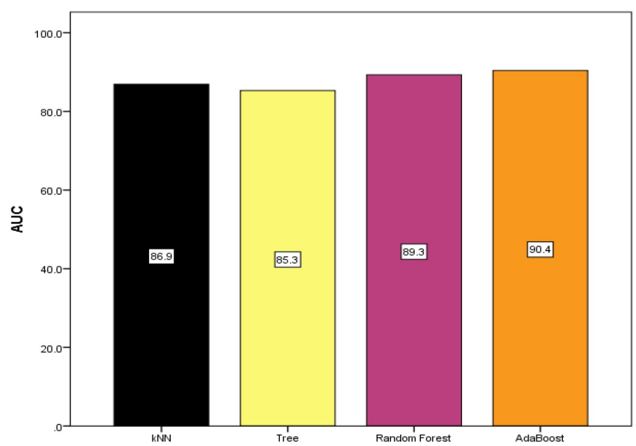

Figure 3. AUC of the classification of HPQ using SMTTs and YOE.

The performance (AUC) in increasing order is classified as: tree (Tree) (85.3%), k-nearest neighbor (kNN) (86.9%), Random Forest (89.3%) and adaptive boosting (AdaBoost) (90.4%), respectively.

Secondly, it was obtained that the four best performing models based on classification accuracy (CA) are shown in Figure 4.

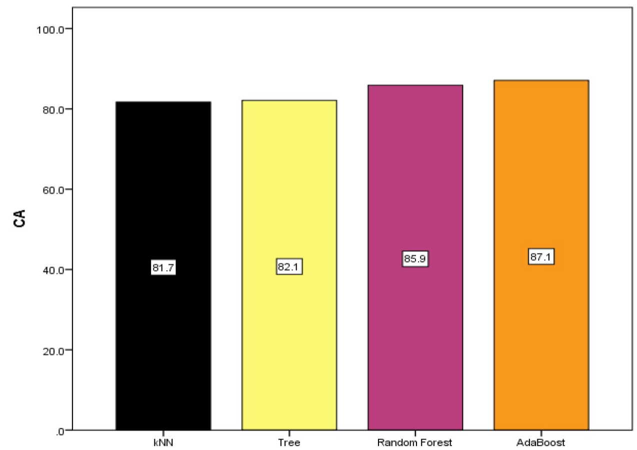

Figure 4. CA of the classification of HPQ using SMTTs and YOE.

The performance (CA) in increasing order is as: kNN (81.7%), Tree (82.1%), Random Forest (85.9%) and AdaBoost (87.1%), respectively.

Thirdly, it was obtained that the four best performing models based on F1 are shown in Figure 5.

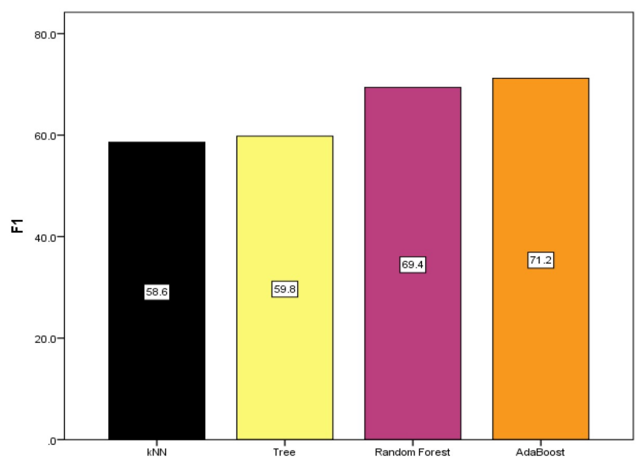

Figure 5. F1 of the classification of HPQ using SMTTs and YOE.

The performance (F1) in increasing order is as: kNN (58.6%), Tree (59.8%), Random Forest (69.4%) and AdaBoost (71.2%), respectively.

Fourthly, it was obtained that the four best performing models based on precision (sensitivity) are shown in Figure 6.

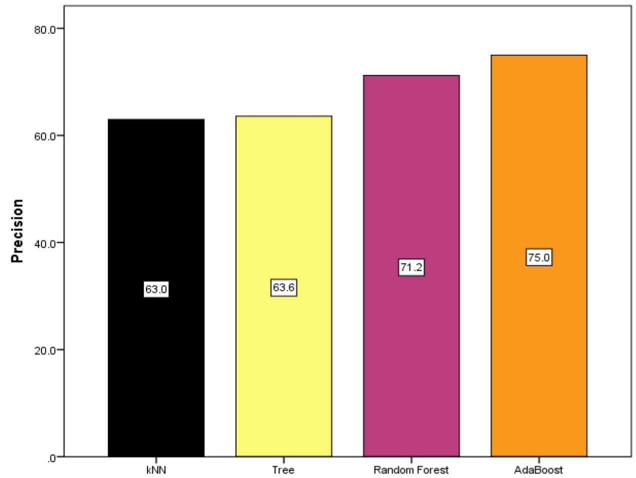

Figure 6. Precision of the classification of HPQ using SMTTs and YOE.

The performance (precision) in increasing order is as: kNN (63.0%), Tree (63.6%), Random Forest (71.2%) and AdaBoost (75.0%), respectively.

Lastly, it was obtained that the four best performing models based on recall (specificity) are shown in Figure 7.

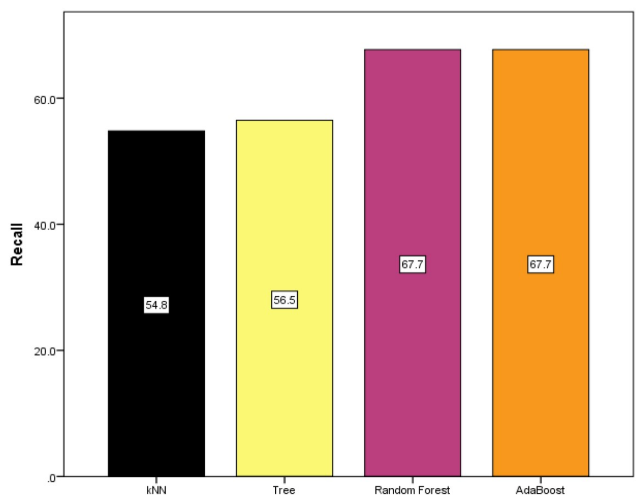

Figure 7. Recall of the classification of HPQ using SMTTs and YOE.

The performance (recall) in increasing order is as: kNN (54.8%), Tree (56.5%), Random Forest (67.7%) and AdaBoost (67.7%), respectively.

Confusion matrix was used to determine the accuracy of the four classification models, and the results are presented as true positives, false positives, false negatives and true negatives.

Firstly, the results of the classification of the instances of true positives are shown in Figure 8.

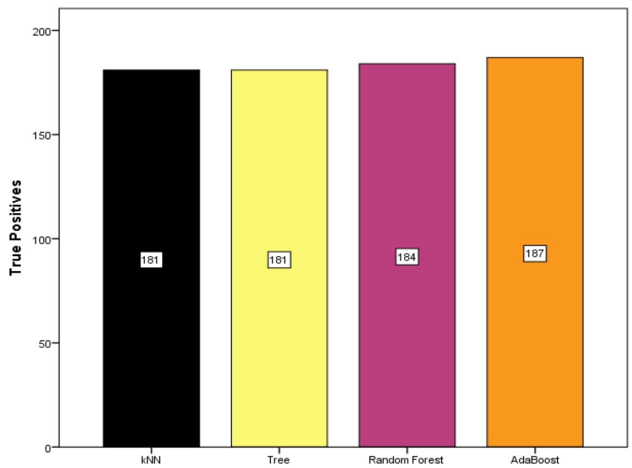

Figure 8. True positives of the classification of HPQ using SMTTs and YOE.

The true positives obtained in increasing order are: kNN (181), Tree (181), Random Forest (184) and AdaBoost (187), respectively.

Secondly, the results of the classification of the instances of false positives are shown in Figure 9.

The false positives obtained in decreasing order are: kNN (20), Tree (20), Random Forest (17) and AdaBoost (14), respectively.

Thirdly, the results of the classification of the instances of false negatives are shown in Figure 10.

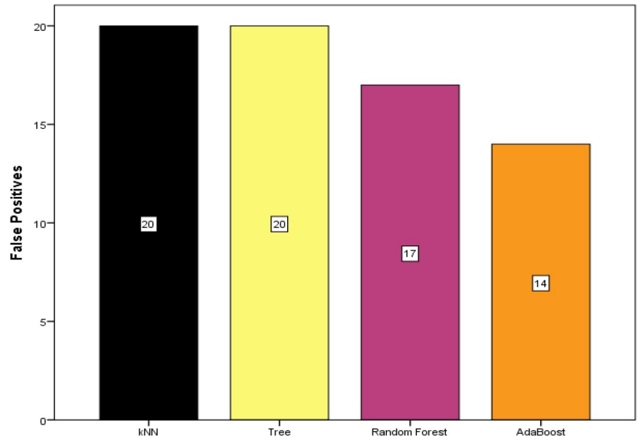

Figure 9. False positives of the classification of HPQ using SMTTs and YOE.

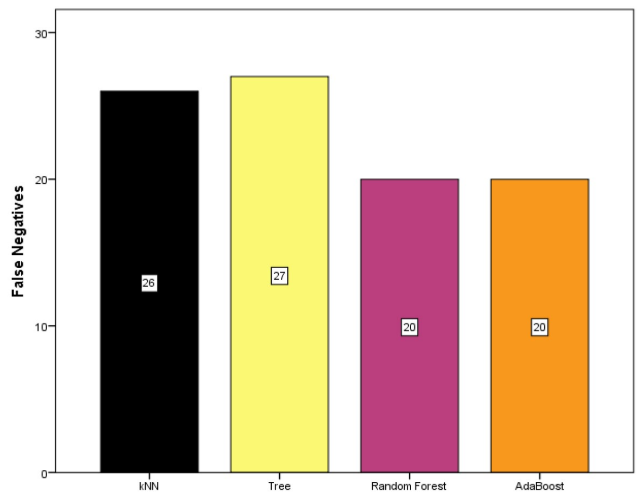

Figure 10. False negatives of the classification of HPQ using SMTTs and YOE.

The false negatives obtained in decreasing order are: Tree (27), kNN (26), Random Forest (20) and AdaBoost (20), respectively.

Lastly, the results of the classification of the instances of true negatives are shown in Figure 11.

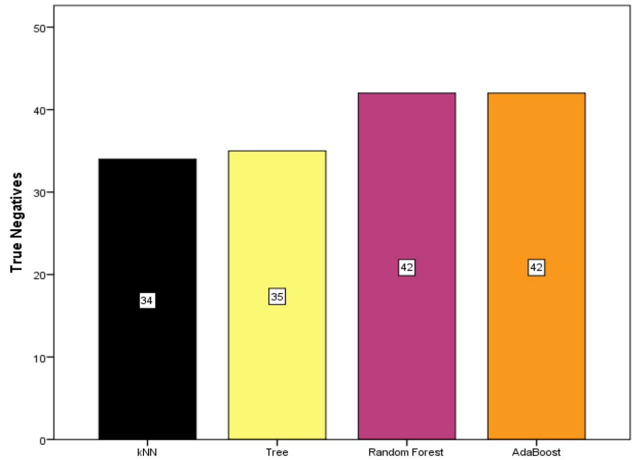

Figure 11. True negatives of the classification of HPQ using SMTTs and YOE.

The true negatives obtained in increasing order are: kNN (34), Tree (35), Random Forest (42) and AdaBoost (42), respectively.

Conclusion

Data mining models have proved useful in classifying if a randomly selected ESV is a fellow or an associate member of the NIESV using their degree of SMTT usage and years of professional experience. The methodology is trusted because the variables are uncorrelated with each other. An ESV is most likely to be an FNIESV if he/she uses SMTTs and has spent substantial years in professional practice. This research has expanded the knowledge in this aspect, which is shockingly absent in extant literature. Further studies will require the use of deep learning methods and the incorporation of more independent variables.

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