A machine learning approach for predicting critical factors determining adoption of Offsite construction in Nigeria.

ABSTRACT

Design/methodology/approach – The research approach is deductive in nature, focusing on finding out the most critical factors through literature review and reinforcing the factors through a 5- point Likert scale survey questionnaire. The responses received were tested for reliability before being run through Machine Learning algorithms to determine the most influencing OSC factors within the Nigerian Construction Industry (NCI).

Purpose –Several factors influence OSC adoption, but extant literature did not articulate the dominant barriers or drivers influencing adoption. Therefore, this research has not only ventured into analyzing the core influencing factors but has also employed one of the best-known predictive means, Machine Learning, to identify the most influencing OSC adoption factors.

Findings – The research outcome identifies seven (7) best-performing algorithms for predicting OSC adoption: Decision Tree, Random Forest, K-Nearest Neighbour, Extra-Trees, AdaBoost, Support Vector Machine, and Artificial Neural Network. It also reported finance, awareness, use of Building Information Modeling (BIM), and belief in OSC as the main influencing factors.

Research Limitation/Implication – Data were primarily collected among the NCI professionals/workers and the whole exercise was Nigeria region-based. The research outcome, however, provides a foundation for OSC adoption potential within Nigeria, Africa and beyond.

Practical implications – The research concluded that with detailed attention paid to the identified factors, OSC usage could find its footing in Nigeria and, consequently, Africa. The models can also serve as a template for other regions where OSC adoption is being considered.

Originality/value – The research establishes the most effective algorithms for the prediction of OSC adoption possibilities as well as critical influencing factors to successfully adopting OSC within the NCI as a means to surmount its housing shortage.

Keywords – Construction, Construction industry, Nigeria, Offsite Construction, Machine Learning

Paper type – Research paper

1.0 INTRODUCTION

Nigeria has been battling housing challenges for a long while (Kolo et al., 2014). Listed as the 7th most populous nation on earth and 1st in Africa with over 213 million inhabitants (UN, 2021), Nigeria has a deficit of over 17 million houses in its major cities (Rahimian et al., 2017). The cities have become overcrowded owing to an insufficient amount of shelter to accommodate their sprawling populations. Despite the slums being created around the cities' suburbs, migration to most urban areas of the nation, estimated at 5.5%, increases daily (Makinde, 2014). The government has schemed different approaches to resolving the housing issues at the federal and state levels but has recorded little or no success.

Public-Private-Partnerships have equally been tried, but it has yielded insignificant progress on housing amelioration. (Okonjo-Iweala, 2014) noted that with Nigeria outputting less than 100,000 units of houses annually, over 700,000 units of homes would be required to offset the housing deficit in about four major cities alone. Scholars have reported in a few articles on the housing challenge being faced in Nigeria as attributable to the approach being employed by the different stakeholders trying to resolve the deficits, while suggesting the propensity of OSC being a out. (Dunmade & Fayomi, 2018; Kolo et al., 2014; Njoku & Adegboye, 2015; Rahimian et al., 2017; Usman, 2019; Windapo & Rotimi, 2012). In other instances, (Rahimian et al., 2017) reported on causal factors influencing OSC adoption, (Dixon-Ogbechi and Adebayo, 2020) examined important factors that determine developers' choice of prefab building type and (Kolo et al., 2014) examined housing challenges and how Offsite Construction can salvage the deteriorating situation.

Majority of the houses being constructed in Nigeria today employ the traditional or conventional construction method, using brick and mortar with other aggregates (Adeagbo and Anigbogu, 2020). This construction method has been in use for centuries. However, few projects have sought alternatives to improve construction with the Nigerian nation. The traditional construction method is very slow, less safe, expensive, cumbersome, results in cost over-run and is easily affected by inclement weather and other external factors (Ajayi et al., 2019; Arif et al., 2017; Blismas & Wakefield, 2009; Gan et al., 2018; Razkenari et al., 2020; Schoenborn, 2012). It generates a lot of waste and does not promote sustainability (Razkenari et al., 2020).

The developed nations of the world and a few developing nations today use other forms of construction to address their housing challenges (Goodier and Gibb, 2007; Nadim & Goulding, 2010; Razkenari et al., 2020; Salman et al., 2013; Waris et al., 2014). This form of construction method is fast, safer, environmentally friendly, promotes sustainability, has better quality and strength, and has been evaluated to be more economical. This new construction approach has evolved over the years, bearing different nomenclatures. Some of the names by which the methodology is known are Prefabricated Building, Pod Construction, Modular Construction, Modular Integrated Construction, Industrial Building System, Modern Method of Construction, Offsite Construction and so on. It is worth noting that Design for Manufacture (DfMA), Design for Assembly (DfA), Design for Excellence (DfX) etc. are concepts that help in standardizing OSC. For this article, Offsite Construction shall be used to aggregate the other forms of modern construction types differing from the traditional method of construction, which is also referred to as the conventional method of construction.

Therefore, Offsite construction (OSC) is constructing a complete house by assembling the different elements or components that would make up a whole building. The members are manufactured in a controlled environment on or off site before being transported to the point of use through coordinated logistics for assemblage (Adeagbo and Anigbogu, 2020).

Offsite Construction (OSC) is rapidly becoming the new normal in the Architecture, Engineering, Construction and Operation (AECO) world, recording more significant popularity in the past 20 years (Wang et al., 2020). Its numerous advantages, such as time-saving (Smith & Quale, 2017), quick on-site assemblage (Gusmao Brissi et al., 2021; O'Neill & Organ, 2016), eco-friendliness (Moradibistouni et al., 2019; Salman et al., 2013), safety (Abueisheh et al., 2020; Babalola et al., 2019), controlled and quality production (Abanda et al., 2017; Tam et al., 2007), ease of handling (Ramos & Lorini, 2013), waste reduction properties (Ajayi et al., 2019; Osmani, 2012) etc., has made it more endearing to construction stakeholders. With countries like the United Kingdom, China, USA, Germany, Malaysia, Hon-Kong, Australia, Netherlands, Sweden, Finland (Badir et al., 2002; Li et al., 2014), and so on vastly employing OSC in most of their construction works, OSC usage around the globe is projected to increase in the coming years. However, despite the numerous attributed advantages of OSC, it has not yet fit into the contextual construction framework of many developing and under-developed countries. There are still factors in the form of barriers that have to be surmounted for OSC to gain the global popularity it is aiming for, especially in developing countries like Nigeria.

Thus, this paper aims to establish the critical factors affecting Offsite Construction adoption in Nigeria and predict how the established factors influence OSC success level. It proposes achieving this aim through the following objectives:

1. To establish the driving and inhibiting factors of OSC in countries where it has adopted through literature studies.
2. To use the established factors through the literature review as independent variables and use iteration through multi-layer feature selection algorithm to uncover the most applicable influencing factors of OSC adoption in Nigeria.
3. To predict the dependent variable, using Machine Learning Algorithm, if OSC would thrive in Nigeria in the coming years.

2.0 LITERATURE REVIEW

Some studies have examined OSC adoption among some countries in America, Africa and Europe, including the UK. Scholars have referenced UK as the yardstick for measuring adoption in a sizable number of articles about the country that seems to have the most used OSC in the time past when OSC first boomed. A large part of OSC works today is of East origin, and China/Hong Kong focus to be precise where OSC seem to have been more adopted in recent times (Badir et al., 2002; Gan et al., 2018; Jiang et al., 2020; Li et al., 2014; Mao et al., 2018; Wu et al., 2019). Other nations highlighted to have adopted OSC and documented its use in their construction methods are the Netherlands, Denmark, Finland, Germany and Canada (Lessing and Brege, 2015). It was observed in the articles that cultural and regional differences account for differing drivers and barriers (Gan et al., 2018). The scholarly articles have identified probable adoption influencing factors.

However, the ones with analytical tools are reported. Below *(See Table 1)* is an extract of the works done, the location in focus and the factors found out regarding OSC adoption.

Table 1: Past Adoption Research works and the Analytical Tools used (See journal tables)

Some scholars have worked on Offsite Construction and its adoption in various forms (Ajayi et al., 2019; Arif et al., 2017; Salman et al., 2013; S. Sepasgozar & Davis, 2018). Their research have outlined various barriers and drivers influencing its use in this modern age (Arif et al., 2017; Blismas and Wakefield, 2009; Gan et al., 2018; Gusmao Brissi et al., 2021; Rahimian et al., 2017; Zhai et al., 2014). Some have dealt with the advantages of OSC in a bid to drive its adoption, while others have looked at the disadvantages as a ground to disregard its adoption. Scholars have identified some critical factors applicable to different locations around the globe (Salman et al., 2013; Wuni and Shen, 2020) and others (Adeagbo and Anigbogu, 2020; Dixon-Ogbechi and Adebayo, 2020; Makinde, 2014) to Nigeria, but none has outlined the most critical factors that can pave way for a wider adoption of OSC within the Nigerian context using Machine Learning algorithms. Some notable factors include, but are not limited to, government policies, incentives and intervention, social and environmental factors, technical and technological factors, cost and economic factors, logistics, skills, etc.

39 factors were deduced from the various literature review and were used to develop a questionnaire survey. The factors, which are examined under related impacts, are government policies on production, government policies on importation, cultural heritage factors about OSC (i.e., being used to a style of building as a result of living in an environment/location, e.g., belief in the use of thatched roof on a round building in

northern Nigeria.), historical factors (failure of OSC in places where it was used), belief system (religious beliefs on building type and style), environmental factors (weather, climate, etc.). In addition, factors such as designers' attitudes, construction site managers, construction site workers, end-users/ building occupiers, client/ investor desire to use OSC for construction were placed under attitudes. Awareness of OSC by designers, awareness of OSC by construction managers, awareness of OSC by construction site workers, awareness of OSC by end-users/ building occupiers, awareness of OSC by clients, awareness of OSC by government, falls under awareness while level of accessibility to loans, accessibility to favorable exchange rate come under funding. Level of availability of bespoke OSC manufacturing company, availability of new or amended form of construction contracts that focus on OSC, availability of contract documentation relating to OSC come under contract documentations, supply chain integration for OSC, Supply chain management for OSC. Technological Advancement (OSC Installation technique), come under logistics. Level of availability of in-house OSC design expertise for manufacturing companies, level of in-house OSC building expertise for construction companies, level of availability of skilled personnel at Design Companies, level of availability of skilled building personnel on construction site come under OSC expertise, Construction knowledge of OSC among Construction professional bodies in Nigeria, level of training/education in Nigerian universities on OSC designs, level of guidance of BIM implementation and utilization on OSC fall under skill development. Cost of OSC Components and Cost of OSC Installation were also looked at.

Predictive scholarly works have also been carried out within the construction sector. (Alaka et al., 2019, 2018) predicted the insolvency of small construction firms using ML models, (Olu-Ajayi et al., 2021; Robinson et al., 2017) predicted building energy consumption. (Alozn & Galadari, 2015; Arditi & Pulket, 2005) used ML to predict the outcome of litigation issues within the construction industry; predicted construction delays using ML algorithm. (Egwim et al., 2021) used ML to predict accident severity levels on construction sites. However, to the best of available knowledge, at the time of this research, no researcher has embarked on using ML algorithms to examine the key factors responsible for the low level of adoption of OSC within the construction industry.

The work left to be done, therefore, is to identify the applicable influencing factors among the barriers that have to be overcome for OSC to gain its ground in the building industry and the critical factors that has to be promoted in order to advance its course among construction stakeholders in Nigeria using multi-layer Machine Learning algorithm.

In a bid to make living better for humans, technology advances through increased knowledge and innovation (Fernandes et al., 2006). Products are designed, manufactured, and they evolve with time and usage. During the lifecycle of an industry or a product, transformational evolution to meet rampant demand and environmental changes become unavoidable (Roberts et al., 2021). The construction industry is not averted to this imminent transformational evolution. With a great demand to have an improved housing systems for the society, the innovation of Offsite Construction should be diffused to many nations' construction industry because it is fast, easily adaptable to site, relatively safer when compared with traditional methods and delay causes can be easily identified and mitigated. It is ecologically friendly and sustainable, lightweight and does not require complex engineering technicalities. (Daniela & Tom' a's, 2016.; Wisdom et al., 2014).

The theoretical approach to this study follows the general theories of adopting technological innovation in industries (Munir, 2003; Ragozzino, 2006) as it best applies to construction and, more precisely, to adopting improved innovation in the construction industry. The theories considered are:

1. Roger's Innovation Diffusion Theory (DTI)
2. Technology Adoption Models (TAM)
3. The Concerns-Based Adoption Theory (C-BAM)
4. The United Theory of Acceptance of Use of Technology (UTAST)

The Concerns-Based Adoption Theory (C-BAM) shall therefore be adopted for this research because it considers Innovation Configuration, Stages of Concern and Level of use. More importantly, it gives room for both feedback from adopters and a means of follow-up on them.

Figure 1: Concern Based Adoption Theory (see journal table)

Source: https://sedl.org/cbam/d

The Innovation Configuration creates a roadmap for team members by which goals would be achieved with high-quality executions (Chanda and Bardhan, 2008). The Stages of Concern address how team leads identify the state of members' minds regarding the newly introduced initiative. The process involves questioning, interviews and feedbacks. Based on the information gathered, the team lead can take necessary action to address each team member's challenge. The Level of Use help identify the way team members are adapting to the use of the new initiative, the challenges they are having and how the issues are being resolved. Finally, the team lead observes the level of use, from non-usage, low usage to advanced usage. This process helps the team lead draw conclusions and measure the success of the newly introduced innovation (Garry, 2010; Hord et al., 2006; Shirley M. Hord et al., 2013; S. M. Hord et al., 2013).

With the topic under study focusing on improved innovation, awareness, attitude, adoption, acceptance, usefulness, ease of use and diffusion of use, this theory addresses the issues relating to why OSC is yet to be adopted as a viable construction method in Nigeria (Lai, 2017; Sepasgozar and Davis, 2018; Straub, 2009)

With respect to Offsite Construction adoption within the NCI, this research consolidates on some earlier mentioned works within the Nigerian and global context in providing relevant information on how OSC can be diffused within the NCI for wider adoption. It also discussed the measures by which the level of satisfaction by users can be appraised or evaluated while not leaving out parameters by which this diffusion can be assessed.

Considering the prefab building constructed in Nigeria e.g. Dolphin Estate, tertiary institution buildings like University of Lagos, Obafemi Awolowo University etc., it can be said that NCI falls into the league of not too late adopters of the OSC construction method and probably early adopters in Africa (Dixon-Ogbechi and Adebayo, 2020). However, there is still a long way to go in improving the knowledge, awareness, appraising and diffusing the use of OSC within the NCI.

3.0 MACHINE LEARNING APPROACH

Machine Learning (ML) is an arm of Artificial Intelligence (AI) focused on analyzing data from the sample data set provided, developing models from trained data set and predicting outcomes from the testing data set. It mimics the way human beings learn, develop character and operates habitually (Sumana, 2021). It employs algorithms and statistical models to learn from the training data set. Machine Learning can be used in supervised training, unsupervised training and reinforcement training data sets (Egwim et al., 2021) One of the major objectives of ML is the use of trained data set to identify a typical pattern or trend in the data set and test such patterns to predict a probable outcome. It is proposed to have a lot of applications in the future owing to its ability to identify patterns earlier unknown (H. A. Alaka et al., 2016; Xie et al., 2020). Interestingly, ML does not need to be outrightly programmed like other computational approaches to identify or predict outcomes. There are libraries of programmes in ML that provide the required algorithms, e.g., Scikit Learn, Numpy, Pandas, MatPlotLib.

Some features that put Machine Learning ahead of other analytical tools are its ability to identify patterns or rhythms earlier unknown in data, the variables options for associating two or more factors and categorization of factors by similarities. Moreover, it can predict outcomes based on specific criteria, group objects or activities based on their history, image recognition and classification due to historical observations, and structure unexplored data (clustering). Some Machine Learning algorithms include Logistic Regression, Random Forest Algorithm, Decision Tree, Linear Discriminant Algorithm, Naïve Bayes, Support Vector Machine, K-Mean Clustering, Artificial Neural Network and Classification and Regression Tree algorithm among others.

Machine Learning has been very impactful in automobiles, robotics, language processing, health and finance. More recently, the Machine Learning approach has been tried in some research works in construction, and they have shown positive outcomes. Such ML research work include Construction Site Safety Indicators (Poh, et al., 2018), Construction Injury Prediction (Tixier et al., 2016), Building life-span prediction (Ji et al., 2021), Building comfortability prediction (Park & Park, 2021), Bankruptcy Prediction of

Construction Businesses (Alaka et al., 2019), Construction Activity Recognition Using Sensors and Machine Learning (Akhavian and Behzadan, 2015). With these positive outcomes, Machine Learning is gradually finding its footing within the construction industry, giving adoption a bright hope using Machine Learning.

Machine Learning, at the time being, is the one of the best-known predictive and analytical tool that exists (Addie, 2019; Johnson, 2020). It is well known for its ability to predict, forecast and in data exploration, including correlation. Various studies in the past have employed various methods in analyzing the adoption of Offsite Construction. Such analytical tool includes Nvivo and Analytics Hierarchy Process- AHP Analysis (Sepasgozar and Davis, 2018), Big Data Analytics tool (Alaka et al., 2019), Capability, Opportunity, Motivation-Behaviour (COM-B) System. See Table 1.

Even though Machine Learning has been known to be the best in analyzing, determining and predicting the most critical factors, no known article has employed the use of multi-variate analysis and Machine Learning in addressing the issue of OSC adoption. The closest to OSC adoption prediction is the *Evaluation of Quality Defects* done by (T. Yu et al., 2019) using the Bayesian Network-Based Model *(See Table 1)*. Therefore, this research work would take advantage of the 'expert' analytical tool in exploring the factors that can foster OSC adoption within the Nigerian construction industry.

4.0 METHODOLOGY

In line with the objectives of this article, a literature review to deduce the prevailing OSC factors globally was carried out. These deduced factors were developed into a questionnaire used to survey the adoption of OSC within the NCI. This approach to research is deductive- taking out facts from extant literature to measure how applicable those facts are to the objectives of a research (Creswell et al., 2003; Wacker, 1998). It employs survey question through factors deduced from literature survey measure the said applicability. The paradigm considered was positivism because it does relate well with quantitative investigations and predictions. (Creswell et al., 2003; Onwuegbuzie and Hitchcock, 2015; Wacker, 1998)

This work is researched by utilizing prediction capabilities for OSC adoption in Nigeria. Data was collected through questionnaires from industry players within the Nigerian construction industry (Brannen & Moss, 2012). First, literature relating to OSC and its adoption was sourced through scholarly search engines like Google Scholar and Scopus (Almalki, 2016; O'Neill & Organ, 2016). The literature survey used key search words and phrases such as adoption, Modular Construction, Offsite Construction and Prefab Constructions, and key authors' names. Specifically, research published on the subject between 2000 to 2021 were considered. A review of these papers informed the potential critical factors responsible for low Offsite Construction adoption level in Nigeria.

The factors that evolved among various vital players of the construction industry towards OSC adoption from the literature studies revolve around policies affecting production and importation, cultural heritage and beliefs and attitudinal reactions (Malhotra, 1999; O'Connor et al., 1992). Also observed were accessibility to funds, belief in the functional properties of OSC component make-up, ease of workability and awareness. In addition, the factors pin-pointed some reactionary displays of interest in adopting OSC as a construction methodology. These factors observed were used to develop a set questionnaire piloted through simple random strategy criteria with seven carefully selected participants (Creswell, 2003; Gregar, 2014.). Five of these participants have construction background and have at a time or the other designed or recommended OffSite Construction methodology for use. The other two were non-subject experts. Some observations such as tenses restructuring, spelling mistakes, regrouping of factors under related headings were made on the questionnaire, others were debated, and necessary corrections were made.

The questionnaire was developed in Microsoft form. Using purposeful sampling technique (Palinkas et al., 2015), the form link was administered to relevant key players in the NCI through e-mails and social media platforms for responses. The targeted responders were architects, civil/structural engineers, electrical engineers, mechanical engineers, building engineers, town/urban planners, quantity surveyors, contractors, academics, real estate investors, and developers. They were considered because they are thought to be actively involved in everyday construction processes in the country and are involved in making and taking decisions bordering around the choice of building materials, technology and methodology to be used on projects. Over 300 forms were sent out. Two hundred twenty-four (224) responses were received, indicating a 74.67% response. Sixty-nine (69) responses were void, leaving one hundred fifty-five (155) responses to analyze. The valid forms account for 69.2% valid response. The average response duration was 11.45 minutes.

The various factors extracted from the literature were put under headings such as policies, design, attitudes, BIM impacts, etc. based on relational effects. These factors (variables) were tagged VR1, VR2…VR39 for nomenclature purpose and easy identification during analysis. *See Table 2 below*. VR1…VR38 makes up the independent variables while VR39 is the dependent variable.

Table 2: Factors Deduced from Questionnaire with variable tag (See journal tables)

A couple of missing data was observed in excel when the responses were exported. The missing data were dealt with using the most occurring figure (mode implication on missing data).

5.0 ANALYSIS AND RESULTS

5.1 Reliability test result

A Cronbach Alpha test was conducted on the responses received from questionnaire survey for the 39 variables examined. The closer a Cronbach Alpha index is to 1, the more reliable the data indicates a strong reliability (Egwim et al., 2021; Wuni & Shen, 2020). A rule of thumb says a 0.7 Cronbach index shows consistency within the survey responses and passes a generally acceptable scientific threshold required for reliability test. A 0.8 outcome is considered a good internal correlation and 0.9 an excellent reliability result (Bhatnagar et al., 2014). The reliability result of the variables indicated 0.782 and which is thus considered a good internal consistency of the variables.

5.2 Data pre-processing

After cleaning and normalization, the data were split into test and train data set (60:40) owing to its small size (Balogun et al., 2021; Joseph, 2022) . When a univariate analysis was run with the variable results, the results did not bring about good predictive models. Clearly, not all the features examined are important as most variables do not contribute meaningfully to the adoption possibilities. If they do, they all would have shown a good predictive model. This reason may be due to the many variables examined together. This created potentials for noise and multicollinearity. Some of these variables are therefore causing noise within the models examined. It shows they do not have a good relationship with the adoption prediction. Below *(Figure 2)* is a correlation matrix that show which variables correlate fairly with each other.

Figure 2: Correlation Matrix of Variables (see journal figures)

As can be deduced from the figure above, only a few variables correlated well on a single correlation. On a scale of 1, the bests only correlate at 0.7. the variables that fared well are VR27 and VR28; VR24 and VR25; VR21 and VR22; VR15 and VR16 and VR13 and VR14. A well-known limitation of single correlation is that it takes out some crucial features with no high correlation with the dependent variable, which is to know if OSC would thrive within the Nigerian construction industry. But when a bi-variate correlation is carried out, where the variables are taken together with another variable, that variable becomes important.

5.3 Feature engineering

However, since the research aims to identify the critical factors influencing the adoption possibilities, and in line with objective 2, a further analysis was run with feature selection. This bi-variate process is better than a single correlation process. As can be deduced from the initial analysis, the correlation process shows a poor relationship between the variables. Therefore, there is a need to look beyond the single correlation matrix as single correlation analysis (a univariate analysis) takes out some important feature with no high correlation with the dependent variable- the adoption level sought. However, when taken together with another feature, that feature becomes very important and requires a multi-variate analysis. Machine Learning would be employed to carry out the required multi-variant analysis since it is known to have some of the best known performing predictive algorithms.

5.4 Feature selection

A predictive model was created with the variables through feature selection and Machine Learning Algorithms to identify which variant is the most important for adoption. Some of the Machine Learning algorithms used in the uni-variant analysis are Decision Tree, Random Forest, XGBRegressor, SGDRegressor, RidgeCV, LarsCV, ElasticNetCV, Extra-Trees (Extremely Randomized Trees), GussianProcessingRegressor, Linear Regression, PoissonRegressor, AdaBoost, K-Nearest Neighbours, Support Vector Machine, Artificial Neural Network, Support Vector Regressor, Bagging Regressor, Bayesian Ridge ElasticNet among others. For the multi-variant analysis, Decision Tree, Random Forest, Extra-Trees (Extremely Randomized Trees), AdaBoost, K-Nearest Neighbours, Support Vector Machine and Artificial Neural Network were used. Each of the multi-variant models performed at the least twice better than the uni-variant model. The model, again, performs relatively better with feature selection. Below are the outcomes with and without feature selection. This shows that these models, from a multi-variant perspective, are the most important.

Table 3: Machine Learning Model Without Feature Selection (See journal tables)

Figure 3: Entire ROC AUC (Without Feature Selection); see journal figures

To resolve the shortcomings of the model outcomes, feature engineering was carried out on the models using Pearson Correlation. Pearson correlation, also known as Pearson Product Moment Correlation (PPMC), is a measure of statistical correlation that use the scale of -1 to +1 to define the linear correlation between a dependent variable and the independent variables (Stephanie, 2021). Thus, an outcome closer to +1 shows a strong correlation to the dependent variable, a zero outcome shows no correlation, while a closer figure to -1 shows a negative correlation (Diah et al., 2020). Below is the result of the feature engineering done.

Table 4: Machine Learning Model With Feature Selection. (See journal tables)

Figure 4: Entire ROC AUC (With Feature Selection); see journal table

Figure 5: Feature selection using Pearson correlation (see journal table)

Table 5: Most Important Factors from Feature Selection (See journal tables)

On completing the multi-variate analysis, about twelve (12) were most correlated. (Variables within the very dark green region, >= 2.0). Consideration was given to the four variables with 0.19 as minor underlining factors due to nearness to 0.2. Of the twelve, the best seven (7) were used to develop the predictive models and showed much better outcomes. Therefore, from a multi-variate perspective, the seven (7) variables are the most important. These factors seem not to be so important on the univariate analysis, but they become very important for prediction on a multi-variate, where they link with other variables.

6.0 DISCUSSION

In line with the second and third objectives of this article, feature selection was carried out. A comparison between the univariate and multivariate analysis shows that the factors obtained through feature selection have stronger influencing factor, as reported in *Figure 5* and *Table 5*. The prediction show that the feature selection factors perform much better than all the factors obtained from the literature review even though they are small in number. The feature selection factors show better accuracy. The ‘not too critical’ factors were generating noise within the model and thus, excluded when subjected to feature selection. The most applicable influencing factors are thus, discussed below.

6.1 Accessibility to loans

Building and construction works are highly capital-intensive ventures (Arif et al., 2017; Bryson, 2019; Fellows & Liu, 2015; Gusmao Brissi et al., 2021; Hendriks & Stokmans, 2020; Nanyam et al., 2017; Njoku & Adegboye, 2015; Pan et al., 2007; Rahimian et al., 2017a; Tan et al., 2020; Tanyanyiwa & Kanyepi, 2020; Zhai et al., 2014). Primary to the success of a construction project is the availability of funds (Hossain et al., 2020; Li et al., 2014). From the land purchase cost to building materials costs and the payment of professional and site workers, enormous amounts of funds are required to complete a building project (Adeagbo and Oyemogum, 2013; Makinde, 2014).

(Okonjo-Iweala, 2014) highlighted developed countries as having muscular financing bodies for building construction industries. For example, the Mortgage bank to GDP ratio is US, UK, Malaysia, Honk-Kong, Europe are 77%, 80%, 32%, 50%, 50% respectively unlike their counterpart Africa nations like Botswana, Ghana and Nigeria where the ratios ridiculously stand at 2%, 2% and 0.5% respectively. Further to the argument is that only about 12,000 contributors have been supported by mortgage saving out of over 3.8million eligible contributors (Okonjo-Iweala, 2014).

To employ OSC, which is known to require massive capital take-off, accessibility of loans, or other means of funding, will be a key driver in establishing OSC as a viable construction method. Beyond just making funds available for construction, the mortgage banks should be re-institutionalized for their proper purpose, the credit should be as seamless as possible, and both the repayment plans and interest rates should be flexible

6.2 Awareness of OSC (By Government, Construction Managers and Designers)

The number of projects carried out in Nigeria using OSC is **scanty**. However, the massive construction works on-going in many parts of the Nigerian states show the level of awareness of OSC is still low as most of the projects are still being executed via the conventional construction method. This indicates that major construction industry players are not aware of OSC yet or have not examined its huge benefits if employed as their construction method (Barton and Wilson, 2021; Gusmao Brissi et al., 2021). The designers and project managers are established chain-links in the construction industry cycle (Dunmade and Fayomi, 2018). They are the first point of call for clients. The adoption success of OSC rests on the awareness, knowledge and specification of OSC as a viable option for construction (Liao, 1996; O'Connor et al., 1992). The government plays a crucial role in introducing any product into its citizens' market as the gatekeeper (Badir et al., 2002; Hashemi and Hadjri, 2014; Nadim and Goulding, 2010; Wong and Yip, 2004). Their policies and laws determine the success of any innovation, which depends on how much knowledge they have about the product (Waris et al., 2014). Therefore, there is a need to herald comprehensive enlightenment and crusade for OSC usage and its benefits within the Nigerian construction industry.

6.3 Level of guidance of BIM, implementation and utilization on OSC

The introduction of BIM to the construction industry is relatively recent and has played a significant role in reshaping the approach to construction design and management in a short time (Abanda et al., 2017). It is just getting institutionalized in the construction practice of most developed countries where OSC has thrived (Chanda and Bardhan, 2008; Liao, 1996). Studies show that not many countries have merged OSC design requirements in their BIM applications (Charef et al., 2019; Di Giuda et al., 2019). Revit, the most conversant BIM software for designers, recently developed a plug-in for DfMA to promote OSC in the UK construction industry in promoting OSC usage among designers. This plug-in is yet to be made public for all as of this writing time. Other BIM applications need to look toward the OSC-BIM merger (Wang et al., 2020). The more knowledge and tool on OSC available for designers, who are the first port of call in the construction industry, the better it would be for OSC to thrive because they can easily recommend OSC in their specifications.

With the outcome of this research indicating BIM guidance, implementation and utilization as a significant factor that would drive OSC adoption in Nigeria, the Nigerian construction industry would need to introduce and institutionalize BIM usage in its construction workbook.

6.4 Designers' attitude (i.e., Architects, Civil/Structural, Building, Mech. and Elect. Engrs.)

Some scholars have opined that the newness of the OSC construction method has steered an attitudinal reaction from key players in the industry, including the design professionals (Adeagbo and Oyemogum, 2013; Kolo et al., 2014; Makinde, 2014; Rahimian et al., 2017a). However, a large percentage are trained in the conventional method of construction and have passed same knowledge down the line over the years. Having to retrain in designing **for manufacture and installation in** construction is strenuous and demanding on their mean time (Wang et al., 2020). Therefore, there is a need to softly introduce OSC through continuous development programmes, retraining courses, seminars and expos where the important role of designers in this new emergence would be stressed (Tam et al., 2007).

6.5 Future of OSC in Africa and Nigeria

With not just a housing deficiency of almost 20 million (prorated from the 17 million deficit of 2014 based on 2.5% annual population growth (Adeagbo and Anigbogu, 2020) and 5.5% migration to urban centres (Makinde, 2014)); but also a housing need with an estimated market prorated at $326billion (133.761 quadrillion by today's conversion) (Makinde, 2014), the future of OSC looks bright if there is maximum cooperation between the government and the policies enacted, and the construction industry key players. The Nigerian and African housing markets will be a good direction to look into for investors.

Relatively, similar outcomes were observed by some earlier researchers on barriers to OSC adoption in other countries. In the UK, for example, (Ajayi and Oyedele, 2018; Goodier and Gibb, 2007; Nadim and Goulding, 2010; Taylor, 2010) reported lack of OSC knowledge and training, clients' indecision, finance, digitalization and standardization of OSC, lack of awareness, unfavorable supply management system and inadequate government support and policies as limiting factors for OSC adoption. In Australia, (Blismas and Wakefield, 2009; Ngoc Nguyen et al., 2020) reported that shortage of skills, adequate OSC knowledge and associated OSC costs limit OSC adoption. In the US, (Gusmao Brissi et al., 2021b; Razkenari et al., 2020) observed clients and ends users' attitudes, availability of finance, and design constraints are inhibiting factors to OSC adoption. (Nanyam et al., 2017) noted that the technological know-how of OSC is a limiting factor in India. (Gan et al., 2018; Jiang et al., 2020; Zhai et al., 2014) reported that in China, inadequate knowledge of OSC by site workers and managers and lack of industry standardization on OSC are the limiting factors. While geographical locations, with their associated factors, cultural factors, and technological advancements account for variance in the impact of these factors, finance, awareness of OSC, technical know-how, attitude, and OSC execution documents seem to be core factors that cut across the construction industries of many nations.

The most applicable influencing factor deduced and discussed from the Machine Learning algorithms output are not entirely new factor. While *Future of OSC in Africa and Nigeria, Level of Guidance of BIM and implementation and utilization on OSC* appear in a modified form of earlier researcher's finding, *Accessibility to loans,* Awareness *of OSC, Designers' attitude, consolidate* previously established influencing factors (Daget and Zhang, 2019; Dixon-Ogbechi and Adebayo, 2020; Gusmao Brissi et al., 2021; Salman et al., 2013; Schoenborn, 2012; Wuni and Shen, 2020). Machine Learning feature selection has brought out the strongly influencing factors in another perspective away from many repeated prevailing factors analyzed by earlier researchers.

7.0 Conclusion

One of the essential factors that drive developed nations is infrastructure development (Okonjo-Iweala, 2014). Many leaders of the Nigerian construction industry have decried the continuous use of conventional means of construction, stating, *"the brick and mortar will not take us far"* (Njoku and Adegboye, 2015). Virtually all the professional bodies associated with the building industry have opined that there is a need to seek an alternative in addressing the housing shortage (Makinde, 2014).

Earlier studies highlighted various adoption barriers and drivers. This study has identified the most applicable OSC influencing factors to the NCI and added an OSC adoption predictive model as a contribution to knowledge. The essence of the model is to guide the NCI and her government when taking decisions on implementing OSC adoption. Their adoption policies can be evaluate using this model and considering the highlighted most applicable influencing factors in taking decisions on OSC adoption and how it may thrive in Nigeria or not. When the model result status indicates one (1), it shows the combined factors under observation would make OSC thrive but when it shows zero (0), the combined factors are not likely to make OSC thrive.

This research has identified funding, BIM application, the attitude of industry professionals, and belief in the future of OSC in Nigeria as the core factors that, if given serious consideration and attention, would help OSC thrive in Nigeria. In addition, availability of in-house building expertise for construction companies, good OSC construction knowledge among industry professionals, availability of skilled design and building personnel on and Offsite and favourable exchange rate are relating factors to the adoption success of OSC with Nigeria construction industry. It should be noted that one single factor would not determine OSC adoption success because the model examines interaction between factors. Therefore, the combined factors would determine the precision capability of the model to predict.

As the giant of Africa, Nigeria is expected to set the pace for Africa in terms of development and economy. Its over 200 million populace is rich enough to transform its economic landscape if its real estate market is well harnessed. With the rapid transformational development in the construction industry worldwide, there is a need to join in on the moving train and on time. While the research focused on identifying the critical factors underlining OSC adoption in Nigeria, the model outcome represents the African continent, with Nigeria being the giant of Africa. The model, however, can serve the construction industry of any geographical location if it is fed the appropriate data from that region. Further research can improve the models' performance through feature engineering and parameter optimization.

8.0 Recommendation

Offsite construction, in a short time, will become the new normal in the construction industry. The professionals within the industry need to rally around this new normal and give its potential a full realization (Sestino et al., 2020; Shankar & Clausen, 2020; Ilori et al., 2002). Academia also should consider Offsite technology as a significant course in the academic curricula. BIM should become a norm in all tertiary institutions and construction workbooks. Provision should be made for OSC construction guide within the Nigerian building codes. The era of manual design has wholly gone and should not be retained in the annals of Nigerian construction practice. Industry players should engage in continuous development programmes like expos, seminars, workshops, etc.

Though this research did not cover the entire construction industry of Nigeria, it has ensured it gathered data from the nation's largest cities where most of the most significant infrastructural developments are on-going; and that represents the major geo-political zones of the nation. Thus, this research hopes to lay the foundation for critical underlining factors that other researchers can build on in promoting OSC within the Nigerian context.

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