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The Learning Curve and Benefit of Artificial Intelligence for the Built Environment

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ABSTRACT

Artificial intelligence (AI) technology has the power to unlock the challenges faced in construction projects such as poor efficiency issues, design errors, and accidents on-site. Therefore, this paper is aimed to evaluate the benefit of implementing AI in South African construction projects. The quantitative approach was adopted for this study. Well-structured questionnaire surveys were disseminated to built environment stakeholders such as quantity surveyors, project managers, construction project managers, contractors and architects. A total of 260 questionnaire surveys were distributed and 223 were received back with an 86% response rate. The findings revealed the learning curve benefit of AI is improved quality of work post-construction, reduces budget overruns, saves time, overcoming shortages of experienced labourers, improves performance on construction work, improves health and safety of the construction projects, elicits faster information exchange, improves productivity, reduces construction risks such as on-site accidents, reduces construction errors, improves customer relations, improves profitability and saves cost. However, the study has indicated that the implementation of AI technology in the built Environment in South Africa is still at an early development stage. The study would hopefully contribute to the body of existing knowledge of AI technology. In Addition, it could assist construction industry professionals to advance their workplaces and organizations.

Keywords: Digitalization, Fourth industrial revolution, Learning curve

INTRODUCTION

Built environment projects remain one of the key sectors in driving economic growth. Furthermore, built environment projects are considered to be successful if they are delivered on time, within budget, and of good quality, which satisfies the client's needs (Luvara et al., 2018). However, numerous factors affect the timely delivery of construction projects, such as construction delays, cost and time overruns, accidents on-site and design errors. As a result, they affect productivity growth of the built environment projects (Lopes *et al.*, 2011). According to Jarkas (2010), the main reasons for poor productivity in the built environment are the employment of unskilled workers and the slow development of adopting the latest technologies.

According to Gotthardt et al., (2019), the adoption and implementation of AI in built environment projects will enhance the learning curve for the built environment and mitigate the poor productivity issues faced by the industry. The adoption of technologies such as AI on built environment projects does not only solve productivity issues but can also improve the visualization of problem areas, expose inefficiencies, and improve construction planning accuracy. Moreover, infusing AI into the learning curve will also prevents accidents on site, as well as cost, and time overruns. Project performance is defined as "the achievement of fitness for purpose in the construction and the absolute realization of client's satisfaction" (Phaladi et al., 2021). Furthermore, developing countries are affected economically because of the lack of growth in construction performance (Chauke et al., 2021). Construction project performance has been drastically affected by poor productivity.

ARTIFICIAL INTELLIGENCE AND THE LEARNING CURVE

A learning curve is a graphical representation of a repetitive task that when done on a continuous basis, leads to a reduction in activity duration, resources and costs (Caruso et al., 2002). The learning curve portrays the cost and benefits of experience when performing routine or repetitive tasks. Furthermore, learning curves are also known as experience curves, cost curves, efficiency curves and productivity curves (Chamber, Stuart & Johnson, 2000). In the broader frame, the 'learning curve' has come to mean that every new activity requires the acquisition of knowledge and skill. It takes time (and therefore money) to master new jobs and new fields, however, later knowledge provides efficiency and leverage, hence the integration of AI in the built environment projects will improve the learning curve (Anzanello & Fogiliatto, 2011). AI in built environment projects will improve the learning curve through the increase in communication, customer involvement, allocating people to the right task, cost savings, and delivery of the project on time. Furthermore, it will eliminate cost and time overruns, reduce poor quality, and reduce absenteeism of labour and wastage (Anzanello & Fogiliatto, 2011). Hence, the integration of AI into the learning curve in the built environment would assist the application of knowledge, skills, tools, and techniques in project activities to meet project requirements since it is the core major fundamental activity to achieve. Understanding the concept of learning curves in the built environment would help each employee to participate in projects and improve project performance, leading to improved productivity on a daily basis (Maley, 2012 & Richardson, 2010).

ARTIFICIAL INTELLIGENCE (AI) AND LEARNING CURVE FOR THE BUILT ENVIRONMENT

Underwood and Khosrowshahi (2012), stated that infusing AI in the built environment projects would indeed improve and add value to the learning curve business processes as many managers globally have realized the benefits associated with it, especially in developed nations. The learning curve for

AI is demonstrated to increase the competitiveness of companies by distributing information in a safer way for better decision-making on construction projects. Ballan and EL-Diraby (2011) backed this up, who said it does not matter if the construction firm is medium or large-sized, the AI benefits will be experienced as long as the technologies are implemented well and correctly understood by the users. Following are the learning curve benefits for the implementation of AI. Adopting technologies offered by the 4IR such as AI and robots can save time, especially when preparing monthly claims to pay contractors. Technological software such as virtual reality, robots, and intelligent machines being adopted on construction projects can save time, and productivity growth can be enhanced (Ballan and El-Diraby, 2011). Contractors will be able to make more profit because of the proper application of AI on construction projects (Khosrowshahi and Underwood, 2012).

The construction industry especially in undeveloped nations experiences communication issues due to the slow adoption of the latest technology (Rivard et al., 2014). Spending more on the latest technologies will speed up companies to improve their productivity and communication methods. (Ballan and El-Diraby, 2011). Therefore, if the communication tools and latest technologies are correctly used communication will improve (Agbevade, 2017). Customer relations can be enhanced when the project participants exchange crucial information more often for AI systems to learn quickly and be able to make better decisions (Underwood and Khosrowshahi, 2012). Construction projects have been impacted by low productivity, which has caused poor project performance, resulting in abandonment, penalties being charged, and poor-quality standards of the project (Phaladi et al., 2021). Learning curve infused with AI will mitigate delays and poor project performance such as design errors, accidents on site and shortages of labourers. Implementing smart machines on the projects would improve their performance and ensure timely delivery of the project. The introduction of AI software would lead to effectiveness and efficiency in carrying out the work by reducing the time taken for the processing of data (Chauke et al., 2021).

RESEARCH METHODOLOGY

The research was conducted in Gauteng Province, South Africa. Targeted areas for the collection of data include Midrand, Sandton, and Randburg which are under the Johannesburg Metropolitan Municipality. The targeted participants were the built environment stakeholders such as contractors, quantity surveyors, architects, construction project managers, construction managers, electrical engineers, mechanical engineers, and civil engineers. A convenience sampling technique was adopted for the study. The reason for choosing convenience sampling was that it saves time and targets participants who are willing to participate in the questionnaire survey (Etikan *et al.,* 2016). This study adopted a questionnaire survey as a method of collecting data from the targeted participants as a primary method of collecting data. In addition, the secondary method of collecting data was through the analysis of published conference papers, dissertations, and journal articles. A total of 260 questionnaires were disseminated to participants and 223 were returned with an 86% response rate. The five-point Likert scale was used to determine the benefits of the learning curve for AI in the built environment. MIS values were ranked starting from the highest to the lowest based on the factors identified under each question. The standard deviation was used to rank the variables that had the same mean item scores. The Cronbach Alpha (CA) was adopted to test consistency and reliability. Humaidi and Said (2011), indicated, "Cronbach Alpha aims to determine the level of correction of items in a set". The CA was calculated using the Statistical Package for Social Science (SPSS). The Cronbach Alpha for artificial intelligence infused in the learning curve was 0.702, which is acceptable. Humaidi and Said (2011) further postulated that a CA value of less than one implies that the reliability test is accepted. Exploratory factor analysis (EFA) can be defined as the "statistical method adopted to decrease a large number of variables to a small number of factors/components reflecting that the cluster of variables is common" (Hadi *et al.,* 2016). The study has adopted EFA for the analysis of the data collected. The testing of the data set was completed with the usage of sample size and strength of the variables between indicators. Furthermore, the Kaiser Meyer Olkin (KMO) test and Bartlett's test of sphericity were conducted for the study. KMO tests were conducted to measure the suitability of a sampling whilst Bartlett's test was conducted to measure the strength of the relationship between the variables. KMO value is sufficient when is larger than 0.5 (Field, 2000). A KMO between the interval of 0.7 and 0.8 is good, values between 0.8 and 0.9 are greater and values above 0.9 are excellent (Pallant, 2013).

FINDINGS

The highest qualifications of the respondents were 34% of the respondents held a bachelor's degree, 24% of the respondents had a diploma, 22% had an honours degree, 15% hold a master's degree whilst 5% held matric certificates. The questionnaire was answered by respondents who had an understanding of artificial intelligence in the built environment. Figure 1 below indicates respondents' profession. The results show that 24.1% were quantity surveyors, 21% of the respondents were Architects, 17.4% the respondents were civil engineers, 13.8% were construction project managers, 11.2% were construction managers 7.1% were electrical engineers, and 5.4% were mechanical engineers.

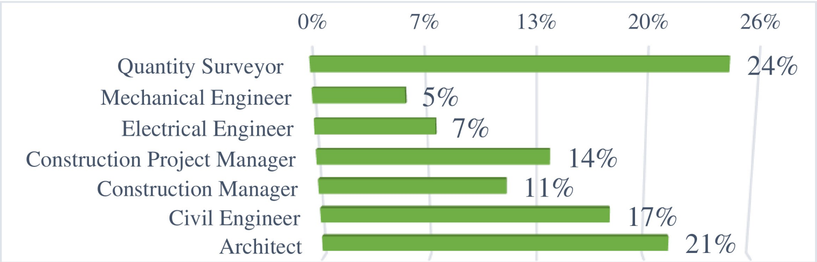

Figure 1: Respondents' profession.

ARTIFICIAL INTELLIGENCE FOR ENHANCED LEARNING CURVE

Descriptive Analysis Results

Table 1 represents the AI benefits for enhanced learning curve for the built environment. The top five results are as follows: 'improves quality of work post-construction' with (MIS = 4.19, SD = 0.510, R = 1), 'reduces budget overruns' with (MIS = 4.08, SD = 0.545, R = 2), 'saves time' with (MIS = 4.01, 0.724, R = 3), 'overcome shortage of experienced labourers' with (MIS = 3.95, SD = 0.701, R = 4), 'improves performance on construction work' with (MIS = 3.93, SD = 0.666, R = 5), 'improves the health and safety of the construction projects' with (MIS = 3.950, SD = 0.697, R = 5). The five lowest results which were ranked by respondents are: 'improves profitability' with (MIS = 3.67, SD = 0.477, R = 11), 'saves cost' with (MIS = 3.75, SD = 0.456, R = 12), 'improves communication amongst the project team' with (MIS = 3.73, SD'= 0.531, R = 13), 'improves tracking and security' with (MIS'= 3.71, SD = 0.571, R = 14), and 'facilitates improved decision making' with (MIS = 3.58, SD = 0.556, R = 15).

Table 1. Benefits of AI infused in the learning curve.

Factors	MIS	SD	CA if Item Deleted	Rank
Improves quality of work post-construction	4.17	0.510	0.703	1
Reduces budget overruns	4.08	0.545	0.700	2
Saves time	4.01	0.724	0.708	3
Overcomes shortages of experienced labors	3.95	0.701	0.712	4
Improves performance on construction work	3.93	0.666	0.711	5
Improves the health and safety of the construction projects	3.93	0.699	0.715	5
Elicits faster information exchange	3.91	0.697	0.713	6
Improves productivity	3.84	0.377	0.685	7
Reduces construction risks such as on-site accidents	3.83	0.643	0.672	8
Reduces construction errors	3.81	0.655	0.682	9
Improves customer relations	3.78	0.615	0.656	10
Improves profitability	3.76	0.477	0.674	11
Saves cost	3.75	0.456	0.675	12
Improves communication amongst the project team	3.73	0.531	0.672	13
Improves tracking and security	3.71	0.571	0.652	14
Facilitates improved decision making	3.58	0.556	0.669	15

MIS = Mean Item Score, SD = Standard Deviation, CA = Cronbach's Alpha

Exploratory Factor Analysis Results

Table 2 indicates the correlation matrix for the benefits of AI-infused in the learning curve. A total of 16 factors were used during analysis and have a value of less than one which implies that the reliability test is accepted.

Table 3 displays the KMO measure of sampling adequacy and Bartlett's test of sphericity. Results show that the KMO has a value of 0.825 which is above the recommended value of 0.5 of which is good. The recommended value for KMO must be 0.5 or above for the test to be acceptable (Field, 2000).

Table 2. Correlation matrix for the benefits of AI-infused in the learning curve.

	BIAI-01	BIAI-02	BIAI-03	BIAI-04	BIAI-05	BIAI-06	BIAI-07	BIAI-08	BIAI-09	BIAI-10	BIAI-11	BIAI-12	BIAI-13	BIAI-14	BIAI-15	BIAI-16
BIAI-01	**1.000**	0.601	-0.241	0.079	-0.128	0.606	0.669	0.715	-0.216	0.457	-0.227	0.415	-0.279	-0.141	0.569	-0.246
BIAI-02	0.601	**1.000**	-0.715	0.072	-0.057	0.930	0.818	0.761	-0.435	0.156	-0.323	0.254	-0.317	-0.347	0.928	-0.723
BIAI-03	-0.241	-0.715	**1.000**	0.187	0.315	-0.724	-0.497	-0.481	0.668	0.081	0.625	-0.039	0.542	0.716	-0.713	0.954
BIAI-04	0.079	0.072	0.187	**1.000**	0.760	0.019	0.307	0.306	0.441	0.464	0.072	0.510	0.479	-0.029	0.065	0.154
BIAI-05	-0.128	-0.057	0.315	0.760	**1.000**	-0.135	0.132	0.095	0.604	0.353	0.238	0.330	0.638	0.118	-0.088	0.282
BIAI-06	0.606	0.930	-0.724	0.019	-0.135	**1.000**	0.789	0.779	-0.435	0.081	-0.322	0.203	-0.376	-0.365	0.914	-0.720
BIAI-07	0.669	0.818	-0.497	0.307	0.132	0.789	**1.000**	0.887	-0.207	0.470	-0.347	0.437	-0.134	-0.389	0.803	-0.537
BIAI-08	0.715	0.761	-0.481	0.306	0.095	0.779	0.887	**1.000**	-0.210	0.488	-0.304	0.423	-0.071	-0.398	0.740	-0.494
BIAI-09	-0.216	-0.435	0.668	0.441	0.604	-0.435	-0.207	-0.210	**1.000**	0.172	0.498	0.041	0.652	0.384	-0.465	0.644
BIAI-10	0.457	0.156	0.081	0.464	0.353	0.081	0.470	0.488	0.172	**1.000**	-0.176	0.601	0.252	-0.238	0.097	0.066
BIAI-11	-0.227	-0.323	0.625	0.072	0.238	-0.322	-0.347	-0.304	0.498	-0.176	**1.000**	-0.287	0.476	0.717	-0.345	0.643
BIAI-12	0.415	0.254	-0.039	0.510	0.330	0.203	0.437	0.423	0.041	0.601	-0.287	**1.000**	0.180	-0.143	0.255	-0.026
BIAI-13	-0.279	-0.317	0.542	0.479	0.638	-0.376	-0.134	-0.071	0.652	0.252	0.476	0.180	**1.000**	0.379	-0.360	0.578
BIAI-14	-0.141	-0.347	0.716	-0.029	0.118	-0.365	-0.389	-0.398	0.384	-0.238	0.717	-0.143	0.379	**1.000**	-0.356	0.756
BIAI-15	0.569	0.928	-0.713	0.065	-0.088	0.914	0.803	0.740	-0.465	0.097	-0.345	0.255	-0.360	-0.356	**1.000**	-0.765
BIAI-16	-0.246	-0.723	0.954	0.154	0.282	-0.720	-0.537	-0.494	0.644	0.066	0.643	-0.026	0.578	0.756	-0.765	**1.000**

Table 3. KMO and Bartlett's test the benefits of AI-infused in the learning curve.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.825
Bartlett's Test of Sphericity	Approx. Chi-Square	4364.285
	Df	120
	Sig.	0.000

Bartlett's test has a significance value of 0.000 which is acceptable since it is less than the assumed value of 0.05.

Table 4 indicates the anti-image correlation matrix, which measures sampling adequacy for the AI benefits infused in the learning curve. All 16 factors were above the assumed value of 0.5, which is good and acceptable.

Table 5 displays the commonalities of a variable where 16 factors are above the recommended value of 0.3. Moreover, the PCA Analysis was adopted as the type of extraction method.

Table 6 displays the total explained variance for the AI benefits infused in the learning curve. Results show that there are four components with a total value of above one. Moreover, they are four factors to be extracted through the usage of the PCA method. The four to be extracted have 44.917%, 23.246%, 9.573%, and 7.417%, respectively with a cumulative percentage of 85.154% before extraction and rotation.

Table 7 displays the rotated component matrix. Results show that the component was extracted through the usage of the Principal Component Analysis method. Moreover, varimax with Kaiser normalization was adopted as a rotation method.

Reliability Tests for the Rotated Factors

Four components were rotated. Component 1 has five (5) factors (BIAI-02, BIAI-06, BIAI-15, BIAI-07, BIAI-08,), Component 2 has four (4) factors (BIAI-14, BIAI-11, BIAI-16, BIAI-03), Component 3 has four (4) factors

Table 4. Anti-image correlation matrix for the benefits of AI-infused in the learning curve.

	BIAI-01	BIAI-02	BIAI-03	BIAI-04	BIAI-05	BIAI-06	BIAI-07	BIAI-08	BIAI-09	BIAI-10	BIAI-11	BIAI-12	BIAI-13	BIAI-14	BIAI-15	BIAI-16
BIAI-01	.800[a]	-0.229	-0.028	0.134	0.134	0.016	0.114	-0.395	-0.102	-0.220	0.101	-0.121	0.457	0.108	-0.196	-0.288
BIAI-02	-0.229	.898[a]	0.183	0.001	-0.140	-0.416	-0.271	0.160	0.091	-0.153	-0.107	0.029	-0.140	-0.282	-0.131	0.158
BIAI-03	-0.028	0.183	.855[a]	-0.016	-0.086	0.326	-0.089	0.001	-0.212	-0.045	-0.042	0.164	0.209	0.031	-0.378	-0.626
BIAI-04	0.134	0.001	-0.016	.783[a]	-0.541	0.070	-0.003	-0.193	-0.072	0.041	-0.032	-0.274	0.089	0.141	-0.106	-0.096
BIAI-05	0.134	-0.140	-0.086	-0.541	.787[a]	0.020	-0.040	0.106	-0.289	-0.100	-0.012	-0.030	-0.247	-0.025	0.024	0.086
BIAI-06	0.016	-0.416	0.326	0.070	0.020	.864[a]	0.017	-0.363	-0.182	0.261	-0.059	0.023	0.241	0.121	-0.342	-0.271
BIAI-07	0.114	-0.271	-0.089	-0.003	-0.040	0.017	.898[a]	-0.432	-0.138	-0.215	0.198	0.052	0.115	0.143	-0.288	-0.119
BIAI-08	-0.395	0.160	0.001	-0.193	0.106	-0.363	-0.432	.848[a]	0.136	-0.144	-0.061	0.105	-0.398	0.105	0.038	0.045
BIAI-09	-0.102	0.091	-0.212	-0.072	-0.289	-0.182	-0.138	0.136	.900[a]	0.077	-0.119	0.097	-0.229	0.126	0.113	0.009
BIAI-10	-0.220	-0.153	-0.045	0.041	-0.100	0.261	-0.215	-0.144	0.077	.791[a]	-0.025	-0.270	-0.071	0.318	0.053	-0.123
BIAI-11	0.101	-0.107	-0.042	-0.032	-0.012	-0.059	0.198	-0.061	-0.119	-0.025	.891[a]	0.377	-0.116	-0.117	-0.161	-0.178
BIAI-12	-0.121	0.029	0.164	-0.274	-0.030	0.023	0.052	0.105	0.097	-0.270	0.377	.759[a]	-0.105	0.053	-0.261	-0.251
BIAI-13	0.457	-0.140	0.209	0.089	-0.247	0.241	0.115	-0.398	-0.229	-0.071	-0.116	-0.105	.772[a]	0.052	-0.157	-0.309
BIAI-14	0.108	-0.282	0.031	0.141	-0.025	0.121	0.143	0.105	0.126	0.318	-0.117	0.053	0.052	.739[a]	-0.491	-0.646
BIAI-15	-0.196	-0.131	-0.378	-0.106	0.024	-0.342	-0.288	0.038	0.113	0.053	-0.161	-0.261	-0.157	-0.491	.797[a]	0.694
BIAI-16	-0.288	0.158	-0.626	-0.096	0.086	-0.271	-0.119	0.045	0.009	-0.123	-0.178	-0.251	-0.309	-0.646	0.694	.744[a]

Table 5. Communalities for the benefits of AI-infused in the learning curve.

Factors	Initial	Extraction
BIAI-01	1.000	0.878
BIAI-02	1.000	0.936
BIAI-03	1.000	0.933
BIAI-04	1.000	0.794
BIAI-05	1.000	0.863
BIAI-06	1.000	0.939
BIAI-07	1.000	0.887
BIAI-08	1.000	0.861
BIAI-09	1.000	0.717
BIAI-10	1.000	0.811
BIAI-11	1.000	0.833
BIAI-12	1.000	0.684
BIAI-13	1.000	0.736
BIAI-14	1.000	0.856
BIAI-15	1.000	0.927
BIAI-16	1.000	0.969

Extraction Method: Principal Component Analysis.

(BIAI-5, BIAI-4, BIAI-13, BIAI-9), Component 4 has three (3) factors (BIAI-10, BIAI-12, BIAI-1).

Component 1 has a CA value of 0.757 with 1 factor (BIAI-16) deleted to boost the test.

Component 2 has a CA value of 0.905.

Component 3 has a CA value of 0.854.

Table 6. Total explained variance for the benefits of AI-infused in the learning curve.

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.187	44.917	44.917	7.187	44.917	44.917
2	3.719	23.246	68.163	3.719	23.246	68.163
3	1.532	9.573	77.737	1.532	9.573	77.737
4	1.187	7.417	85.154	1.187	7.417	85.154
5	0.572	3.574	88.728			
6	0.419	2.621	91.349			
7	0.311	1.944	93.294			
8	0.239	1.491	94.785			
9	0.230	1.438	96.222			
10	0.174	1.089	97.311			
11	0.130	0.813	98.124			
12	0.100	0.626	98.750			
13	0.076	0.474	99.224			
14	0.063	0.396	99.620			
15	0.046	0.285	99.905			
16	0.015	0.095	100.000			

Extraction Method: Principal Component Analysis.

Table 7. Rotated component matrix[a] for the benefits of AI-infused in the learning curve.

	Component			
	1	2	3	4
BIAI-02	0.938			
BIAI-06	0.937			
BIAI-15	0.926			
BIAI-07	0.820			
BIAI-08	0.794			
BIAI-14		0.897		
BIAI-11		0.822		
BIAI-16		0.729		
BIAI-03		0.706		
BIAI-05			0.918	
BIAI-04			0.819	
BIAI-13			0.738	
BIAI-09			0.650	
BIAI-10				0.845
BIAI-12				0.747
BIAI-01				0.642

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

Component 4 has a CA value of 0.847. Four components extracted have CA values of above 0.70 which makes the results acceptable or good. This was further justified by Pallant (2013) who said that a CA value of above 0.70 implies the acceptability of the test.

The naming of components for the AI benefits infused in the learning curve.

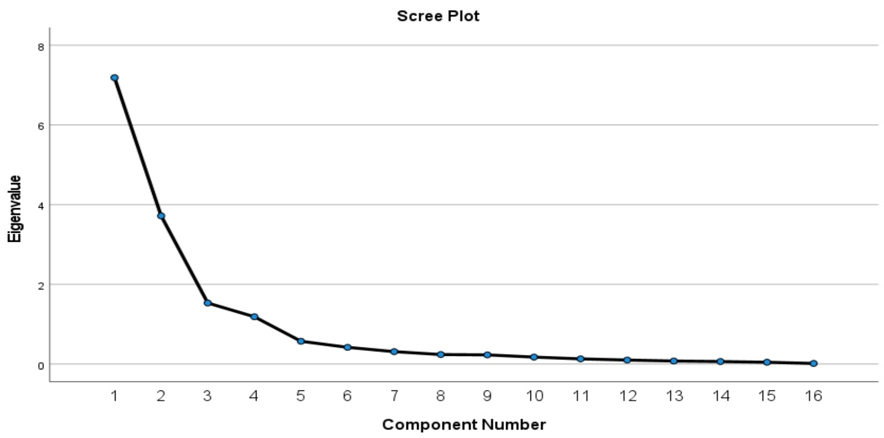

Figure 2: Scree plot diagram for the benefits of AI-infused in the learning curve.

Component 1 – Enhancement of Finance

Factors for this component suggest that the implementation of AI systems and machines would enhance financial implications experienced on construction projects since the adoption of AI would save costs and time, reduce construction design errors, improve profitability and eliminate shortages of experienced labourers. Again, AI improves performance on construction projects.

Component 2 – Improvement of Quality Standards

The implementation of AI systems and intelligent machines would definitely improve health and safety on construction projects, and reduce budget overruns which leads to makes some of the projects being abandoned owing to financial implications encountered. In addition, there will be a faster way of exchanging information amongst the project participants.

Component 3 – Reduction

Factors suggest that there would be a reduction of construction risks, errors as well as improved customer relations and tracking and security on construction projects.

Component 4 – Improvements on the Construction Site

Factors imply that they would be a significant improvement if AI is implemented effectively in construction projects. Moreover, there would be an improvement in productivity, decision making and communication amongst project team members.

CONCLUSION AND RECOMMENDATIONS

The study has further revealed the benefits such as improved productivity and profitability, reduced budget overruns, reduced construction errors, and faster information exchange. The findings of the study were backed by various researchers and scholars. Finally, the findings of the study will add significant value to the body of knowledge on infusing AI into the learning curve for improved service delivery of the built environment projects. The study is, therefore, recommending that government institutions and professional regulatory bodies should encourage company owners to use the 4IR technologies. They should also support them financially, particularly in the case of small and medium firms.

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