Journal of Engineering and Technology for Industrial Applications

ISSN ONLINE: 2447-0228

ITEGAM-JETIA

Manaus, v.10 n.47, p. 50-62. May/June., 2024.
DOI: https://doi.org/10.5935/jetia.v10i47.1072

RESEARCH ARTICLE OPEN ACCESS

AWARENESS AND ADOPTION READINESS OF MACHINE LEARNING TECHNOLOGY IN THE CONSTRUCTION INDUSTRY OF A DEVELOPING COUNTRY: A CASE OF NIGERIA

***Samuel Osusha Loya[1], Emmanuel Chidiebere Eze[2], Imoleayo Abraham Awodele[3], Onyinye Sofolahan[4], Olayinka Omoboye[5]**

[1]Quantity Surveying Department, Federal Polytechnic Kaltungo, Nigeria.
[2]Department of Architecture and Built Environment, Northumbria University Newcastle, UK.
[3]Construction Management and Quantity Surveying Department, Durban University of Technology, Durban, 4001, South Africa.
[4]Quantity Surveying Department, Lagos State University of Science and Technology, Ikorodu Nigeria.
[5]School of Applied Management, Westminster Business School, University of Westminster, London, UK.

[1] http://orcid.org/0009-0008-9146-8181 , [2] http://orcid.org/0000-0001-7919-6322 , [3] http://orcid.org/0000-0003-1602-7294 , [4] http://orcid.org/0009-0008-1023-4843 , [5] http://orcid.org/0000-0002-3565-7745

Email: *loya.osu@gmail.com, emmanueleze001@gmail.com, a.imole@yahoo.com, onyxnwoko@gmail.com, o.omoboye@westminster.ac.uk.

ARTICLE INFO

Article History
Received: March 13th, 2024
Revised: June 03th, 2024
Accepted: June 25th, 2024
Published: June 28th, 2024

Keywords:
Awareness,
Adoption readiness,
Machine learning,
Construction industry,
Sustainability.

ABSTRACT

This study investigated the awareness of the Nigerian construction organisations on some identified ML application areas, and the readiness of the organisations to adopt ML learning in the identified application areas. A comprehensive Literature review was undertaken to identify the application areas of ML, then, a well-structured questionnaire was developed and used to gather relevant data from construction professionals using the snowball sampling method via electronic means. 143 valid responses were obtained, and the gathered data were analysed using arrays of descriptive and inferential analytical tools. The study revealed that the critical applications areas of ML with higher awareness level and adoption readiness in Nigeria are (1) Health and Safety prediction and management, (2) Waste management, (3) Prediction of and management of construction costs, (4) Risk Management, (5) Structural Health Monitoring and Prediction, and (6) Building Life-Cycle assessment and management. Further, a significant statistical difference was observed between the opinions of the participants regarding the awareness and adoption readiness of the various ML application areas. This study identified critical application areas of ML where the awareness and adoption readiness are very high, thus, signalling the preparedness of the Nigerian construction industry (NCI) to embrace ML to drive sustainable construction.

I. INTRODUCTION

The construction industry is considered a significant sector on a worldwide scale since it plays a key role in promoting growth and development in countries by driving infrastructure development and creating employment opportunities [1]. Despite its significant economic contributions, the industry is recognised for its poor productivity, low cost, quality concerns, and time-consuming performances, among other challenges [2]. The slow acceptance of new and innovative technology and methods, along with the fragmented and traditional nature of the construction industry, exacerbates this predicament [3].

The necessity for sophisticated technologies in order to fulfil the industry's productivity and growing requirements for technological advancements arises from the inadequacy of conventional construction methods to achieve anticipated competitive outcomes [4]. The conventional practices in the construction business are no longer effective in promoting the global aim of sustainability in all human activities [5]. Sustainability is essential and acts as the bridge between environmental and developmental issues, and it influences the responses of governments, professionals, and environmental groups. The traditional approach does not make any meaningful impact on sustainability, and it has also been cited as one of the major causes of construction projects falling behind expected performance outcomes [6].

Artificial intelligence (AI) holds tremendous opportunities and potential opportunities to revolutionise the construction industry by enhancing productivity and addressing some of the performance challenges of the industry [7]. AI has the potential to kickstart a new industrial revolution during the transition to digitalization. AI is a comprehensive entity that includes all other digital technologies, with Machine learning being a component of it. Machine learning artificial intelligence (AI) assists construction experts and organisations in comprehending intricate issues, organising large amounts of data, accelerating learning processes, and producing answers to problems more rapidly [8]. By employing iterative machine learning techniques and analysing historical and real-time data to forecast and learn from it, AI and machine learning provide cost-saving advantages, aid in uncovering concealed patterns, enhancing quality, and improving responsiveness [9]. Machine learning (ML) plays a significant role in sustainable computing and has been identified as an emerging technology that effectively facilitates the adoption of sustainable practices [10]. Specific machine learning algorithms possess significant ramifications for sustainable innovation objectives and are important for tackling construction industry problems [11]. Machine learning, a branch of Artificial Intelligence (AI), focuses on creating and implementing computer programmes that can learn from previous data to model, control, or forecast using statistical methods without direct programming [12]. Machine learning is used in a wide range of fields and scenarios. Examples include our daily lives, healthcare, security, and agriculture [11]. It has been observed that machine learning algorithms aid in predicting unpredictable performance difficulties, monitoring them in real time, and detecting vulnerabilities in the system [13]. Data mining is the most prominent use of machine learning, among several others [14]. Machine learning can be utilised to build relationships between different features, increasing the design and efficiency of the system. The dataset consists of features that can be categorised as binary, continuous, or categorical.

Even though studies that touched on AI abound, there is limited research in academic literature on the use of Machine Learning technology in the construction industry from the viewpoint of developing economies. Prior studies primarily focus on technical or application-specific elements. For instance, [15] examined how AI can be used to address supply chain issues. [16] studied the use of Machine Learning AI in vehicle manufacturing, whereas [17] examined how AI is being applied in the retailing business. [14] suggested a technical framework for digital platforms using machine learning. [13] conducted a cutting-edge review of Machine Learning Algorithms (MLA) to forecast the efficiency of biological wastewater treatment processes. [11] Investigated the use of supervised and unsupervised machine learning methods in sustainable engineering. An examination of the literature from the perspective of advanced nations suggests a steady increase in the implementation of innovative tools and digital technologies. But the story is different when considering developing economies like Nigeria. This is due to many reasons and challenges. [18] assert that efforts at digitalization of the industry have been hampered by low levels of digital and smart technologies, cost factors, absence of qualified personnel and lack of capacity, and absence of standard references among other factors. [19] attributed the low level of adoption of innovative technologies to its infancy state in Nigeria.

With the growing interest in AI and machine learning in different economic sectors (construction inclusive), the extent of awareness and use of machine learning technologies in the field of construction management in Nigeria is uncertain, despite its widespread acceptance and significant advantages in other industries. This study aims to address this significant gap by evaluating the level of awareness and readiness for adopting machine learning technology in the construction industry of Nigeria. The specific objectives are (1) to assess the awareness of the Nigerian construction organisations on some identified ML application areas, and (2) to determine their readiness to adopt ML learning in the identified application areas. ML can be applied in different areas of applications in construction and comprehending the awareness as well as the adoption readiness of the construction stakeholders will aid in decision-making that triggers and brings the needed changes, particularly in the adoption and implementation of ML technologies in the construction industry. This study will also contribute to the sustainability discourse and targets of the sector as AI and ML are critical contributors to the digitalization and sustainability of the construction sector.

II. THEORETICAL REFERENCE.

II.1 MACHINE LEARNING AWARENESS AND ADOPTION IN CONSTRUCTION.

The idea of developing machines exhibiting intelligence like humans (otherwise known as Artificial Intelligence) can be traced back to fields of computer science, fiction, philosophy, and engineering [20]. Sixty years after Alan Turing's test for machine intelligence [21], intelligent machines are now outperforming humans in domains such as learning [22]. A major capability of machine learning is the utilization of a trained dataset in identifying a trend or pattern to predict an outcome [23]. Unlike other computational approaches, ML does not require outright programming before identifying or predicting such outcomes. Such ability gives ML an edge over other analytical tools. ML has the capability of predicting outcomes based on historical observations, image recognition and group objects. The required algorithms to carry out this task are provided by existing libraries of programmes. Such libraries include Numpy, MatPlotLib, Pandas and Scikit [23].

There are mainly two categories of Machine learning (ML) and these are Shallow learning and Deep learning.

Shallow Learning - This is the traditional machine learning where data transformation and learning occur in a single layer. In this, data description occurs using pre-defined features [24]. Shallow Learning is further categorized into three; supervised learning, unsupervised learning, and Reinforcement learning data sets [25]. Over the years, the most used shallow algorithms in construction are K-nearest Neighbors (KNN), Support Vector Machines (SVM), Logistic Regression, Linear Regression, and Decision Trees (DT) [26].

Deep Learning - A most recent approach in ML that has proven to give more reliable predictions than conventional ML techniques (known as shallow learning) is the Deep Learning approach [12], [27]. Deep learning is an advanced development of Artificial

Neural Networks (ANNs). Typical deep learning architecture network structures that have gained prominent attention in construction are Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and transfer learning [26].

The role of innovative technologies in improving time and cost performance, productivity improvement, learning and safety performance is widely acknowledged in the literature. Within the non-construction sectors, [28] reported that the awareness level of AI usage in the libraries of tertiary education institutions is high, but their adoption is low. The awareness of machine learning is very low among financial institutions, and their adoption of credit risk prediction is not in place in developing countries [29]. In the media sector, [30] reported a high awareness level of the role of ML in new production, while [31] found a low awareness of the usefulness of AI in the media. In the energy sector, the awareness level is however high [32].

In the construction industry, via interviews with construction experts, [33] reported a low level of awareness and acceptability of AI. Low awareness and acceptance are among the major barriers to the widespread adoption of AI and other emerging digital technologies in the NCI. The knowledge, awareness and usage of automation techniques are limited in the NCI [34]. Found a moderate level of awareness of construction 4.0 technologies, and their adoption readiness in the construction industry is at the initial level [35]. Notwithstanding the low awareness and adoption of some industry 4.0 technologies, there is an absence of studies that have focused on some specific applications of ML in the construction industry. Within the construction industry, there is a dearth of studies on the awareness and adoption readiness of construction organisations to adopt ML in specific activities in construction.

II.2 APPLICATION AREAS OF MACHINE LEARNING IN THE CONSTRUCTION INDSUTRY.

ML technology is essential and makes a significant impact in the construction industry, evident in its growing popularity in the sector. According to [36], ML is making a significant impact in the construction industry, making it a powerful tool for automating processes in the construction industry [36]. For [37] and [38] believe it has the potential and capacity to manage tacit and explicit knowledge in the management of construction projects. In their study, [39] identified Robotics/Automation, and Big Data Analytics as two machine learning technologies that are currently being adopted in the construction industry worldwide.

Machine Learning has a wide range of applications in the construction industry highlighted as follows:

Site Works: The use of robotics for construction activities such as loading, brick/block laying and painting is becoming more apparent [39]. Such adoption of robotics is highly beneficial to construction sites by helping significantly reduce time spent on repetitive tasks as well as improve efficiency. The major robotics applied for construction according to [39] are interior wall painting robots, KIST floor robotics, ASRERRISK robot and WASEDA robot.

Health and Safety in Construction Sites: The construction business is regarded as one of the most hazardous businesses globally, and this has made health and safety in construction a topmost priority for stakeholders in the sector [40]. Due to the inefficiency of the traditional approach involving the use of questionnaires to collect data [41], machine learning is found to offer high-tech solutions to safety problems that include temporary and permanent injuries in construction sites.

Decision Tree (DT), and Neural network techniques have been adopted in developing models that assess unsafe acts while working on scaffolds [42]. In their assessment of Big Data and Data Analytics utilization in construction, [39] found that new technologies capable of predicting site incidents and issuing prompt warnings have been adopted to improve risk detection and assessment during construction. Technology such as smart wearables capable of collecting relevant data and machine learning algorithms that address possible site incidents as well as creating new strategies for increased efficiency were also adopted in construction [43]-[44]. Also, a computer vision-based approach has been used in addressing postural-based hazards [45]. [40] affirmed the adoption of ML to develop construction site safety indicators as well as injury prediction in construction sites [46]. [47] in his study used Random Forest (RF) and Stochastic Gradient Tree Boosting (SGTB) to develop safety models capable of predicting the type of injury and the body part accurately as well as providing a reliable probable forecast of likely outcomes should an accident occur. A study by [48] combined CNN with a physical fatigue model to detect the level of fatigue among workers on the construction site.

Assessment of Workforce and Activity Recognition: To assist construction project managers in ensuring project deliverables are met, models that can monitor the activities of construction workers on site were developed. [49] developed a model that can detect automatically if a worker on the site is working within a designated boundary. Similarly, [50], proposed a CNN-based model that monitors the activities carried out by workers during reinforcement work.

Cost prediction and Management: Machine learning techniques have been adopted in the prediction of cost of various projects such as highway projects [51],[52], railway projects [53], hydro-power projects [54], building projects [55-56], and tunnel projects [57]. Fuzzy mathematics has been used to develop cost-estimating models [55]. Artificial Neural Network has also been used in estimating the cost of structural projects [56]. For [57] developed a DBM (Deep Boltzmann Machines) based cost estimation model.

Risk identification and Management: An exceptional aspect of ML is its ability the predict danger before it occurs, which aids humans in determining preventive measures for such dangers before they occur [58]. According to [59], machine learning can assist in reducing risks in construction sites by identifying risks and measuring their impacts. Consequently, numerous research on the application of machine learning in the prediction and assessment of risks in construction sites have been carried out [60],[61]. An ML model was developed to assess the risks of delays in high-rise building projects in Nigeria [60]. An expanded cloud model was used to assess potential risks on construction sites [61].

Building Energy Management: The prediction of long to medium-term electricity consumption in buildings is made easier with the adoption of machine learning technology. RNN models were used by [62] for the prediction of long-period heat demand in commercial buildings. [63] in their study developed a neural network-based model that can forecast medium-term to long-term electricity consumption.

Structural Health Monitoring and Prediction: CNN, DBN and CNN are deep learning approaches that have been adopted in developing vibration-based and vision-based monitoring techniques for the purpose of investigating construction materials durability prior to and after construction [64], [65]. For pavement stress detection and classification, [66] developed a DCNN model. A deep learning-based model was developed to detect asphalt and pavement ruts [67],[68]. According to [69] used softmax regression to develop a CNN model for predicting the compressive strength of recycled concrete before construction, and [70] developed a DNN-based model for predicting foamed concrete strength which will assist engineers in optimizing mixture design.

Building Occupancy Modelling and Performance Simulation: The building occupancy model is developed to predict a building energy requirement using the potential number of occupants as the basis for the prediction. This enables construction firms to simulate the building requirements before construction. Simulation results enhance proper and efficient energy allocation to building facilities. According to [71] developed a GAN model for occupancy modelling which outperformed two conventional occupancy modelling approaches (Inhomogeneous Markov Chain and Agent-based Model). For [72] proposed a DNN model that outperformed the performance of a Building Performance Simulation (BPS) at a faster rate.

Building Life-Cycle: ML has also been adopted for building life-span prediction [73], the bankruptcy of construction business prediction [74], and building comfortability prediction [75].

Schedule Management: [76] developed a schedule-learning platform with the adoption of a support vector machine (SVM) and artificial neural network (ANN) ensemble. [77] in their study used a machine learning algorithm to identify the major causes of construction delay.

Based on the foregoing literature review and other related matters, 20 ML application areas were identified and summarized in Table 1.

Table 1: Areas of application of machine learning in construction.

Code	ML Application area in construction	Source(s)
ML01	Site works (e.g., wall painting, plastering, etc.)	[39]
ML02	3D models classification in BIM	[78-79]
ML03	Prediction of and management of construction costs	[51-52, 55-57]
ML04	prediction of the energy system behaviour of buildings	[63]
ML05	Prediction of short-term cooling loads of buildings	[80]
ML06	detection and classification of pavement stress	[66]
ML07	Rutting prediction of asphalt pavement	[67-68]
ML08	prediction of design energy of buildings	[63]
ML09	Prediction of recycled concrete compressive strength and failure	[69-70]
ML10	Waste management	[22]
ML11	construction Workforce Assessment and Activity Recognition	[49], [81]
ML12	Prediction of the long-term heating and electricity loading of buildings	[63]
ML13	Construction equipment assessment and activity recognition	[82]
ML14	prediction of heavy equipment parameters	[83]
ML15	Building Occupancy Modelling and Performance Simulation.	[71-72]
ML16	Health and Safety prediction and management	[39-40], [45-46], [48]
ML17	Schedule Management	[76], [78]
ML18	Risk Management	[58-61]
ML19	Structural Health Monitoring and Prediction	[64-70]
ML20	Building Life-Cycle assessment and management	[73-75]

Source: Authors, (2024).

III. MATERIALS AND METHODS.

III.1 RESEARCH DESIGN.

This research was guided by a post-positivism philosophical lens which allowed for the use of a quantitative research design approach. Quantitative research allows for the collection of numerical data that can be statistically analysed to provide a reliable and objective research outcome [84]. A close-ended questionnaire was utilised in the collection of primary data owing to its capacity to reach larger audiences separated by space and distance in a relatively shorter time. Data collected from close-ended questionnaires are measurable and quantitative [18]. An internet-mediated questionnaire was used since it enables data collection to take place remotely, economically and at a much faster rate [85]. The online survey is an eco-friendly means of data collection as it involves no use of papers made from trees/forests [86]. Construction professionals in Nigeria were the respondents and units of analysis in the study.

III.2 QUESTIONNAIRE DESIGN, SAMPLING AND DATA COLLECTION.

The questionnaire was designed to have three sections. The first section garnered data on the background information of the respondents, and information obtained in this section served as a quality check to data obtained from the other two sections. The second section gathered data on the awareness level of the respondents regarding the selected application areas of machine learning in the construction industry. The participants were required to rate the variables based on their experiences and knowledge of the level of awareness of the application areas of machine learning in construction on a 5-point Likert scale where; 1= very low awareness, 2= low awareness, 3= moderate awareness, 4= high awareness, and 5= very high awareness. The third section collected data on the adoption readiness of machine learning in the construction industry. The respondents were required to rate the variables based on their organisations' level of readiness to adopt machine learning in the identified applications areas in their construction projects, on a 5-point Liker scale, where (1= very low readiness level, 2= low readiness level, 3=moderate readiness level, 4=high readiness level, and 5 very high readiness level). The Likert scale offers a better reliability coefficient and improves the chances of getting adequate results that represent the true reality of the research interest [87]. Further, the Likert scale is not cumbersome and enables the respondents to choose from available options their level of agreement or disagreement on a statement with ease [88]. The content and face validity of the questionnaire were ascertained via a pilot study of a small proportion of the sample population (5 construction practitioners and 7 academics), to get the adequacy, suitability, correctness, and fluency of the contents (questions) of the questionnaire to meet the study objectives. Piloting a survey prior to the actual survey is in line with the recommendations of [89]. The inputs from these experts were incorporated into the questionnaire before launching the actual survey.

It was impractical to obtain a separate sampling frame of construction professionals (Engineers, architects, builders, and quantity surveyors) with knowledge and experience in Machine learning (ML), therefore, the study was not restricted to any state or region of Nigeria. Also, the need to obtain significant responses informed the choice of not limiting the study to an area. The survey participation criteria are (i)Experts experienced in construction project delivery, (ii) knowledge of machine learning as well as other emerging technologies applicable to construction, and (iii) involvement in project delivery in Nigerian cities/regions. These criteria are boldly written in the introductory section of the questionnaire to ensure that only qualified experts take part in the study [90]. The researchers have taken the highlighted measures to ensure that the questionnaire obtained reliable and acceptable data whose analyses would yield credible outcomes that represent the true status of affairs with regard to machine learning applications in Nigeria.

The snowball sampling was adopted in the administration of the questionnaire to the construction experts via electronic means (Google form). The snowball sampling technique has the capability to increase the response rate as it is reliant on an effective referral system [91], and thus, completely driven by the respondents. The initial set of respondents was identified via the preliminary survey and from the researcher's cycle [92]. The Google form is amenable to Microsoft Excel and the statistical package for social science (SPSS) used for data analysis. After a sampling period that lasted for 16 weeks, a total of 157 responses were received, out of which only 143 responses were usable. The responses of 14 participants who indicated 'No' to the question regarding knowledge of industry 4.0 technologies (including Machine learning), were discarded. The 143 responses obtained in this study are higher than previous, similar technology and sustainability-focused studies that utilised snowball sampling and electronic means. For example, 134 responses were obtained and used by [93], 105 were gathered by [1], and 133 were obtained by [94]. Thus, the 143 responses for this study are satisfactory for the arrays of analyses carried out and presented in the results and discussion section of this paper. Although considering that the study was not limited to any specific region of Nigeria, the 143 could be argued to be small, however, data collection from experts involving emerging technologies in construction via electronic means usually returns a low response rate [95].

III.3 DATA ANALYSIS METHODS UTILISED.

Descriptive and inferential statistical techniques were used to analyse the gathered data. Frequency and percentage were used to analyse the background information of the respondents. Mean score ($\bar{x}$) and standard deviation (SD) were utilised in ranking the assessed variables based on the relative weightings. The mean normalisation value (NV) was used to determine the most critical factors assessed. Variables with NV $\geq$ 0.50 were considered critical [96]. The relative importance index (RII) was further used to determine the importance of the ranking of the variables. For interpretation purposes the scale: 0 < RII $\leq$ 20% (not high); 20 < RII $\leq$ 40% (very little high); 40 < RII $\leq$ 60 (somewhat high); 60 < RII $\leq$ 80% (high); and 80 < RII $\leq$ 100% (very high) by [97] was adapted. The Kendall's coefficient of concordance or (Kendall's W) and Chi-square (X^2) value were used to determine the overall level of agreement in the ranking of the variables by the respondents. Analysis of variance (ANOVA) was used to determine if there is a statistically significant difference between the various respondents' groups regarding, the awareness level of the application areas of ML in construction, and the adoption readiness of the experts to use ML in the identified application areas. The use of ANOVA for comparison of different survey respondents' groups is common in construction literature [8], [97]. However, prior to all these tests, Cronbach's alpha coefficient was used to determine the reliability of the gathered data. The results showed that the data are highly reliable and of good quality, as the Cronbach's alpha coefficient of 0.944 and 0.909 were obtained for awareness level and adoption readiness of ML, which are closer to 1 [98]. The skewness and kurtosis values from the descriptive test were used to determine the normality of the data. It is advised that the skewness value should range from -2 to 2, and the kurtosis value fall within -7 to 7 [99], and based on the results obtained, the data were adjudged to be normally distributed.

IV. RESULTS AND DISCUSSIONS.

IV. 1 RESPONDENTS BACKGROUND INFORMATION.

Results in Table 2 showed that 32.87% of the respondents are in consulting business, 43.36% are in contracting, and 23.78% are clients. This is a fair representation of the three key stakeholders in the built environment. The profession of the participant's showed Engineers are more with 28.67%, followed by Quantity Surveyors (25.17%), then, project managers (25.17%), Builders (14.69%), Architects (12.59%), and other professions (1.40%). This is a good distribution of the experts who drive innovation penetration in the construction industry. Furthermore, 91.61% of these professionals are chartered members of their various professional bodies, and only a negligible number 8.39% are probationers. The years of experience of the professionals showed that those who have spent 11-15 are constitute 43.36% of the participants. This is followed by those with 16-20 years' experience (21.68%), then 6-10 years' experience (18.88%), 3- 5 years ' (10.49%) and lastly those with 20 years and above (5.59%). Overall, the average years of the experience of the participants was 13 years, and this is a considerable length of time to have acquired sufficient experience and knowledge to contribute meaningfully to the success of this study. Further, the respondents have the requisite education to understand the content of the questionnaire as the minimum level of education attained by the respondents is HND.

Table 2: Background information of the respondentes.

Variables	Classification	Frequency	%
Business of organisations	Consulting	47	32.87
	Contracting	62	43.36
	Clients	34	23.78
	TOTAL	**143**	**100.00**
Profession of respondents	Architect	18	12.59
	Builders	21	14.69
	Engineers	41	28.67
	Quantity Surveyors	36	25.17
	Project managers	25	17.48
	Other (Environmentalist=1, Town planner = 1)	2	1.40
	TOTAL	**143**	**100.00**
Years of experience	3-5years	15	10.49
	6-10 years	27	18.88
	11-15 years	62	43.36
	16-20 years	31	21.68
	20+ years	8	5.59
	TOTAL	**143**	**100.00**
Educational Qualification	Higher National Diploma (HND)	10	6.99
	Bachelor of Science/technology (B.Sc./Batch)	42	29.37
	Master’s Degree (MSc./M.Tech.)	79	55.24
	Doctorate degree (PhD)	12	8.39
	TOTAL	**143**	**100.00**
Professional affiliation	Chartered members	131	91.61
	Probationer	12	8.39
	TOTAL	**143**	**100.00**

Source: Authors, (2024).

IV. 2 AWARENESS OF ML APPLICATION AREAS IN CONSTRUCTION

Table 3 shows the results obtained on the awareness of the application areas of machine learning in the construction industry by the respondents. Overall, the respondents showed that they have a high awareness level of ML application areas, and this is premised on the overall mean score of 3.86 (RII=77.14%). Further, RII values showed that 11(55%) of the variables fell within the 'high' category, and 9(45%) were within the 'very high' category. Further, the top ranked application areas with NV>0.50 are prediction of the energy system behaviour of buildings ($\bar{x}$=4.41; NV=1.00), Prediction of short-term cooling loads of buildings ($\bar{x}$=4.41; NV=0.99), Health and Safety prediction and management ($\bar{x}$=4.29; NV=0.89), Waste management ($\bar{x}$=4.28; NV=0.88), Prediction of and management of construction costs ($\bar{x}$=4.22; NV=0.83), Risk Management ($\bar{x}$=4.20; NV=0.81), Structural Health Monitoring and Prediction ($\bar{x}$=4.11; NV=0.73), Building Life-Cycle assessment and management ($\bar{x}$=4.11; NV=0.73), and 3D models classification in BIM ($\bar{x}$=4.04; NV=0.67).

The ANOVA results (Table 3, columns 7 & 8) showed that the views of the respondents’ groups (consultants, contractors and clients), have a non-significant difference with a p-value≥0.05 in nine of the variables. Eleven of the variables, however, showed a divergent view among the respondents, as the p-value<0.05 was obtained. The differences in knowledge and experiences as well as different organisational technology cultures could have an impact on this result. Further, the overall ANOVA is significant with p-value =0.042 and F=3.248. Based on this, the study concluded that there is a significant statistical difference in the awareness level of the consultants, contractors and clients regarding the awareness level of ML application areas in construction.

From Kendall's test, the critical X^2 of 30.114 from the table is less than the calculated X^2 of 238.66. This implies closely related rankings with insignificant differences in the opinions of the participants. The use of the chi-square values of Kendall's test to interpret the relatedness of assessed variables ranking within participants is evident in the literature [90, 93].

Table 3: Awareness of ML applications areas in construction.

Code	ML Application area in construction		NV	RII	Remark	Rank	ANOVA	
							F-stat	Sig.
ML01	Site works (e.g., wall painting, plastering, etc.)	3.67	0.340	73.43%	H	14	2.483	0.087
ML02	3D models classification in BIM	4.05	0.68a	80.98%	VH	9	17.245	0.000*
ML03	Prediction of and management of construction costs	4.22	0.83a	84.34%	VH	5	10.324	0.000*
ML04	prediction of the energy system behaviour of buildings	4.41	1.00a	88.25%	VH	1	10.115	0.000*
ML05	Prediction of short-term cooling loads of buildings	4.41	0.99a	88.11%	VH	2	10.430	0.000*
ML06	detection and classification of pavement stress	3.29	0.00	65.73%	H	20	1.528	0.220
ML07	Rutting prediction of asphalt pavement	3.36	0.07	67.27%	H	17	3.155	0.046*
ML08	prediction of design energy of buildings	3.50	0.19	69.93%	H	16	0.407	0.666
ML09	Prediction of recycled concrete compressive strength and failure	3.35	0.06	66.99%	H	18	0.957	0.386
ML10	Waste management	4.28	0.88a	85.59%	VH	4	10.763	0.000*
ML11	construction Workforce Assessment and Activity Recognition	3.69	0.35	73.71%	H	12	0.132	0.876
ML12	Prediction of the long-term heating and electricity loading of buildings	3.32	0.03	66.43%	H	19	3.090	0.049*
ML13	Construction equipment assessment and activity recognition	3.61	0.29	72.17%	H	15	1.260	0.287
ML14	prediction of heavy equipment parameters	3.71	0.38	74.27%	H	11	1.894	0.154
ML15	Building Occupancy Modelling and Performance Simulation.	3.69	0.35	73.71%	H	12	1.046	0.354
ML16	Health and Safety prediction and management	4.29	0.89a	85.87%	VH	3	7.464	0.001*
ML17	Schedule Management	3.87	0.52a	77.48%	H	10	9.145	0.000*
ML18	Risk Management	4.20	0.81a	84.06%	VH	6	25.577	0.000*
ML19	Structural Health Monitoring and Prediction	4.11	0.73a	82.24%	VH	7	4.176	0.017*
ML20	Building Life-Cycle assessment and management	4.11	0.73a	82.24%	VH	7	2.833	0.062
ANOVA	N	143						
	Kendall's W[a]	0.088						
	calculated Chi-Square (X^2) value	238.66						
	Critical Chi-Square (X^2) value from Table	30.114						
	df	19						
	Asymptotic level of significance	0.000						
		Between Groups	**Within Groups**	**Total**				
	Sum of Squares	5.054	108.97	114.028				
	df	2	140	142				
	Mean Square	2.527	0.778					
	F	3.248						
	Sig.	0.042						

*p-value≤0.05; [a]Normalisation value ≥0.50 indicate criticality of assessed variables

Source: Authors, (2024).

IV. 2 ADOPTION READINESS OF ML APPLICATION AREAS IN CONSTRCTION

Table 4 shows the results obtained on the adoption readiness of ML in assessed application areas in the construction industry. Overall, the participants indicate high adoption readiness of ML in the various areas of application in construction, and this is based on the overall mean of 3.83 (RII=76.75%). A further breakdown of each ranking of the adoption readiness on each application area showed that 14(70%) of the variables fell within the 'high' category, and 6(30%) were within the 'very high' category. Notwithstanding, the top six ranked application areas based on relative weights of the adoption readiness and whose NV>0.50 are Prediction of and management of construction costs ($\bar{x}$=4.34; NV=1.00), Health and Safety prediction and management ($\bar{x}$=4.32; NV=0.99), Risk Management ($\bar{x}$ =4.32; NV=0.99), Building Life-Cycle assessment and management ($\bar{x}$=4.26; NV=0.93), Waste management ($\bar{x}$=4.16; NV=0.84), and structural Health Monitoring and Prediction ($\bar{x}$=4.11; NV=0.79).

The ANOVA result shows that the opinion of the participants differs significantly in 70% of the assessed ML application areas. The adoption readiness of the ML in the application areas had a p-value<0.05, and thus, was ranked differently by the consultants, contractors and clients. The result further revealed that 30% of the variables were ranked in a similar way by the respondents, as their p-value >0.05. The significant differences observed in the adoption readiness of ML in construction could be based on the financial capabilities of the different organisations, and their technology innovation culture and policies. Furthermore, the overall ANOVA is significant with p-value =0.050 and F=3.061. This is confirmation that there is a significant statistical difference in the adoption readiness of the consultants, contractors and clients to adopt ML in some or all of the application areas in construction.

From Kendall's test, the critical X^2 of 30.114 from the table is less than the calculated X^2 of 251.29. This implies an insignificant difference and similar rankings of the variables within the participants' groups. The use of the chi-square values of Kendall's test to interpret the relatedness of assessed variables ranking within participants is evident in the literature [90], [93].

Table 4: Adoption readiness of ML in construction.

Code	ML Application area in construction	□	NV	RII	Remark	Rank	ANOVA	
							F-stat	Sig.
ML01	Site works (e.g., wall painting, plastering, etc.)	3.97	0.66[a]	79.44%	H	8th	17.367	0.000*
ML02	3D models classification in BIM	3.80	0.50[a]	75.94%	H	11th	1.231	0.295
ML03	Prediction of and management of construction costs	4.34	1.00[a]	86.71%	VH	1st	3.785	0.025*
ML04	prediction of the energy system behaviour of buildings	3.83	0.54[a]	76.64%	H	10th	1.825	0.165
ML05	Prediction of short-term cooling loads of buildings	3.52	0.25	70.49%	H	15th	10.774	0.000*
ML06	detection and classification of pavement stress	3.25	0.00	65.03%	H	20th	6.231	0.003*
ML07	Rutting prediction of asphalt pavement	3.31	0.06	66.29%	H	18th	8.578	0.000*
ML08	prediction of design energy of buildings	3.45	0.18	68.95%	H	17th	5.236	0.006*
ML09	Prediction of recycled concrete compressive strength and failure	3.52	0.25	70.49%	H	15th	6.225	0.003*
ML10	Waste management	4.16	0.84[a]	83.22%	VH	5th	9.066	0.000*
ML11	construction Workforce Assessment and Activity Recognition	3.80	0.50[a]	75.94%	H	11th	1.231	0.295
ML12	Prediction of the long-term heating and electricity loading of buildings	3.31	0.05	66.15%	H	19th	5.291	0.006*
ML13	Construction equipment assessment and activity recognition	3.78	0.49	75.66%	H	13th	2.282	0.106
ML14	prediction of heavy equipment parameters	3.91	0.61[a]	78.18%	H	9th	4.726	0.010*
ML15	Building Occupancy Modelling and Performance Simulation.	3.99	0.68[a]	79.86%	H	7th	4.415	0.014*
ML16	Health and Safety prediction and management	4.32	0.99[a]	86.43%	VH	2nd	3.906	0.022*
ML17	Schedule Management	3.78	0.49	75.66%	H	13th	1.504	0.226
ML18	Risk Management	4.32	0.99[a]	86.43%	VH	2nd	5.374	0.006*
ML19	Structural Health Monitoring and Prediction	4.11	0.79[a]	82.24%	VH	6th	1.351	0.262
ML20	Building Life-Cycle assessment and management	4.26	0.93[a]	85.17%	VH	4th	4.605	0.012*
	N	143						
	Kendall's W[a]	0.092						
	calculated Chi-Square (X^2) value	251.29						
	Critical Chi-Square (X^2) value from Table	30.114						
	df	19						
	Asymptotic level of significance	0.000						
		Between Groups	**Within Groups**	**Total**				
	Sum of Squares	3.853	88.134	91.987				
	df	2	140	142				
ANOVA	Mean Square	1.927	0.630					
	F	3.061						
	Sig.	0.050						
*p-value≤0.05; [a]Normalisation value ≥0.05 indicate criticality of assessed variables.								

Source; Authors, (2024).

IV. 3 DISCUSSION OF FINDINGS

The study revealed nine critical ML application areas with very high awareness levels. The corresponding readiness of the organisations to adopt ML in these application areas (Figure 1) is briefly discussed below.

The study revealed that ML is applied in the Prediction of the energy system behaviour of buildings (ML04) as well as the Prediction of short-term cooling loads of buildings (ML05). This function helps in the design and management of energy requirements and consumption in a building. The use for the prediction of the heat demand of commercial buildings was demonstrated by [68] using the RNN model. While the awareness of these functions (ML04 and ML05) is 'very high', their adoption readiness is rated 'high'. This shows how important energy management is for buildings, and in recent times where the global energy cost is high, there is a need to adopt ML to guide the design and management of energy in building projects.

Another key application area according to this study is 'Health and Safety prediction and management (ML16)'. ML helps in the identification of possible sources of accidents and injuries on construction sites, and this enables proactive planning of mitigation strategies to avoid the occurrence of accidents on construction projects. The importance of ML in accident and injury prediction and prevention on-site is evident in studies such as [39], [46]. The 'Health and Safety prediction and management' function of ML has very high awareness and adoption readiness according to the participants. The waste management (ML10) function of ML is also important in the construction industry. Poor waste management in the construction industry has been a critical cause of cost and time overruns and the distortion of environmental aesthetics through the build-up of waste in landfills. ML algorithm in AI technologies offers quick and more effective ways of different waste identification, sorting and disposal from site [22]. The waste management function of ML also has a 'very high' awareness and adoption readiness.

ML's role in the prediction and management of construction costs is one that has been given adequate attention in construction management literature. It is an essential function of the ML in construction projects, be it building or civil engineering construction as evident in [52], [55]. The awareness and adoption readiness of ML's role in the prediction and management of construction costs (ML03) is very high.

Risk Management (ML18) goes beyond just the identification of hazards on construction sites. It includes every measure taken to prevent such risks from happening. Risks include those that could have important on the overall baselines of the projects which include time, cost and other events that can retard or even lead to stoppage of work on site. The role of ML in risk prediction and management is well-documented in the literature [60], [61]. While the awareness of ML's role in risk management is very high, the adoption readiness of the industry to apply ML in the management of risks is also very high.

ML plays a pivotal role in determining the structural health of a building or structure. The use of ML in Structural Health Monitoring and Prediction (ML19) can take place either before or after construction, and this is supported by literature [64], [69]. It is rated very high in both awareness level and adoption readiness by the participants.

Studies have shown that ML helps in Building Life-Cycle assessment and management (ML20). The life cycle prediction of ML goes beyond building projects but also the survival of or otherwise of a construction business [73], [74]. The application area has very high awareness and adoption readiness according to this study. Keeping and maintaining a 3D model library is difficult and expensive. The use of ML in the classification of 3D models from traditional CAD is the fastest and most efficient way to maintain a robust 3D model library for reuse on a project. the application of ML for 3D models classification (ML02) in BIM (ML02) is vital and has been identified as a novel way of BIM development in the built environment [78].

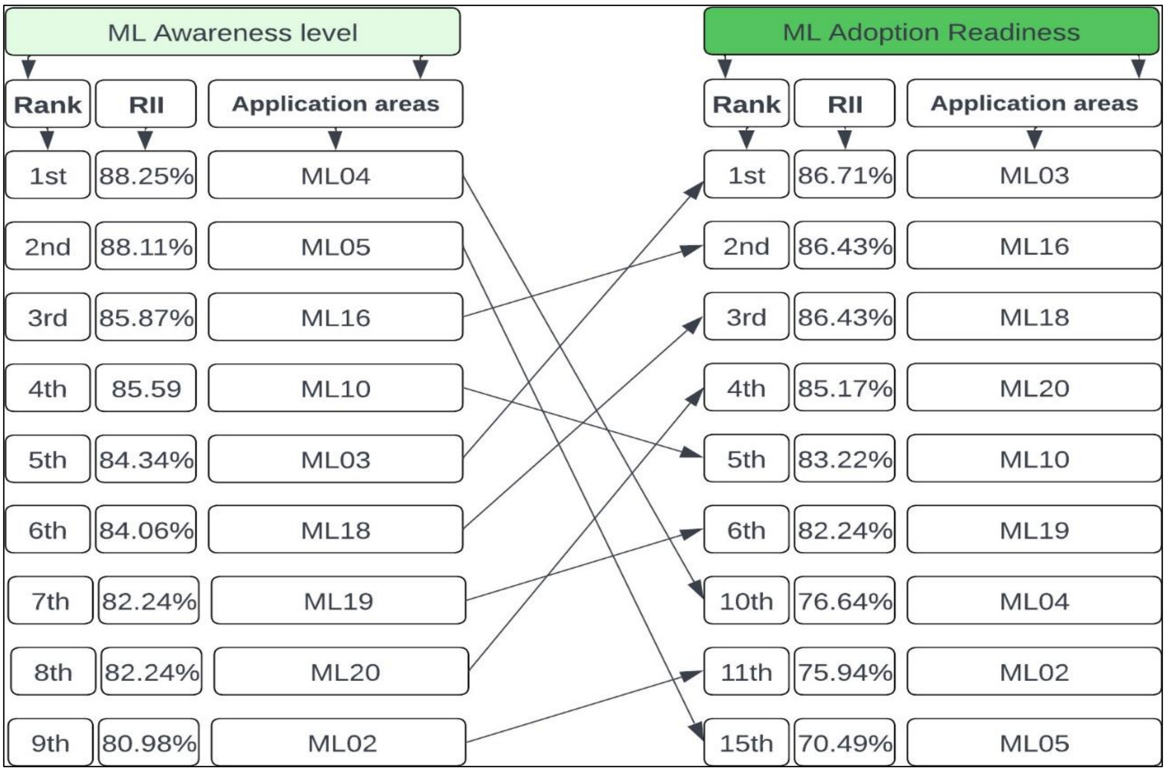

Figure 1: ML application areas with very high awareness and their corresponding adoption readiness.
Source: Authors, (2024).

V. CONCLUSIONS

This study investigated the awareness of the Nigerian construction organisations on some identified ML application areas, and the readiness of the organisations to adopt ML learning in the identified application areas. The study utilised structured questionnaires to remotely gather relevant data from construction professionals within the sampled organisations using a snowball sampling technique. Arrays of descriptive and inferential statistical tools were used to analyse the gathered data, and meaningful results were obtained and discussed and conclusions drawn.

It was found that the awareness and adoption readiness of Nigerian construction organisations on the assessed ML application areas is high. Also, six of the nine application areas with very high awareness levels equally have a very high adoption readiness level. These critical ML application areas are (1) Health and Safety prediction and management, (2) Waste management, (3) Prediction of and management of construction costs, (4) Risk Management, (5) Structural Health Monitoring and Prediction, and (6) Building Life-Cycle assessment and management. Although, within the various organisations, there were agreements in the way they rated the variables according to Kendall's test, the overall ANOVA test revealed a significant statistical difference between the opinions of the participants regarding the awareness and adoption readiness of the various ML application areas.

This study offers some useful implications in the built environment. First, it provides an overall idea of the awareness and adoption readiness of construction organisations regarding the utilisation of ML to carry out various prediction functions in the life of construction projects. Soaring energy bills is a global problem, and the use of ML in predicting how the energy system of a building will behave will help construction experts and other stakeholders to produce energy-efficient buildings to drastically reduce energy losses in buildings. ML helps in the construction industry's drive towards a more sustainable built environment.

ML is based on Artificial intelligence, and it has the potential to offer construction organisations improved production efficiency and productivity. Construction organisations can gain from the knowledge presented in this study to explore ways of integrating ML in their operational functions to curb risks and waste, and in addition, improve cost prediction and management.

The application areas of ML cover the key activities that happen in construction. Thus, the adoption of ML in carrying out these functions will help in meeting the sustainability targets of the industry. Thus, could guide the government in making favourable policies and regulations to encourage their penetration in construction. While the awareness of ML is high among the participants, incorporating it into the tertiary education curriculum will further improve the awareness of the future built environment experts from the various engineering and environmental sciences faculties and departments.

This study contributed to the body of knowledge in the Nigerian context, despite this, the sample size, research approach and number of variables assessed could limit its generalisation. A similar study should be embarked upon using the mixed research approach to confirm or improve on what has been found in this study. A study that could focus on specific construction professionals, e.g., Quantity surveyors, Engineers, etc., could be carried out to comprehend the depth of ML diffusion and penetrate among the various professional groups in the country.

VI. AUTHOR’S CONTRIBUTION

Conceptualization: Samuel Osusha Loya, Emmanuel Chidiebere Eze, Imoleayo Abraham Awodele
Methodology: Emmanuel Chidiebere Eze, Onyinye Sofolahan, Olayinka Omoboye
Investigation: Samuel Osusha Loya, Emmanuel Chidiebere Eze, Imoleayo Abraham Awodele, Onyinye Sofolahan, Olayinka Omoboye
Discussion of results: Samuel Osusha Loya, Emmanuel Chidiebere Eze, Imoleayo Abraham Awodele, Onyinye Sofolahan, Olayinka Omoboye
Writing – Original Draft: Samuel Osusha Loya, Emmanuel Chidiebere Eze, Imoleayo Abraham Awodele.
Writing – Review and Editing: Samuel Osusha Loya, Emmanuel Chidiebere Eze, Imoleayo Abraham Awodele, Onyinye Sofolahan, Olayinka Omoboye.
Resources: Samuel Osusha Loya, Emmanuel Chidiebere Eze, Imoleayo Abraham Awodele, Onyinye Sofolahan, Olayinka Omoboye.
Supervision: Emmanuel Chidiebere Eze, Imoleayo Abraham Awodele, Olayinka Omoboye.
Approval of the final text: Samuel Osusha Loya, Emmanuel Chidiebere Eze, Imoleayo Abraham Awodele, Onyinye Sofolahan, Olayinka Omoboye.

VII. REFERENCES

[1] A.I. Awodele, M.C. Mewomo, and E.C. Eze, “Inhibitors to the Adoption of Building Information Modelling in Modular Construction: A Case Study of the Nigerian Construction Industry”, Journal of Construction in Developing Countries, vol. 28 no. 2, pp.19-36, 2023.

[2] E.A. Sekou, “Promoting the use of ICT in the construction industry: Assessing the factors hindering usage by building contractors in Ghana”, MSc dissertation, Kwame Nkrumah University of Science and Technology, 2012.

[3] R. Ruparathna, and K. Hewage, “Review of contemporary construction procurement practices”, Journal of Management in Engineering, vol. 31, no. 3, pp.04014038, 2015. https://doi.org/10.1061/(asce)me.1943-5479.00002799.

[4] Y. Yang, M. Pan, and W. Pan, “Co-evolution through interaction of innovative building technologies: The case of modular integrated construction and robotics”, Automation in Construction, vol. 107, no.4, pp. 1-10, 2019.

[5] W.E. Rees, “Achieving sustainability: reform or transformation? In The Earthscan reader in sustainable cities”, Routledge, pp.22-52, 2021.

[6] E.C. Eze, O. Sofolahan, R.A. Ugulu, and E.E. Ameyaw, “Bolstering circular economy in construction through digitalization”, Construction Innovation. DOI 10.1108/CI-10-2023-0245, 2024.

[7] O.J. Adebowale, and J.N. Agumba, “Artificial Intelligence technology applications in building construction productivity: a systematic literature review”, Acta Structilia, vol. 30, no.2, pp.161-195, 2024.

[8] I.A. Awodele, M.C. Mewomo, A.M.G. Municio, A.P. Chan, A. Darko, R. Taiwo, N.A. Olatunde, E.C. Eze, and O.A. Awodele, “Awareness, adoption readiness and challenges of railway 4.0 technologies in a developing economy”, Heliyon, p.e25934, 2024. https://doi.org/10.1016/j.heliyon.2024.e259344.

[9] S. Bag, G. Yadav, P. Dhamija, and K.K. Kataria, “Key resources for industry 4.0 adoption and its effect on sustainable production and circular economy: an empirical study”, Journal of Cleaner Production, vol. 281, 2021.

[10] V.A. Wankhede, R. Agrawal, A. Kumar, S. Luthra, D. Pamucar, and Ž. Stević, "Artificial intelligence an enabler for sustainable engineering decision-making in uncertain environment: a review and future propositions", Journal of Global Operations and Strategic Sourcing, Vol. ahead-of-print No. ahead-of-print, 2023.

[11] V. Bhatnagar, S. Sharma, A. Bhatnagar, and L. Kumar, “Role of machine learning in sustainable engineering: a review”, IOP Conference Series: Materials Science and Engineering, vol. 1099, no.1, pp.12036, 2021.

[12] S. Kotsiantis, I. Zaharakis, and P. Pintelas, “Supervised machine learning: A review of classification techniques”, Emerging Artificial Intelligence Application in Computer Engineering, vol.160, pp.3-24, 2007.

[13] B. Sundui, O.A. Ramirez Calderon, O.M. Abdeldayem, J. L¨azaro-Gil, E.R. Rene, and U. Sambuu, “Applications of machine learning algorithms for biological

wastewater treatment: updates and perspectives", Clean Technologies and Environmental Policy, vol. 23, no.1, Doi: 10.1007/s10098-020-01993-x, 2021.

[14] M. Ribeiro, K. Grolinger, and M.A. Capretz, "Mlaas: Machine learning as a service", In 2015 IEEE 14th international conference on machine learning and applications (ICMLA), pp.896-902, 2015.

[15] B. Hellingrath, and S. Lechtenberg, "Applications of artificial intelligence in supply chain management and logistics: focusing onto recognition for supply chain execution. The art of structuring: Bridging the gap between information systems research and practice", pp.283-296, 2019. DOI: 10.1007/978-3-030-06234-7_27

[16] Q. Demlehner, D. Schoemer, and S. Laumer, "How can artificial intelligence enhance car manufacturing? A Delphi study-based identification and assessment of general use cases", International Journal of Information Management, vol.58, pp.102317, 2021.

[17] F.D. Weber, and R. Schütte, "State-of-the-art and adoption of artificial intelligence in retailing", Digital Policy, Regulation and Governance, vol. 21, no.3, pp.264-279, 2019.

[18] J. Aliu, and A.E. Oke, "Construction in the digital age: exploring the benefits of digital technologies", Built Environment Project and Asset Management, vol. 13 No. 3, pp. 412-429, 2023. DOI: https://doi.org/10.1108/BEPAM-11-2022-01866.

[19] A. Ebekozien, and C. Aigbavboa, "COVID-19 recovery for the Nigerian construction sites: the role of the fourth industrial revolution technologies", Sustainable Cities and Society, vol.69, pp.102803, 2021.

[20] B. Buchanan, "A (very) brief history of artificial intelligence", AI Magazine, vol.26, no.4, pp.53, 2005.

[21] A. Turing, "Computing Machinery and Intelligence", Mind, vol.59, no.236, pp.433-460, 1950.

[22] S.O. Abioye, L.O. Oyedele, L. Akanbi, A. Ajayi, J.M.D. Delgado, M. Bilal, O.O. Akinade, and A. Ahmed, "Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges", Journal of Building Engineering, vol.44, 2021. DOI: https://doi.org/10.1016/j.jobe.2021.1032999.

[23] G. Xie, Chen, Tiange, Y. Li, Chen, Tingyu, X. Li, and Z. Liu, "Artificial intelligence in nephrology: How can artificial intelligence augment nephrologists' intelligence?", KDD, vol.6, pp.1–6, 2020. DOI: https://doi.org/10.1159/0005046000.

[24] A. Mahmoud, "Introduction to Shallow Machine Learning", Available at: https://shorturl.at/bEI26 [accessed 7th March 2024].

[25] C. Egwim, H. Alaka, O. Toriola-Coker, H. Balogun, F. Sunmola, "Applied artificial intelligence for predicting construction projects delay", Machine Learning with Applications, vol.6, pp.1-15, 2021. DOI: https://doi.org/10.1016/j.mlwa.2021.1001666.

[26] Y. Xu, Y. Zhou, P. Sekula, and L. Ding, "Machine learning in construction: From shallow to deep learning", Developments in the Built Environment, vol.6, pp.1-13, 2021.

[27] Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning", Nature, vol.521, pp.7553, 2015.

[28] O.K. Abayomi, F.N. Adenekan, O.A. Adeleke, T.A. Ajayi, and A.O Aderonke, "Awareness and perception of the artificial intelligence in the management of University libraries in Nigeria", Journal of Interlibrary Loan, document Delivery & Electronic Reserve, vol. 29, no.1-2, pp.13-28, 2020.

[29] A.A. Iorkaa, M. Barma, and H. Muazu, "The assessment of financial institutions' awareness and application of machine learning techniques for credit risk prediction- the case of Nigeria", Annals. Computer Science Series, vo.19, no.1, pp.16-22, 2021.

[30] W.A. Udoh, I. Nsude, and A.S. Oyeleke, "Awareness of artificial Intelligence for news production among journalists in Ebonyi State Nigeria, International Journal of Network and Communication Research, vol.7, no.1, pp.33-45, 2022.

[31] J.S. Guanah, "Mainstream media and artificial intelligence awareness amongst residents of Asaba metropolis, Delta State, Nigeria", Journal of Contemporary Social Research, vol.5, no.1, pp.65-79, 2021.

[32] J.O. Mobayo, A.F. Aribisala, S.O. Yusuf, and U. Belgore, "Artificial intelligence: Awareness and adoption for effective facilities management in the energy sector", Journal of Digital Food, Energy & Water Systems, vol.2, no.2, pp.1-18, 2021.

[33] I.C. Osuizugbo, and A.S. Alabi, "Built environment professionals' perceptions of the application of artificial intelligence in construction industry", Covenant Journal of Research in the Built Environment (CJRBE), vol. 9, no.2, pp.48-66, 2021.

[34] A.E. Oke, J. Aliu, P.O. Fadamiro, P.O. Akanni, and S.S. Stephen, "Attaining digital transformation in construction: An appraisal of the awareness and usage of automation techniques", Journal of Building Engineering, vol.67, pp.1-13, 2023. DOI: https://doi.org/10.1016/j.jobe.2023.1059688.

[35] N.A. Olatunde, A.M. Gento, V.N. Okorie, O.W. Oyewo, M.C. Mewomo, and I.A. Awodele, "Construction 4.0 technologies in a developing economy: awareness, adoption readiness and challenges", Frontiers in Engineering and Built Environment, vol. 3 no. 2, pp. 108-121, 2023. DOI: https://doi.org/10.1108/FEBE-08-2022-0037.

[36] P.M. Teicholz, "Labor-productivity declines in the construction industry: Causes and Remedies", 2013. Available at: https://www.aecbytes.com/viewpoint/2004/issue_4.html (Accessed on: 11/01/2024).

[37] R. Sacks, G. Mark, and B. Ioannis, "Building information modelling, artificial intelligence and construction", Technology Developments in the Built Environment, vol.4, 2020. DOI: https://doi.org/10.1016/j/dibe.2020.1000111.

[38] D. Singer, M. Bügler, A. Borrmann, and L.O. Center, "Knowledge based bridge engineering-artificial intelligence meets building information modeling", Proceedings of the EG-ICE Workshop on Intelligent Computing in Engineering, 2016.

[39] M. Regona, T. Yigitcanlar, B. Xia, and R.Y.M. Li, "Opportunities and adoption challenges of AI in the construction industry: A prisma review", Journal of Open Innovation: Technology, Market, and Complexity, Vol.8, no.45, 2022. DOI: https://doi.org/10.3390/joitmc80100455.

[40] C.Q.X. Poh, C.U. Ubeynarayana, and Y.M. Goh, "Safety leading indicators for construction sites: A machine learning approach", Automation in Construction, vol.93, pp.375–386, 2018. DOI: https://doi.org/10.1016/j.autcon.2018.03.0222.

[41] L. Straker, A. Campbell, J. Coleman, M. Ciccarelli, and W. Dankaerts, "In vivo laboratory validation of the physiometer: a measurement system for long-term recording of posture and movements in the workplace", Ergonomics, vol.53, no.5, pp.672–684, 2010.

[42] Y.M. Goh, and D. Chua, "Neural network analysis of construction safety management systems: A case study in Singapore", Construction Management and Economics, vol.31, no.5, pp460-470, 2013.

[43] X. Yan, H. Li, A.R. Li, and H. Zhang, "Wearable imu-based real-time motion warning system for construction workers' musculoskeletal disorders prevention", Automation in Construction, vol.74, pp.2–11, 2017.

[44] L. Wonil, E. Seto, K.Y. Lin, and G.C. Migliaccio, "An evaluation of wearable sensors and their placements for analyzing construction worker's trunk posture in laboratory conditions", Applied Ergonomics, vol.65, pp. 424-436, 2017.

[45] J. Seo, S. Han, S. Lee, and H. Kim, "Computer vision techniques for construction safety and health monitoring", Advanced Engineering Informatics, vol.29, no.2, pp.239–251, 2015.

[46] E. Harirchian, V. Kumari, K. Jadhav, R.R. Das, S. Rasulzade, and T. Lahmer, "A machine learning framework for assessing seismic hazard safety of reinforced concrete buildings", Applied Sciences (Switzerland), vol.10, no.20, pp.1–18, 2020.

[47] A.J.-P. Tixier, M.R. Hallowell, B. Rajagopalan, and D. Bowman, "Application of machine learning to construction injury prediction", Automation in Construction, vol.69, pp.102–114, 2016. DOI: https://doi.org/10.1016/j.autcon.2016.05.016.

[48] Y. Yu, H. Li, X. Yang, L. Kong, X. Luo, and A.Y. Wong, "An automatic and non-invasive physical fatigue assessment method for construction workers", Automation in Construction, Vol. 103, pp.1–12, 2019. DOI: https://www.sciencedirect.com/science/article/pii/S0926580 518308422.

[49] Q. Fang, H. Li, X. Luo, L. Ding, T.M. Rose, W. An, and Y. Yu, (2018). Detecting non-hardhatuse by a deep learning method from far-field surveillance

videos. Automation in Construction, Vol.85, pp.1–9, 2018. http://www.sciencedirect.com/science/article/pii/S0 926580517304429.

[50] H. Luo, and C. Xiong, "Convolutional neural networks: vision-based workforce activity assessment in construction", Automation in Construction, vol.94, pp.282–289, 2018. https://doi.org/10.1016/j.autcon.2018.06.007.

[51] S. Kim, "Hybrid forecasting system based on case-based reasoning and analytic hierarchy process for cost estimation", Journal of Civil Engineering and Management, vol.19, no.1, pp.86-96, 2013.

[53] M. Gunduz, L.O. Ugur, and E. Ozturk, "Parametric cost estimation system for light rail transit and metro trackworks", Expert Systems with Applications, vol.38, no.3, pp.2873-2877, 2011.

[52] G. Mahalakshmi, and C. Rajasekaran, "Early cost estimation of highway projects in India using artificial neural network. In: Das, B., Neithalath, N. (eds) Sustainable Construction and Building Materials. Lecture notes in civil engineering", Springer, Singapore, 2019. https://doi.org/10.1007/978-981-13-3317-0_599.

[54] M. Gunduz, and H.B. Sahin, "An early cost estimation model for hydroelectric power plant projects using neural networks and multiple regression analysis", Journal of Civil Engineering and Management, vol.21, no.4, pp.470-477, 2015.

[55] X. Wang, "Application of fuzzy math in cost estimation of construction project", Journal of Discrete Mathematical Sciences and Cryptography, vol.20, no.4, pp.805-816, 2017.

[56] V. Chandanshive, and A.R. Kambekar, "Estimation of building construction cost using artificial neural networks", Journal of Soft Computing in Civil Engineering, vol.3, no.1, pp.91-107, 2019.

[56] N.I. El-Sawalhi, and O. Shehatto, "A neural network model for building construction projects cost estimating", Journal of Construction Engineering and Project Management, vol.4, no.4, pp.9-16, 2014.

[57] K. Petroutsatou, and S. Lambropoulos, "Road tunnels construction cost estimation: A structural equation model development and comparison", Operational Research, vol.10, no.2, pp.163-173, 2010.

[57] M. Rafiei, and H. Adeli, "Novel machine-learning model for estimating construction costs considering economic variables and indexes" Journal of Construction Engineering and Management, Vol.144, no.12, 2018. DOI: https://doi.org/10.1061/(ASCE)CO.1943-7862.0001570.

[58] N.V. Tam, and N.Q. Toan, "Reasearch trends on machine learning in construction management: A scientoetric analysis", Journal of Applied Science and Technology Trends, vol.2, no.3, pp.96-104, 2021.

[59] A. Gondia, A. Siam, W. El-Dakhakhni,and A.H. Nassar, "Machine learning algorithms for construction projects delay risk prediction", Journal of Construction Engineering and Management, vol.146, no.1, 2020. DOI: https://doi.org/10.1061/(ASCE)CO.1943-7862.0001736.

[60] M.O. Sanni-Anibire, R.M. Zin, and S.O. Olatunji, "Machine learning model for delay risk assessment in tall building projects", International Journal of Construction Management, vol.22, no.11, pp.2134-2143, 2020. DOI: https://doi.org/10.1080/15623599.2020.17683266.

[61] H. Liu, and G. Tian, "Building engineering safety risk assessment and early warning mechanism construction based on distributed machine learning algorithm", Safety Science, vol.120, pp.764-771, 2019.

[62] A. Rahman, and A. Smith, "Predicting heating demand and sizing a stratified thermal storage tank using deep learning algorithms", Applied Energy, vol.228, pp.108–121, 2018.

[63] A. Rahman, V. Srikumar, and A.D. Smith, "Predicting electricity consumption for commercial and residential buildings using deep recurrent neural networks", Applied Energy, vol.212, pp.372-385, 2018.

[64] Y. Zhong, and J. Xiang, "A two-dimensional plum-blossom sensor array-based multiple signal classification method for impact localization in composite structures", Computer- Aided Civil and Infrastructural Engineering, vol.31, no.8, pp.633–643, 2016.

[65] J. Shan, W. Shi, and X. Lu, "Model-reference health monitoring of hysteretic building structure using acceleration measurement with test validation", Computer-Aided Civil and Infrastructural Engineering, vol.31, no.6, pp.449–464, 2016.

[66] S. Khaitan, K. Gopalakrishnan, A. Choudhary, and A. Agrawal, "Deep convolutional neural networks with transfer learning for computer vision-based data-driven pavement distress detection", Construction and Building Matererials Vol.157, pp. 322–330, 2017.

[67] S. El-Badawy, and A. Awed, "Performance of mepdg dynamic modulus predictive models for asphalt concrete mixtures: local calibration for Idaho", Journal of Materials in Civil Engineering, vol.24, no.11, 2012. DOI: https://doi.org/10.1061/(ASCE)MT.1943-5533.0000518.

[68] Y. Tian, J. Lee, T. Nantung, and J. Haddock, "Calibrating the mechanistic empirical pavement design guide rutting models using accelerated pavement testing", Journal of the Transportation Research Board, vol.2672, no.40, pp.304–314, 2018.

[69] F. Deng, Y. He, S. Zhou, Y. Yu, H. Cheng, and X. Wu, "Compressive strength prediction of recycled concrete based on deep learning", Construction and Building Materials vol.175, 2018. DOI: https://doi.org/10.1016/j.conbuildmat.2018.04.169.

[70] T. Nguyen, A. Kashani, T. Ngo, and S. Bordas, "Deep neural network with high-order neuron for the prediction of foamed concrete strength", Computer-Aided Civil and Infrastructural Engineering, vol.34, no.4, pp.316–332, 2019.

[71] Z. Chen, and C. Jiang, "Building occupancy modelling using generative adversarial network", Energy Build. 174, 372–379, 2018.

[72] S. Singaravel, J. Suykens, P. Geyer, "Deep-learning neural-network architectures and methods: using component-based models in building-design energy prediction", Advanced Engineering Informatics, vol.38, pp.81-90, 2018. DOI: https://doi.org/10.1016/j.aei.2018.06.004.

[73] S. Ji, B. Lee, M.Y. Yi, "Building life-span prediction for life cycle assessment and life cycle cost using machine learning: A big data approach", Building and Environment, vol. 205, 2021. DOI: https://doi.org/10.1016/j.buildenv.2021.108267.

[74] H. Alaka, L. Oyedele, H. Owolabi, O. Akinade, M. Bilal, and S. Ajayi, "A big data analytics approach for construction firms failure prediction models", IEEE Transactions on Engineering Management, vol.66, pp.689–698, 2019. DOI: https://doi.org/10.1109/TEM.2018.2856376.

[75] H. Park, and D.Y. Park, "Comparative analysis on predictability of natural ventilation rate based on machine learning algorithms", Building and Environment, vol. 195, 2021. DOI: https://doi.org/10.1016/j.buildenv.2021.107744.

[76] Y. –R. Wang, C.Y. Yu, and H.H. Chan, "Predicting construction cost and schedule success using artificial neural networks ensemble and support vector machines classification models", International Journal of Project Management, vol.30, no.4, pp.470-478, 2012.

[77] H. Kim, L. Soibelman, and F. Grobler, "Factor selection for delay analysis using knowledge discovery in databases", Automation in Construction, vol.17, no.5, pp.550-560, 2008.

[78] L. Wang, Z. Zhao, and X. Wu, "A deep learning approach to the classification of 3D models under BIM environment', International Journal of Control, Automation and Systems, vol. 9, pp.179–188, 2016.

[79] L. Wang, Z.K. Zhao, and N. Xu, "Deep belief network based 3d models classification in building information modeling", International Journal of Online Engineering, vol.11, no.5, pp.57–63, 2015.

[80] C. Fan, F. Xiao, and Y. Zhao, "A short-term building cooling load prediction method using deep learning algorithms", Applied Energy, vol.195, pp.222–233, 2017.

[81] X. Luo, H. Li, D. Cao, F. Dai, J. Seo, and S. Lee, "Recognizing diverse construction activities in site images via relevance networks of construction-related objects detected by convolutional neural networks", Journal of Computing in Civil Engineering, vol.32, no.3, 2018. DOI: https://doi.org/10.1061/(ASCE)CP.1943-5487.0000756.

[82] K.M. Rashid, and J. Louis, "Times-series data augmentation and deep learning for construction equipment activity recognition", Advanced Engineering Informatics vol.42, 2019. DOI: http://www.sciencedirect.com/science/article/pii/S1474034619300886.

[83] C. Hernandez, T. Slaton, V. Balali, R. Akhavian, "A deep learning framework for construction equipment activity analysis", in: Computing in Civil Engineering 2019: Data, Sensing, and Analytics. American Society of Civil Engineers Reston, VA, pp.479–486. DOI: https://ascelibrary.org/doi/labs/10.1061/9780784482438.061.

[84] J. Aliu, C. Aigbavboa, and W. Thwala, "A 21st Century Employability Skills Improvement Framework for the Construction Industry", 2021. DOI: https://doi.org.10.1201/9781003137504.

[85] I.F. Mohamed, D.J. Edwards, M. Mateo-Garcia, G. Costin, and W.D.D. Thwala, "An investigation into the construction industry's view on fire prevention in high-rise buildings post Grenfell", International Journal of Building Pathology and Adaptation, vol. 38, no.3, pp. 451-471, 2020. DOI: https://doi.org/10.1108/IJBPA-05-2019-0048.

[86] W.N. Nwaki, and C.E. Eze, "Lean construction as a panacea for poor construction projects performance", Journal of Engineering and Technology for Industrial Applications (ITEGAM-JETIA), vol.6, no.26, pp.61-72, 2020. doi: https://doi.org/10.5935/jetia.v6i26.723.

[87] A. Joshi, S. Kale, S. Chandel, and D.K. Pal, "Likert scale: explored and explained", British Journal of Applied Science and Technology, vol.7, no.4, pp.396, 2015.

[88] H. Taherdoost, "What is the best response scale for survey and questionnaire design; review of different lengths of rating scale/attitude scale/Likert scale", International Journal of Academic Research in Management, vol.8, no.1, pp.1-10, 2019. Available at SSRN: https://ssrn.com/abstract53588604.

[89] K.L. Moores, G.L. Jones, and S.C. Radley, "Development of an instrument to measure face validity, feasibility and utility of patient questionnaire use during health care: the QQ-10", International Journal for Quality in Health Care, vol.24, no.5, pp.517-524, 2012.

[90] E.C. Eze, O. Sofolahan, and O.G. Omoboye, "Assessment of barriers to the adoption of sustainable building materials (SBM) in the construction industry of a developing country", Frontiers in Engineering and Built Environment, vol.3, no.3, pp.153-166, 2023. DOI: https://doi.org/10.1108/FEBE-07-2022-0029.

[91] D.D. Heckathorn, "Comment: snowball versus respondent-driven sampling", Sociological Methodology, vol.41, no.1, pp.355-366, 2011. doi: 10.1111/j.1467-9531.2011.01244.x.

[92] W. Nwaki, O. Sofolahan, and E. Eze, "Inhibitors to earth-based materials adoption in urban housing construction: The view of design experts", Civil and Sustainable Urban Engineering, vol.3, no.2, pp.123–137, 2023. DOI: https://doi.org/10.53623/csue.v3i2.329.

[93] D. Aghimien, M. Ikuabe, L.M. Aghimien, C. Aigbavboa, N. Ngcobo, and J. Yankah, "PLS-SEM assessment of the impediments of robotics and automation deployment for effective construction health and safety", Journal of Facilities Management, 2022. DOI: https://doi.org/10.1108/JFM-04-2022-0037.

[94] E.C Eze, D.O. Aghimien, C.O. Aigbavboa, and O. Sofolahan, "Building information modelling adoption for construction waste reduction in the construction industry of a developing country", Engineering, Construction and Architectural Management, Vol. ahead-of-print No. ahead-of-print, 2022 DOI: https://doi.org/10.1108/ECAM-03-2022-0241.

[95] E.A. Ameyaw, D.J. Edwards, B. Kumar, N. Thurairajah, D.G. Owusu-Manu, and G.D. Oppong, "Critical factors influencing adoption of blockchain-enabled smart contracts in construction projects", Journal of Construction Engineering and Management, vol.149, no.3, pp.1-16, 2023.

[96] R. Osei-Kyei, and A.P. Chan, "Developing a project success index for public–private partnership projects in developing countries", Journal of Infrastructure Systems, vol.23, no.4, 2017. 04017028.

[97] N. Al Azmi, G. Sweis, R. Sweis, and F. Sammour, (2023). Exploring Blockchain-enabled smart contracts technology implementation within ready-mixed concrete plants industry in Saudi Arabia", International Journal of Construction Management, vol.23, no.14, pp.2400-2408, 2023. DOI: 10.1080/15623599.2022.2059914.

[98] J. Pallant, "SPSS Survival Manual: A step-by-step guide to data analysis using SPSS for windows", (Version 12), 2nd ed., Allen & Unwin, Crows Nest NSW, 2005.

[99] J.F. Hair, W.C. Black, B.J. Babin, R.E. Anderson, "Multivariate data analysis: Pearson new international edition. Essex: Pearson Education Limited vol.1, no.2, 2010. Available at: https://shorturl.at/SYZ04.