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Decision Making Model for Identifying the Cyber Technology Implementation Benefits for Sustainable Residential Building: A Mathematical PLS-SEM Approach

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Abstract: Sustainability principles should be implemented during all the phases of the decision-making process of constructing residential buildings to achieve maximum gains without compromising the function of such projects. This study identified and examined the benefits of implementing cyber technology in residential building projects, with a view to promoting the sustainability of such projects. The benefits of cyber technology were identified from previous studies, which were then contextually explored via survey questionnaires within the Nigerian building industry. The results from the exploratory factor analysis (EFA) technique showed that the cyber technology benefits could be categorized into five constructs, namely, planning, transparency, efficiency, productivity, and quality. In addition, partial least square structural equation modelling (PLS-SEM) was used to develop the benefits model. The results showed that transparency related benefits were crucial benefits for implementing cyber technology. The study's results will serve as a reference for decision-makers looking to decrease costs and increase sustainability by using cyber technology in the Nigerian construction sector.

Keywords: cyber technology; sustainability; residential building projects; PLS-SEM; benefits; EFA

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Citation: Kineber, A.F.; Oke, A.; Hamed, M.M.; Alyanbaawi, A.; Elmansoury, A.; Daoud, A.O. Decision Making Model for Identifying the Cyber Technology Implementation Benefits for Sustainable Residential Building: A Mathematical PLS-SEM Approach. *Sustainability* **2023**, *15*, 2458. https://doi.org/10.3390/su15032458

Academic Editor: Gianluca Mazzucco

Received: 23 December 2022
Revised: 11 January 2023
Accepted: 27 January 2023
Published: 30 January 2023

1. Introduction

Residential construction is one of the important community characteristics that define a country's citizens' high quality of life and well-being [1]. Residential buildings use over 40% of the world's electricity and contribute up to one-third of global greenhouse gas emissions (GHG emissions) in both developed and developing countries [2]. Nonetheless, in a rapidly changing and urbanizing world, residential allocation cannot keep up with demand [3]. Rapid urbanization in emerging nations is limiting low-wage workers' access to affordable homes in emerging as well as developed nations [4]. It is estimated that 828 million impoverished people in developing nations live in slums and inadequate housing. By 2020, it is anticipated that this number would increase to 1.4 billion [3,5,6]. In particular, in some developing countries, the construction industry still follows traditional labor-intensive industry practices, with high energy consumption, environmental pollution, safety risks, and low productivity in project delivery [7]. These regions have witnessed tremendous growth, which underscores the importance of residential architecture in guaranteeing a standard of life [8]. As a consequence, all governments have emphasized affordable housing construction by implementing many affordable housing regulations [1].

However, there is a dispute regarding whether low-income households can purchase residential constructions [3]. Estimates show that up to 30 percent of construction costs are wasted due to inefficiencies, errors, delays, and poor communications [9]. Design errors, changes, or updates to the design model may cause delays, and if they are not communicated in real time to the building site, there is a danger of cost and schedule overruns. Thus, real-time access to design model changes may assist project managers in making educated judgments. Moreover, adjustments performed on site must be reflected in the 0as-built model for buildings' lifetime management. Currently, as-built models are manually updated after creation; as a result, they are susceptible to errors since not all changes are fully recorded.

The literature emphasizes the need of designing ecologically friendly and resource-efficient "sustainable buildings" [10]. Wolstenholme et al. [11] further advise changing the construction industry by embracing effective and sustainable building principles. Moreover, building experts are unable to quantify the environmental impacts of buildings as they occur during development [12]. Therefore, virtual models provide a substantial long-term advantage by facilitating the recording of as-built information, team cooperation, and visualization of building progress, but their application is currently mostly restricted to the preconstruction period [13]. Computer-aided design (CAD) models and building information models (BIM) are examples of virtual models. Extending the usage of these models throughout the building, operation, and maintenance stages of a facility's lifetime may provide substantial additional benefits. Integration of virtual and real building models has been shown to increase information and knowledge management from design through construction and maintenance, hence boosting construction process control [14].

Several researchers, such as Chin et al. [15,16] and Sørensen [17], have sought to integrate virtual models and physical construction by using various data collecting methods (e.g., digital cameras, laser scanners, radio frequency identification tags). However, current methods do not allow for bidirectional integration or communication between virtual models and physical construction. This two-way integration and communication are crucial for improving facility feedback and control. Real-time, bidirectional coordination between virtual models and the physical structure is an effective method for giving feedback and control. Bi-directional coordination is the integration of virtual models and real artefacts in such a manner that modifications to one are automatically reflected in the other [18]. In addition, computing resources are, necessary, to integrate closely the virtual models and the physical structure to ensure bi-directional coordination, so that changes in one environment are automatically reflected in the other. This method is known as the cyber–physical systems approach. "Cyber-physical system" is used in the context of this study to refer to the integration and coordination of virtual models and physical constructions. Cyber–physical systems employ sensors to connect the cyber world (such as information, communication, and intelligence) to the physical world [19].

The cyber–physical systems approach will increase progress monitoring, construction process control, as-built documentation, and environmentally responsible building practices. In addition, it has been shown that developing cyber technologies, such as the Internet of Things, big data, cloud computing, and artificial intelligence, efficiently contribute to industrial intelligence, particularly in the construction sector [20]. In recent years, however, these technologies have steadily invaded several building sector domains to provide effective design optimization, performance assessment, resource management, risk monitoring, energy conservation, emission reduction, and project delivery [21]. Intelligent processes in the construction industry are still in their infancy and lag behind other industrial sectors, particularly in developing nations [22]. Meanwhile, novel technologies are only partly accepted in some domains, and there is macro-level research on their incorporation into the building industry. We formulated the following research question for this empirical investigation based on our arguments: What are the benefits of using cyber technology in the building industry? This research attempts to investigate the benefits of using cyber technology for attaining sustainability in residential architecture utilizing causal inference approaches, such as structural equation modelling (SEM).

2. Benefits of Cyber Technology Adoption

There are a lot of benefits for cyber technology adoption in the construction sector. These benefits are listed and summarized in Table 1 based on previous studies of different researchers. A systematic internet search was conducted via different databases—Scopus, Web of Science (WOS), JSTOR, and ProQuest—to review different research papers related to the research topic. This was conducted using specific keywords, either separately or in combination, such as 'benefits', 'cyber technology', 'residential buildings', 'adoption', and 'implementation'.

Table 1. Summary of the benefits of cyber technology adoption in the construction sector.

Code	VARIABLES	[23]	[24]	[25]	[26]	[27]	[28]	[29]	[30]	[31]	[20]	[32]	[33]	[34]	[35]
B1	Construction Planning	*	*			*				*		*			
B2	Project Monitoring	*		*	*			*							
B3	Storage of construction life cycle data		*		*			*			*				
B4	Saves Time and Cost	*	*		*		*			*					*
B5	Increase in quality	*			*	*		*					*		
B6	Increased collaboration among the professionals		*						*						
B7	Increased productivity		*		*			*			*			*	
B8	Reduced construction error			*		*							*		*
B9	Increased revenue	*	*						*		*			*	
B10	Captures challenges in real time		*		*										
B11	Cost and time efficiency	*					*		*					*	
B12	Maximizes the desired outcome				*						*		*		
B13	It aids in competitive advantage	*		*	*		*				*			*	
B14	Improved transparency	*						*					*		
B15	Information sharing	*			*			*			*	*			*
B16	It ensures reduced paperwork	*		*		*			*	*			*	*	

3. Research Methodology and Model Construction

From the literature assessment on the benefits of cyber technology, as shown in Figure 1, a list of 16 benefits was compiled and deemed acceptable for the adoption of cyber technology. Then, a questionnaire poll was conducted by distributing a list of cyber technology's benefits to home construction specialists with appropriate industry expertise using an online hyperlink via google forms. The anonymity of the respondents was preserved by only asking about the respondents' occupations and avoiding asking about their names. It was performed to verify the comprehensiveness and clarity of the cyber technology benefits in conjunction with the exploratory factor analysis (EFA) investigation of these variables and their categories.

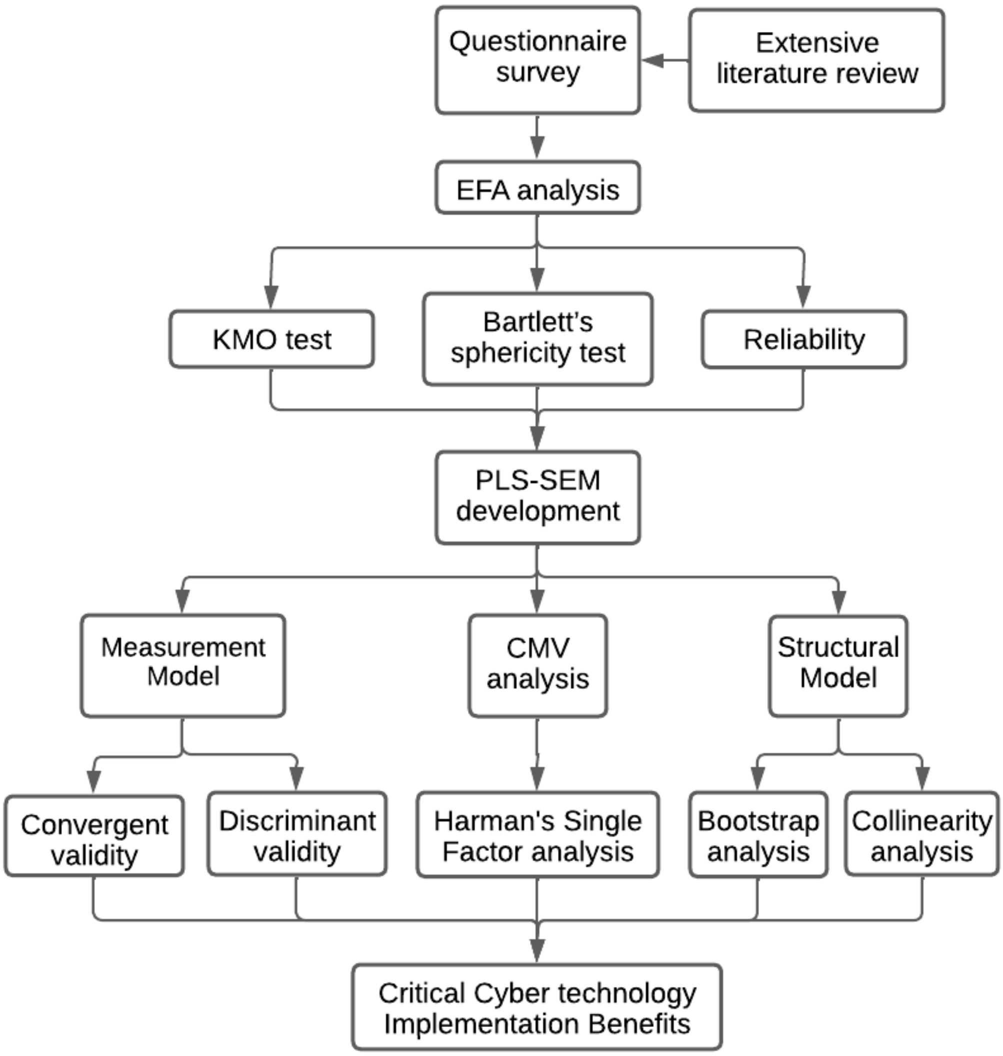

Figure 1. Research design.

3.1. Model Development

The partial least square structural equation modelling (PLS-SEM) has gained a great deal of interest in a variety of disciplines, including business research and the social sciences [36]. Recently, major SSCI publications have published several studies focusing on the PLS-SEM methodology [37–39]. The most recent version of the programme, SMART-PLS 3.2.7, was used to analyze the acquired data to estimate the importance of the cyber technological obstacles using SEM. Initially, PLS-SEM was recognised for its superior forecasting capabilities over covariance-based structural equation modelling (CB-SEM) [40] even though the differences between the two tactics are quite minor [41]. This study's statistical analysis included the measurement and structural model assessment approach.

3.1.1. Common Method Variance

The common method bias (CMB) was calculated using the common method variance (CMV). CMB assists in elucidating the disparity (or mistake) in the conclusion of an analysis that is due to the measuring technique rather than the constructs represented by the measurements [42]. CMV might also be regarded as a variance overlap that could be attributable not just to constructs but also to the measuring instrument types that were used [42]. CMV is especially problematic when information, such as a self-administered questionnaire, is obtained from a specific source [43,44]. In some situations, self-reported data might exaggerate or reduce the number of examined links, causing problems [44,45].

Given that all data in this research are self-reported, subjective, and received from a single source, this may be significant. Consequently, it is essential to address these issues to identify any common procedure variances. As described in Harman's experiment (1976), a rigorous, methodical, one-factor test was conducted [46]. The factor analysis revealed a single component that accounted for the bulk of the variation [44].

3.1.2. Construct Validity Analysis

Typically, the methodologies of confirmatory factor analysis (CFA) and exploratory factor analysis (EFA) are utilized for factor analysis. In this research, CFA is used to evaluate the structure underlying several variables in hypotheses or theories including such variables. On the other hand, EFA is used to collect information on relations and many variables and to reduce numerous variables to a small number of fundamental structures [47]. EFA is intended for interval data or ordinal data. A scatterplot graph demonstrates that the variables are partially or entirely interrelated. The strategy is used to minimize the number of factors to represent a collection of variables with a lesser number of variables. The formula is indicated below in Equation (1):

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

where a_i are the factor loadings (or scores) for variable I, F is the factor to be analyzed, and e_i is the part of the variable that cannot be explained by the factors.

In the present study, principal multivariate analytic techniques, such as EFA, which assisted the researcher in examining the major constructs or structure of cyber technology obstacles constructs, were used. It was utilized to test the constructs' validity by analyzing the unidimensionality, reliability, and validity of the measurement items of particular constructs (i.e., measurement models). Principal component analysis (PCA) was chosen over principal axis factoring (PAF), picture factoring, maximum probability, and alpha factoring [48] because PCA is more accurate and less conceptually difficult. When there is no previous theory or model and preliminary solutions are obtained in EFA, PCA is recommended [47].

Thompson [48] observed that PCA is the default form in many statistical tools and is hence the method most often utilized in EFA. Varimax rotation was chosen over straight Oblimin or Promax because it aims to maximize load distribution across variables. Varimax is also appropriate for basic factor analysis and is a great general method that facilitates the elucidation of components. [49]. The 16 variables, along with the 119-sample size used in the current study, are considered suitable for factor analysis [50].

3.1.3. Measurement Model

The measurement model discloses the present link between items and their latent structure [51]. The subsequent subsections examined the convergent and discriminant validity of the measurement model in extensive detail.

Convergent Validity

Convergent validity is the level of concordance between two or more measures (benefits) of the same construct (group) [52]. It is known to be a subset of the construct's validity. Using three tests, the convergent validity of the generated constructs in PLS may be assessed [53]: Cronbach's alpha (α) composite reliability scores (ρ_c), and average variance extracted (AVE). Nunnally and Bernstein [54] proposed a ρ_c value of 0.7 as the threshold of 'modest' reliability of the composite. For all types of study, scores over 0.70 and 0.60 for exploratory studies were deemed acceptable. [55]. AVE was the last examination. It is a typical metric used to evaluate the convergent validity of a model's constructs, with values more than 0.50 indicating an acceptable convergent validity [55].

Discriminant Validity

Discriminant validity denotes that the phenomenon being assessed is empirically distinct and shows that no measures can identify the phenomenon being studied in SEM [56]. Campbell and Fiske [57] argued that for discriminatory validity to be proven, the similarity across measures need not be too great.

Structural Model Analysis

The purpose of this research was to model the importance of cyber technology's benefits using SEM. The route coefficients between observed coefficients must be determined for this to occur. In this instance hypothesized one-way causal link (path relation) was proposed between £ (benefits of cyber technology constructs) and μ (benefits of cyber technology implementation). Here, the structural relationship between £, μ, and €1 formula in the structural model, which was identified as the inner relation, may be represented as the following linear Equation (2) [56]:

$$\mu = \beta \text{£} + \text{€}1 \quad (2)$$

where (β) is the path coefficient linking benefits of cyber technology constructs and the residual variance at this structural level is supposed to reside in (€1). Here, β is the standardized regression weight, identical to the β weight of a multiple regression model. Its sign should agree with what the model forecasts and be statistically important. The matter now is how to establish the significance of the path coefficient, β. As with CFA, a bootstrapping technique available in the SmartPLS3.2.7 software was employed to evaluate the standard errors of the path coefficients. This was conducted with 5000 subsamples grounded on a suggestion made by Henseler et al. [36], which in turn defined the *t*-statistics for proposition testing. A total of four structural equations for cyber technology benefits constructs were formed for the PLS Model, representing the inner relations between the constructs and Equation (2).

4. Data Collection and Case Study

To explore the benefits of cyber technology, a broader variety of prospective residential building sector players in the Nigerian construction industry were asked to complete a questionnaire. This survey was composed of three major sections: the respondent's demographic profile, the benefits of cyber technology (Table 1), and the open-ended questions (to add any benefits that the participants considered essential to be identified).

It was necessary to contact contractors, consultants, and clients. They might be further categorised by profession/occupation as follows: quantity surveyors, construction professionals, architects, and engineers. Respondents judged the benefits of cyber technology based on their knowledge and experience using a 5-point Likert scale, with 5 being extremely high, 4 being high, 3 being average, 2 being small, and 1 denoting no or a very small. This scale was used in some previous studies [57–64]. In this study, convenience sampling approaches were used. This is to guarantee that each member has an equal probability of being chosen. Therefore, the sample size was determined using the approach of purposive sampling. Due to the nature of the study, which seeks input from building industry specialists, this is the case. Moreover, the sample size that was used in this study was based on the methodological purpose analysis [65]. Yin [66] advised that the sample size for SEM should exceed 100. Due to the use of the SEM methodology, a total of 98 participants out of 119 were contacted in person (self-administered), yielding an approximate 82% response rate. This rate of return was deemed acceptable for this sort of investigation [67,68].

5. Data Analysis and Results

5.1. Common Method Bias

Common method bias is an error measurement (variance) that compromises the validity of the research. This indicates the systematic error variance of the measured and estimated variables [56]. This may be assessed using Harman's single-factor evaluation of model structures, which reveals different structural measurements [28]. In this research, the single-factor test was utilized to assess the standard method's variance [57]. If the total variance of the components is less than 50%, then the common method bias has no impact on the results [28]. The findings suggest that the first set of components accounts for 34.0% of the overall variance, indicating that the common method variance cannot impact the outcomes since it is less than 50% [28].

5.2. Exploratory Factor Analysis (Questionnaire I)

Utilizing exploratory factor analysis (EFA), the factorability structure of 16 items of the benefits of cyber technology was found. For connection, several well-known factorability characteristics have been used. Kaiser–Meyer–Olkin (KMO) is a factor homogeneity assessment that is often used to ensure that the partial correlations between variables are at their lowest [69]. The KMO index ranges from 0 to 1, with a value of at least 0.6 indicating a successful factor analysis [70]. The Bartlett sphericity test also confirms that the association matrix is the identity matrix, with $p < 0.05$ being statistically significant [71,72].

The KMO and Bartlett tests are shown in Table 2 for the different benefits of adopting cyber technology. The KMO metric shows whether or not the data supplied for the factor analysis are appropriate for the factor analysis. Bartlett's test of sphericity determines whether or not the data under examination are suitable for factor analysis. The KMO coefficient is 0.724 (72.4%) which exceeds the minimum required value of 0.70 (70%). This indicates that the factors or benefits are more than enough for factor analysis. Moreover, the p-value of Bartlett's test of sphericity (0.005) falls within the required 5% significance level of ($p < 0.05$) at a degree of freedom of 102 and an approximate chi-square of 149.825. This demonstrates that exploratory factor analysis is sufficient for the discovered data on cyber technology's benefits. Examining the scree plot in Figure 2 reveals a distinct split at the eighth component. The number of components that should be created by the analysis is denoted by the point on the graph where the slope of the curve is levelling off. Observation reveals the existence of eight categories of components.

Table 2. KMO and Bartlett's test coefficients of the benefits.

Kaiser–Meyer–Olkin (KMO) Measure of Sampling Adequacy.		**0.724**
Bartlett's Test of Sphericity	**Approx. Chi-Square**	149.825
	df.	102
	Sig.	0.005

Table 3 shows the matrices of the eight extracted components about the various identified benefits of cyber technology. The matrices indicate the individual relationship (positive or negative) between each factor and each extracted component. In addition, total variance explained the benefits of cyber technology in the construction industry with the principal component analysis (PCA) extraction method. It reveals the presence of eight components with initial eigenvalues exceeding 1, explaining the 14.23%, 13.92%, 11.85%, 11.05%, 10.78%, 10.69%, 9.94%, and 9.68% variances, respectively (Table 4). Table 5 shows the rotated component matrix of the various benefits of cyber technology adoption in the construction industry. After 21 iterations, the rotation converged with the initial eigenvalues of 1. The highlighted matrices indicate the benefits that have the least variation concerning the initial eigenvalue.

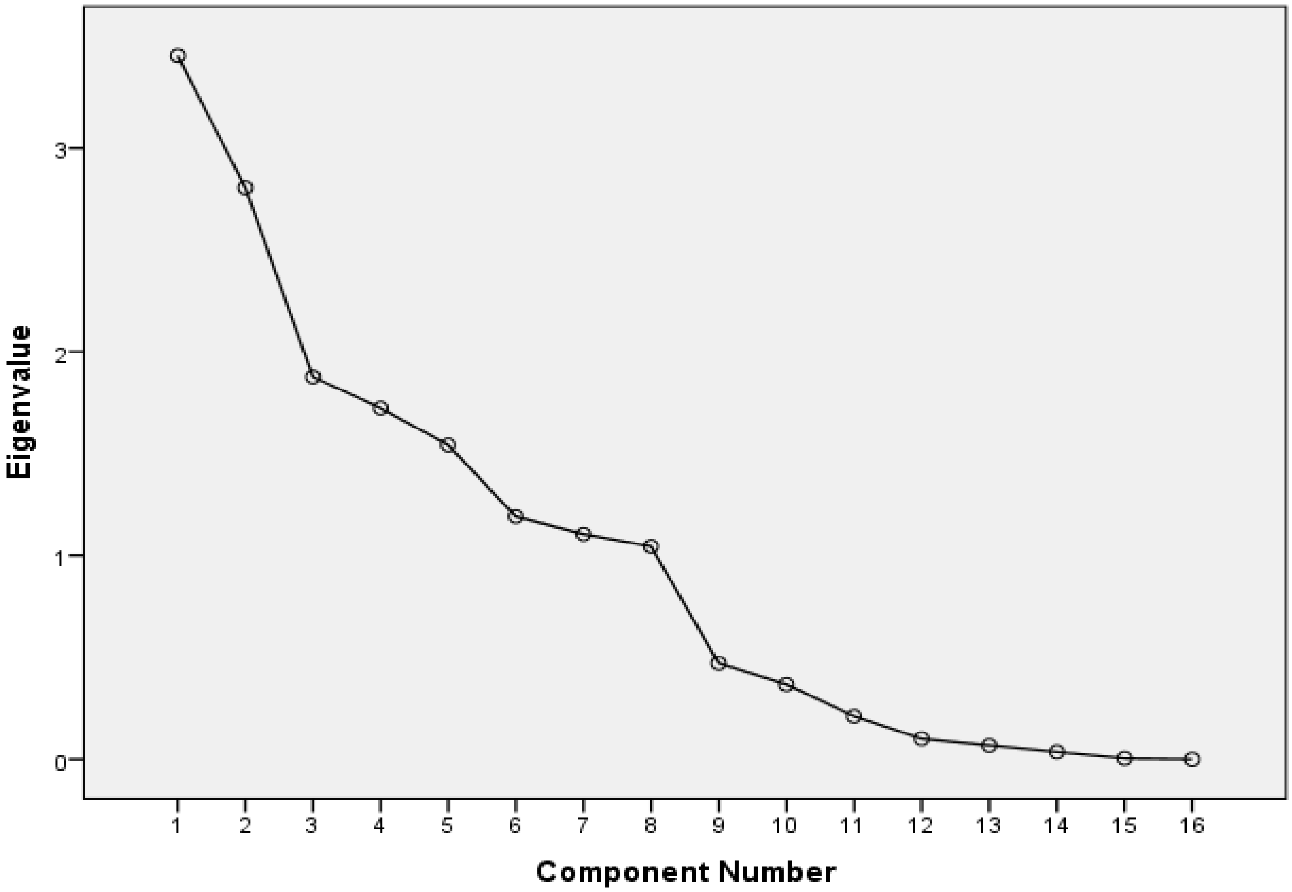

Figure 2. The scree plot of loadings of the benefits of cyber technology in the construction industry.

Table 3. Benefits component matrix.

Benefits	Component							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
F1	0.173	0.182	0.773	0.041	−0.312	−0.307	−0.197	−0.067
F2	0.131	0.389	−0.353	0.637	0.049	0.414	0.101	0.192
F3	0.145	0.059	0.497	0.628	−0.390	−0.165	0.345	0.090
F4	−0.692	0.343	0.314	−0.231	0.249	0.283	0.151	−0.010
F5	−0.706	−0.472	−0.030	−0.250	0.054	−0.036	0.308	−0.190
F6	0.736	−0.492	0.234	0.071	0.219	0.167	0.164	0.005
F7	0.503	0.232	0.092	−0.034	0.563	−0.008	0.174	−0.486
F8	−0.220	−0.453	0.296	0.146	0.371	0.411	−0.258	0.420
F9	−0.446	0.400	−0.319	0.384	0.258	−0.261	−0.438	−0.018
F10	0.477	−0.528	−0.370	0.169	−0.299	0.275	0.173	−0.115
F11	−0.208	0.395	−0.241	−0.420	−0.402	−0.005	0.343	0.446
F12	0.063	0.767	0.291	0.189	0.295	0.084	0.266	0.146
F13	0.621	0.080	0.159	−0.501	0.343	−0.080	0.091	0.365
F14	0.356	0.198	0.241	−0.292	−0.375	0.454	−0.511	−0.036
F15	0.297	0.730	−0.184	−0.217	−0.207	0.294	0.040	−0.334
F16	0.701	0.121	−0.400	−0.071	0.126	−0.413	−0.116	0.258

Extraction Method: Principal component analysis.

Table 4. Benefits total variance explained.

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.453	21.582	21.582	2.277	14.231	14.231
2	2.806	17.536	39.118	2.227	13.919	28.150
3	1.877	11.729	50.847	1.897	11.854	40.004
4	1.723	10.770	61.617	1.767	11.045	51.049
5	1.542	9.639	71.256	1.724	10.778	61.827
6	1.191	7.444	78.701	1.710	10.687	72.514
7	1.105	6.906	85.607	1.590	9.937	82.451
8	1.045	6.529	92.135	1.549	9.684	92.135

Table 5. Benefits' rotated component matrix.

Benefits	Factors	Component							
		1	2	3	4	5	6	7	8
Aids construction planning	F1	0.062	0.209	−0.009	0.034	0.759	−0.369	0.102	0.353
Helps in the storage of construction lifecycle data	F2	0.049	−0.008	−0.146	0.023	0.019	0.946	−0.005	0.011
Increase in quality	F3	−0.087	−0.040	0.133	0.009	0.928	0.253	−0.018	−0.145
Aids project monitoring	F4	−0.551	0.738	−0.065	−0.080	−0.176	−0.047	−0.143	−0.013
Increased collaboration among the professionals	F5	−0.630	−0.032	0.058	−0.124	−0.279	−0.413	−0.152	−0.482
Increased productivity	F6	0.316	−0.277	0.686	−0.244	0.115	0.056	0.473	0.019
Saves a lot of time and cost	F7	0.245	0.278	0.250	0.361	−0.118	0.079	0.741	−0.047
Reduced construction error	F8	−0.158	0.088	0.096	−0.916	−0.114	0.077	0.092	0.068
Increased revenue	F9	0.027	0.179	−0.911	−0.025	−0.112	0.192	0.070	−0.128
Captures challenges in real time	F10	0.024	−0.787	0.422	0.048	−0.074	0.259	0.073	0.000
Cost and time efficiency	F11	0.060	0.230	0.104	0.302	−0.116	0.050	−0.858	−0.015
Maximizes the desired outcome	F12	0.134	0.766	0.006	0.187	0.240	0.444	0.067	0.007
It aids in competitive advantage	F13	0.709	0.312	0.519	−0.050	−0.144	−0.163	0.033	0.119
Improved transparency	F14	0.043	−0.043	0.131	0.036	0.021	−0.033	−0.032	0.946
Information sharing	F15	0.041	0.212	0.043	0.740	−0.143	0.303	−0.007	0.487
It ensures reduced paperwork	F16	0.922	−0.195	−0.010	0.189	−0.087	0.061	0.030	−0.038

Extraction Method: Principal component analysis. **Rotation Method:** Varimax with Kaiser Normalization. Rotation converged in 11 iterations.

Table 6 shows the factors/benefits that share a common attribute concerning the extracted components. Factors with the same/similar extraction coefficients are grouped in the components. Table 7 shows the various groupings of the benefits of the adoption of cyber technology in construction. The benefits are grouped according to the commonalities of their extraction coefficients. On the other hand, the factor loadings indicate the eigenvalues of each factor with the specified eigenvalue of 1. However, all loading factors are more significant than 0.5 except B4, B13, B9, and B16. Consequently, the accepted groups based on EFA analysis on all 16 items is 7, as follows planning, transparency, efficiency, productivity, and quality.

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

Commonalities	
Benefits	**Extraction**
F1	0.892
F2	0.944
F3	0.966
F4	0.908
F5	0.911
F6	0.935
F7	0.912
F8	0.862
F9	0.946
F10	0.861
F11	0.892
F12	0.900
F13	0.966
F14	0.908
F15	0.945
F16	0.930

Extraction Method: Principal component analysis.

Table 7. Component factor/benefits groups.

S/N	Component Factors	Code	Benefits	Factor Loadings
1	Component 1	B1	Aids construction planning	0.759
		B12	Maximizes the desired outcome	0.766
2	Component 2	B3	Helps in the storage of construction lifecycle data	0.946
		B6	Increased collaboration among the professionals	0.068
		B14	Improved transparency	0.946
3	Component 3	B11	Cost and time efficiency	0.602
		B8	Reduced construction error	0.096
		B2	Aids project monitoring	0.738
4	Component 4	B4 *	Saves a lot of time and cost	0.341
5	Component 5	B13 *	It aids in competitive advantage	0.309
		B9 *	Increased revenue	0.192
6	Component 6	B15	Information sharing	0.740
		B7	Increased productivity	0.686
7	Component 7	B16 *	It ensures reduced paperwork	0.322
8	Component 8	B5	Increase in quality	0.928
		B10	Captures challenges in real time	0.522

* These items were excluded due to low-loading.

For the factors determined by EFA, reliability statistics are compiled. Based on the greatest loading of each variable in the structure matrix, variables for each phase of the factor have been established. According to Nunnally [73], for newly formed measurements, an alpha value of Cronbach larger than 0.6 is adequate. In contrast, when the normal value is 0.7, those more than 0.75 are considered to be very accurate. The findings of the alpha Cronbach values are thus suitable since they are more than 0.70. All object average correlations are greater than 0.3, indicating the existence of consistent internal variables [74].

5.3. Measurement Model

Internal reliability, convergent validity, and discriminant validity must be assessed while evaluating reflecting measurement models (CSFs) in PLS-SEM. After establishing the reliability and validity of the measurement model, the structural model will be examined [75]. As illustrated in Table 8, all constructs in the model meet the threshold of α and $\rho_c > 0.70$ and, therefore, are acceptable [76].

Table 8. The result of convergent validity.

Constructs	Cronbach's Alpha	Composite Reliability	AVE
Planning	0.774	0.824	0.701
Transparency	0.701	0.778	0.549
Efficiency	0.761	0.840	0.628
Productivity	0.703	0.869	0.769
Quality	0.725	0.879	0.784

In addition, as shown in Table 4, all structures have passed the AVE test. The appropriate AVE level should be more than 0.5 [53]. Using PLS algorithm 3.0, the estimated AVE values (Table 5) for all components in this investigation are more than 50%. These results indicate that the measurement model is internally convergent and consistent. This shows that the measuring components are appropriately measured for each construct (group) and do not assess any other construct in the study model. High outer loads on a structure suggest a tight connection between the key components of each structure. As a general rule, objects with very low outer loadings (below 0.4) must be routinely removed from the scale [41]. Figure 3 depicts the outside loadings of all measurement models. Consequently, all exterior loads are permitted.

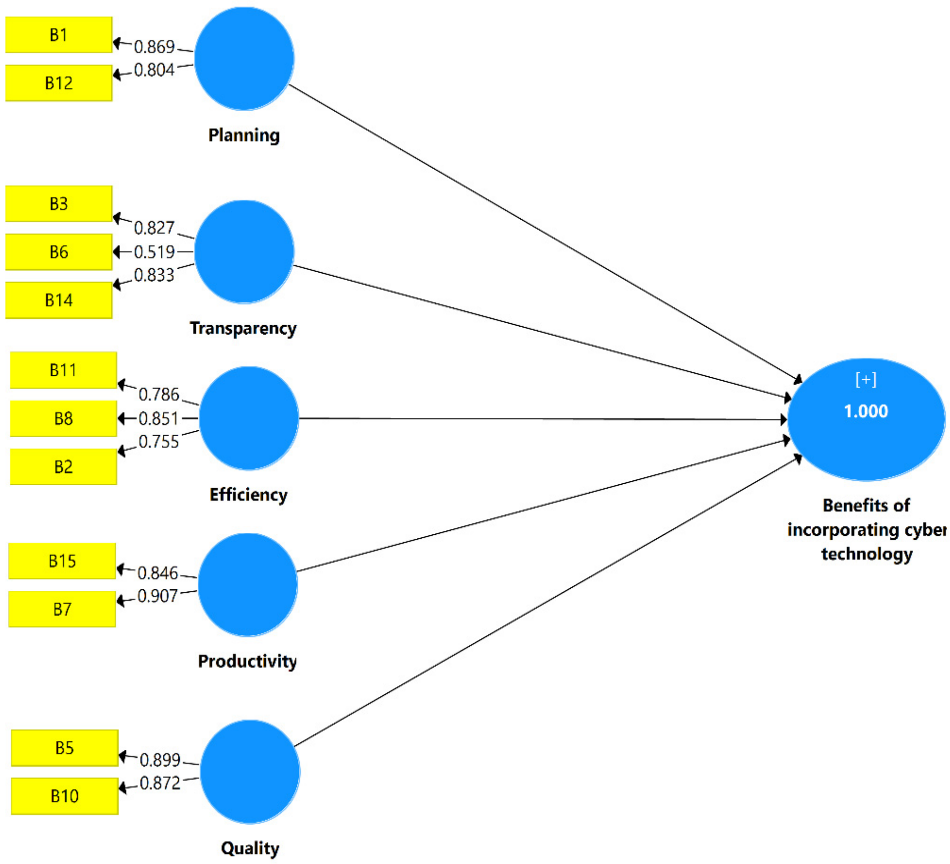

Figure 3. The PLS-SEM model.

The square root of the AVEs (Table 9) exceeded their correlations with all other constructs, indicating that neither construct is associated with the other. In addition, the data suggest that each predictor has the largest loading (Table 9) on the respective construct. Eventually, a high level of unidimensionality may be ensured for each construct.

Table 9. Discriminant validity.

Constructs	Efficiency	Planning	Productivity	Quality	Transparency
Efficiency	0.799				
Planning	0.12	0.837			
Productivity	0.298	0.234	0.877		
Quality	0.247	0.115	0.225	0.885	
Transparency	0.255	0.618	0.383	0.233	0.741

5.4. Path Model Validation

Once it is discovered that the benefits of cyber technology constitute a formative construct, the collinearity among the construct's formative objects is investigated by calculating the value of the variable inflation factor (VIF). All VIF values are substantially below 3.5, indicating that these subdomains separately contribute to the higher-order components. Additionally, the relevance of the route coefficients is predicted using a bootstrapping method. All findings are statistically significant at the 0.01 level for all pathways (Figure 4) [52].

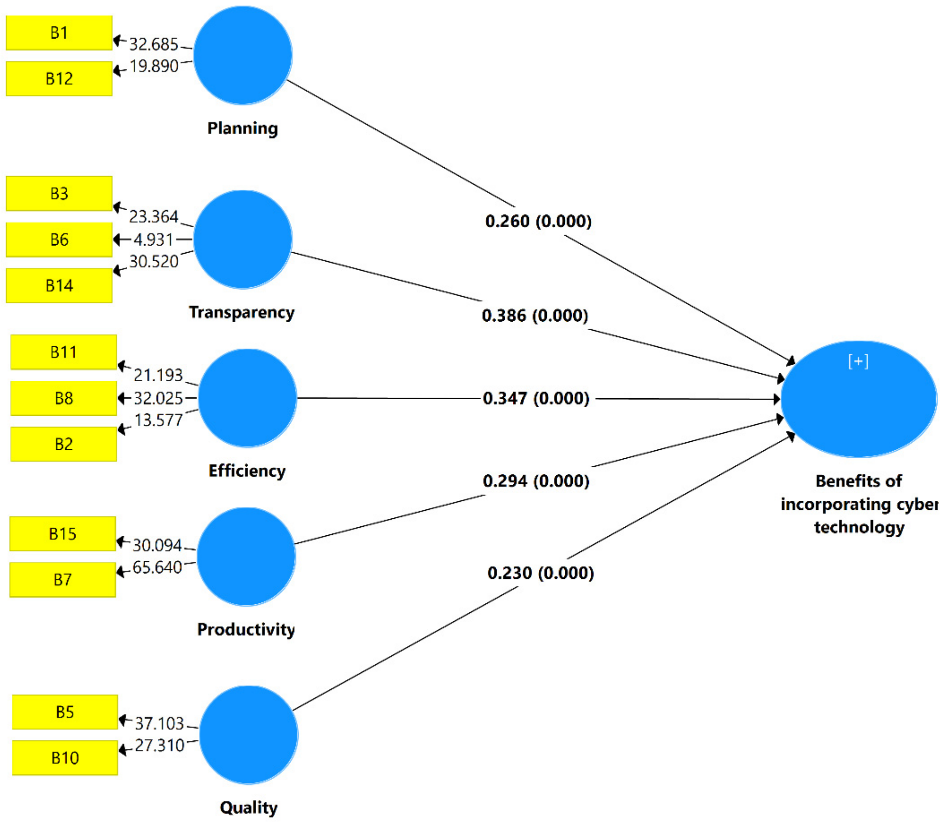

Figure 4. Path model.

6. Discussion

Despite widespread reliance on cyber technology in construction in many industrialised nations, its use in poorer ones is minimal. Nigeria, like many other developing nations, has had challenges and inconsistencies in construction standards. Although it is anticipated that new technologies will have a significant impact on the industry, it is still difficult to assess the implications and potential benefits of cyber technology, as well as its effects on the various stakeholders, critical components of the supply chain, and the various phases of the life cycle of construction projects [77]. This highlights the need for using cyber technology concepts to address these difficulties. Top management's acceptance of cyber technology as an important platform/component of their projects will be greatly influenced by practitioners' understanding of cyber technology and its essential building activities. The suggested model demonstrates that the five cyber technology component benefits have a significant influence on cyber technology deployment. This may improve the viability of residential construction projects. Therefore, by implementing cyber technology, construction companies may save costs and time, as well as improve quality without sacrificing project functions. The next part illustrates how the PLS-SEM model's components may be used to rank the benefits of cyber technology.

6.1. Transparency

The significance of transparency is crucial. The PLS-SEM model suggests that the "transparency" component has the greatest influence on the benefits of cyber technology deployment, with an external coefficient of 0.386. This first primary component includes benefits such as aiding in the storage of construction lifecycle data, increasing professional communication, and enhancing transparency. Given the numerous parties involved in the construction process, Tang et al. [78] asserted that a large storage capacity sensing system is necessary because an as-built documentation system must be able to capture sufficient data or information for facility management as they are generated during the project. In this instance, a mobile PC with an embedded reader might be used to scan the tags for their identifiers, and as-built data could be appended or connected to the scanned component ID [27]. The tag IDs and accompanying information or documentation may be kept in the project database for future querying and reference. Depending on the component being monitored, operating and maintenance data may be included in enormous document files. With technologies such as cyber technologies, intercommunication and cooperation inside and outside the construction industry's specialties are improved [79]. This is a significant improvement in building operations that mostly entail vertical communication [19], but this constrains the amount of progress that can be made on a building project. There is an evident need for efficiency in managing the building process, and cyber technologies provide possibly the finest opportunity to enhance the construction process via improved integration and transparency [18]. This justifies its inclusion in the building processes [80].

6.2. Efficiency

The second major component relates to "efficiency". It includes benefits such as cost and time savings, reduced construction errors, and assistance with project monitoring. With an external coefficient of 0.347, the effect of "efficiency" on the benefits of cyber technology seems to be significant. This indicates that the success rate of deploying cyber technology is greater than the average (medium–high level). An important feature of construction delivery is the capacity to deliver building products on schedule and within budget [81]. Using cyber technology, this can be accomplished. According to Onyegiri et al. [25], cost and time efficiency are key benefits of building technology. Accuracy and efficiency are the primary objectives of integrating technology into building [31]. By simplifying building procedures to well-defined protocols, cyber technologies offer significant assistance to the accomplishment of this purpose. This minimizes the typical number of process mistakes [25]. In addition, on the topic of whether or not the prototype enhances progress monitoring, the evaluators praised the prototype systems and compared them favorably to the current manual method of providing status updates [27]. Nonetheless, a few of the assessors recommended more research into how to determine whether the installed components are genuinely in place, as opposed to just being in the correct spot (e.g., bolted or attached to the connecting member as in the case of steel placement). According to Bosche and Haas [82], there are already sensors that can monitor various placement scenarios (such as steel installation); hence, it may be preferable to employ placement sensors, since this will assist in determining whether components are positioned adjacently. The problem with this sort of sensor is that it only monitors one variable [25].

6.3. Productivity

The third major component relates to "productivity". On the scale of cyber technology adoption benefits, this factor, which includes benefits such as information exchange and increased productivity and has an external coefficient of 0.29 and ranks third. According to Sabol (2007), the deployment of cyber technology has led to a rise in productivity. This is shown by the different achievements and developments made by individuals who have accepted this evolutionary innovation. In addition, the productivity of works has increased dramatically in comparison to earlier building methods [25]. Construction operations before the present make knowledge exchange among construction experts very difficult [26]. As a result of the intrinsic characteristics of cyber technologies, the use of cyber technologies facilitates the exchange of information among experts [83].

6.4. Planning

The fourth subscale on the scale of cyber technology adoption benefits relates to "planning". Externally, it has a coefficient of 0.260. This includes benefits such as facilitating construction planning and optimising the intended output. The use of cyber technology in building planning and forecasting is also possible. Multiple construction sites may utilize RFID technologies (e.g., ultra-wideband, chirp spread spectrum), GPS and image-based technologies to collect near misses, close calls, the resources involved, and the site layout [34]. In the project planning phase, these data may be utilized to construct a generalised model that can be optimized to provide dependable and safety-conscious site layout designs [24]. This sort of CPS application promotes the continual collection and analysis of construction data to inform or enhance the planning phase of construction. The cyber–physical systems approach will increase progress monitoring, construction process control, as-built documentation, and environmentally responsible building practices [79]. Akanmu et al. [23] assessed that the output, which is the implementation of the design via efficient construction and maintenance, had been realized in full.

6.5. Quality

"Quality" is the final subscale on the scale of benefits for the deployment of cyber technology. Externally, it has a coefficient of 0.260. This includes benefits such as enhancing the quality and capturing issues in real-time. Cyber technologies improve upon conventional building techniques [23]. Traditional building methods have their drawbacks and downsides. According to Bhave et al. [24], cyber technologies enhance the quality of building processes and products. This is a significant advantage of the invention. Cyber technologies are very vital to the building sector [84]. According to You and Wu [19], it provides a potential for real-time, seamless information flow between the design and construction teams, allowing for swift decision-making in the construction industry.

7. Managerial Implications

Some important "signs" may be generated by reorganizing the benefits of cyber technology implementation. Building stakeholders may find these "signs" helpful in efficiently implementing cyber technology in their projects. Furthermore, this reorganization may be useful for developing a benchmark from which construction players can systematically and efficiently introduce cyber technology. Such a framework may play a significant role in the benefits identified in this study. This, we believe, will enhance productivity and sustainability in the Nigerian construction industry and other developing countries.

By addressing these benefits, stable, sustainable, and efficient construction can be attained within the Nigerian construction industry. Moreover, as most developing countries have similar construction practices, the results presented in this study may also catalyze the adoption of cyber technology in other developing countries. By extension, the reduction in project time and cost can translate to more success in the building industry when robotics is implemented. Notwithstanding the aforementioned gains, this study specifically contributes to knowledge in the building industry in the following ways:

- A database of the benefits of the implementation of cyber technology and its different components has been presented;
- Building owners and other key players in the building industry are offered a robust platform for assessing cyber technology implementation to enhance the planning and execution of building projects;
- A sound scientific proof that provides adequate guidance on the adoption of cyber technology in Nigeria and other developing countries is showcased;
- Most research efforts have been devoted to the implementation of construction cyber technology in developed nations. However, very limited studies are available for developing nations such as Nigeria. Therefore, our study has assessed the benefits of the implementation of cyber technology in Nigeria and the attendant benefits of enhancing the quality of local projects. Moreover, our study also highlighted the benefits of cyber technology, prominently minimizing construction costs, and efficient cost-spreading to make projects more profitable and successful;
- A partial least square (PLS-SEM) prediction technique is proposed for assessing the implementation of cyber technology in the Nigerian construction industry and other developing countries. Therefore, decision-makers can rely on the results provided here to deploy robotics.

8. Theoretical Implications

The application of cyber technology for enhancing a project's success is increasingly becoming popular in many enterprises. In the context of the Nigerian construction sector, our study has been able to provide a model to assess the benefits of implementing cyber technology. Furthermore, the different benefits of applying cyber technology are also analyzed. Likewise, our study provides an important link between the theoretical and practical applications of cyber technology. Therefore, our study is the first to have analyzed and assessed the various benefits of the implementation of cyber technology in the Nigerian construction sector. Furthermore, this study lays a good foundation for further research studies in assessing the benefits of the implementation and adoption of cyber technology in similar developing countries. With the comprehensive theoretical and mathematical analysis presented, the PLS-SEM technique has been applied to identify the five most important components of these benefits. Finally, the foundation laid in this study can be useful for policymakers in mapping out strategies for incorporating robotics into construction.

9. Conclusions

In a great number of nations, cyber technology is seen as a highly beneficial instrument for maximizing monetary value and boosting the goals and sustainability of a project. In contrast, the use of cyber technology in emerging nations is quite limited. Similar to several other emerging nations, Nigeria has seen disparities and anomalies in the quality of housing, especially large-scale projects. Cyber technology is suggested as a remedy for this issue. Therefore, this research has used SEM to estimate the importance of cyber technology's benefits. EFA analysis has been applied to the identified benefits of cyber technology found via a literature study. The model is then experimentally validated using the PLS-SEM approach and data from 97 Nigerian construction industry experts. The model's outputs will serve as a guide for construction experts in Nigeria and other poor nations in cutting costs and improving sustainability via the use of cyber technologies by identifying the most important benefits.

Author Contributions: Research Idea: A.F.K. Conceptualization, A.F.K.; methodology, A.F.K.; software, A.F.K.; validation, A.F.K.; formal analysis, A.F.K.; investigation, A.F.K.; resources, all authors.; data curation, all authors.; writing—original draft preparation, A.F.K.; writing—review and editing, all authors.; visualization, all authors.; supervision, A.F.K.; project administration, A.F.K.; funding acquisition, all authors. All authors have read and agreed to the published version of the manuscript.

Funding: This study is supported via funding from Prince Sattam bin Abdulaziz University project number (PSAU/2023/R/1444).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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