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Cyber Technology Implementation Barriers for Sustainable Buildings: A Novel Mathematical Partial Least Square Structural Equation Modelling

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Abstract: To reap the most advantages while maintaining the functioning of residential building projects, sustainability concepts should be included at all stages of the construction decision-making process. This research identified and investigated the barriers to the employment of cyber technology in residential construction projects in order to ensure their long-term viability. Prior research identified cyber technology barriers, which were then contextually explored using a questionnaire survey in the Nigerian construction business. An exploratory factor analysis (EFA) revealed that cyber technology hurdles may be classified into five constructs: knowledge, government, culture, project nature, and regulations. The barriers model was also built using partial least square structural equation modelling (PLS-SEM). According to the findings, project-related constraints were key impediments to the implementation of cyber technology. The findings of this study might serve as a guide for decision-makers in Nigeria's construction industry looking to decrease costs and boost sustainability via the use of cyber technology.

Keywords: building projects; construction revolution; cyber technology; project success; sustainability

1. Introduction

One of the pillars of every nation's society, the residential construction sector helps to ensure its residents enjoy a good quality of living and a high level of contentment [1]. Developed and developing nations' residential structures are responsible for as much as a third of the world's total power usage and GHG emissions [2]. However, as the globe evolves and urbanizes, residential allocation will not be able to meet the rising demand [3]. In both developed and developing nations, rapid urbanization is making it harder for low-income people to find low-cost housing [4].

Around 828 million people are believed to be living in slums and other inadequate housing conditions in developing countries. It is hypothesized that by 2020, this number will have increased to 1.4 billion [3,5,6]. For instance, the construction field in some developing nations to rely on outdated, labour-intensive industrial techniques that are linked to high levels of energy consumption, environmental damage, and safety concerns, as well as low levels of productivity in the actual implementation of projects [7]. With such rapid development, it is clear that residential building is essential to maintaining the standard of living in these regions [8]. As a consequence, all of the nation's governments have made the construction of inexpensive housing a top priority by enacting various regulations regarding affordable housing [1]. Nonetheless, there is some controversy about whether low-income residents can afford to live in these residential buildings [3].

According to a variety of estimates, inefficiencies, mistakes, delays, and poor communications may raise the cost of construction by as much as 30% [9]. The chance of cost and schedule overruns is increased if design faults, alterations or revisions to the design model are not conveyed to the construction site immediately. Hence, providing project managers with constant access to evolving design models may help them make more wise decisions. The as-built model used in lifecycle management should also be updated to reflect any alterations made onsite. The current process for updating as-built models after construction is complete is laborious and error-prone since not all modifications are captured.

Previous research has brought up the need to develop "sustainable buildings" that are not harmful to the environment and make effective use of resources [10]. Wolstenholme et al. [11] call for further transformation of the construction industry via the use of efficient and environmentally friendly building methods. In addition, construction industry professionals cannot accurately quantify structures' environmental impacts while being constructed [12]. Accordingly, virtual models' long-term benefits stem from the fact that they provide as-built information documentation, team communication, and building progress visualization. Despite these benefits, their use is mostly restricted to the preconstruction phase at now [13]. Two forms of virtual models are models made using computer-aided design (CAD) and building information modelling (BIM). If these models are used throughout the construction, operation, and maintenance phases of a facility's life cycle, the potential benefits will be considerably enhanced. Virtual models and physical construction may be combined to improve information and knowledge management throughout the design, construction, and maintenance stages, which will ultimately give greater control over the construction process [14].

Many researchers, including Chin et al. [15,16] and Sørensen [17], used several data collection technologies, such as laser scanners, digital cameras, and radio frequency identification tags, to link virtual models and actual buildings. Current technologies, however, do not provide two-way integration or communication between physical and virtual models. Improvements in facility feedback and control are impossible to achieve without this form of bidirectional integration and communication. Bidirectional coordination in real time between virtual models and physical structures allows for efficient feedback or control. The term "bi-directional coordination" refers to the act of synchronizing changes made to an object's digital or physical representation [18]. In addition, computing resources are required for "cyber–physical systems" integration, which involves synchronising the virtual models with the actual building so that adjustments made in one environment are reflected in the other to maintain bidirectional coordination.

Cyber–physical system, as used here in this research, is a system in which virtual models are tightly coupled with and coordinated with their physical counterparts. Cyber–physical systems using sensors allow for a connection between the virtual world (which includes information, communication, and intelligence) and the real world [19]. As-built documentation, construction process management, and environmentally responsible building practises are just some of the areas that may benefit from a cyber–physical systems-based approach to improvement. The construction industry, in particular, stands to benefit greatly from the incorporation of emerging cyber technologies such as the Internet of Things (IoT), big data, artificial intelligence (AI), and cloud computing [20]. Design enhancement, performance evaluation, resource management, risk management, energy conservation, pollution reduction, and project delivery are just a few of the areas that have benefitted from the gradual adoption of these technologies in the construction industry in recent years [21].

Notwithstanding these developments, the construction industry remains behind other industrial sectors, especially in developing nations, when it comes to the implementation of intelligent processes [22]. Yet, revolutionary technologies are only being employed in a select few sectors, and their efficacy in the building industry has only been the subject of a few large studies. Consequently, the following question for its empirical investigation: what prevents the construction sector from using cyber technology? This research plans to employ causal inference techniques such as structural equation modelling (SEM) to look at the challenges of using cyber technology to reach sustainability goals in residential construction.

2. Barriers Affecting the Adoption of Cyber Technology in Construction

Previous research has made various contributions to the application of new technologies; nevertheless, relatively few studies have been conducted on the obstacles that pre-vent new technologies from being adopted [23]. As a result, the scope of the literature study was broadened to include research on the obstacles to implementing cutting-edge technologies, including cyber technology, automation, and robots [23]. This resulted in 17 variables/indicators that might be considered to reflect the obstacles listed in Table 1, in which the asterisk (*) symbol indicates in which reference these obstacles were listed. According to the findings of Nnaji and Karakhan [24], there are 13 major obstacles to using new technology for managing safety and health in the workplace. The results of a survey sent out to 102 construction industry experts from around the United States revealed the following five barriers to be the most pressing: “expensive upfront investment required”, “need for extensive training before achieving optimal performance”, “concerns regarding the availability of technical support”, “doubts regarding the reliability of these technologies”, and “client rarely demands the use of these technologies”.

According to Osunsanmi et al. [25], using RFID with mobile technologies for monitoring construction workers on site is restricted in South Africa due to the high cost of these technologies and their low level of technical expertise. According to the findings of yet another study carried out in the United States, the primary obstacles to the widespread use of robotics in construction include the immaturity of the relevant technologies, the nature of the industry itself, the complexity of the technical processes involved, the lack of economic feasibility, and the absence of a strong culture of innovation. All these factors combine to make widespread use of robotics in construction extremely difficult. On the other hand, in a study carried out in the Malaysian construction industry by Yahya et al. [26], the main barriers to the widespread use of construction robotics were found as follows: the high costs associated with the acquisition, upkeep, and modernization of the new technologies.

According to Mahbub [27], financial investments, access to technical knowledge and equipment, compatibility with current construction practises and operations, the status of the labour force, and the industry’s characteristics and culture all influence the degree to which the construction industry is prepared to use construction automation and robotics. In their examination of the prominent barriers to IR 4.0 adoption among U.S.-based construction companies, Demirkesen and Tezel [28] found that a lack of uniformity, legal and contractual difficulties, and the cost of implementation were the most significant challenges. According to a systematic review by [29], technical limitations, problems with standardisation, haphazard technology design, development, and implementation, a lack of studies of the factors influencing the acceptance of new technologies, and a lack of understanding of the human aspects of technological change are the primary obstacles to achieving digital skin on the construction site. Following an examination of the various research studies related to the hindrances in adopting cyber technology in the construction sector, it is important to note that this particular study primarily relied on the construction of a barrier model based on the investigation conducted by Yap et al. [23] for two reasons. First, it is the most recent study in the literature regarding this topic. Second, it gathered the barriers based on an extensive review of 15 studies on this topic over the past decade.

Table 1. Summary of barriers affecting the adoption of cyber technology in construction.

		References													
S/N	**Barriers**	[30]	[31]	[32]	[33]	[34]	[35]	[36]	[37]	[38]	[39]	[40]	[41]	[42]	[43]
B1	Uniqueness of construction finished products		*	*	*										
B2	Discreteness of construction process	*		*	*		*								*
B3	Uncertainty of construction resource		*	*	*				*						
B4	Complexity and huge uncertainty	*			*		*				*				
B5	Harsh construction environment with high risk	*	*	*				*							*
B6	Lack of awareness			*	*			*				*			*
B7	High initial cost of implementation														*
B8	Fragmented construction process	*					*			*			*		
B9	Lack of standardized tool			*		*					*		*		
B10	Government regulations	*			*		*							*	
B11	Lack of interest from clients					*								*	*
B12	Inadequate horizontal and vertical communication	*	*	*			*			*		*	*		*
B13	Insufficient government support				*		*							*	
B14	Professional complacency		*		*				*				*		*
B15	Resistance to change		*												*
B16	Lack of market familiarity				*			*	*				*		
B17	Inadequate public-private partnership	*		*		*					*		*		*

3. Research Method

The review of literature on obstacles related to cyber technology revealed 17 potential barriers that could impede its progress, as shown in Figure 1. To gain a deeper understanding of these obstacles, a questionnaire survey was conducted among residential construction professionals who possessed industry expertise. The survey provided a list of the identified cyber technology barriers, and an exploratory factor analysis (EFA) was conducted to assess their comprehensiveness and clarity, taking into account the various variables and categories associated with them.

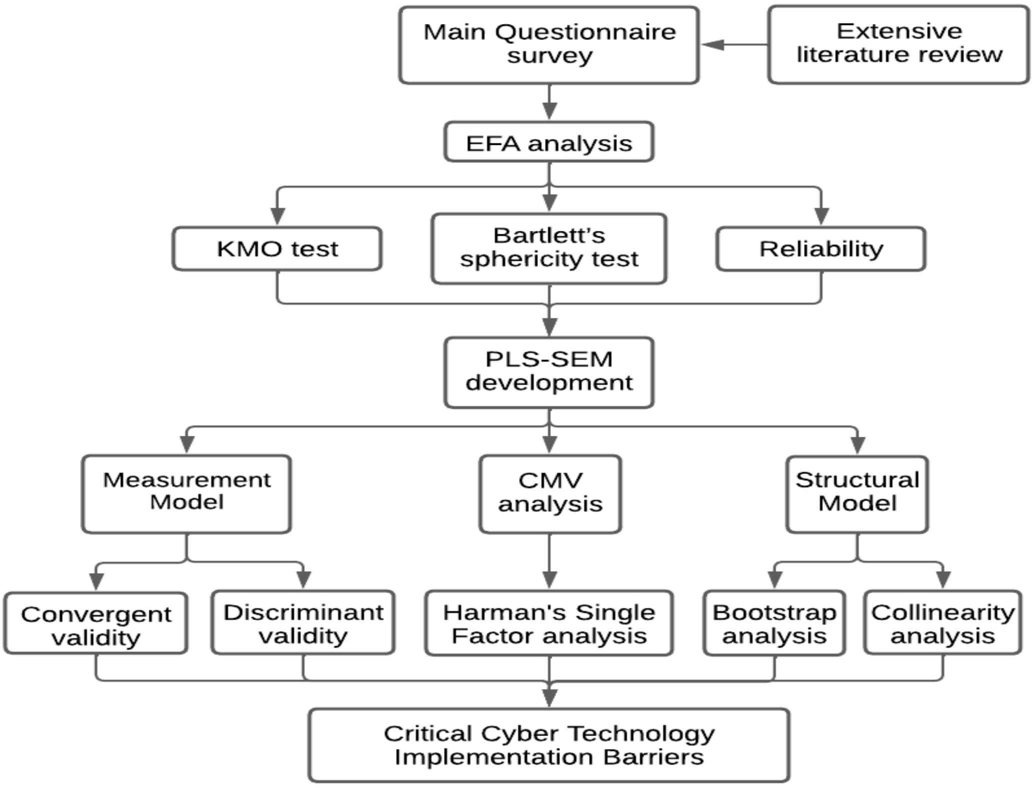

Figure 1. Research design.

3.1. Model Development

Partial least squares structural equation modelling (PLS-SEM) has attracted a lot of attention across different fields, such as business research and the social sciences [44]. In recent times, numerous studies on the PLS-SEM methodology have been published in major SSCI publications [45–47]. To evaluate the significance of the identified cyber technological obstacles using SEM, the acquired data were analysed using the latest version of PLS-SEM software, SMART-PLS 3.2.7. At first, partial least squares structural equation modelling (PLS-SEM) was widely lauded for its ability to provide better predictions compared to covariance-based structural equation modelling (CB-SEM) [48], despite the fact that the two methodologies have only minor differences [49]. The statistical analysis conducted in this study encompassed an evaluation of both the measurement and structural models.

3.1.1. Common Method Variance

To assess the discrepancy or inaccuracy in the study's conclusions due to measurement techniques rather than the constructs represented by the measures, The common method bias (CMB) was determined by computing the common method variance (CMV). Unlike the constructs, CMB focuses on the measurement method used in the analysis [50]. CMV may also be seen as a variance overlap that can be attributed to constructs and the kind of measurement devices used. This is another way of looking at CMV [50]. CMV is especially problematic where data, such as a questionnaire to be filled out by the respondent, are obtained from a certain source [51,52].

In some situations, self-reported data may overemphasize or limit the extent of the researched associations, resulting in problems [52,53]. This issue can be important, particularly given that the information is based on self-reporting, subjective, and obtained from only one source. Thus, it is vital to recognize shared method variances and tackle these concerns. One approach to achieving this is by conducting a thorough and structured test focused on one factor, much like Harman's (1976) test, to establish whether a single factor is present in the factor analysis. This factor accounts for most variance [52].

3.1.2. Construct Validity Analysis

Confirmatory factor analysis (CFA) and exploratory factor analysis (EFA) are commonly used for factor analysis. In this study, CFA was used to assess the underlying structure of various variables in hypotheses and theories, while EFA was used to gather information on relationships between multiple variables and to condense a large number of variables into a few fundamental structures [54]. EFA is suitable for analysing ordinal or interval data. A scatterplot illustrates the interrelationships between the variables, whether they are only partially or fully linked. The purpose of EFA is to reduce the number of components required to represent a set of variables. The formula for conducting EFA is presented as Equation (1).

$$X_i = a_{i1}F_1 + a_{i2}F_2 + \ldots + a_{im}F_m + e_i \tag{1}$$

In this formula, "X_i" represents the ith standardized measurable variable, "a_i" refers to the factor loading or score for variable "i", "F" represents the factor under analysis, and "e_i" represents the portion of the variable that cannot be accounted for by the factors.

Key multivariate analytic methods, such as exploratory factor analysis (EFA), were employed to aid the researchers in examining the fundamental structures or structure among cyber technology barrier elements. The primary use of principal component analysis (PCA) was to evaluate the one-dimensional, reliable, and valid measurement items for particular constructs, also known as measurement models. PCA was preferred over other factor analysis approaches such as principal axis factoring (PAF), image factoring, maximum probability, and alpha factoring due to its greater precision and ease of use [55].

If EFA reveals potential answers but no pre-existing theory or model, PCA may be the next best step [54]. PCA is often used in exploratory factor analysis (EFA) since it is the standard implementation in many statistical tools, as stated by Thompson [56]. Instead of using a simple oblimin or Promax rotation, we opted for Varimax rotation, which balances the workload evenly across all variables. Furthermore, Varimax is a superb all-around method for enhancing the clarity of factors and is therefore applicable to basic factor analysis [57]. It is believed that the chosen sample size of 119 and the number of variables included in this research, totalling 17, are sufficient for factor analysis [58].

3.1.3. Measurement Model

The measurement model uncovers both the underlying structure of the items and their present interrelationships [59]. Later sections presented a detailed examination of the convergent and discriminant validity of the measurement model.

Convergent Validity

The concept of convergent validity refers to how well distinct measures (barriers) of the same construct agree with one another [60]. It is recognized as a component of construct validity. To evaluate the convergent validity of the PLS-calculated constructs, three tests were developed as follows: Cronbach's alpha (α), composite reliability scores (ρ_c) and average variance extracted (AVE) [61]. It was proposed by Nunnally and Bernstein [62] that a ρ_c value of 0.7 represents the point at which the composite's dependability may be considered "moderate". Values over 0.70 were deemed appropriate for all studies, whereas those above 0.60 were deemed suitable for exploratory studies [63]. Finally, the last test was AVE. Convergent validity of model constructs is often evaluated using this method, with values over 0.50 indicating sufficient convergent validity [63].

Discriminant Validity

Discriminant validity indicates that the phenomenon under evaluation is empirically distinct and that the phenomenon cannot be identified by any available measures [64]. When establishing discriminative validity, Campbell and Fiske [65] argued that the degree to which different measures are alike should not be excessive.

Structural Model Analysis

In order to determine which constraints on cyber technology are most pressing, this research used SEM. For this to occur, we must determine the route coefficients between the observed ones. Based on the data shown later below in Figure 4, it was believed that £ (barriers of cyber technology structures) were directly responsible for μ (barriers of cyber technology implementation). Here, we may use a linear equation, as shown in Equation (2), to depict the inner relationship between the £, μ and €1 structures in the structural model as follows [66]:

$$\mu = \beta \text{ £} + \text{€}1 \tag{2}$$

In this situation, the connection between the cyber technology barrier constructs is represented by the path coefficient (β), and the residual variance at this structural level is expected to be present in (€1). The standardized regression weight (β) is similar to the β weight in a multiple regression model. If the weight is found to be statistically significant, its sign should align with the prediction of the model.

The main concern at present is assessing the significance of the path coefficient (β). As with CFA, the standard errors of the path coefficients were computed using a bootstrapping technique integrated into the SmartPLS 3.2.7 software. Based on the recommendations of Henseler et al. [44], the t-statistics for hypothesis testing were calculated using 5000 subsamples. Equation (2) was used to build four structural equations for the cyber technology barrier constructs in the PLS Model, each expressing an inner relation between the constructs.

4. Data Collection and Case Study

To explore the impact of cyber technology on operations in the Nigerian residential building industry, a questionnaire was distributed to a wider range of potential participants. The survey consisted of three main sections: the first collected demographic information from the respondents, the second section focused on obstacles posed by cyber technology (detailed in Table 1), and the third section contained open-ended questions.

The outreach had three key targets: contractors, consultants, and customers. Occupation is a second method of categorizing them. Quantity surveyors, construction workers, architects, and engineers. The Likert scale was used to rate the hindrances of cyber technology by the participants in this study. Each obstacle was rated by the respondents based on their knowledge and experience. The scale ranged from 1 (no or very small) to 5 (extremely high) with the intermediate values being 2 (small), 3 (average), and 4 (high). This rating system has been implemented in various prior studies [67–72]. The study used a sample strategy known as convenience sampling. This aims to guarantee that all eligible members have a fair chance of being chosen. Convenience sampling is a non-probability sampling technique where the researcher selects participants based on their ease of availability and willingness to participate in the study. In other words, participants are chosen because they are convenient to reach, rather than being selected randomly. Thus, the sample size was chosen by means of purposive sampling. This is due to the fact that surveying building industry specialists is crucial to the methodology of the research. Purposive sampling is a non-probability sampling technique where the researcher selects participants based on a specific purpose or criteria, such as their expertise, experience, or knowledge about a particular topic. This method is often used in qualitative research when the researcher is looking for a specific type of participant or when the population is difficult to access.

Furthermore, the sample size for this study was determined by a thorough assessment of the planned methodology [73]. According to Yin [74], a sample size of 100 or more is recommended for SEM. The response rate for the study's in-person (self-administered) survey was 82%, with 98 respondents out of 119 participating. This rate of return was considered appropriate for this inquiry [75,76].

5. Data Analysis

5.1. Common Method Bias

The reliability of research might be compromised by common method bias, a kind of error (variance) measurement. This refers to the variance in measured and estimated variables that is due to systematic error [57]. Harman's single-factor model evaluation shows how this may be quantified by measuring a number of different structural elements [28]. This study evaluated the standard deviation using the single-factor test [58]. If the total variance of the components is less than 50%, there is a possibility that the results are not affected by common method bias [28]. Given that the initial set of components explains only 22.0% of the total variance, it is evident that the results are not influenced by common method variance, as it is less than 50% [28].

5.2. Exploratory Factor Analysis (Questionnaire I)

EFA was used to examine the factorability structure of 17 items linked to cyber technology barriers. Connections have been made using a wide variety of well-known factorability parameters. It is usual practice to utilize Kaiser–Meyer–Olkin (KMO), a factor homogeneity measure, to ensure that partial correlations among variables are small [77]. When doing factor analysis, the KMO index should be at least 0.6 to be considered valid [78]. Bartlett's sphericity test also shows that the identity matrix serves as the association matrix at $p < 0.05$ [79,80].

Table 2 shows the KMO and the Bartlett test for the various barriers to adopting cyber technology in the study area. The KMO statistic is used to determine if the data provided for factor analysis are suitable for analysis. Bartlett's test of sphericity is also used to determine if the data under investigation are appropriate for factor analysis. In this case, the KMO coefficient is 0.703, which is above the required threshold of 0.70. This indicates that there are sufficient factors or barriers for factor analysis. Additionally, the *p*-value obtained from Bartlett's test of sphericity (0.005) meets the 5% significance level ($p < 0.05$) for a degree of freedom of 105 and an estimated chi-square value of 145.911. This suggests that the data concerning the identified barriers are appropriate for conducting exploratory factor analysis. A review of the plot in Figure 2 reveals a clear breakpoint at the eighth component. The point on the plot where the curve's slope levels off indicates the number of components that the analysis should generate. It is evident from the plot that there are eight groups of factors.

Table 2. Kaiser–Meyer–Olkin KMO and Bartlett's Test coefficients of the barriers.

Kaiser–Meyer–Olkin (KMO)		0.703
Bartlett's Test of Sphericity	**Approx. Chi-Square**	145.911
	df	105
	Sig.	0.005

Table 3 presents the matrices that show the relationship between the eight identified barriers for cyber technology and the extracted components. The matrices indicate whether the relationship between each factor and each component is positive or negative. The principal component analysis (PCA) extraction method was used to explain the total variance of the barriers to adopting cyber technology in the construction industry. The research confirmed the presence of eight components with initial eigenvalues greater than 1, explaining variances of 13.57%, 13.17%, 12.75%, 11.98%, 11.10%, 10.28%, 9.46%, and 9.46%, respectively (as shown in Table 4). Table 5 displays the rotational component matrix for the hurdles to construction sector use of cyber technology. After 11 iterations, the matrix was produced, with the rotation convergent on the initial eigenvalues of 1. The highlighted matrices in the table in bold font reflect the barriers with the smallest initial eigenvalue variation.

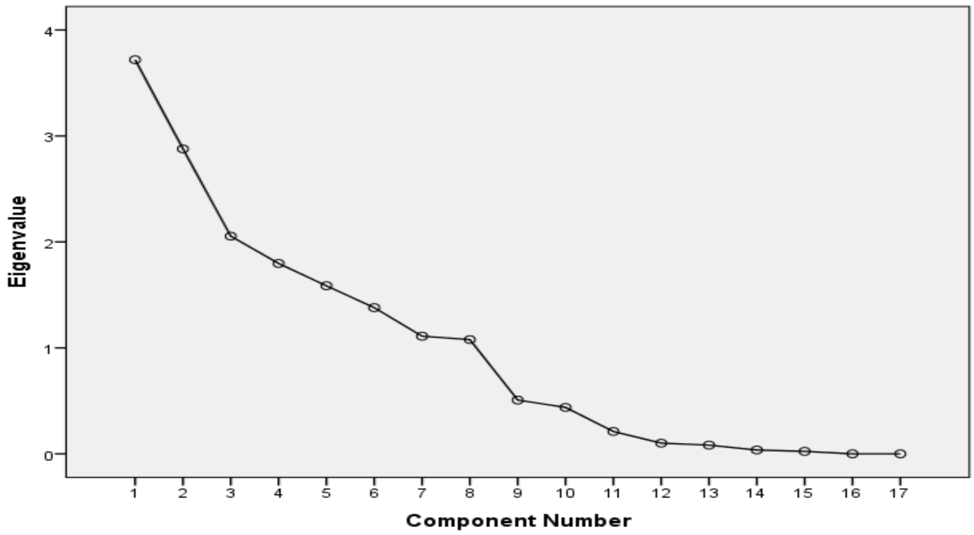

Figure 2. Scree Plot.

Table 3. Barrier component matrix.

Barriers	Components							
	1	2	3	4	5	6	7	8
B1	0.009	0.309	0.751	0.344	−0.202	0.017	−0.269	0.015
B2	0.115	0.368	−0.206	−0.586	0.359	0.502	0.145	0.082
B3	−0.014	0.198	0.806	−0.262	−0.066	0.249	0.225	0.302
B4	−0.705	0.179	−0.126	0.477	0.259	0.119	0.224	−0.065
B5	−0.590	−0.609	−0.128	0.165	−0.077	−0.183	0.325	−0.051
B6	0.786	−0.321	0.333	0.081	0.232	−0.005	0.209	−0.021
B7	0.419	0.342	0.088	0.101	0.408	−0.438	0.296	−0.394
B8	−0.074	−0.521	0.062	0.217	0.559	0.395	−0.225	0.125
B9	−0.519	0.310	−0.186	−0.438	0.303	−0.180	−0.474	−0.071
B10	0.544	−0.415	0.014	−0.437	−0.271	0.168	0.274	−0.158
B11	−0.222	0.303	−0.415	0.150	−0.503	0.116	0.214	0.494
B12	−0.082	0.768	0.091	0.129	0.423	0.089	0.229	0.197
B13	0.670	0.142	−0.165	0.532	0.147	−0.204	−0.011	0.352
B14	0.352	0.236	0.000	0.378	−0.294	0.502	−0.347	−0.356
B15	0.198	0.739	−0.302	0.055	−0.250	0.143	0.197	−0.379
B16	0.664	0.246	−0.183	−0.244	−0.071	−0.418	−0.263	0.295
B17	−0.622	0.284	0.525	−0.193	−0.184	−0.315	0.047	−0.086

Table 4. Barriers total variance explained.

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.719	21.879	21.879	2.308	13.574	13.574
2	2.878	16.929	38.808	2.239	13.170	26.743
3	2.054	12.082	50.890	2.167	12.748	39.491
4	1.797	10.568	61.458	2.037	11.982	51.473
5	1.586	9.328	70.787	1.887	11.099	62.572
6	1.380	8.115	78.902	1.747	10.278	72.850
7	1.110	6.531	85.433	1.608	9.462	82.312
8	1.078	6.340	91.774	1.608	9.462	91.774

Table 5. Barriers rotated component matrix.

Barriers	Code	Component							
		1	2	3	4	5	6	7	8
Lack of awareness	B6	0.087	0.222	0.015	**0.740**	−0.005	−0.352	0.395	0.088
High initial cost of implementation	B7	0.067	−0.022	−0.134	−0.012	0.019	**0.960**	0.011	−0.008
Fragmented construction process	B8	−0.039	−0.062	0.125	**0.930**	−0.030	0.259	−0.105	−0.029
Complexity of projects and its huge uncertainties	B4	−0.617	**0.700**	−0.088	−0.111	−0.016	−0.047	−0.047	−0.113
Harsh construction environment with high risk	B5	−0.637	−0.064	**0.019**	−0.244	−0.132	−0.408	−0.480	−0.164
Lack of standardized tool	B9	0.280	−0.297	**0.678**	0.109	−0.226	0.042	0.010	0.493
Government regulations	B10	0.198	0.248	0.225	−0.081	0.379	0.057	−0.070	**0.776**
Uniqueness of construction finished products	B1	−0.200	0.091	**0.110**	−0.125	−0.876	0.085	0.055	0.092
Lack of interest from clients	B11	0.075	**0.220**	−0.911	−0.095	−0.041	0.180	−0.127	0.053
Inadequate horizontal and vertical communication	B12	0.041	−0.820	**0.355**	−0.040	0.081	0.211	−0.030	0.091
Insufficient government support	B13	0.027	0.234	0.116	−0.085	**0.365**	0.040	−0.052	−0.823
Discreteness of construction process	B2	0.089	**0.751**	0.034	0.252	0.212	0.458	−0.003	0.097
Professional complacency	B14	**0.633**	0.344	0.607	−0.208	−0.037	−0.133	0.116	0.054
Resistance to change	B15	0.028	−0.039	0.145	−0.013	0.063	−0.023	**0.938**	−0.028
Lack of market familiarity	B16	0.024	0.187	0.034	−0.140	**0.762**	0.302	0.466	0.018
Inadequate public-private partnership	B17	**0.924**	−0.137	0.029	−0.104	0.198	0.035	−0.054	0.047
Uncertainty of construction resource	B3	−0.279	0.144	−0.492	**0.603**	0.306	−0.235	−0.262	0.041

The bold font indicates the barriers with the smallest initial eigenvalue variation close to one.

Table 6 displays the different factors that have similar characteristics, which were identified through the extracted components. The factors that have comparable extraction coefficients are grouped into components. Meanwhile, Table 7 presents the various groupings of barriers to the adoption of cyber technology in the construction industry, based on the similarities in their extraction coefficients. The factor loadings indicate the eigenvalues of each factor relative to the stated eigenvalue of 1. However, not all loading factors exceed the threshold of 0.5, as only B1, B3, and B12 have loading factors lower than this threshold. Thus, the exploratory factor analysis of all 17 items yields six accepted groups, which are Knowledge, Government, Culture, Project, Regulations, and Partnership.

Table 6. Commonalities of the barriers to the extracted components.

Commonalities	
Barriers	**Extraction**
B1	0.892
B2	0.944
B3	0.966
B4	0.908
B5	0.911
B6	0.935
B7	0.912
B8	0.862
B9	0.946
B10	0.861
B11	0.892
B12	0.900
B13	0.966
B14	0.908
B15	0.945
B16	0.930
B17	0.923

Table 7. Component factor/barrier groups.

S/N	Component Factors	Code	Barriers	Factor Loadings
1	Component 1 (Knowledge)	B6	Lack of awareness	0.740
		B16	Lack of market familiarity	0.665
2	Component 2 (Government)	B7	High initial cost of implementation	0.960
		B11	Lack of interest from clients	0.620
		B13	Insufficient government support	0.762
3	Component 3 (Culture)	B8	Fragmented construction process	0.930
		B14	Professional complacency	0.633
4	Component 4 (project)	B4	Complexity of projects and its huge uncertainties	0.700
		B15	Resistance to change	0.938
		B2	Discreteness of construction process	0.558
5	Component 5	B1 *	Uniqueness of construction finished products *	0.110
		B12 *	Inadequate horizontal and vertical communication *	0.355
6	Component 6 (Regulations)	B5	Harsh construction environment	0.069
		B10	Government regulations	0.776
7	Component 7 (Partnership)	B9	Lack of standardized tool.	0.678
		B17	Inadequate public-private partnership	0.924
8	Component 8	B3 *	Uncertainty of construction resource *	0.303

* These items were excluded due to low-loading.

The study has computed reliability statistics for the factors derived from the exploratory factor analysis. The variables associated with each factor were chosen based on their highest loading values in the structure matrix. According to Nunnally's criterion (1994), new measurements must have a Cronbach alpha value above 0.6. For instance, values exceeding 0.75 are considered highly reliable when the average value is 0.7. Since the obtained Cronbach alpha values are greater than 0.6, the results are reliable. Additionally, all items have average set correlations above 0.3, which suggests that they share consistent internal variables [55].

5.2.1. Measurement Model

In the SEM-PLS analysis of reflecting measurement models (CSFs), internal consistency, convergent validity, and discriminant validity must all be assessed. The structural model will be examined after establishing the validity and reliability of the measurement model [81]. Table 8 shows that all model constructs are valid since their α and ρ_c values are all greater than 0.70 [82].

Table 8. The result of convergent validity.

Constructs	Cronbach's Alpha	Composite Reliability	AVE
Knowledge	0.728	0.745	0.550
Government	0.853	0.931	0.872
Culture	0.785	0.788	0.598
Project	0.907	0.941	0.843
Regulations	0.708	0.872	0.774
Partnership	0.715	0.859	0.755

Table 4 indicates that all constructs meet the criteria for average variance extracted (AVE) compliance, with AVE values exceeding 0.5, which is considered acceptable [61]. Table 5 displays the results obtained from using the PLS algorithm 3.0, which indicates that all the constructs in the study have AVE estimates above 50%. This indicates that the measurement model is internally convergent and consistent, meaning that each construct is adequately measured by its own set of measuring items within the study model. A high outer load of an item indicates a strong connection and relationship with its relevant components. Conversely, items with outer loadings below 0.4 are generally considered to have poor visibility and should be removed from the scale [49]. Figure 3 displays the outer loadings of the measurement models for all items. The results indicate that all external loads, except for B11, which has been eliminated due to its low loading, are satisfactory.

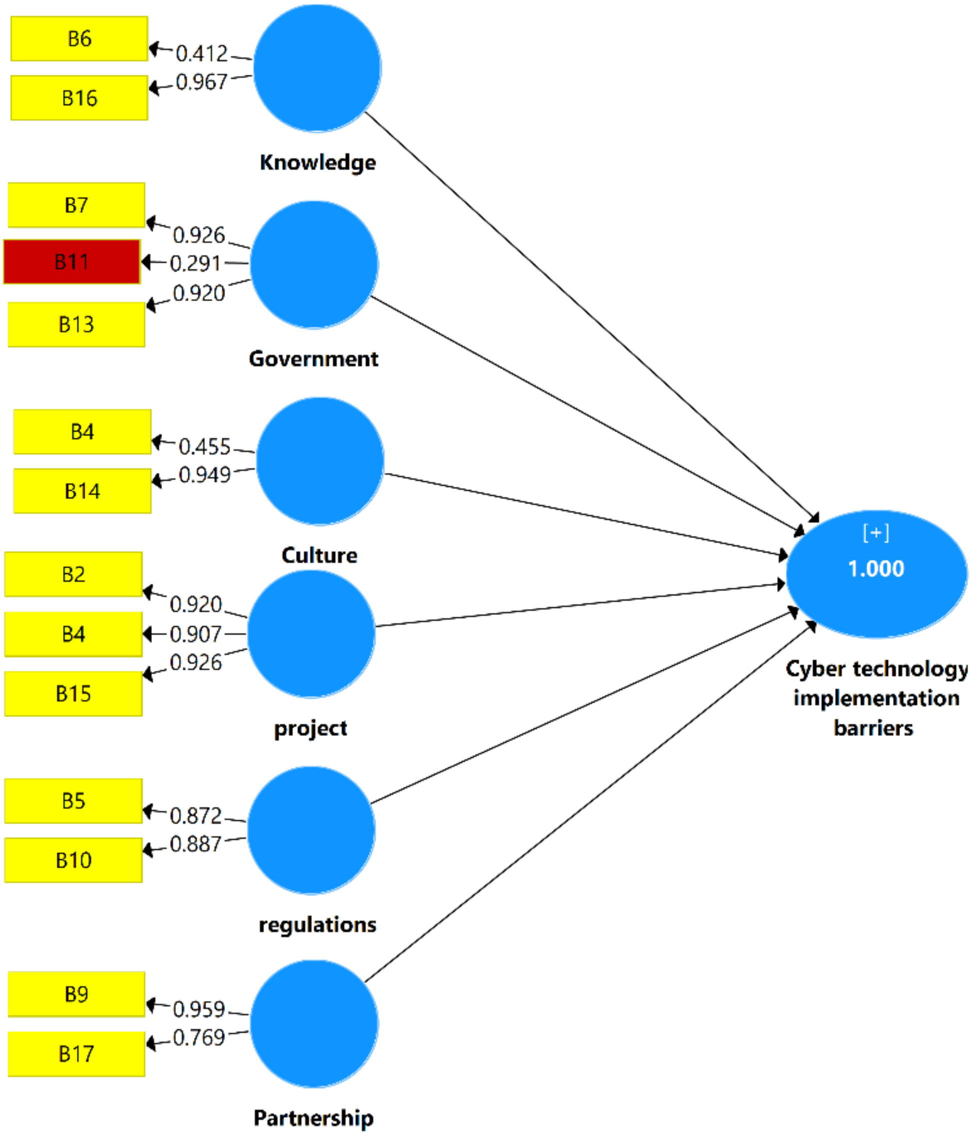

Figure 3. The PLS-SEM model.

5.2.2. Discriminant Validity

Table 9 shows that the square root of the average variance extracted (AVE) for each construct is greater than its correlation with any other construct, which suggests that there is no significant relationship between the constructs. In addition, the AVE values being high suggest that each predictor variable has a strong association with its respective construct, as depicted in Table 9. This indicates that each construct is measuring a single underlying dimension or concept with high precision.

Table 9. Discriminant validity.

Constructs	Culture	Government	Knowledge	Partnership	Regulations	Project
Culture	**0.742**					
Government	0.682	**0.934**				
Knowledge	0.612	0.684	**0.741**			
Partnership	0.063	0.066	0.078	**0.869**		
Regulations	0.605	0.764	0.664	0.08	**0.88**	
project	0.709	0.813	0.686	0.038	0.747	**0.918**

5.2.3. Path Model Validation

The collinearity among the objects in the formative construct of cyber technology barriers was examined by calculating the variable inflation factor (VIF) values. It was found that all VIF values were below 3.5, indicating that the subdomains contribute independently to the higher-order constructs. To test the significance of the path coefficients, a bootstrapping method was used, which revealed that all paths were statistically significant at the 0.01 level [60] (as presented in Figure 4). Figure 4 displays that the partnership construct had a p-value of 0.477, indicating that it was not statistically significant.

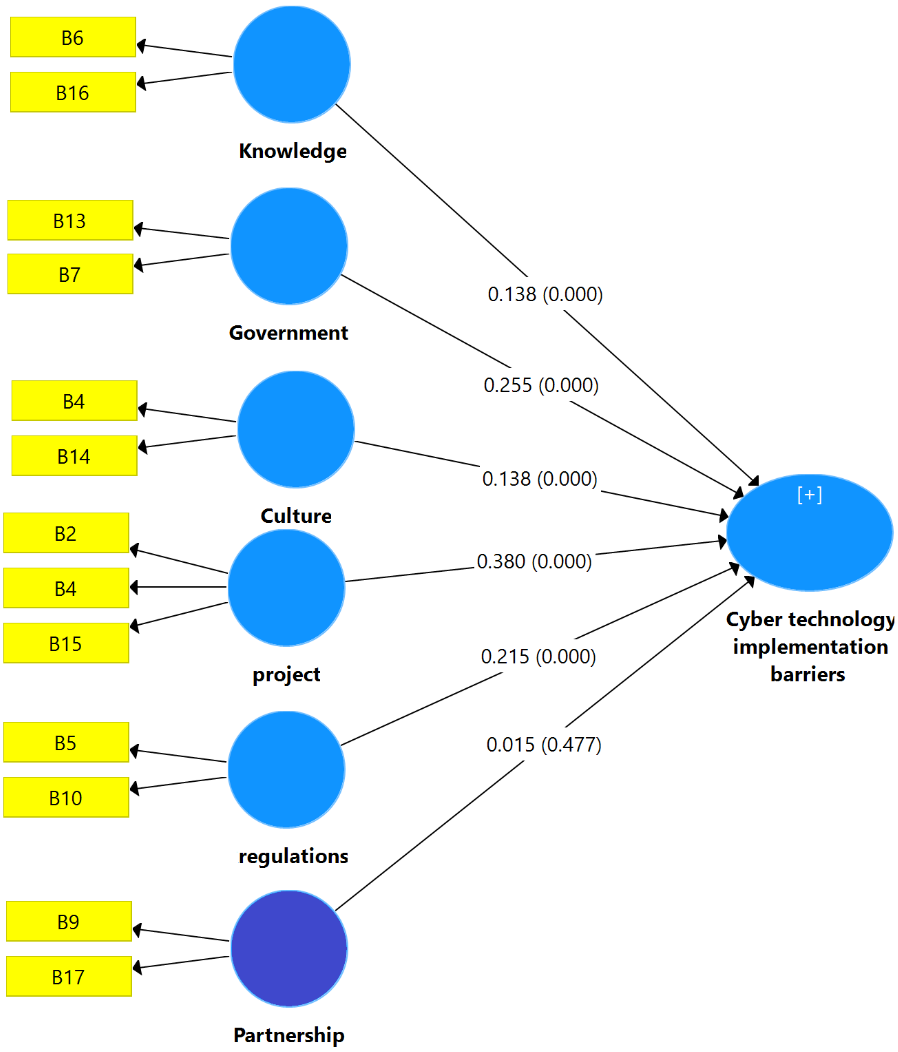

Figure 4. Path model.

6. Discussion

In contrast to many developed countries where the construction industry heavily relies on cyber technology, the adoption of such technology in the building sector is still in its early stages in developing countries, including Nigeria. The potential benefits of cyber technology and its impact on stakeholders, different phases of a construction project's lifecycle, and key components of the supply chain are not yet fully understood, despite the anticipation that emerging technologies will revolutionize the construction industry. Additionally, Nigeria has faced construction quality issues and paradoxes [83]. For this reason, concepts of cyber technology must be used to address these issues. Cyber technology as a core platform or element in projects is more likely to be authorized by higher management if practitioners are familiar with cyber technology and its necessary construction activities. According to the proposed model, six distinct elements of cyber technology have a negative impact on its broad adoption, five of which were statistically significant. This will have a beneficial effect on the long-term sustainability of residential development projects. The obstacles associated with cyber technology can be rated using the components of the PLS-SEM model, as explained in the next section. Money and time can be saved while enhancing quality in the construction sector by using cyber technology, without compromising the project's essential competencies.

6.1. Project Nature

According to the PLS-SEM model, the characteristics of a building project play a crucial role in determining the barriers to implementing cyber technology. The "Project" component has the highest impact on these barriers, with an external coefficient of 0.380. This principal component includes barriers related to project complexity, uncertainty, resistance to change, and the unique nature of the construction industry. Compared to the assembly line approach used in manufacturing, the construction business is characterized by its high degree of discreteness, lack of structure, and non-linear workflow. It is unusual for tasks to be linked in a linear sequence [84]. Instead, tasks and current activity are linked to one another via resource sharing or dependencies. Tasks are routinely delegated to subcontractors with varying expertise, making it challenging for project owners and general contractors to collect reliable data from them.

Construction organization and management are hindered by incompatible information flows because of the time and energy needed to coordinate them and the resulting discrepancies in participants' knowledge of the project [36]. Each variable in a dynamic building process may be considered autonomous, and the complicated and unpredictable results that emerge from their interactions result from this. Certain construction management concepts and its associated implementation tools, such as the work breakdown structure (WBS), critical path method (CPM), and earned value management (EVM), have been criticised for their inability to handle the complexity of today's building projects [85].

Even when managers have created a comprehensive construction plan, the high unpredictability of a project usually results in numerous changes to the plan as it progresses [86]. When it comes to building practices, many companies are staunchly unyielding [42]. They are set on using just one standard method of building. Ref. [30] states that one of the biggest challenges to integrating cyber technology into the building sector is people's reluctance to adapt to new ways of doing things.

6.2. Government

The second principal component is related to "Government". It comprises barriers, such as high initial cost of implementation, lack of client interest, and insufficient government support. With an external coefficient of 0.255, the "Government" seems to have a significant influence on cyber technology barriers. This suggests that the success factors for implementing cyber technology notwithstanding government constraints are bigger than the typical range of success factors (which is considered to be high to medium). Wang [87] claims that, with the exception of the construction sector, the introduction of new technology is accompanied by substantial financial outlays across the world's economies. This is because the cost of their adoption, purchase and implementation are usually very high as there are little or no alternative to their adoption and implementation. For the vast majority of developing nations, this is a show-stopper when considering its implementation [88].

Clients are the initiator of any construction project. Their contribution is essential to guarantee the project's success [89]. However, their lax attitude toward adopting technologies such as cyber technologies undermines its intended purpose [20]. Over the years, government support for technology adoption has been insufficient [90]. This is seen in the low budget and poor enabling environment provided for such sectors of the economy. This scarcity makes the adoption of cyber innovations a herculean undertaking for all parties concerned, and, as a result, decreases the expectations of innovators [38].

6.3. Regulations

The component with the third-highest eigenvalue is associated with "Regulations", which pertains to obstacles such as government regulations and challenging construction conditions. It has an external coefficient of 0.215, making it the third most significant barrier to the adoption of cyber technology. Construction sites are frequently plagued by noisy, dusty, and muddy conditions, and certain subterranean ventures may be susceptible to geological risks, such as water inrush and collapse [32]. The challenging construction environment presents significant obstacles to acquiring data and network communication for intelligent systems, as well as the reliability of precision equipment, which have external coefficients of 0.215 in the "Regulations" component. In addition, workers in such an environment may not always be able to concentrate on their surroundings, and the lack of real-time information may prevent them from responding promptly to dangerous situations. This insecurity also hinders their willingness to collaborate with mechanical equipment, which are the primary enablers of cyber technology [84]. However, inefficient governmental regulations make adopting and implementing cyber technologies cumbersome and difficult for professionals. Some of them make offensive laws that are tantamount to technological advancement [33]. In addition, lack of necessary skills is most important. This implies that government has a huge role to play in adopting technologies in the construction industry.

6.4. Knowledge

"Knowledge" is the fourth subscale on the scale of hurdles to implementing cyber technology. It has a 0.138 external coefficient. These includes obstacles such as a lack of awareness and market familiarity. The lack of understanding about cyber technology is a significant impediment to its adoption in the construction business, particularly in developing nations. This might be caused by a negative attitude towards technology [33]. New technologies are hard to be well known in the construction market [31].

6.5. Culture

The last subscale on the scale of barriers that should be avoided for implementing cyber technology relates to "Culture", with an external coefficient of 0.138. This involves barriers, such as fragmented construction processes and professional complacency. This is a major feature of the construction industry. There are work processes that require many forms of sub-contracting, making the use of cyber technologies very difficult [36]. Cyber technologies are not streamlined for many fragmentations, making their usage difficult for professionals. According to Chen et al. [20], many divisions in construction processes inhibit the adoption of any technology. Many construction professionals are complacent and unserious with their professional ethics [87]. Many do not seek current knowledge in their areas of expertise, making them lag in developmental strides in the construction industry [89]. With all-around technological advancement, cyber technologies are affected greatly by this complacency.

7. Managerial Implications

The implementation of cyber technology can greatly benefit the building industry by overcoming the obstacles that currently hinder its adoption. Building stakeholders can use the insights gained from this study to efficiently introduce cyber technology into their projects, while a benchmark can be established to systematically and efficiently incorporate it into the construction process. By eliminating the barriers identified in this study, the Nigerian construction industry and other developing nations can become more productive and sustainable, resulting in stable, sustainable, and effective construction. This study also suggests that the use of robotics can be increased in other developing nations with similar building techniques, resulting in faster project completion and reduced costs, ultimately leading to greater success for the construction sector.

The study contributes to our understanding of the construction industry by providing a database of obstacles to adopting cyber technology, as well as a robust framework for evaluating the use of robots in planning and executing construction projects. The benefits of cyber technology, such as cost-effectiveness and reduced construction expenses, are also emphasized, highlighting the potential for increased profitability and success of projects. Finally, the study proposes a prediction approach for assessing the use of cyber technology in the Nigerian construction industry and other developing countries, providing decision-makers with greater confidence in adopting cyber technology in the following ways:

- Our research has compiled an exhaustive database of the obstacles that impede the application of cyber technology and its numerous components.
- A sophisticated platform is offered for building owners and other significant construction industry players to assess and adopt robots, which may improve the planning and implementation of construction projects.
- Our research provides credible scientific data and recommendations for the implementation of cyber technology in Nigeria and other developing nations.
- Although the majority of study on deploying cyber technology has concentrated on the construction sectors of developed countries, there are few studies available for developing nations such as Nigeria. Thus, our research has studied the obstacles to using cyber technology in Nigeria and highlighted the advantages of enhancing the quality of local initiatives. In addition, we have emphasized how cyber technology may considerably cut construction costs and promote the proper distribution of expenses to make projects more lucrative and successful.
- In order to assess the application of cyber technology in the Nigerian construction industry and other emerging countries, we have developed a partial least squares structural equation modelling (PLS-SEM) prediction method. Hence, decision-makers may rely on the outcomes of our research in order to use robots.

8. Theoretical Implications

The use of cyber technology to improve project success has gained popularity in many industries. In the Nigerian construction sector, our study has developed a model to assess the implementation requirements of cyber technology and analysed various barriers that impede its application. The research bridges the gap between the theoretical and practical use of cyber technology and is the first to completely investigate and evaluate the hurdles to using cyber technology in the Nigerian construction industry.

This study offers a good basis for future research on the obstacles to integrating cyber technologies in comparable developing nations. The PLS-SEM approach has been used to determine the five most significant components of these obstacles. The results and analysis of this research may aid policymakers in formulating plans for adopting robots into the building industry.

9. Limitations and Future Work

This study presents a valuable connection between academic research and practical application in industry. However, there are some limitations that could be addressed in future research endeavours, for example:

- Increasing the sample size could improve the robustness of the findings.
- Additionally, future studies could focus on modelling the interactions among different user groups in the industry.

Despite these limitations, this study recognizes that research is an ongoing process and recommends future investigations in the following areas:

- This study presents the application of cyber technology for construction projects in Nigeria and attempts to address related issues. However, there is room for further investigation into implementing cyber technology for construction projects.
- Another area of research may consider assessing the effect of cyber technology on students' performance in Nigerian universities.

10. Conclusions

This research has offered useful insights into the obstacles preventing the deployment of cyber technology in the Nigerian construction industry. The study has modelled the priority of these barriers using SEM and analysed them through EFA analysis. The results of the study will serve as a guide for building professionals in Nigeria and other developing countries to effectively adopt cyber technology and overcome the identified barriers to improve project outcomes. This study has also demonstrated the potential of cyber technology to enhance project success in the construction sector. However, the implementation of cyber technology in developing economies is still modest. Thus, the research advises that construction industry stakeholders raise their awareness and knowledge-sharing in order to promote the implementation of cyber technology. Future research can build on the findings of this study by exploring the inter-relationship between different industrial user groups and assessing the impact of cyber technology on construction project outcomes. Overall, this study contributes to bridging the gap between theory and practice in the application of cyber technology in the construction sector in developing countries. By adopting cyber technology, building professionals can reduce costs, enhance sustainability, and ultimately improve the quality of housing in these countries.

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References

1. Chan, A.P.; Adabre, M.A. Bridging the gap between sustainable housing and affordable housing: The required critical success criteria (CSC). *Build. Environ.* **2019**, *151*, 112–125. [CrossRef]
2. Sbci, U. Buildings and climate change: Summary for decision-makers. United Nations Environmental Programme. *Sustain. Build. Clim. Initiat. Paris* **2009**, *1*, 62.
3. Gan, X.; Zuo, J.; Wu, P.; Wang, J.; Chang, R.; Wen, T. How affordable housing becomes more sustainable? A stakeholder study. *J. Clean. Prod.* **2017**, *162*, 427–437. [CrossRef]
4. Dezhi, L.; Yanchao, C.; Hongxia, C.; Kai, G.; Hui, E.C.-M.; Yang, J. Assessing the integrated sustainability of a public rental housing project from the perspective of complex eco-system. *Habitat Int.* **2016**, *53*, 546–555. [CrossRef]
5. Al-Saadi, R.; Abdou, A. Factors critical for the success of public-private partnerships in UAE infrastructure projects: Experts' perception. *Int. J. Constr. Manag.* **2016**, *16*, 234–248. [CrossRef]
6. Bezuidenhout, L. From Welfare to Community Development-the Role of Local Congregations as Agents of Development in the Mangaung Metropolitan Area. Doctoral Dissertation, University of the Free State, Bloemfontein, South Africa, 2019.
7. Chan, A.P.C.; Darko, A.; Olanipekun, A.O.; Ameyaw, E.E. Critical barriers to green building technologies adoption in developing countries: The case of Ghana. *J. Clean. Prod.* **2018**, *172*, 1067–1079. [CrossRef]
8. Durdyev, S.; Ismail, S.; Ihtiyar, A.; Bakar, N.F.S.A.; Darko, A. A partial least squares structural equation modeling (PLS-SEM) of barriers to sustainable construction in Malaysia. *J. Clean. Prod.* **2018**, *204*, 564–572. [CrossRef]
9. Dimakis, N.; Filippoupolitis, A.; Gelenbe, E. Distributed building evacuation simulator for smart emergency management. *Comput. J.* **2010**, *53*, 1384–1400. [CrossRef]
10. Kineber, A.F.O.I.; Oke, A.E.; Chileshe, N.; Buniya, M.K. Identifying and Assessing Sustainable Value Management Implementation Activities in Developing Countries:The Case of Egypt. *Sustainability* **2020**, *12*, 9143. [CrossRef]
11. Wolstenholme, A.; Austin, S.A.; Bairstow, M.; Blumenthal, A.; Lorimer, J.; McGuckin, S.; Rhys Jones, S.; Ward, D.; Whysall, D.; Le Grand, Z. Never Waste a Good Crisis: A Review of Progress since Rethinking Construction and Thoughts for Our Future. 2009. Available online: https://repository.lboro.ac.uk/articles/report/Never_waste_a_good_crisis_a_review_of_progress_since_Rethinking_Construction_and_thoughts_for_our_future/9460931 (accessed on 11 April 2023).
12. Russell-Smith, S.V.; Lepech, M.D. Cradle-to-gate sustainable target value design: Integrating life cycle assessment and construction management for buildings. *J. Clean. Prod.* **2015**, *100*, 107–115. [CrossRef]
13. Jiao, Y.B. The Design of the Logistics Information Sharing Platform Based on Cloud Computing. In *Advanced Materials Research*; Trans Tech Publications: Stafa-Zurich, Switzerland, 2013; pp. 3220–3223.
14. Shen, W.; Hao, Q.; Mak, H.; Neelamkavil, J.; Xie, H.; Dickinson, J.; Thomas, R.; Pardasani, A.; Xue, H. Systems integration and collaboration in architecture, engineering, construction, and facilities management: A review. *Adv. Eng. Inform.* **2010**, *24*, 196–207. [CrossRef]
15. Chin, S.; Yoon, S.; Choi, C.; Cho, C. RFID+ 4 D CAD for progress management of structural steel works in high-rise buildings. *J. Comput. Civ. Eng.* **2008**, *22*, 74–89. [CrossRef]
16. Golparvar-Fard, M.; Savarese, S.; Peña-Mora, F. Interactive Visual Construction Progress Monitoring with D4 AR—4D Augmented Reality—Models. In Proceedings of the Construction Research Congress 2009: Building a Sustainable Future, Seattle, WA, USA, 5–7 April 2009; pp. 41–50.
17. Sørensen, E. *The Materiality of Learning: Technology and Knowledge in Educational Practice*; Cambridge University Press: Cambridge, UK, 2009.
18. Akanmu, A.; Anumba, C.; Messner, J. Active monitoring and control of light fixtures during building construction and operation: Cyber-physical systems approach. *J. Archit. Eng.* **2014**, *20*, 04013008. [CrossRef]
19. You, Z.; Wu, C. A framework for data-driven informatization of the construction company. *Adv. Eng. Inform.* **2019**, *39*, 269–277. [CrossRef]
20. Chen, B.; Wan, J.; Shu, L.; Li, P.; Mukherjee, M.; Yin, B. Smart factory of industry 4.0: Key technologies, application case, and challenges. *IEEE Access* **2017**, *6*, 6505–6519. [CrossRef]
21. Kaewunruen, S.; Sresakoolchai, J.; Ma, W.; Phil-Ebosie, O. Digital twin aided vulnerability assessment and risk-based maintenance planning of bridge infrastructures exposed to extreme conditions. *Sustainability* **2021**, *13*, 2051. [CrossRef]
22. Oesterreich, T.D.; Teuteberg, F. Understanding the implications of digitisation and automation in the context of Industry 4.0: A triangulation approach and elements of a research agenda for the construction industry. *Comput. Ind.* **2016**, *83*, 121–139. [CrossRef]
23. Yap, J.B.H.; Lam, C.G.Y.; Skitmore, M.; Talebian, N. Barriers to the adoption of new safety technologies in construction: A developing country context. *J. Civ. Eng. Manag.* **2022**, *28*, 120–133. [CrossRef]
24. Nnaji, C.; Karakhan, A.A. Technologies for safety and health management in construction: Current use, implementation benefits and limitations, and adoption barriers. *J. Build. Eng.* **2020**, *29*, 101212. [CrossRef]
25. Osunsanmi, T.O.; Oke, A.E.; Aigbavboa, C.O. Barriers for the Adoption of Incorporating RFID with Mobile Technology for Improved Safety of Construction Professionals. In Proceedings of the Construction Industry Development Board Postgraduate Research Conference, Johannesburg, South Africa, 28–30 July 2019; Springer: Berlin/Heidelberg, Germany, 2019; pp. 297–304.

26. Yahya, M.Y.B.; Hui, Y.L.; Yassin, A.B.M.; Omar, R.; anak Robin, R.O.; Kasim, N. The challenges of the implementation of construction robotics technologies in the construction. In Proceedings of the MATEC Web of IConBEE2018: International Conference on Built Environment and Engineering 2018, Nusajaya, Johor, Malaysia, 29–30 October 2018; EDP Sciences: Les Ulis, France, 2019; p. 05012.
27. Mahbub, R. Readiness of a developing nation in implementing automation and robotics technologies in construction: A case study of Malaysia. *J. Civ. Eng. Archit.* **2012**, *6*, 858.
28. Demirkesen, S.; Tezel, A. Investigating major challenges for industry 4.0 adoption among construction companies. *Eng. Constr. Archit. Manag.* **2021**, *3*, 1470–1503.
29. Edirisinghe, R. Digital skin of the construction site: Smart sensor technologies towards the future smart construction site. *Eng. Constr. Archit. Manag.* **2018**, *26*, 184–223. [CrossRef]
30. Akanmu, A.; Anumba, C.; Messner, J. Integrating virtual models and physical construction. In Proceedings of the 6th International Conference on Innovation in Architecture, Engineering and Construction, Loughborough, UK, 6–8 March 2010; pp. 393–402.
31. Bhave, A.; Garlan, D.; Krogh, B.; Rajhans, A.; Schmerl, B. Augmenting Software Architectures with Physical Components. In Proceedings of the ERTS2 2010, Embedded Real Time Software & Systems, Toulouse, France, 19–21 May 2010.
32. Onyegiri, I.; Nwachukwu, C.; Jamike, O. Information and communication technology in the construction industry. *Am. J. Sci. Ind. Res.* **2011**, *2*, 461–468. [CrossRef]
33. Akanmu, A.A.; Anumba, C.J.; Messner, J.I. An RTLS-based approach to cyber-physical systems integration in design and construction. *Int. J. Distrib. Sens. Netw.* **2012**, *8*, 596845. [CrossRef]
34. Akanmu, A.; Anumba, C.; Messner, J. Scenarios for cyber-physical systems integration in construction. *J. Inf. Technol. Constr.* **2013**, *18*, 240–260.
35. Chen, H.-M.; Chang, K.-C.; Lin, T.-H. A cloud-based system framework for performing online viewing, storage, and analysis on big data of massive BIMs. *Autom. Constr.* **2016**, *71*, 34–48. [CrossRef]
36. Wollschlaeger, M.; Sauter, T.; Jasperneite, J. The future of industrial communication: Automation networks in the era of the internet of things and industry 4.0. *IEEE Ind. Electron. Mag.* **2017**, *11*, 17–27. [CrossRef]
37. Liu, Y.; Xu, X. Industry 4.0 and cloud manufacturing: A comparative analysis. *J. Manuf. Sci.* **2017**, *139*, 034701. [CrossRef]
38. Al-Rakhami, M.; Alsahli, M.; Hassan, M.M.; Alamri, A.; Guerrieri, A.; Fortino, G. Cost efficient edge intelligence framework using docker containers. In Proceedings of the 2018 IEEE 16th International Conference on Dependable, Autonomic and Secure Computing, 16th International Conference on Pervasive Intelligence and Computing, 4th International Conference on Big Data Intelligence and Computing and Cyber Science and Technology Congress (DASC/PiCom/DataCom/CyberSciTech), Athens, Greek, 12–15 August 2018; pp. 800–807.
39. Chen, F.; Luo, D.; Xiang, T.; Chen, P.; Fan, J.; Truong, H.L. IoT Cloud Security Review: A Case Study Approach Using Emerging Consumer-oriented Applications. *ACM Comput. Surv. (CSUR)* **2021**, *54*, 1–36. [CrossRef]
40. Gu, W.; Foster, K.; Shang, J.; Wei, L. A game-predicting expert system using big data and machine learning. *Expert Syst. Appl.* **2019**, *130*, 293–305. [CrossRef]
41. de Soto, B.G.; Georgescu, A.; Mantha, B.; Turk, Ž.; Maciel, A. Construction Cybersecurity and Critical Infrastructure Protection: Significance, Overlaps, and Proposed Action Plan. 2020. Available online: https://doi.org/10.20944/preprints202005.0213.v1 (accessed on 11 April 2023).
42. Queiroz-Sousa, P.O.; Salgado, A.C. A review on OLAP technologies applied to information networks. *ACM Trans. Knowl. Discov. Data* **2019**, *14*, 1–25. [CrossRef]
43. You, Z.; Feng, L. Integration of industry 4.0 related technologies in construction industry: A framework of cyber-physical system. *IEEE Access* **2020**, *8*, 122908–122922. [CrossRef]
44. Henseler, J.; Hubona, G.; Ray, P.A. Using PLS path modeling in new technology research: Updated guidelines. *Ind. Manag. Data Syst.* **2016**, *116*, 2–20. [CrossRef]
45. Banihashemi, S.; Hosseini, M.R.; Golizadeh, H.; Sankaran, S. Critical success factors (CSFs) for integration of sustainability into construction project management practices in developing countries. *Int. J. Proj. Manag.* **2017**, *35*, 1103–1119. [CrossRef]
46. Lee, C.; Hallak, R. Investigating the moderating role of education on a structural model of restaurant performance using multi-group PLS-SEM analysis. *J. Bus. Res.* **2018**, *88*, 298–305. [CrossRef]
47. Hult, G.T.M.; Hair, J.F., Jr.; Proksch, D.; Sarstedt, M.; Pinkwart, A.; Ringle, C.M. Addressing endogeneity in international marketing applications of partial least squares structural equation modeling. *J. Int. Mark.* **2018**, *26*, 1–21. [CrossRef]
48. Hair Jr, J.F.; Matthews, L.M.; Matthews, R.L.; Sarstedt, M. PLS-SEM or CB-SEM: Updated guidelines on which method to use. *Int. J. Multivar. Data Anal.* **2017**, *1*, 107–123. [CrossRef]
49. Hair, J.F.; Ringle, C.M.; Sarstedt, M. PLS-SEM: Indeed a silver bullet. *J. Mark. Theory Pract.* **2011**, *19*, 139–152. [CrossRef]
50. Podsakoff, P.M.; MacKenzie, S.B.; Lee, J.-Y.; Podsakoff, N.P. Common method biases in behavioral research: A critical review of the literature and recommended remedies. *J. Appl. Psychol.* **2003**, *88*, 879. [CrossRef]
51. Glick, W.H.; Jenkins, G.D., Jr.; Gupta, N. Method versus substance: How strong are underlying relationships between job characteristics and attitudinal outcomes? *Acad. Manag. J.* **1986**, *29*, 441–464. [CrossRef]
52. Strandholm, K.; Kumar, K.; Subramanian, R. Examining the interrelationships among perceived environmental change, strategic response, managerial characteristics, and organizational performance. *J. Bus. Res.* **2004**, *57*, 58–68. [CrossRef]

53. Williams, L.J.; Cote, J.A.; Buckley, M.R. Lack of method variance in self-reported affect and perceptions at work: Reality or artifact? *J. Appl. Psychol.* **1989**, *74*, 462. [CrossRef]
54. Williams, B.; Onsman, A.; Brown, T. Exploratory factor analysis: A five-step guide for novices. *Australas. J. Paramed.* **2010**, *8*, 1–13. [CrossRef]
55. Field, A. *Discovering Statistics Using SPSS (3. baskı)*; Sage Publications: New York, NY, USA, 2009.
56. Thompson, B. *Exploratory and Confirmatory Factor Analysis: Understanding Concepts and Applications*; American Psychological Association: Washington, DC, USA, 2004. [CrossRef]
57. Costello, A.B.; Osborne, J. Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Pract. Assess. Res. Eval.* **2005**, *10*, 7.
58. Olanrewaju, O.I.; Kineber, A.F.; Chileshe, N.; Edwards, D.J. Modelling the relationship between Building Information Modelling (BIM) implementation barriers, usage and awareness on building project lifecycle. *Build. Environ.* **2021**, *207*, 108556. [CrossRef]
59. Al-Ashmori, Y.Y.; Othman, I.; Rahmawati, Y.; Amran, Y.H.M.; Sabah, S.H.A.; Rafindadi, A.D.; Mikić, M. BIM benefits and its influence on the BIM implementation in Malaysia. *Ain Shams Eng. J.* **2020**, *11*, 1013–1019. [CrossRef]
60. Hulland, J. Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strateg. Manag. J.* **1999**, *20*, 195–204. [CrossRef]
61. Fornell, C.; Larcker, D.F. Evaluating structural equation models with unobservable variables and measurement error. *J. Mark. Res.* **1981**, *18*, 39–50. [CrossRef]
62. Nunnally, J.C.; Bernstein, I. The role of university in the development of entrepreneurial vocations: A Spanish study. In *Psychometric Theory*; McGraw-Hill: New York, NY, USA, 1978; pp. 387–405.
63. Wong, K.K.-K. Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. *Mark. Bull.* **2013**, *24*, 1–32.
64. Hair, J.F.; Anderson, R.E.; Babin, B.J.; Black, W.C. *Multivariate Data Analysis: A Global Perspective*; Pearson Education: Upper Saddle River, NJ, USA, 2010; Volume 7.
65. Campbell, D.T.; Fiske, D.W. Convergent and discriminant validation by the multitrait-multimethod matrix. *Psychol. Bull.* **1959**, *56*, 81. [CrossRef]
66. Alkilani, S.G.R.Z. *Performance MEASUREMENT and Improvement Model for Small and Medium Contractors in Developing Countries*; The University of New South Wales: Sydney, Australia, 2018.
67. Lai, N.K. Value Management in Construction Industry. Master's Thesis, Universiti Teknologi Malaysia, Johor Bahru, Malaysia, 2006.
68. Al-Yami, A.M. An Integrated Approach to Value Management and Sustainable Construction during Strategic Briefing in Saudi Construction Projects. Ph.D. Thesis, Loughborough University, Loughborough, UK, 2008.
69. Jaapar, A.; Endut, I.R.; Bari, N.A.A.; Takim, R. The impact of value management implementation in Malaysia. *J. Sustain. Dev.* **2009**, *2*, 210–219. [CrossRef]
70. Oke, A.E.; Ogunsemi, D.R. Value management in the Nigerian construction industry: Militating factors and the perceived benefits. In Proceedings of the Second International Conference on Advances in Engineering and Technology, Nanjing, China, 24–25 December 2011; pp. 353–359.
71. Oke, A.E.; Ogunsemi, D.R. Key competencies of value managers in Lagos state, Nigeria. In Proceedings of the 5th West Africa Built Environment Research (WABER) Conference, Accra, Ghana, 12–14 August 2013; pp. 773–778.
72. Phyo, W.W.M.; Cho, A.M. Awareness and practice of value engineering in Myanmar construction industry. *Int. J. Sci. Eng. Technol. Res.* **2014**, *3*, 2022–2027.
73. Badewi, A. Investigating Benefits Realisation Process for Enterprise Resource Planning Systems. Ph.D. Thesis, School of Aerospace, Transport and Manufacturing, Cranfield University, Cranfield, UK, 2016.
74. Yin, R.K. *Case Study Research: Design and Methods*, 4th ed.; Applied Social Research Methods Series; Sage: Thousand Oaks, CA, USA, 2009; Volume 5. [CrossRef]
75. Kothari, C. *Research Methodology Methods and Techniques*, 2nd ed.; New Age International Publishers: New Delhi, India, 2009.
76. Wahyuni, D. The research design maze: Understanding paradigms, cases, methods and methodologies. *J. Appl. Manag. Account. Res.* **2012**, *10*, 69–80.
77. Sharma, S. *Applied Multivariate Techniques*; John Wiley Sons: Hoboken, NJ, USA, 1996.
78. Tabachnick, B.G.; Fidell, L.S.; Ullman, J.B. *Using Multivariate Statistics*; Pearson: Boston, MA, USA, 2007; Volume 5.
79. Tavakol, M.; Dennick, R. Making sense of Cronbach's alpha. *Int. J. Med. Educ.* **2011**, *2*, 53. [CrossRef] [PubMed]
80. Pallant, J. *SPSS Survival Manual*, 3rd ed.; McGrath Hill: New York, NY, USA, 2007.
81. Hair, J.F.; Black, W.C.; Babin, B.J.; Anderson, R.E.; Tatham, R.L. *Multivariate Data Analysis (Vol. 6)*; Pearson Prentice Hall: Upper Saddle River, NJ, USA, 2006.
82. Hair Jr, J.F.; Hult, G.T.M.; Ringle, C.; Sarstedt, M. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*; Sage Publications: Thousand Oaks, CA, USA, 2016.
83. Mantha, B.R.; de Soto, B.G. Cyber security challenges and vulnerability assessment in the construction industry. In Proceedings of the Creative Construction Conference 2019, Budapest, Hungary, 29 June–2 July 2019; Budapest University of Technology and Economics: Budapest, Hungary, 2019; pp. 29–37.

84. Salmi, T.; Ahola, J.M.; Heikkilä, T.; Kilpeläinen, P.; Malm, T. Human-robot collaboration and sensor-based robots in industrial applications and construction. In *Robotic Building*; Springer: Berlin/Heidelberg, Germany, 2018; pp. 25–52.
85. Ansah, R.H.; Sorooshian, S.; Mustafa, S.B. Lean construction: An effective approach for project management. *ARPN J. Eng. Appl. Sci.* **2016**, *11*, 1607–1612.
86. Salem, O.; Solomon, J.; Genaidy, A.; Minkarah, I. Lean construction: From theory to implementation. *J. Manag. Eng.* **2006**, *22*, 168–175. [CrossRef]
87. Wang, L.-C. Enhancing construction quality inspection and management using RFID technology. *Autom. Constr.* **2008**, *17*, 467–479. [CrossRef]
88. Fan, H.; Xue, F.; Li, H. Project-based as-needed information retrieval from unstructured AEC documents. *J. Manag. Eng.* **2015**, *31*, A4014012. [CrossRef]
89. Liu, C.; Xu, X. Cyber-physical machine tool–the era of machine tool 4.0. *Procedia Cirp.* **2017**, *63*, 70–75. [CrossRef]
90. Akinci, B.; Anumba, C. Sensors in construction and infrastructure management. *J. Inf. Technol. Constr.* **2008**, *13*, 69–70.