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The Challenges of Implementing Cognitive Computing in Small Construction Projects: A Data-Driven Perspective

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Abstract

This study aims to identify and analyze the challenges of implementing cognitive computing in small construction projects, where decision-making, process optimization, and sustainability enhancements are crucial yet challenging. The research adopts a mixed-methods approach, integrating a thorough literature review, quantitative evaluation, and structural equation modeling (SEM) to explore the relationships between the identified barriers and the effective application of cognitive computing. The findings reveal significant hurdles, including complexity in customization ($\beta = 0.327$, $t = 9.848$, $p < 0.001$), data integrity and integration issues ($\beta = 0.389$, $t = 14.534$, $p < 0.001$), financial and cultural constraints ($\beta = 0.295$, $t = 7.850$, $p < 0.001$), and ethical and privacy concerns ($\beta = 0.319$, $t = 8.963$, $p < 0.001$). These barriers impede the seamless adoption of cognitive computing technologies. This research contributes novel insights into the specific challenges faced by small construction projects and provides practical recommendations to overcome these obstacles. By addressing these challenges, this study offers valuable guidance for stakeholders aiming to leverage cognitive computing to improve project outcomes in the construction industry. The novelty of this research lies in its focus on small-scale projects, a relatively underexplored area, and its comprehensive analysis of the multifaceted barriers that hinder the successful implementation of cognitive computing.

Keywords: Cognitive Computing; Economics; Sustainability; Construction; Small Construction.

1. Introduction

Cognitive computing is a promising technology that has the potential to revolutionize the construction industry by enhancing decision-making, optimizing processes, and enhancing overall project outcomes. However, effective cognitive computing implementation in modest construction initiatives presents unique challenges that must be addressed [1]. Small construction projects typically need more resources and encounter obstacles when implementing cognitive computing. According to industry statistics, a significant portion of the construction industry comprises minor construction initiatives. In the United States, minor construction enterprises account for approximately 99 percent of the industry [2]. These initiatives frequently have limited budgets, personnel, and time, making it difficult to surmount the

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initial costs associated with cognitive computing implementation. According to research, construction projects generate immense data, but their management and utilization could be more efficient [3]. In modest construction projects, limited data sources, inconsistent data collection methods, and shortened project durations can inhibit the availability of high-quality data necessary for cognitive computing systems. Studies indicate that data quality issues impact between 30 and 40 percent of construction projects, which can compromise the efficacy and dependability of mental models.

In addition, the technical knowledge required to implement cognitive computing successfully can hinder smaller construction projects. According to a survey conducted by industry specialists, approximately 70% of construction companies need help to locate professionals with the necessary artificial intelligence and machine learning skills [4], [5]. Small initiatives may need more resources to employ or train personnel with the specialized cognitive computing knowledge required for implementation [6]. Important considerations also include cultural factors such as resistance to change. According to a study conducted by a construction research institute, approximately sixty percent of construction professionals view resistance to change as a significant barrier to implementing new technologies. To successfully implement cognitive computing in modest construction projects, overcoming cultural obstacles and nurturing an innovative and receptive culture are crucial [7, 8].

Integration complexity exacerbates the difficulties encountered by tiny construction initiatives. According to research, approximately forty percent of construction companies need help incorporating various software tools and systems [9, 10]. This complexity is amplified in small initiatives with limited technical knowledge and resources, hindering the seamless integration of cognitive computing technologies. To overcome these obstacles, a comprehensive comprehension of the unique barriers encountered by minor construction projects and the development of tailored strategies are required [11]. By overcoming these obstacles, modest construction projects can leverage the benefits of cognitive computing, thereby enhancing decision-making, boosting productivity, and attaining superior project outcomes.

This manuscript addresses a cavity in the literature by investigating the obstacles to implementing cognitive computing in the context of minor construction projects. In addition, it contributes to the literature by employing an in-depth methodology based on structural equation modeling (SEM) to analyze the complex relationships between the barriers and their influence on the successful implementation of cognitive computing in minor construction projects. Prior research examined the difficulties in applying cognitive computing to the construction industry, but relatively little attention has been paid to small-scale building projects [2]. This paper takes a fresh look at the limitations and problems encountered by small-scale construction projects when employing cognitive computing technologies. This paper employs structural equation modelling (SEM) to investigate the connections between the identified obstacles and their influence on the effective implementation of cognitive computing in minor construction projects. Utilizing SEM permits a systematic investigation of the interdependencies and complex dynamics among the obstacles, yielding significant insights into the underlying factors that drive the adoption and integration of cognitive computing technology.

This paper fills in these gaps in the literature by providing insightful analyses of the specific obstacles faced by small construction projects, as well as a sound technique for understanding the complex interactions between these obstacles. The findings of this study will facilitate the successful implementation of cognitive computing technologies by contributing to the development of targeted strategies and practical recommendations for stakeholders involved in minor construction projects. The remainder of this article is organized as follows: Section 2 provides a comprehensive review of the literature related to cognitive computing in construction, highlighting the key challenges and gaps in existing research. Section 3 outlines the research methodology, including the mixed methods approach and the application of structural equation modeling (SEM) to analyze the data. Section 4 presents the results of the study, focusing on the identified barriers to cognitive computing implementation in small construction projects. In Section 5, the findings are discussed in the context of existing literature, with an emphasis on practical implications and strategies for overcoming the challenges identified. Finally, Section 6 concludes the article by summarizing the key contributions of the research, addressing its limitations, and suggesting directions for future studies.

2. Literature Review

Various studies have explored the use of cognitive computation in the construction sector and found various challenges to its general acceptance. While these research findings provide insightful information, it is vital to look at the obstacles to the use of cognitive computing in small-scale building projects [12, 13]. This section surveys related work and identified the most significant obstacles to minor construction undertakings. Previous research has highlighted the potential and benefits of cognitive computing in the construction industry, including enhanced decision-making, safety, and productivity. However, little attention has been paid to the unique obstacles that modest construction projects confront when employing cognitive computing technologies [14, 15]. The literature identifies limited resources, including financial constraints, inadequate infrastructure, and a need for qualified personnel, as a common barrier. Small construction projects frequently have limited budgets, making allocating funds for cognitive computing implementation's initial costs difficult [16]. In addition, modest initiatives may need more technical expertise to create and maintain cognitive computing systems [17, 18]. The accessibility and integrity of data have also been identified as significant obstacles. Construction projects generate vast data, but their management and utilization could be more efficient. Accessing diverse and high-quality data may be difficult for small construction projects due to limited project duration, inconsistent data acquisition methods, and data divisions within the organization [19].

Ethical and privacy considerations are crucial in the implementation of cognitive computing. A survey conducted by an association for the construction industry reveals that 80% of construction professionals are concerned about the potential misuse or mistreatment of sensitive data in cognitive computing [20]. Establishing robust data privacy practices and resolving ethical data management and security concerns can be complex for small construction projects. Ensuring data privacy, complying with regulations, and addressing ethical concerns are essential, but minor construction projects may need more resources and knowledge to establish robust data privacy practices. Economic factors, such as the difficulty of demonstrating a clear return on investment (ROI), can hinder the implementation of cognitive computing in minor construction initiatives [21, 22]. Especially for minor initiatives with limited data and resources, quantifying the financial benefits and measuring the impact on project outcomes are complex tasks. In the construction industry, cultural factors, such as resistance to change, have been identified as barriers to technology adoption. This includes minor construction projects in which a conservative culture and skepticism towards new technologies may impede the adoption and incorporation of cognitive computing [23].

Integration complexity is an additional substantial barrier. Small construction projects frequently employ diverse software tools and platforms, making integrating cognitive computing systems difficult. More technical knowledge and assets are needed to complicate the integration procedure [24, 25]. Minor construction project stakeholders can develop targeted strategies and interventions to surmount these obstacles by identifying and comprehending them. In the context of little construction projects, addressing these obstacles will contribute to successfully incorporating and integrating cognitive computing technologies, enhancing decision-making, increasing efficiency, and attaining improved project outcomes. Table 1 presents the identified factors considering barriers to adopting cognitive computing in small construction projects.

Table 1. Identified factors considering barriers to adopting cognitive computing in small construction projects

Category	Code	Description	References
Complexity and Customization	CC-CC1	Complex integration with existing workflows and project management systems.	Fernando & Bandara (2022) [22]; Waqar et al. (2023) [23]
	CC-CC2	Customizing cognitive solutions to specific project specifications.	Manshahia et al. (2022) [20]; Waqar et al. (2023) [21]
	CC-CC3	Insufficient data accessibility and difficulties in ensuring data quality.	Waqar & Almujibah, (2023) [17]; Xu et al. (2020) [19]
Limited Data Availability	CC-LA1	The limited volume of available data hinders the system's capacity to learn and produce precise insights.	Koc et al. (2020) [15]; Waqar et al. (2023) [18]
	CC-LA2	The limited availability of historical data hinders the system's ability to make accurate predictions.	Li et al. (2018) [13]; Dushkin & Mohov (2021) [14]
	CC-LA3	Cognitive models are unreliable when based on inconsistent or insufficient data.	Griffin (2019) [11]; Ustun et al. (2018) [12]
Data Quality and Integration	CC-DI1	More data quality results in reliable insights and accurate forecasts.	Li et al. (2022) [8]; Sánchez et al. (2020) [7]
	CC-DI2	Inconsistent data sources and formats impede integration and analysis.	Chen et al. (2018) [9]; Martínez (2021) [10]
	CC-DI3	More accurate or adequate data is needed to maintain the dependability and efficiency of cognitive computing models.	Behera et al. (2022) [5]; Chen et al. (2020) [6]
Ethical and Privacy Concerns	CC-EP1	Noteworthy is the protection of data privacy and compliance with privacy regulations.	Gunasekhar & Teja (2021) [4]; Waqar et al. (2023) [26]
	CC-EP2	Establishing explicit data ownership and obtaining consent can be challenging in modest construction endeavors.	Caputo (2023) [27]
	CC-EP3	Transparency and explainability of cognitive computing models are crucial but can be challenging to achieve in modest initiatives.	Wang (2021) [2]; Waqar et al. (2023) [28]
Economic and Culture	CC-EC1	Budgetary and material constraints impede the allocation of funds for cognitive computing implementation.	Fernando & Bandara (2022) [22]; Manshahia et al. (2022) [20]
	CC-EC2	In modest construction initiatives, it can be challenging to demonstrate a distinct return on investment (ROI) for cognitive computing.	Behera et al. (2019) [23]; Waqar et al. (2023) [29]
	CC-EC3	A risk-averse culture may inhibit the adoption of new technologies, such as cognitive computing.	Behera et al. (2019) [29]; Johnson et al. (2021) [30]
Scalability and Integration	CC-SI1	Resource constraints limit the viability of minor construction initiatives.	Kajić et al. (2019) [31]; Waqar et al. (2023) [24]
	CC-SI2	Integration difficulties between cognitive computing systems and existing project management and workflows.	Mutis et al. (2018) [32]; Rawung & Poai (2023) [33]
	CC-SI3	Difficulties associated with assuring data compatibility and seamless data integration.	Manshahia et al. (2022) [20]; Xu et al. (2020) [19]

2.1. Integration of Cognitive Computing in Construction: A Literature Overview

Cognitive computing has shown tremendous potential in transforming various aspects of the construction industry, particularly in enhancing decision-making, optimizing processes, and improving overall project outcomes [34, 35]. While the benefits of cognitive computing are well-documented, most existing studies have primarily focused on large-scale projects [36]. This emphasis leaves a significant gap in understanding the challenges faced by small-scale construction projects [37]. Addressing this gap is crucial, as these smaller initiatives often operate under different constraints, such as limited resources and tighter timelines [38]. This research seeks to explore these specific challenges and provide insights into how cognitive computing can be effectively integrated into small construction projects.

2.2. Identifying Gaps in Existing Research

The literature on cognitive computing in construction has extensively discussed its potential advantages, including improved safety, productivity, and efficiency in project management [39]. However, there is a lack of focused research on the unique obstacles encountered by smaller construction projects [40]. Challenges such as data quality, integration issues, and ethical concerns have been identified in broader studies, yet these challenges manifest differently in smaller projects, where resource limitations are more pronounced [41]. The complexity of integrating cognitive computing into existing workflows in small construction projects requires further investigation. This study aims to fill this research gap by providing a detailed analysis of these challenges and offering tailored solutions.

2.3. The Need for Focused Research on Small Construction Projects

Small construction projects represent a significant portion of the industry but often face distinct challenges compared to larger projects [42]. These projects typically operate with constrained budgets, shorter timelines, and less access to specialized expertise, making the implementation of advanced technologies like cognitive computing particularly difficult [43]. Despite the recognition of these challenges, much of the existing research has not differentiated between the needs of large and small projects [44]. There is a need for a more focused examination of how small projects can overcome the barriers to cognitive computing implementation. This research contributes to this area by exploring the specific needs and challenges of small construction projects and proposing strategies to address these obstacles.

2.4. Addressing the Research Gap

The current body of research provides a comprehensive overview of cognitive computing’s potential in the construction industry but often overlooks the unique challenges faced by small construction projects [45]. Given the prevalence of small projects within the industry, this oversight is significant [46]. The present study addresses this gap by focusing on the challenges and barriers specific to small-scale construction projects. Through a detailed examination of these issues and the application of a mixed-methods approach, including structural equation modeling, this research offers valuable insights and practical recommendations that are specifically tailored to the context of small construction enterprises.

3. Research Methodology

This investigation consists of three main phases. The first phase entails conducting a literature review to identify the most significant obstacles to implementing cognitive computing in minor construction projects. In the second phase, quantitative analysis and hypothesis testing are performed to investigate the relationships between the identified barriers and their influence on the successful adoption of cognitive computing [47]. The final phase employs structural equation modeling to validate the hypothesized relationships and gain a deeper understanding of how the barriers interact and influence the implementation of cognitive computing in minor construction projects [18]. Figure 1 is a flowchart depicting the sequential progression of the study through these three phases.

3.1. Main Questionnaire Development and Data Collection

A questionnaire was created to quantify cognitive computing implementation difficulties in modest construction projects. The questionnaire was carefully constructed to gauge the identified impediments on a 5-point Likert scale from strongly disagree to agree strongly. 230 questionnaires were sent to respondents and personally given to construction experts [20]. The response rate is the number of valid replies per total surveys issued. The 230 surveys yielded 103 helpful replies, a 44 % response rate [25]. The sample size of 103 respondents is suitable for this study since it matches past cognitive computing implementation research in the construction sector [20, 21]. These studies show that 100-200 respondents are sufficient for examining study objectives-related correlations and trends. Respondents may rate each obstacle on a 5-point Likert scale in the questionnaire. This approach allowed quantitative analysis and hypothesis testing by quantifying answers on a standardized scale [23, 24]. The proposed technique draws on past research in the field.

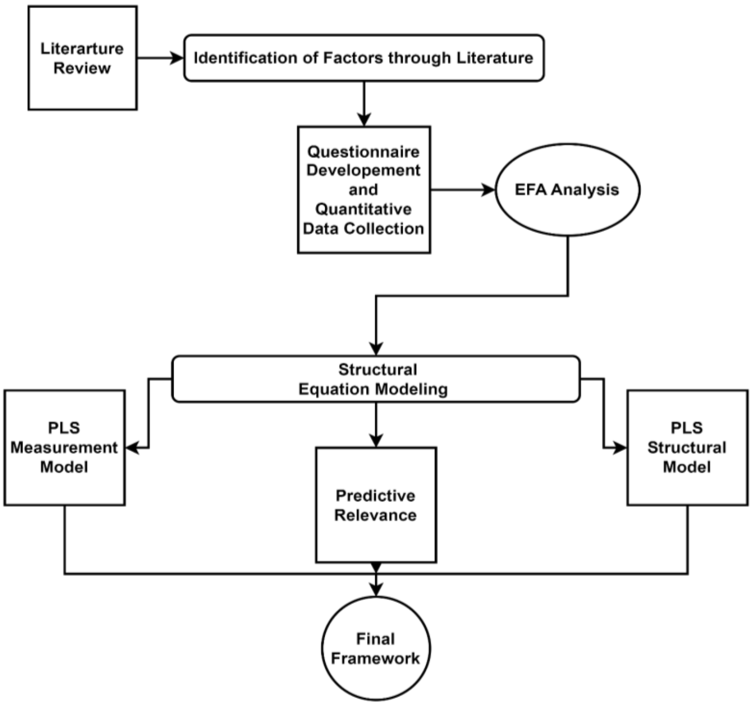

Figure 1. Flow chart of the study

3.2. Data Collection Process

Sample Size and Selection Criteria:

The data collection process for this study involved distributing a structured questionnaire to professionals working in the construction industry. The target population consisted of individuals involved in small construction projects, including project managers, engineers, architects, and other stakeholders. A total of 230 questionnaires were distributed, and 103 valid responses were collected, resulting in a response rate of approximately 44%. The sample size of 103 respondents is consistent with similar studies in the field, providing sufficient data for the quantitative analysis and hypothesis testing. The selection criteria for participants were based on their involvement in small construction projects, with an emphasis on those who had experience or familiarity with the challenges of implementing cognitive computing technologies.

Questionnaire Design:

The questionnaire was carefully designed to capture the various barriers and challenges associated with cognitive computing implementation in small construction projects. It was divided into several sections, each focusing on different aspects such as complexity and customization, data quality and integration, financial and cultural constraints, and ethical and privacy concerns. Each item in the questionnaire was measured using a 5-point Likert scale, ranging from "strongly disagree" to "strongly agree." This approach allowed for the quantification of respondents' perceptions and provided a standardized method for evaluating the identified barriers.

Quantitative Evaluation Methods:

The quantitative evaluation was conducted using a combination of exploratory factor analysis (EFA) and structural equation modeling (SEM). These methods were chosen for their ability to identify underlying relationships between observed variables and to validate the hypothesized relationships between barriers to cognitive computing implementation.

3.3. Validation and Reliability of the Survey Instruments

During and after the data collection phase, several measures were implemented to ascertain the validity and dependability of the survey instruments employed in this inquiry. Initially, the questionnaire was developed with the assistance of industry experts and after a comprehensive review of the existing literature. An exclusive subset of construction industry experts, not comprising the primary study population, engaged in an experimental testing phase to evaluate this initial iteration. To ensure the content's veracity, the pilot test's responses were incorporated into the queries to enhance their lucidity, comprehensiveness, and relevance. In addition, to evaluate the dependability of the survey instruments, we calculated the Cronbach's alpha coefficient for the questionnaire items that pertained to each identified obstacle to the deployment of cognitive computing. As a rule, Cronbach's alpha values of 0.7 or greater are considered adequate indicators of the dependability of an internal consistency measure. It was extremely important to ensure that the components of each scale consistently assessed the same construct. As an extension of the reliability analysis, the internal consistency of responses was verified by recalculating Cronbach's alpha for the entire dataset after data collection. In addition, an examination was conducted on item-to-total correlations to identify any items that exhibited weak correlations with the overall scale. Such correlations would indicate potential issues with the questions' relevance or the respondents' comprehension. The exhaustive process of validation guarantees the validity and reliability of the survey instruments, so augmenting the credibility of the study's outcomes. By adhering to rigorous methodological principles and addressing specific concerns related to the reliability of survey instruments and the design of questionnaires, this study establishes a solid foundation for subsequent investigations concerning the obstacles posed by cognitive computing in small-scale building projects.

3.4. EFA Analysis

Exploratory Factor Analysis (EFA) was used to evaluate data and identify impediments to cognitive computing deployment in modest construction projects. EFA is a statistical method for finding hidden components that explain observed variable correlations. EFA determined the obstacles' factor structure using questionnaire answers. Principal component and common factor analyses were used to analyze the obstacles' interrelationships [25, 30]. EFA extracted factors using eigenvalues, factor loadings, and variances explained. Eigenvalues and factor loadings show how much variation each element explains. Eigenvalues larger than 1, scree plot analysis, and theoretical considerations determined the number of retained components. Based on high-factor loading items, the factors were labeled and interpreted. This method revealed cognitive computing implementation obstacles in modest building projects [31, 33]. This research used EFA to examine the factor structure of the barriers and their interactions and patterns. The EFA analysis helped with hypothesis testing and exploring the factors' connections with other variables. In conclusion, the EFA analysis used in the methodology identified the underlying issues and structures that hinder cognitive computing application in small construction projects.

3.5. PLS Measurement Model

The suggested model was tested using SmartPLS 4 and Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM can analyze complicated latent construct-observed variable connections. PLS-SEM examined convergence and discrimination. Convergent validity assesses how well the model's construct elements represent a shared notion. Each construct's factor loadings, AVE and CR, were examined [22, 32]. Factor loadings show the strength of the association between items and their construct, AVE measures the variation contained by the construct, and CR evaluates item internal consistency. Discriminant validity measures how different conceptions are. The square root of the AVE was compared to create relationships. Discriminant validity is demonstrated if the square root of the AVE for each concept exceeds its correlation with other constructs [17, 19]. SmartPLS 4 PLS-SEM study assessed convergent and discriminant validity. The factor loadings, AVE, CR, and construct correlations revealed the model's constructs' reliability and uniqueness. Convergent and discriminant validity in the PLS-SEM analysis ensures that the measurement model is trustworthy, and the constructs differ, making the research more robust [30, 31]. This approach verifies data veracity and quality, boosting research credibility. To ensure methodological transparency, the SEM was conducted using a two-step approach. Initially, a measurement model was established to validate the reliability and validity of the constructs. Subsequently, a structural model was developed to examine the relationships between the barriers and cognitive computing implementation. The model specifications included the assessment of model fit using indices such as the Chi-square/df ratio, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA). Diagnostics were performed to assess the robustness of the statistical analysis, ensuring that the findings are reliable and valid indicators of the barriers' impacts on cognitive computing implementation in the construction industry.

3.6. PLS Structural Model

In addition to EFA and PLS-SEM, a structural model analysis was performed. The bootstrap analysis tested the study's five hypotheses in structural model analysis. Bootstrap methodology resamples the dataset to estimate model parameter standard errors and significance levels. The procedure generates bootstrap samples to estimate model parameters and test hypotheses. Bootstrap analysis calculated each hypothesis's O, M, STDEV, t-statistics, and p-values [24, 25]. The sample means, and standard deviation are determined from the resampled bootstrap datasets, whereas the original sample value is the dataset estimate. To evaluate the estimated coefficients, t-statistics, and p-values were calculated. T-statistics show the ratio of the estimated coefficient to its standard error, and p-values indicate the likelihood of receiving a value as extreme as the observed estimate under the null hypothesis. This determines the model variable associations' relevance. This research used bootstrap analysis to test hypotheses [17, 20]. The study estimated standard errors, calculated t-statistics and p-values, and assessed structural model linkages. The bootstrap technique improves hypothesis testing's validity and reliability, offering a firm statistical basis for evaluating data and forming conclusions.

3.7. Predictive Relevance

Predictive relevance (Q^2) was examined with structural model analysis. Q^2 compares the model's endogenous components' predictive performance to a simple mean to assess its predictive power and relevance. Each endogenous construct's Q^2 value represents the model's exogenous constructions' variance explanation [23, 25]. It shows the model's predictive power. The model captures variable correlations and makes meaningful predictions if Q^2 is high. Q^2 assessed the structural model's predictive value in explaining endogenous construct variance. The simple mean model, which assumes the mean of the dependent variable is the best predictor, was compared to the Q^2 data. Structural models have higher Q^2 values than simple mean models, indicating more incredible predictive performance. Q2's assessment helps cognitive computing in small construction projects forecast outcome characteristics [30, 31]. It assesses the model's prediction capability and helps evaluate the practical importance of the structural model's linkages. This research investigates the variables' correlations and the model's practical significance in predicting and explaining the outcomes of interest by examining Q^2.

4. Results and Analysis

4.1. Demographic Details

This study's demographics include participants' education, age, professional experience, and vocations. 27% have a Bachelor's degree, whereas 49% have a Master's. 9% have PhDs, and 15% have other degrees. Participants' ages vary. 31% are 26–30, and 28% are 31–35. 9% of participants are over 40, 15% are 21–25, and 17% are 36–40. Professionally, the participants vary. 26% had 0-5 years of experience, 28% had 5-10 years, and 26% had 11-15 years. 10% of participants have 16-20 years or more of experience. 53% of participants are civil engineers, followed by 18% architects. Safety managers make up 3%, project managers 14%, and others 12%. The biggest professional experience category is 34%, with 11-15 years. 31% and 13% have 5-10 and 16-20 years of experience. 16% and 6% of participants are under 5 and over 20 years old, respectively. This study's participants are varied in education, age, professional experience, and vocation, offering a broad view of cognitive computing deployment in modest construction projects (See Figure 2).

Figure 2. Demographic details respondents

4.2. Exploratory Factor Analysis

Table 2 shows the item-underlying factor connection strength. EFA factor loadings indicate each item's importance with the specified factors. In Table 2, most items have factor loadings over 0.6, showing a strong link with their factors. CC-CC1 is strongly associated with Factor 1 (Cognitive Computing - Critical Challenges) with a factor loading of 0.917. CC-LA1, CC-LA2, and CC-LA3 had high factor loadings of 0.902, 0.845, and 0.795, demonstrating a significant association with Factor 2 (Cognitive Computing - Limited Availability). Two variables, CC-EP3 and CC-EC3, did not fulfill the minimal threshold and were eliminated from further study. Low factor loadings or cross-loading errors imply a weak or inconsistent link with any specified factor. EFA factor loadings reveal the intensity and direction of item-factor correlations. The item is a good predictor of the factor if its factor loading is high [17, 19]. These findings help identify and evaluate cognitive computing implementation hurdles in small construction projects. Factor loadings are essential for assessing item relevance to factors. EFA analysis uses a minimum threshold of 0.6 to confirm that the chosen items have a significant association with their factors and are trustworthy indicators of the obstacles under examination.

Table 2. Exploratory factor analysis

Activities	1	2	3	4	5	6
CC-CC1	0.917					
CC-CC2	0.819					
CC-CC3	0.789					
CC-LA1		0.902				
CC-LA2		0.845				
CC-LA3		0.795				
CC-DI1			0.881			
CC-DI2			0.732			
CC-DI3			0.687			
CC-EP1				0.785		
CC-EP2				0.755		
CC-EP3						
CC-EC1					0.798	
CC-EC2					0.678	
CC-EC3						
CC-SI1						0.787
CC-SI2						0.682
CC-SI3						0.655

Excluded Variables = CC-EP3; CC-EC3 due to low loading or cross-loading errors.

4.3. PLS Measurement Model Development

Table 3 shows the convergent validity analyses' Cronbach's alpha (CA), composite reliability (CR), and average variance extracted (AVE) for each concept. These measurements determine the measurement model's convergent validity and build internal consistency and reliability. Cronbach's alpha (CA) measures internal consistency, demonstrating each construct's items' dependability. Internal consistency increases with Cronbach's alpha. Composite reliability (CR) uses item correlations to evaluate construct consistency. CR over 0.7 is acceptable. AVE assesses the construct's variation relative to measurement errors. Convergent validity increases with AVE, indicating that concept elements share much variation. Table 3 shows internal solid consistency and convergent validity [24, 29]. Most constructions have good internal consistency, with Cronbach's alpha scores from 0.713 to 0.865. Composite reliability values exceed 0.7. The constructs capture more variation than measurement errors, as seen by the AVE values of 0.631 to 0.846. Most notions have convergent validity with these AVE values. CC-DI3 (Data Quality and Integration 3) was removed from the analysis owing to low factor loadings or cross-loading problems. Thus, CC-DI1 and CC-DI2 form the Data Quality and Integration construct. The constructs' internal consistency and convergent validity support the measuring model's reliability and validity, indicating that they capture the desired notions.

Heterotrait-Monotrait (HTMT) examination of concept discriminant validity is shown in Table 4. The HTMT ratio evaluates discriminant validity by comparing correlations across constructs to average correlations within the same construct [19]. The table shows HTMT values and the ratio of construct correlations to construct average correlations. The constructions are different if the value is below 0.85. The HTMT values in Table 4 show discriminant validity for most constructs. Since they compare a construct to itself, diagonal values are ignored. The HTMT scores below the diagonal show construct discriminant validity.

Since the HTMT score of 0.505 between CC (Complexity and Customization) and DI (Data Quality and Integration) is below 0.85, these two constructions are separate. HTMT scores for additional concept pairings, such as EC (Economic and Culture) and EP (Ethical and Privacy Concerns), EP and LA (Limited Data Availability), and EC and LA, also suggest discriminant validity. The HTMT values between DI and EC, DI and EP, and DI and SI (Scalability and

Integration) are substantially more significant, but they still satisfy the 0.85 criterion, showing adequate discriminant validity [18]. The HTMT analysis findings in Table 4 show that the constructs in the research have discriminant validity and are different and not strongly linked. This suggests that each construct reflects a distinct obstacle to cognitive computing deployment in modest building projects.

Table 3. Convergent validity results indicating Cronbach alpha, composite reliability, and average variance extracted.

Category	Code	Loadings	VIF	CA	CR	AVE
Complexity and Customization	CC-CC1	0.727	1.388	0.713	0.836	0.631
	CC-CC2	0.825	1.375			
	CC-CC3	0.826	1.427			
Limited Data Availability	CC-LA1	0.760	1.489	0.865	0.888	0.727
	CC-LA2	0.971	1.485			
	CC-LA3	0.814	1.765			
Data Quality and Integration	CC-DI1	0.901	1.760	0.729	0.88	0.786
	CC-DI2	0.872	1.978			
	CC-DI3	Deleted	1.920			
Ethical and Privacy Concerns	CC-EP1	0.928	2.459	0.818	0.916	0.846
	CC-EP2	0.911	1.938			
	CC-EP3	Deleted	2.560			
Economic and Culture	CC-EC1	0.920	2.143	0.793	0.906	0.828
	CC-EC2	Deleted	2.147			
	CC-EC3	0.900	1.389			
Scalability and Integration	CC-SI1	Deleted	1.375	0.844	0.928	0.865
	CC-SI2	0.936	1.427			
	CC-SI3	0.924	1.489			

Table 4. HTMT analysis for discriminant validity

Constructs	CC	DI	EC	EP	LA	SI
Complexity and Customization=CC						
Data Quality and Integration=DI	0.505					
Economic and Culture=EC	0.248	0.317				
Ethical and Privacy Concerns=EP	0.233	0.414	0.286			
Limited Data Availability=LA	0.121	0.054	0.036	0.081		
Scalability and Integration=SI	0.215	0.271	0.226	0.171	0.127	

Table 5 shows the Fornell-Larcker criteria analysis findings for concept discriminant validity. The Fornell-Larcker criteria contrast the square root of each construct's average variance extracted (AVE) with construct correlations. This criterion determines if AVE values exceed inter-construct correlations, demonstrating discriminant validity. The top triangular matrix shows construct correlations, whereas the diagonal shows AVE values [14]. To measure discriminant validity, the Fornell-Larcker criteria advise comparing each construct's square root AVE with its correlations with other components. Discriminant validity is demonstrated when the square root of the AVE for a concept exceeds its correlation with other constructs [25]. Table 5 shows that AVE square roots are diagonal. Comparing these values with the top triangular matrix correlations, the square root of each construct's AVE is consistently more enormous than the correlations with other constructs.

The square root of the AVE for the CC (Complexity and Customization) construct is 0.794, which is higher than its correlations with other constructs. Discriminant validity suggests CC is unique from the other conceptions. DI, EC, EP, LA, and SI follow similar patterns. The square roots of their AVE values are more significant than the correlations with other variables, demonstrating their discriminant validity. Table 5's Fornell-Larcker criteria analysis shows that the study's constructs are discriminant [29]. The square root of each construct's AVE is consistently more extensive than the correlations with other constructs, demonstrating that the constructs are different and represent distinctive hurdles to cognitive computing application in modest construction projects.

Table 5. Fornell-Larcker criterion for discriminant validity

Constructs	CC	DI	EC	EP	LA	SI
Complexity and Customization=CC	0.794					
Data Quality and Integration=DI	0.383	0.887				
Economic and Culture=EC	0.165	0.247	0.91			
Ethical and Privacy Concerns=EP	0.185	0.32	0.232	0.92		
Limited Data Availability=LA	-0.043	0.024	-0.012	0.051	0.853	
Scalability and Integration=SI	0.175	0.216	0.183	0.144	0.115	0.93

Table 6 shows variable construct cross-loading values. These numbers show the strength of the association between each variable and its intended construct and the possibility for cross-loading onto additional constructs [22]. The table shows that variables load more on their intended construct than others. Compared to other constructions, Complexity and Customization variables like CC-CC1, CC-CC2, and CC-CC3 have greater loadings on the CC construct (0.727, 0.825, and 0.826). These factors are strongly correlated with Complexity and Customization. Other factors also have more extraordinary relationships with their intended constructions. Compared to other constructs, variables in the Data Quality and Integration construct (CC-DI1 and CC-DI2) load more fantastically on the DI construct (0.901 and 0.872). Economic and Culture, Ethical and Privacy Concerns, Limited Data Availability, and Scalability and Integration factors follow the same trend. The variables match their intended constructions, indicating construct validity. Other constructions have modest cross-loading values [23]. The dimensions' discriminant validity suggests they reflect distinct impediments to cognitive computing application in small construction projects. Table 6's cross-loading values support the variables' associations with their constructs, proving the measurement model's construct and discriminant validity.

Table 6. Cross-loading criterion for discriminant validity

Variables	CC	DI	EC	EP	LA	SI
CC-CC1	**0.727**	0.185	0.013	0.101	-0.069	0.033
CC-CC2	**0.825**	0.419	0.152	0.124	-0.018	0.17
CC-CC3	**0.826**	0.271	0.189	0.204	-0.031	0.179
CC-DI1	0.364	**0.901**	0.236	0.291	0.031	0.252
CC-DI2	0.312	**0.872**	0.2	0.276	0.01	0.125
CC-EC1	0.139	0.31	**0.92**	0.216	-0.03	0.14
CC-EC3	0.162	0.131	**0.9**	0.207	0.01	0.197
CC-EP1	0.201	0.292	0.24	**0.928**	0.056	0.161
CC-EP2	0.136	0.297	0.184	**0.911**	0.037	0.102
CC-LA1	-0.126	0.007	-0.031	0.02	**0.76**	0.082
CC-LA2	-0.018	0.05	-0.006	0.039	**0.971**	0.113
CC-LA3	-0.07	-0.056	-0.02	0.078	**0.814**	0.091
CC-SI2	0.195	0.205	0.179	0.145	0.079	**0.936**
CC-SI3	0.127	0.197	0.162	0.123	0.137	**0.924**

CC= Complexity and Customization; DI= Data Quality and Integration; EC= Economic and Culture; EP= Ethical and Privacy Concerns; LA= Limited Data Availability; SI= Scalability and Integration.

The research tested the associations between the independent constructs (CC, DI, EC, EP, LA, SI) and the dependent construct (CCI - Cognitive Computing Implementation) in Table 7. The table shows each hypothesis's O, M, STDEV, t-statistics, and p-values. Statistical analysis determines whether hypotheses are accepted or rejected. Accepted hypotheses show a substantial link between the independent and dependent constructs, whereas rejected hypotheses suggest a non-significant relationship.

This research accepted all hypotheses except H5 (Limited Data Availability → Cognitive Computing Implementation). Accepted hypotheses:

The t-statistics and p-values support these assumptions, demonstrating that these separate constructs substantially influence cognitive computing implementation in the research.

Hypothesis testing findings in Table 7 show how constructs affect Cognitive Computing Implementation. The accepted hypotheses emphasize crucial elements that promote cognitive computing adoption in the investigated area.

Table 7. Hypothesis testing of the study

Hypothesis	Relation	(O)	(M)	(STDEV)	T statistics	P values	Results
H1	CC → CCI	0.327	0.325	0.033	9.848	0	Accepted
H2	DI → CCI	0.389	0.382	0.027	14.534	0	Accepted
H3	EC → CCI	0.295	0.287	0.038	7.85	0	Accepted
H4	EP → CCI	0.319	0.311	0.036	8.963	0	Accepted
H5	LA → CCI	0.041	0.057	0.074	0.558	0.577	Rejected
H6	SI → CCI	0.267	0.259	0.041	6.519	0	Accepted

(O)= Original sample; (M)=Sample mean; (STDEV) =Standard deviation; CC= Complexity and Customization; DI= Data Quality and Integration; EC= Economic and Culture; EP= Ethical and Privacy Concerns; LA= Limited Data Availability; SI= Scalability and Integration; CCI= Cognitive Computing Implementation.

Figure 3's path loadings and p-values reveal the strength of the latent construct-observed indicator correlations. These values affect the strength of the links and how much the indicators assess their structures. Researchers may use route loadings and p-values to determine construct correlations and the most important markers for each construct [30]. This study clarifies the measurement model's validity and reliability and the structural model. Figure 3 and the p-values show the measurement model in PLS-SEM and the path loadings between latent constructs and observable indicators.

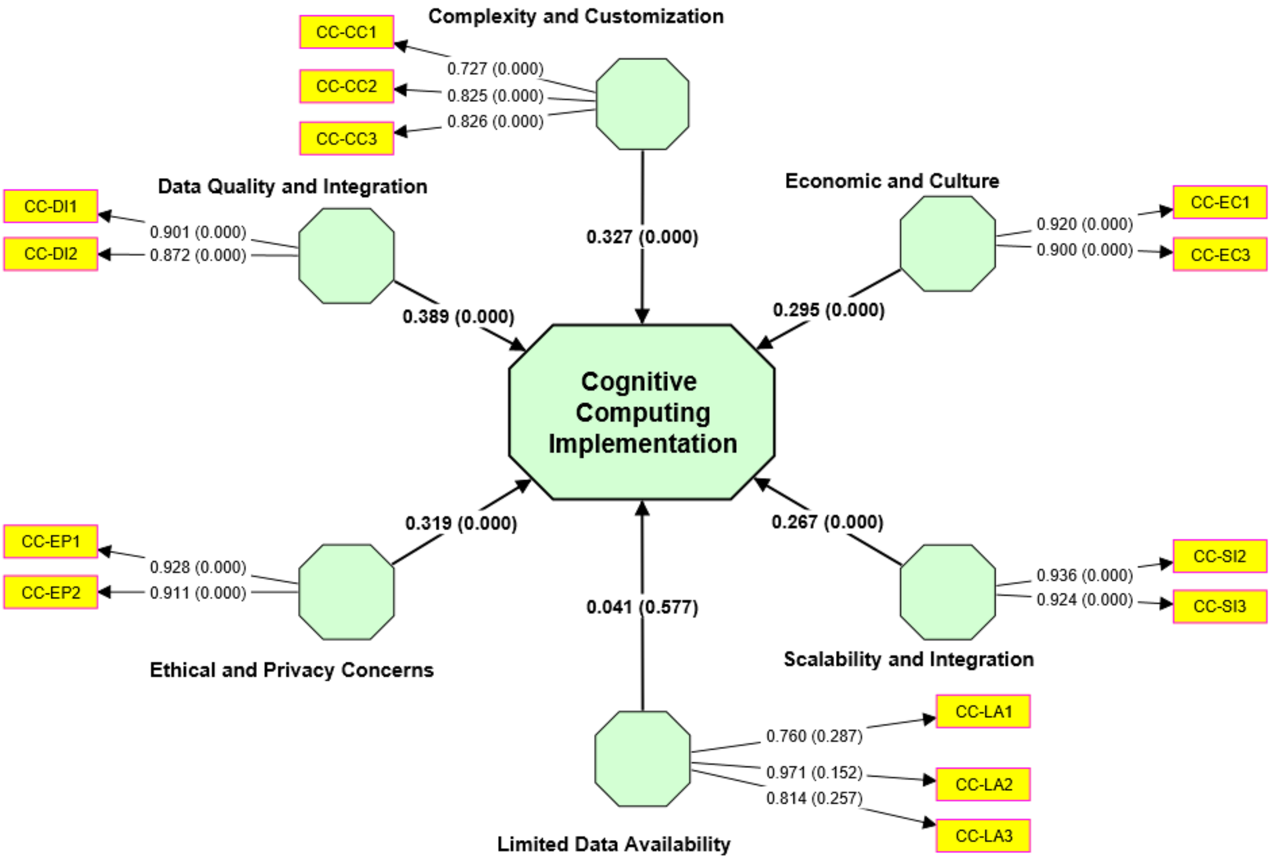

Figure 3. PLS SEM measurement model indicating path loadings with p values

PLS-SEM measurement model Figure 4 shows route loadings between latent components and indicators. These route loadings show the links between unobserved constructs (factors or variables) and measured variables or items. Path loadings show connection strength and direction. They show how closely indications match constructions [23]. Figure 4 shows path loadings as arrows between constructions and indicators. Path loading T-statistics indicate association importance. Higher T-values indicate a more vital construct-indicator link.

4.4. Predictive Relevance Q^2

Table 8 shows the model's predictive relevance analysis for Cognitive Computing Implementation. The table shows the model's predictive capability and performance. The model's total variance in Cognitive Computing Implementation is the dependent variable's sum of squares. Total is 4968.000. The SSO value is the dependent variable's original squares. It evaluates cognitive computing implementation variation without considering model predictions. SSO is 3900.123.

The sum of squares of errors (SSE) assesses the model's unexplained variance or prediction mistakes—the difference between projected and fundamental Cognitive Computing Implementation values. The model's predictive potential is assessed by the Q^2 value, which is 1 minus SSE/SSO. It estimates how much of the Cognitive Computing Implementation variance the model explains. In this investigation, Q^2 is 0.215, suggesting that the model explains 21.5% of Cognitive Computing Implementation variance [25]. The model may explain a considerable percentage of Cognitive Computing Implementation variance, suggesting predictive value. The model still has unexplained variations or forecast mistakes. The model may need further investigation to improve its forecasting power and accuracy.

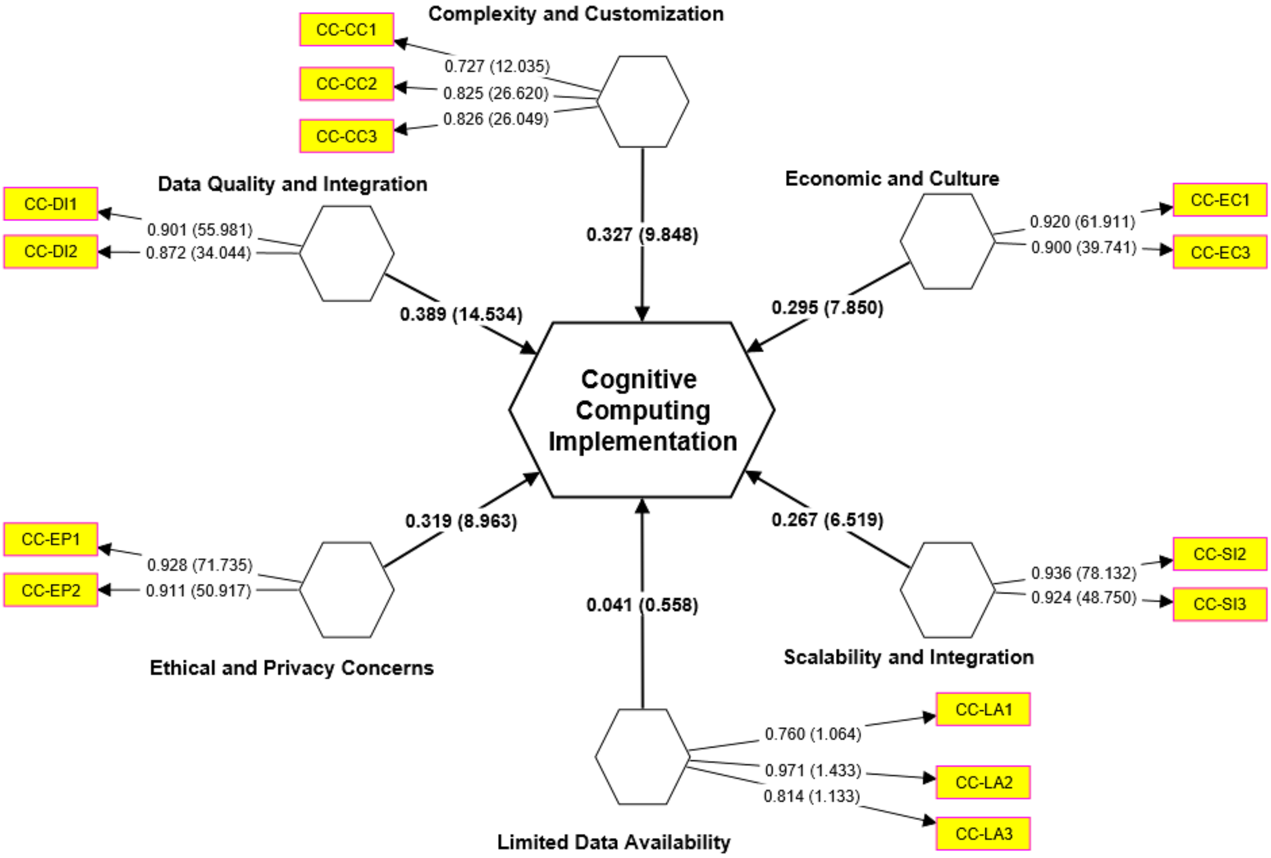

Figure 4. PLS SEM measurement model indicating path loadings with T-stat value

Table 8. Predictive relevance of the study

Total	SSO	SSE	Q^2 (=1-SSE/SSO)
Cognitive Computing Implementation	4968.000	3900.123	0.215

5. Discussion

This study aimed to investigate the obstacles to cognitive computing implementation in minor construction initiatives. Using a mixed-methods approach, a comprehensive literature review, quantitative analysis, and structural equation modeling were employed to investigate the relationships between the identified barriers and cognitive computing implementation. Identifying facilitators for cognitive computing adoption is crucial to overcoming the noted barriers. Enhanced training programs can prepare the workforce to deal with complexity and customization issues. Partnerships with technology providers can improve data quality and integration. Government incentives and supportive policies can address economic barriers, while a strong emphasis on ethical practices and data protection can mitigate privacy concerns. Promoting these facilitators will be key to accelerating cognitive computing adoption in the construction industry. Simplifying the integration of cognitive computing technologies into current workflows and project management systems should be the top priority for small construction projects to overcome the barriers posed by complexity and customization. This entails minimizing complexity while tailoring solutions to meet the demands of projects. Effectively managing data complexity will necessitate putting plans into practice, which will include concentrating on creating user-friendly interfaces and streamlined integration procedures without sacrificing the customization requirements of specific projects. Improving data integration and quality is crucial to using cognitive computing in construction effectively. To guarantee consistency and dependability, this can be accomplished by implementing standardized data collection techniques across projects.

Complexity and Customization (CC) and Cognitive Computing Implementation (CCI) are positively correlated, according to the first hypothesis (H1). The analysis revealed a statistically significant positive correlation (β= 0.327, t = 9.848, p 0.001), confirming the hypothesis (see Table 9). This suggests that the likelihood of effective cognitive computing implementation in minor construction initiatives increases as complexity and customization increase. This finding is consistent with previous research emphasizing the significance of addressing advanced technology implementation's unique complexities and customization needs [14, 17].

The second hypothesis (H2) postulated that Data Quality and Integration (DI) is positively related to Cognitive Computing Implementation (CCI). The data strongly supported this hypothesis (β= 0.389, t = 14.534, p 0.001) [21, 48, 49]. This suggests that improved data quality and effective integration of data sources contribute to the successful implementation of cognitive computing. It highlights the importance of comprehensive data management practices and integration strategies for maximizing the potential of cognitive computing technologies [22, 24].

The relationship between Economic and Culture (EC) and Cognitive Computing Implementation (CCI) was investigated in the third hypothesis (H3). The analysis revealed a significant positive correlation (β = 0.295, t = 7.85, p 0.001), validating hypothesis 3. This suggests favorable economic conditions and a supportive organizational culture are essential for implementing cognitive computing in modest construction projects. Organizations must align economic incentives and cultivate a culture encouraging technological innovation and adoption [29, 30].

The relationship between Ethical and Privacy Concerns (EP) and Cognitive Computing Implementation (CCI) was investigated in the fourth hypothesis (H4). The results indicated a statistically significant positive correlation (β = 0.319, t = 8.963, p 0.001), confirming hypothesis 4. This result highlights the significance of resolving ethical and privacy concerns when implementing cognitive computing. Organizations should prioritize the development of comprehensive ethical frameworks, data protection measures, and privacy policies to mitigate potential concerns and promote trust in cognitive computing technologies [31, 33].

Limited Data Availability (LA) and Cognitive Computing Implementation (CCI) are related, according to the fifth hypothesis (H5). The analysis did not significantly support this hypothesis (β= 0.041, t = 0.558, p = 0.577). In the context of this study, this indicates that limited data availability may not be a significant barrier to the implementation of cognitive computing in minor construction initiatives. Future research could delve deeper into this relationship and investigate potential factors that influence the impact of data availability on cognitive computing implementation [18], [32].

The sixth hypothesis (H6) looked at stability and integration (SI) and cognitive computing implementation (CCI). Hypothesis 6 was supported by the study, which showed a significant positive correlation (β = 0.267, t = 6.519, p 0.001). The importance of flexible and seamless solutions for the effective implementation of cognitive computing is highlighted by this research. Organizations should give top priority to creating scalable architectures and effective integration methods in order to facilitate the seamless incorporation of artificial intelligence technologies into current systems [19], [21].

Table 9. Comparison with previous research

Aspect	Present Study Findings	Previous Studies	Comparison/Analysis
Complexity and Customization	Significant impact ($\beta = 0.327$, $t = 9.848$, $p < 0.001$)	Identified as a major challenge in general construction projects	Quantifies the impact and highlights the exacerbated challenges in small construction projects.
Data Quality and Integration	Positive relationship ($\beta = 0.389$, $t = 14.534$, $p < 0.001$)	Recognized as critical but focused on large projects	Emphasizes the need for standardized data management practices, particularly in small projects with inconsistent data collection methods.
Limited Data Availability	Not a significant barrier ($\beta = 0.041$, $t = 0.558$, $p = 0.577$)	Previously identified as a significant barrier	Divergence suggests that small projects prioritize managing existing data effectively rather than acquiring new data.
Financial and Cultural Constraints	Significant barrier ($\beta = 0.295$, $t = 7.850$, $p < 0.001$)	Commonly noted in large projects	Confirms financial constraints are even more pronounced in small projects, where ROI is harder to justify.
Ethical and Privacy Concerns	Significant concern ($\beta = 0.319$, $t = 8.963$, $p < 0.001$)	Consistently identified as a challenge	Reinforces the need for robust data protection and ethical frameworks, particularly important in smaller projects with less regulatory oversight.
Scalability and Integration	Significant impact ($\beta = 0.267$, $t = 6.519$, $p < 0.001$)	Acknowledged in previous research	Highlights the importance of scalable solutions tailored to small projects, emphasizing modular and adaptable technologies.

In general, the research's outcomes provide valuable information regarding the challenges associated with cognitive computing in small construction initiatives. Complexity and customization, data quality and integration, economic and cultural issues, moral and security concerns, scalability, and integration all have a significant impact on the successful adoption of cognitive computing, as shown by the results. These results highlight the significant challenges that must be addressed when implementing cognitive computing technologies. This has practical implications for construction industry businesses. The identified barriers not only hinder the adoption of cognitive computing in small construction projects but also directly impact project outcomes. Complexity and customization demands can lead to prolonged implementation times and increased costs, affecting project timelines and budgets. Poor data quality and integration issues can result in inaccurate analyses, leading to flawed decision-making and inefficiencies in project management.

Economic and cultural barriers may stifle innovation, limiting the adoption of potentially transformative technologies. Ethical and privacy concerns can erode stakeholder trust, while scalability and integration challenges could restrict the ability to leverage cognitive computing solutions fully, impacting overall project performance and success.

Experts highlighted significant ethical and privacy concerns affecting the adoption of cognitive computing in small construction projects. Data privacy and security were primary issues, with concerns about inadequate protections leading to potential breaches of sensitive project and personnel information. The lack of transparency in cognitive computing models also raised worries about accountability, as stakeholders might not fully understand or trust the decision-making processes, particularly in smaller projects with limited technical expertise. Additionally, issues surrounding consent and data ownership were noted, with the use of data from subcontractors, workers, or clients often occurring without explicit permission, leading to ethical dilemmas. These concerns contribute to resistance against adopting cognitive computing technologies, as fears of data breaches, mistrust in system outputs, and potential job displacement create significant barriers, especially in smaller projects where resources and expertise are constrained.

5.1. Financial and Cultural Barriers

Financial Barriers:

Financial constraints are a significant challenge in the implementation of cognitive computing in construction projects, particularly in small-scale endeavors. Small construction projects often operate with limited budgets, making it difficult to allocate funds for the initial investment required for cognitive computing technologies. These projects typically prioritize essential expenditures, such as labor, materials, and basic project management tools, leaving little room for advanced technological implementations. The cost of acquiring, customizing, and integrating cognitive computing solutions can be prohibitively high, especially when these projects must also contend with short-term cash flow concerns. In contrast, large construction projects usually have more substantial financial resources at their disposal. They can justify the investment in cognitive computing by leveraging economies of scale, where the cost is distributed across larger budgets and longer project timelines. Additionally, large projects are more likely to secure external funding or partnerships that can offset the cost of technology adoption. Consequently, while financial barriers are present in both small and large projects, they are more acute in small projects due to tighter budgets and a limited ability to absorb additional costs.

Cultural Barriers:

Cultural barriers, including resistance to change and a risk-averse mindset, are prevalent across the construction industry but manifest differently in small and large projects. In small construction projects, cultural barriers are often rooted in a conservative approach to project management. Small firms may lack the organizational structure and resources to support innovation, leading to a reliance on traditional methods that are perceived as tried and tested. The smaller scale of these projects also means that any mistakes or failures in adopting new technologies can have a disproportionate impact on the project's success, reinforcing a cautious approach. Furthermore, the management and staff in small projects may have less exposure to technological advancements, resulting in a lack of familiarity and comfort with cognitive computing solutions.

In contrast, large construction projects typically involve multiple stakeholders, including large firms with established research and development (R&D) departments and a history of technological adoption. These organizations may have a more progressive culture that is open to innovation and technological change. However, cultural barriers in large projects can arise from the complexity of managing change across diverse teams and departments. While there may be a corporate-level mandate to adopt new technologies, individual teams or departments may resist due to concerns about disruption to established workflows or the perceived complexity of new systems. Additionally, in large projects, the sheer scale and number of stakeholders can create bureaucratic inertia, where decision-making processes become slow and cumbersome, further complicating the adoption of cognitive computing technologies.

Comparison of Financial and Cultural Barriers:

The key difference between small and large projects in terms of financial and cultural barriers lies in the scale and resources available to manage these challenges. Small projects face more immediate financial constraints and a higher level of risk aversion, which makes the adoption of cognitive computing technologies particularly challenging. In contrast, large projects, while not immune to financial and cultural barriers, have more resources and organizational support structures to mitigate these challenges. However, large projects may encounter additional layers of complexity due to the involvement of multiple stakeholders and the need to manage change across large, diverse teams.

5.2. Data Integrity and Integration Issues

The study identified several critical data integrity and integration issues that pose significant challenges to the practical implementation of cognitive computing in small construction projects. One of the primary concerns is the inconsistent quality of data collected across different phases of a project. Small projects often lack standardized data collection protocols, leading to fragmented and unreliable data sets. This inconsistency makes it difficult to integrate data from various sources, such as project management systems, sensors, and manual inputs, into a cohesive cognitive computing framework. Additionally, the study found that small projects frequently encounter difficulties in ensuring the accuracy and completeness of the data due to limited resources and time constraints. These data integrity issues undermine the reliability of cognitive models, resulting in flawed decision-making processes. The inability to seamlessly integrate diverse data sources further complicates the deployment of cognitive computing technologies, as it prevents the creation of comprehensive and accurate predictive models. Without addressing these challenges, small construction projects are likely to experience limited benefits from cognitive computing, as the effectiveness of these technologies heavily depends on the quality and integration of the underlying data.

5.3. Scalability and Connectivity Issues in Small Construction Projects

In small construction projects, scalability and connectivity challenges often arise due to limited resources and infrastructure. Scalability issues manifest when projects struggle to expand or customize cognitive computing solutions within their constrained budgets and timelines, unlike larger projects that can justify the cost of more flexible, scalable systems. Connectivity problems are also common, particularly in sites with inadequate technological infrastructure, such as unreliable internet access, which hampers real-time data sharing and integration of cognitive computing tools, leading to inefficiencies and delays.

Recommended Strategies to Address These Challenges:

To overcome these challenges, small projects can adopt modular cognitive computing solutions, starting with essential functionalities and adding more as needed, which reduces upfront costs and allows for scalability. Leveraging cloud-based services can also mitigate connectivity issues by providing flexible, powerful computing resources without the need for extensive on-site infrastructure. Additionally, investing in reliable mobile connectivity solutions and partnering with technology providers for tailored support can further enhance scalability and connectivity, ensuring that small projects can effectively implement cognitive computing technologies.

5.4. Strategies for Overcoming Identified Barriers

Given the challenges noted, it is critical to provide feasible suggestions that can help industry participants get beyond these obstacles to effectively implement cognitive computing in modest construction projects [50, 51]. First, developing adaptable cognitive computing solutions that can be customised to the unique requirements of minor construction projects is necessary to manage the complexity and customization challenges [52]. Industry experts and technology suppliers should work together to create flexible platforms that can satisfy the requirements of these initiatives. Building companies need to invest in robust data management systems that assure the integrity and accessibility of project data to surmount data quality and integration issues. The efficient operation of cognitive computing applications can be enhanced by implementing standardised data formats and protocols, which can help to facilitate the seamless integration of various data sources [26].

Fostering an organisational culture that encourages innovation and technology advancement might help to mitigate constraints related to culture and economy. To increase the viability of their cognitive computing investments, construction companies should investigate finance options like government incentives for technical innovation or joint ventures with tech companies. Clear rules and laws governing the use of cognitive computing technologies are important due to ethical and privacy concerns [39]. Building confidence among all parties engaged in building initiatives can be facilitated by assuring transparency in the accumulation, utilisation, and preservation of data. Construction companies must clearly demonstrate the return on investment (ROI) of integrating cognitive computing into small construction projects to overcome economic barriers [42]. Addressing cultural barriers involves cultivating an innovative and technology-receptive organizational culture. This can be facilitated through targeted training programs, workshops, and the promotion of success stories demonstrating the tangible benefits of cognitive computing adoption.

Although this study did not find that a lack of data availability was a significant obstacle, it is nonetheless imperative that businesses routinely evaluate the ways in which they acquire and store data. Ensuring the availability of enough and pertinent data will facilitate the future successful application of cognitive computing technologies. Construction companies should give top priority to developing scalable cognitive computing solutions and efficient integration methodologies to handle scaling and integration difficulties. This entails implementing scalable and flexible cloud-based solutions and making sure cognitive computing systems can be readily integrated with the current IT infrastructure.

5.5. Practical Implications

The practical implications of this study are significant for stakeholders in the construction industry. By understanding the specific barriers to cognitive computing implementation and their direct impacts on project outcomes, industry practitioners can develop targeted strategies to mitigate these challenges. For instance, enhancing data management practices, fostering a culture of innovation, and establishing clear ethical guidelines can pave the way for the successful adoption of cognitive computing. These strategies not only address the immediate challenges but also contribute to building a resilient and technologically advanced construction sector. Construction companies must clearly demonstrate the return on investment (ROI) of integrating cognitive computing into small construction projects to overcome economic barriers. Addressing cultural barriers involves cultivating an innovative and technology-receptive organizational culture. This can be facilitated through targeted training programs, workshops, and the promotion of success stories demonstrating the tangible benefits of cognitive computing adoption. To mitigate ethical and privacy concerns, establishing robust data privacy practices is paramount. This includes setting clear data ownership and consent mechanisms, alongside prioritizing the transparency and explainability of cognitive computing models. Such measures will not only address privacy concerns but also build trust among stakeholders regarding the ethical use of cognitive computing technologies.

The challenge of limited data availability in small construction projects requires innovative solutions for data collection and accessibility improvement. Exploring new data collection methods, such as IoT devices and mobile applications, can enhance the volume and variety of data available for analysis. Improving data accessibility through centralized databases and cloud storage solutions will further enable the effective use of cognitive computing technologies. To ensure scalability and seamless integration of cognitive computing technologies, construction companies should develop strategies to overcome resource constraints and technical challenges. This includes allocating resources for training personnel in AI and machine learning skills and providing technical support to facilitate the integration of cognitive computing solutions. Such measures will enable companies to leverage these technologies effectively, despite the challenges posed by limited resources and technical complexities.

6. Conclusion

This research examined the challenges of using cognitive computing in small construction projects. An extensive literature study, quantitative evaluation, and structural equation modelling were used to examine the connections between different obstacles and the adoption of cognitive computing. The findings provide insight on the elements that influence cognitive computing's successful uptake in the building industry. These observations clarified the subtle contextual underpinnings of the adoption hurdles of cognitive computing and offered practical illustrations of the benefits and problems encountered construction sector. A more comprehensive picture of the future for cognitive computing in construction is provided by the integration of these qualitative findings, which deepens our grasp of the intricate interactions between industry practices and technical progress.

It has been shown that the usage of cognitive computing is positively and significantly related to challenges with data integration and quality, economic and cultural concerns, privacy and ethical issues, and scalability. However, the research could not find a statistically significant link between the implementation of cognitive computing in the study environment and the lack of readily available data. This suggests that other aspects of adopting cognitive computing in smaller building endeavors may be more important. The results of this research help us understand the challenges that cognitive computing deployment in the construction sector faces better. When implementing cognitive computing technologies, the importance of complexity, data quality, economic and cultural aspects, ethical and privacy concerns, scalability, and integration challenges is highlighted. For organizations in the construction business, the findings have application. Organizations may effectively expand their ability to deploy cognitive computing technologies by overcoming these barriers. This in turn may improve operational effectiveness, decision-making procedures, and project results in general. It is important to recognize the limitations of this research. Future research could expand upon these findings by examining the long-term effects of cognitive computing implementation in the construction industry through longitudinal studies. Furthering our comprehension of cognitive computing implementation in minor construction projects could be facilitated by investigating regional barriers and considering additional factors. In conclusion, this research contributes to the existing literature by shedding light on the obstacles preventing the implementation of cognitive computing in minor construction projects. The findings provide valuable direction for organizations seeking to implement cognitive computing technologies in the construction industry, enabling them to surmount obstacles and maximize the potential benefits of these innovative solutions.

6.1. Limitations and Future Research

Subsequent investigations must aspire for a more extensive geographical scope and maybe utilize longitudinal research methods to document the progressive integration of cognitive computing in the construction sector throughout time. Furthermore, investigating how geographical variations influence the adoption hurdles for cognitive computing may provide further understanding of how these difficulties fluctuate in various scenarios. Through the integration of these useful suggestions and the recognition of the constraints concerning the generalizability and extent of the present investigation, this study not only adds to the body of knowledge regarding cognitive computing in the construction sector but also provides practitioners with important takeaways. As indicated, future research directions will deepen our knowledge of how cognitive computing technologies may be applied successfully in various construction project scenarios, which will eventually impel the sector towards increased operational effectiveness and technical innovation.

7. Declarations

7.1. Author Contributions

Conceptualization, S.N. and A.A.; methodology, S.H.; formal analysis, O.B.; investigation, O.B.; resources, A.A.; data curation, A.A.; writing—original draft preparation, A.A.; writing—review and editing, S.N.; visualization, S.H.; supervision, K.A.A.; project administration, K.A.A.; funding acquisition, K.A.A. All authors have read and agreed to the published version of the manuscript.

7.2. Data Availability Statement

The data presented in this study are available in the article.

7.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

7.4. Conflicts of Interest

The authors declare no conflict of interest.

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