Impact of Drivers on Implementation of the Construction Automation: A PLS SEM Approach

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Abstract

The construction industry is evolving at a global scale due to increasing demand, and automation has shown significant potential for improving efficiency and sustainability. This study investigates the relationship between key drivers of construction automation—cultural, technical, and industrial—and the successful implementation of automation technologies. Through a mix of qualitative and quantitative methods, including a pilot survey, exploratory factor analysis (EFA), and structural equation modeling (SEM), the study identifies the most critical drivers influencing automation adoption in construction projects. Key findings highlight that cultural drivers (such as innovation orientation and risk tolerance) and technical drivers (such as advanced technologies and system integration) have the most significant impact on automation adoption, contributing to over 40% of the variance in automation implementation. Moreover, construction planning and accuracy were found to be the two main benefits of automation, with a planning impact factor of 0.878 and accuracy factor of 0.623. These results offer practical implications for construction industry professionals by identifying critical success factors for automation adoption, which can lead to improved project outcomes, enhanced safety, and sustainability.

Keywords:

Construction automation drivers; construction automation implementation; automated construction technologies.

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Highlights:

- Cultural, technical, and industrial drivers significantly impact construction automation.
- Planning and accuracy are key benefits of implementing construction automation.
- The study uses PLS-SEM to analyze the link between automation drivers and implementation.
- Automation enhances construction efficiency, reduces waste, and improves project accuracy.

1. Introduction

The architect, engineering, construction, and operation (AECO) business is anticipated to contribute approximately 15% by 2030 towards worlds “gross-domestic-product (GDP)”. According to study the business of construction-industry is one of the important economic areas that determine the healthier life and well-being of a country's people [1]. A researcher stated that the construction projects, particularly the building projects consumes 40 percent energy of the world approximately and are accountable for world’s one-third gas discharge impacting the greenhouse effect [2]. Pertaining to the population and economic growth activities and concentration in cities, achieving the universal sustainability objectives are of utmost importance. In addition, Ning et al. (2021), Pan et al. (2018) and Wu et al. (2013) stated that the continuous development of such places contributed to increase the urban population [3]–[5]. In a world that is increasingly urbanizing and changing, construction allocation cannot keep pace with demand. In many emerging nations, the construction sector has undergone significant transformations due to the necessity to achieve national goals. By 2020 the population growth is projected to be 1.4 billion [6]. These areas have undergone enormous expansion, with a focus on the need of construction to provide a minimum standard of living.

Therefore, A. Al Rashid et al. (2020) also confirmed that mostly all authorities have emphasized on the reasonable building construction projects by establishing a range of technologies and policies [7]. Though, the affordability of such arrangements for low-income individuals remains debatable. In addition, Akinradewo et al. (2021) stated that the construction sector in these nations lacks competitiveness to meet sustainable development goals in accordance with international standards [8]. Gusmao Brissi et al. (2022) and Xing et al. (2020) stated that these projects remain plagued by many source issues, such as monetary overruns, schedule interruptions, incompletion, collapse risks, quality degradation, creating hurdles in receiving desired outcomes [9]. Such initiatives encounter several obstacles. Numerous projects have been cancelled or halted due to the low amount of investment in this area. In all emerging nations, the construction sector satisfies government, societal, and consumer needs, falling behind other related companies.

In addition, the sustainability topic in the indigent construction sector is neither been addressed nor resolved. According to Sijila et al. (2019), the literature has thus emphasized on "sustainable buildings" since they are environmentally benign and cost-effective [10]. According to Dedov et al. (2019), applying efficient and sustainable construction methods will transform the building sector [11]. Moreover, stakeholders in the construction industry are unable to estimate the environmental implications of buildings while they are being constructed. Consequently, construction automation deployment could be included through the lifecycles of a project by using the strategies that are sustainable. Chea et al. (2020) also confirmed that the utilization of automation in construction is recognized as the most revolutionary developments for construction (building) plans [12]. Yang & Pan (2021) stated that the automation could be utilized in construction business as advanced gear that can be operated remotely by utilizing the remote data acquisition of the sensors to perform autonomous execution of tasks using the numeric data [13]. The deployment of automation necessitates the use of adaptable equipment (mechanical/ electrical) to perform construction operations and tasks. Numerous construction companies deployed current construction technologies to reduce the usage of resources and avoid wastages [14], [15].

To address the gaps identified in previous studies, this research aims to provide a comprehensive analysis of construction automation's drivers and implementation outcomes. Previous literature has often focused on the technological advancements and their theoretical benefits without delving deeply into the specific factors that facilitate or hinder the adoption of these technologies in the construction industry. This study bridges this gap by investigating the critical cultural, technical, and industrial drivers that influence the successful implementation of construction automation, thereby providing a nuanced understanding of the automation landscape.

Moreover, the integration of automation in construction has been touted for its potential to enhance efficiency, reduce waste, and improve overall project management. Studies such as those by Hamid 2016 have demonstrated significant improvements in time management and quality control through automation [16]. However, there remains a need to empirically validate these claims across diverse construction environments and project scales [17]. This research employs a robust Partial Least Squares Structural Equation Modeling (PLS-SEM) approach to examine the relationships between various automation drivers and implementation outcomes, providing empirical evidence on the effectiveness of automation in enhancing construction processes and sustainability.

The introduction of construction technologies that are based on automation on-site has shown to provide support and other benefits, involving substantial reduction of waste, efficient time management, flexibility in operating conditions, and improved quality, although the primary rate is high. Huang et al. (2021) and Akinradewo, et al. (2019) found that at the enterprise stage, the economic payback value in long-term and the investment return could be utilized for assessing the sustainability of investments in automation implementation [18], [19]. Even though robotics has become a famous tool to resolve construction issues in some technologically advanced nations, specifically for investigation of various construction markets utilizing computerized technologies, the vast majority of developing nations have yet to give this technology serious consideration [20]. In the construction sector of third-world countries, only a negligible number of companies have effectively utilized automation prefabrication [21]. Despite the modest rate of automation application, evolutionary research on novel automation and robot technology is integrated for construction locations. The advent of 3D printing, which may be employed to structurally generate benign structures for concrete and bridges, is a revolutionary technical leap [22].

Anthropoid automation technology combines human intellect with swiftness, effectiveness, and strength of the robotic system attached to the human body (e.g., exoskeleton). Hence, it provides an ability of handling the complicated and constrained tasks. With the exception of these new breakthroughs, the construction sector has not employed the opportunities presented by such technological developments [23]. While several sectors (medical profession utilizing motorized division), have relied on and fully studied the use of automation technology, the widespread automation applications in construction division is long overdue owing to many obstacles [24]. The introduction of automation in the construction sector is slow. When creating various types of construction (building) jobs, it is necessary to use numerous automated single-task assembly robots. Automation technology application is expected to handle concerns like shortage of labors and risks associated with workers safety, specifically in high-rise projects, and increase the sustainability of the construction sector [25]. The construction industry's low degree of automation retards other sectors. Though the robotic systems improve production, and the safety, security, and health of workers there exist serious dangers towards the automation applications, according to a study involving 11 large European construction companies and governmental bodies. These include technical and commercial hazards as well as significant implementation costs. However, Ekanayake et al. (2021) indicated that a numerous studies endeavored to classify factors that influence acceptance, particularly for specific tasks for construction sector [26].

Additionally, the current study aims to fill the gap in understanding how construction automation can address pressing challenges in the industry, such as labor shortages, safety risks, and the need for sustainable practices. Despite the recognized potential of automation to revolutionize construction, its adoption has been slow and uneven. By systematically analyzing the specific drivers that impact automation implementation, this research provides valuable insights into how these technologies can be leveraged to overcome industry obstacles. This study's findings will offer practical implications for construction professionals, policymakers, and researchers, highlighting the pathways to achieving more efficient, safe, and sustainable construction practices through the strategic deployment of automation technologies.

The studies here typically concentrate on worldwide construction enterprises rather than construction sector developing nations. Existing research has not provided a comprehensive examination of the obstacles to the traditional application of automation in building operations within construction sector. Filling this need demands considerable expertise of building [27], [28]. For this study, we created the following research questions. What are the advantages and effects of automation in construction industry? What are the prerequisites and motivators for using automation in construction industry? Consequently, this research was conducted to address the research gap by scientifically investigating the relationship among automation drivers and adoption, as well as the effect of integrating automation in the construction sector, considering the modelling approach such as “partial least squares”.

Study employed the context namely, global–local context (GLC), which highlights the global significance of research topic. In addition, this technique simultaneously illustrates and emphasizes the topics under review. Thus, "developing" nations, have adopted the strategy since the regional climate is conducive to producing such precision (i.e., demonstrating its significance). The findings of this study could be valuable to many construction professionals (including bidders, legislators, and architects) and other developing nations where construction projects follow similar standards. The utilization of automation will assist in enhancing the resources that will improvise the whole environment of the building, this research will provide crucial information that may help in making judgments on the success of construction projects. The structure of this article is as follows: Section 2 reviews the relevant literature on construction automation and its drivers. Section 3 outlines the research methodology employed in this study, including data collection and analysis methods. Section 4 presents the results and findings from the data analysis. Section 5 discusses the implications of these findings for the construction industry. Finally, Section 6 concludes the study and provides recommendations for future research.

This study introduces a comprehensive framework for understanding the multifaceted drivers—cultural, technical, and industrial—impacting the implementation of construction automation, specifically tailored to developing nations. Unlike existing studies that predominantly focus on technological advancements, this research bridges the gap by examining the interplay of these drivers and their real-world implications through an empirically validated PLS-SEM approach. Additionally, the study highlights the significant contributions of automation to construction planning and accuracy, providing actionable insights that align with global sustainability goals while addressing regional challenges in labor shortages and resource management. This nuanced analysis positions the research as a pioneering contribution to the evolving discourse on automation in construction.

2. Model Development (Related Literature)

Karel Capek created the concept of automation-based robots in 1921. Drones, humanoids, and self-driving cars are now employed in farms, workplaces, residences, roadways, and other community locations (including eateries, shopping mall, and entertainment and recreation parks) [16], [29]. Automation (field of science and engineering), since 1920s has been a promising and expanding. At first, automations were restricted to factories and warehouses and used for hard repetitive activities, however they are now a vital component of human civilization. Currently, automation is used for a variety of functions, including food production, healing of diseases, education, and drain cleaning. As shown by the rapid use of robots in the construction sector, the rate of automation expansion is accelerating dramatically [30]. The socioeconomic judgements of human civilization have been significantly improved by automation. In order to enable industrial intelligence and smart production, the paradigm of the global manufacturing network is changing, relying more on automation and artificial intelligence. Schuck (2021) stated that there are primarily two categories of automation: field automation and service automation [31].

In domestic settings like as homes, public and community parks, and diners, the latter have being often termed as humanoids. Field automations are specialized, one-of-a-kind robots built to function in a particular environment, such as land, aerial, or maritime applications. Three generations of automation advancements may be identified [32], [33]. The initial generation of automations were largely used for repetitive activities and robotics. Second-generation automations are those concerned with warfare, the development of tasks, entertainment, and research. Automations of the third generation are focused with intelligence that can cooperate and live with humans. The automation-based robotics are generally used to comprehend behavior patterns and natural languages, as well as to react to human behavior. Robots that are automated allow for active customer service and decision-making [34], [35].

Cortens et al. (2020) characterized drivers as locations where enough discoveries assure a company's business triumph. The drivers are considered necessary for operation, planning, and directing to ensure success [36]. Based on the technology implementation concept, customer acceptance is determined by the willingness of the operator to advance technologically in daily life to perform tasks. Other studies have investigated the application of technology in daily life. Typically, researched theories view the forces behind technology adoption as components of success. The “theory of reasoned-action (TRA)” focuses on the components of consciously scheduled activities. A “task abstraction module (TAM)” was created to gauge operator acceptance of high-tech innovations. Similar to TRA and TAM, the “unified-theory-of-acceptance and use-of-technology (UTAUT)” is recognized approach [37].

In order to improve the use of automated tools created for building projects, precise techniques and tools are required. Automation is an approach that includes the application of techniques that spur the improvement of Environmental along with building work [38], [39]. Hashimoto et al. (2021) stated that fastest developments in automotive and robotic sciences are being done by computer based operational approaches which facilitate implementations to discover trends, perform analyses, along with forecast based on multiple data sources [40]. In practically all sectors, several techniques are used to improve the accuracy, excellence, and speed of particular operations [41]. The construction sector is influenced by emission-producing machinery and facilities. By substituting automation technology for such equipment, environmental contamination may be reduced, and a friendlier atmosphere created. Including the robots of which the main purpose might not impact the ecosystem, despite the fact that they may have significant environmental effects. The purpose of automation is to investigate their impact on the environment, even though they have significant environmental implications. Additionally, automation is meant to explore new settings that are inaccessible to humans. Modernization in the construction business is contingent on the sector's willingness to incorporate new technology. Implementing innovative technology helps to alleviate a number of challenges that might impact the construction sector [42], [43].

Key cultural drivers specifically identified to account for the adoption and implementation of automation in construction include:

Innovation Orientation: A strong culture of innovation and technological advancements tends to stimulate and support the adoption of new automation technologies. Companies with a stronger-than-average culture of innovation tend to invest more in and apply automated solutions to remain competitive [44].

Work Ethic and Efficiency: Cultures driven by work ethic and efficiency will tend to see more gains from the adoption of automation for increased productivity and the reduction of manual labor [47].

Risk Tolerance: Cultures that lean toward accepting more risks generally lean toward experimentation with newly introduced technologies—automation, for example—despite existing uncertainties or other initial costs.

Collaboration and Communication: A culture of collaboration and good communication among teams and across departments supports the smooth implementation of automation technologies, making it possible to plan better, integrate, and solve problems.

These aspects of culture are attributed to be drivers for the adoption and implementation of automation by the fact that it provides an environment for the support of technological change, stimulates innovation, and promotes efficiency and collaboration. This ultimately leads.

Bao & Li (2020) found that promoted for support of construction-science, claiming about sector's inherent conservatism has failed to change construction processes. Despite the availability of innovative approaches that potentially cut building costs, progress has been slow. Consequently, the implementation of modern building techniques may increase the efficiency of jobs and lower the high costs associated with construction projects [45]. The deployment of automation improves working conditions by minimizing employees' exposure to hazardous jobs and lowering the number of such tasks. Implementing automation may increase occupational safety by doing dangerous jobs in hazardous environments that would otherwise be done by people. The adoption of automation has decreased worker and laborer injuries [46], [47]. Problems develop with the consistency and quality of employees' work, and fewer workers may be needed to reduce labor costs. Currently, automation is supplementing human labor in the construction business to reduce the quantity of humans [48], [49]. Table 1 and Table 2 highlight, respectively, advantages and factors influencing the acceptance of robotics. Similarly, Figure 1 depicts the conceptual foundation for this investigation.

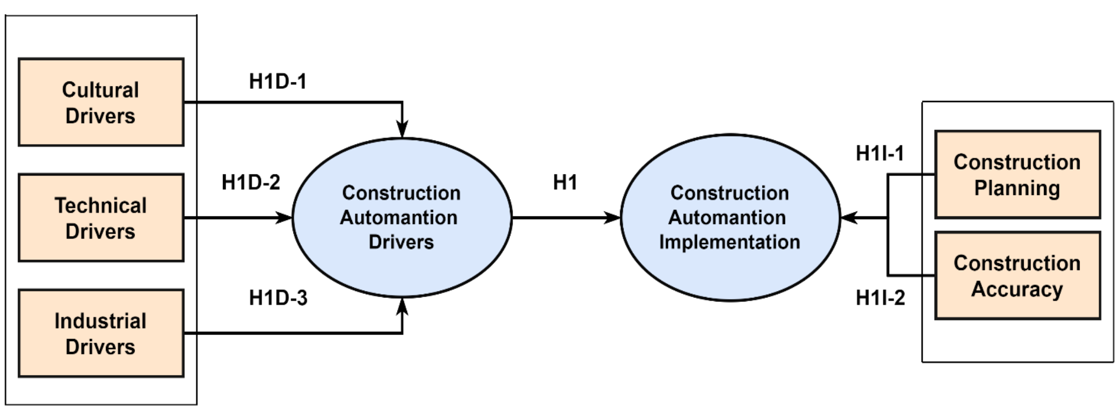

Figure 1. Impact of construction automation drivers on construction automation implementations.

H1= Construction automation drivers have significant impact on construction automation implementation in construction projects.

H1D-1 Cultural drivers have significant relation with construction automation drivers.

H1D-2 Technical drivers have significant relation with construction automation drivers.

H1D-3 Industrial drivers have significant relation with construction automation drivers.

H1I-1 Construction planning have significant relation with construction automation implementation.

H1I-2 Construction accuracy have significant relation with construction automation implementation.

Table 1: Indicated factors towards automation process for construction (building) projects.

Code	Drivers	References
AD1	Construction industry globalization and integration	[50], [51]
AD2	Technology revolution	[52]–[54]
AD3	Environmental friendliness of technological innovation	[55], [56]
AD4	Software representation and synthetic vision	[57]–[59]
AD5	The need for interconnection and convergence	[60], [61]
AD6	Utilization of information and communication technologies in the building sector	[62]
AD7	Rapid development of software development technologies	[63]–[65]
AD8	The industry's dynamic, field- and project-based character.	[66], [67]
AD9	Combination of conventional and advanced technologies	[68], [69]
AD10	The importance of urbanization	[70]

Table 2: Benefit indicators of automation for construction (building) projects

Codes	Benefits	References
AI1	Enhances real-time planning and reduces wasted time	[7], [71]
AI2	Reduces work intensity	[12], [13]
AI3	Reduces dependency on direct labor	[14], [15]
AI4	Enhances the efficiency of building processes	[72]
AI5	Greater command of the production procedure	[28], [73]
AI6	Superior precision to that of site workers	[26], [27], [74]
AI7	Decreases risk	[75], [76]
AI8	Enhances productivity and enhances work quality	[16], [29]
AI9	Improves current construction facilities and gear	[30], [31], [77]
AI10	Superior requirements for health and safety measures	[11], [32]
AI11	Reduces building material waste	[33], [34], [36]

3. Materials and Methods

The research technique includes the creation of model (theoretical based) that outlines a literature analysis employed to generate the transitional concepts (or hypotheses), validated using empirical evidence. The conceptual modelling approach is divided into three steps: (I) define the model's construct; (ii) organize or group the model's constructs; and (iii) develop links among the model's constructs. Following this procedure, the model's findings were achieved, as shown in Figure 1. Figure 2 depicts how the research strategy basing on Hall et al. (2022) and Jin (2020) work [78]. Due to the novelty of automation, To reach a certain subpopulation group, we used stratified sampling in this research. Because the present survey is related with an issue affecting automation, this methodology was recommended to aid in the collection of extremely trustworthy and precise data [79], [80]. The sampling advantages of the stratified process are stated follows: (I) "Bias reduction in sample of case selection;" (ii) Allowing working set to extrapolate to all population. The stratification considers the population variation all three sectors (consumer, service provider, and advisor), and the majority of five subsectors".

The selection of variables in this study followed a structured approach, combining both a review of the relevant literature and expert input. Initially, key variables related to construction automation drivers and implementation benefits were identified through an extensive review of existing studies. This included factors like cultural, technical, and industrial drivers, and benefits such as construction planning and accuracy, which had been discussed in prior research.

To refine these variables, we engaged with a panel of industry experts to ensure practical relevance and applicability. The panel consisted of professionals with a minimum of 10 years of experience in construction automation, including project managers, civil engineers, and architects. Each expert was selected based on their professional background, academic qualifications, and contributions to construction technology through published research or industry recognition.

The qualitative input from these experts was gathered through semi-structured interviews and focused group discussions. Experts were asked to assess the initial list of variables in terms of relevance, potential impact, and their own experiences in automation deployment. Based on this input, we adjusted the list by eliminating redundant factors and emphasizing variables with high practical importance, such as innovation orientation, risk tolerance, and system integration.

This expert input was critical in shaping the final questionnaire used in the pilot survey. The feedback helped in refining the survey instrument to better capture the nuances of automation drivers and their implementation outcomes. The final variables used in the study were thus validated both by literature and qualitative insights from industry practitioners, ensuring a comprehensive and contextually relevant set of factors for the analysis.

Reviewers rated robotics based adaptation advantages on a 5-point Likert scale, with 5 indicating very high and 1 indicating extremely low, and scores of high, medium, and low fallings around 5 and 1. This method of scoring has been widely used in a variety of studies, including construction management studies. The purpose of the research was to give stakeholders with a selection of building project-specific alternatives [81], [82]. The sample size was established in accordance with. More than thirty (30) cases, including the mean, median, and mode for a normal distribution curve, were deemed sufficient for further investigation [83], [84].

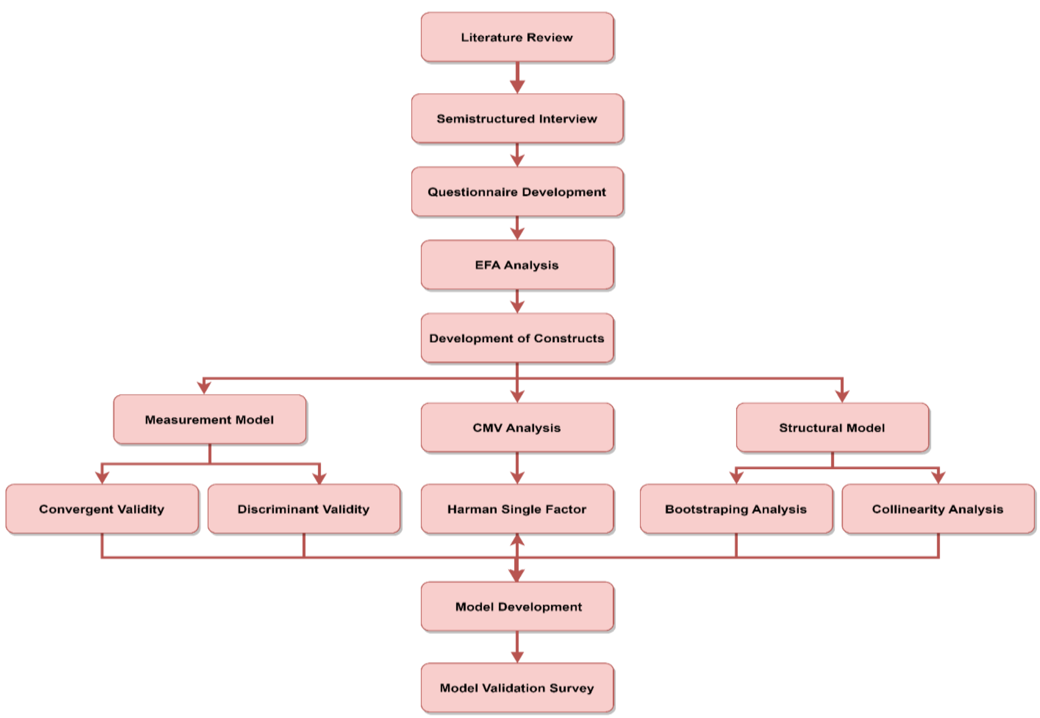

Figure 2. Flowchart of the study.

Naghshbandi et al. (2021) stated, in contrast, that for robust SEM sample size considering at least 200 is necessary [85]. According to Bock (2015), a particularly complex route model requires a sample size of minimum 200 or more, although Lekan et al. (2021) deemed a sample size of 100 or more to be sufficient [86], [87]. Because this investigation used the SEM approach, 166 participants were selected from a pool of 260 construction specialists. Members were directly enlisted (self-administered) and did a questionnaire for SEM assessment; the rate of response was around 64%, that was judged acceptable for the research.

The survey process included both pilot and main surveys to gather comprehensive data from building specialists.

Pilot Survey: Initially, a pilot survey was conducted with a sample of 30 building specialists to test the clarity and relevance of the questionnaire. Feedback from this pilot phase was used to refine the survey instrument.

Main Survey: The main survey was then distributed to a broader sample of 200 building specialists across various regions and sectors within the construction industry. Out of these, 166 responses were received, resulting in a response rate of 83%.

Representativeness: The 166 building specialists included in the final sample were carefully selected to represent a wide range of roles and expertise within the construction industry. This included professionals from different levels of the construction hierarchy, such as project managers, site engineers, architects, and consultants. Additionally, the sample covered various types of construction projects, including residential, commercial, and infrastructure developments, ensuring a comprehensive representation of the industry.

This diverse and well-distributed sample enhances the reliability and validity of the findings, providing a robust basis for understanding the drivers and benefits of construction automation within the construction context.

Experts were selected based on a rigorous process to ensure their relevance and expertise in construction automation. Selection criteria included professional background, with candidates chosen from diverse fields such as civil engineering, project management, and architecture. A minimum of 10 years of industry experience was required, along with advanced academic credentials (Master’s or Ph.D.) and membership in professional bodies like ASCE or PMI. Additionally, candidates who had published research on construction automation or received industry recognition were prioritized. Geographical diversity was also considered to incorporate a broad range of perspectives, ensuring comprehensive and credible insights into refining the drivers and benefits of construction automation.

3.1 Analysis of Exploratory Factors

The "exploratory factor analysis (EFA)” is used for exploring the groupings (questionnaire based) issued for construction industry specialists. EFA requires between 150 and 300 samples or observations [88], [89]. However, Bock (2015) suggested that the investigators had considerable flexibility regarding the sample size for factor analysis [87]. Therefore, bigger sample sizes are recommended in relation to the considered variables. Adaloudis & Bonnin Roca (2021) indicated that twenty to fifty variables or parameters are suitable for factor analysis [51]. Some studies needed few variables if the sample size was big enough due to the fact that if the number of variables exceeded this threshold, the individual aspects could not be adequately assessed [90], [91]. The population included in the current research was deemed to be a representative sample over all relevant ranges. As a result, the current study's 10 discovered variables and 166 completed questionnaires were found appropriate for analysis of factors.

3.2 Equation Modeling using Structural and Analytical Method

A literature review was conducted to investigate the deployment of automation, and four models were evaluated to generate the best practicable model for applying automation in building projects. Models investigated included multiple linear regression (MLR) but was not considered due to the correlations between non-observed variables, structural equation modelling (SEM), artificial neural networks (ANNs), and system dynamics (SD) [92], [93]. It is a significant constraint on the use of regression models [94], [95]. Similarly, SD could not be used since the nature of survey data unrelated with era. ANNs are considered the tool for forecasting, whereas the objective of this research is to determine how the drivers of automation construction adoption affect construction automation application [29], [31].

Because the SEM approach elaborates the in between relationship of various observable along with unobservable aspects, it is appropriate for this study's analysis. SEM is a good tool for addressing problems involving variables. SEM method was used for model development and established the correlations between construction automation drivers and construction automation deployment.

Ogunrinde et al. (2021) and Schuck (2021) stated that “SEM is a well-known non-empirical method for evaluating parameters and testing hypotheses” [31], [77]. Likewise, Alfalih (2022) and Hamid et al. (2016) verified in a MIS (Management Information Systems) Quarterly study journal bulletin that this approach has been enhanced throughout many decades [16], [30]. SEM is a well-known and well-understood data analysis tool in the field of social science. This method was considered for study since it has been frequently utilized in building industry research. This method allowed us to concurrently test hypothesized associations [11], [32].

We utilized the “partial least squares model (PLS)”, that contains both reflective and formative variables, to identify the correlations between construction automation drivers and construction automation deployment. It makes it possible to examine the construction automation drivers and the impacts of construction automation mechanism [77]. PLS-SEM allows for a detailed assessment of complex models for resemblance to data, testing of explicit parameter assumptions in addition to resemble with data.

Resultant model describes relationships between constructs (like construction automation drivers) along with experience indicators for PLS. The reason of this technique in this work was to keep the study model's variables and parameters within a reasonable range in relation to the estimated sample size and SEM's other factors.

4. Results

4.1 Respondents Characteristics

The respondent’s profession, organization, experience, and knowledge about construction automation were gathered as background information. 10.24 percent were architects, 8.43 percent were quantity-surveyors, 37.95 percent were civil engineers, 9.64 percent were M&E engineers, and 23.29 percent were project managers, according to Table 3. Table 3 displays the professional experience of the respondents; 22.89% had < 5, 32.7% had 6 to 10, 21.2% had 11 to 15, 33.13% had 16 to 20, and 7.23% had professional experience of > 21 years. Table 3 displays the respondents' degree of robotics knowledge, with three potential responses: 84.34% of respondents replied "Yes" to the question concerning automation expertise, 12.05% answered "No," and "Maybe," suggesting they were uncertain about the answer. Table 3 displays the respondent organization position in which 42.17% respondent were contractor, 39.76 respondents were consultant and 18.07% percent respondents were client.

Table 3: Demographic details of the 166 respondents involved in this study.

Category	Classification	Frequency	%
Profession	Architect	17	10.24
	Quantity Surveyor	14	8.43
	Civil Engineer	63	37.95
	M&E Engineer	16	9.64
	Project Manager	39	23.49
	Other	17	10.24
Organization	Contractor	70	42.17
	Consultant	66	39.76
	Client	30	18.07
Construction Industry Experience	0-5 Years	38	22.89
	6-10 Years	55	33.13
	11-15 Years	51	30.72
	16-20 Years	10	6.02
	Over 20 Years	12	7.23
Knowledge of Construction Automation	Yes	146	84.34
	No/May be	20	12.05

4.2 Identifying and Categorizing the Model’s Constructs

EFA was used to investigate a total of 10 components important to construction automation drivers and 11 things pertaining to the advantages of construction automation deployment. Numerous well-known factorability characteristics were used during model creation. The “KMO” a homogeneity of factor dimension that is extensively used to determine if partial correlations between items are insignificant. For effective analysis of factors, the KMO index must be between 0 and 1 and should have 0.60 value at least [11], [32]. The Bartlett sphericity test reveals either the matrix of correlation is the same. Ha et al. (2018) and Hunhevicz & Hall (2020), suggests that the sphericity test of Bartlett is necessary for an adequate factor analysis [33], [35]. It was significant for construction automation drivers (x2 (70) = 124.51, $p < 0.05$) and for advantages of implementation of robotics (x2 (96) = 260.00, $p < 0.05$). In addition, the whole bias of anti-correlation image's matrix is more than 0.5 and speculative, based on the inclusion of particular components in the analysis of factor.

The EFA test results identified two significant components with eigenvalues greater than 1. These components explain 46.85% of the total variance, indicating that nearly half of the variability in the data can be attributed to these factors [96]. This suggests that the identified factors are robust and significantly impact the constructs under study. The exclusion of cross-loading variables (e.g., AD5, AI7, and AI9) due to their low factor loadings further refines the model, ensuring that only the most relevant variables are included. This step enhances the reliability and validity of the factor analysis. According to the primary communalities, which assess variation among variables as assessed across all factors, lesser values (0.3 or less) indicate variables that don't go along with the result factor. All initial communalities were seen to be above the threshold in this study, and all factor loadings were greater than zero [39], [97].

Exploratory component analysis for the 10 relevant construction automation driving aspects revealed two factors with eigenvalues greater than 1. Approximately 46.85 % of the overall variance and eigenvalues were accounted for by the two components. Notably, AD5 was omitted main analysis due to cross loading, as seen in Table 4. In addition, the EFA findings suggested 9 factors are significant for deployment of construction, with two elements being retrieved. Nine components pertinent to construction automation derivers were also found using EFA, with one extracted factor having eigenvalues > 1. The variance and eigenvalues accounted for 57.81% of the overall variance. As demonstrated in Tables 4 and 5, however, two cross-loading variables (AI7 and AI9) were omitted from research.

Evaluation of the EFA-extracted factors was performed via statistical validity. Using the matrix structure's highest factor loading for each parameter, the factor loadings of phases (or groups) were determined. It is also demonstrated in the table a positive reliability test result. Author states that the Cronbach alpha value for newly established dimensions should be better than 0.6, even though the predicted value was 0.7, and values > 0.8 were judged credible [98]. Thus, the overall Cronbach estimates are considered acceptable, since they were more than 0.6, and the average variable correlations were > 0.3 for all components, indicating that the inner variables were harmonious.

Table 4: Exploratory aspect analysis of automated construction drivers.

Variables	**Component**			**Cronbach Alpha**
	1	**2**	**3**	
AD10	.846			.752
AD9	.805			
AD1	.668			
AD5				
AD4		.822		.735
AD7		.819		
AD2		.663		
AD6			.773	
AD3			.764	.701
AD8			.638	
"Extraction Method: Principal Component Analysis." "Rotation Method: Varimax with Kaiser Normalization." "Variable AD5 excluded because of loading less than 0.4."				

Table 5: Exploratory factor analysis of benefits of automated construction implementation.

	Component		Cronbach Alpha
	1	2	
AI2	.765		.771
AI5	.736		
AI4	.703		
AI3	.619		
AI1	.580		
AI11	.573		
AI7			
AI9			
AI10		.825	.775
AI6		.821	
AI8		.781	
Eigen Value	2.979	2.168	
% Variance	27.081	19.708	
"Extraction Method: Principal Component Analysis." "Rotation Method: Varimax with Kaiser Normalization." "Variable AI7 and AI9 excluded because of loading less than 0.4."			

4.3 Common Method Bias

CMV-Common method bias, also known for observed and anticipated variables is the statistical error variance, refers to the estimation of errors of variance that impact the samples validity. It is estimated using the single-factor model proposed by Kim et al. (2020) and Vähä et al. (2013), which recommends several building measures [38], [99]. In this investigation, the variance was calculated using a single-factor test. If the total variable variance < 50 percent, the conventional technique's bias has a negligible effect on findings. "If all components can be reduced to a single factor or if one component explains the majority of the total covariance across all variables, a significant common method variance may be found when conducting such a single-factor test". As indicated in Figure 3, the variance of the common technique cannot be changed by a factor of less than 50%, as the primary group of variables covers for 30.96 percent of the complete variance.

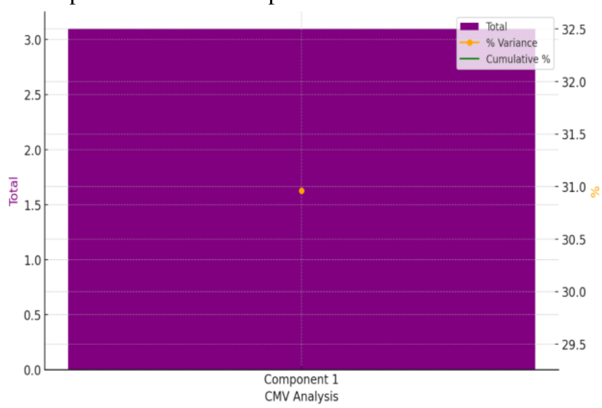

Figure 3. CMV analysis results using sum squared loadings.

4.4 First-Order Construct Measurement Model

The theoretical research model depicted in Figure 1 is replicated by the SEM in Figure 3. As shown in Tables 1 and 2, the model structures of each construction automation driver and implementation advantages model were thorough and categorized based on elements derived from the literature. The assessment model involves estimates of:

(i) Reliability of indicator

(ii) Combined reliability

(iii) Variance (extracted average) and

(iv) Discriminant ability

In the present investigation, 300 iterations of the PLS method were performed using the parameters provided by Hashimoto et al. (2021) and Stasiak-Cieślak & Grabarek (2019): weighting scheme and path, variance of 1Abort criteria of 1.0 x 10-5, data matrix with a mean of 0, highest interactions of 300 [39], [40].

Normally, indications with loadings in the range of 0.40 to 0.65 externally are eliminated amd discarded. if their discarding leads in a considerable improvement in the composite's and AVE's dependability. As stated by Gusmao Brissi et al. (2022) and Xing et al. (2020) the criteria was found to be incompatible with external load-variables less than 0.60, and they were disqualified from further analysis [71], [100]. At this level, the components of an indicator account for about half of its variation. The strength used to express the variance is greater than the variance. The external loadings for all measurement model variables are displayed in Figure 3 and Table 4 [101]. Consequently, all external loads exceeded 0.60, were considered adequate. Because the Cronbach alpha limits computational sensitivity in respect to the number of variables investigated; the core constancy of composite reliability (cr) was assessed; values more than 0.70 were considered acceptable. For elaborative study, results over 0.60 are generally appropriate [12], [13]. According to Table 6, all models satisfied the cr criteria of >0.70 and were thus approved. The AVE is a method that is widely used to evaluate the convergent cogency of model constructs with values larger than 0.50, indicating a suitable value in accordance with. As seen in Table 7, all structures passed the test.

Based on observed criteria, discriminant analysis was specifically described for components that differ considerably from other constructs. Because of this, the demonstration of discriminative validity (DV) shows a construct distinguishes singularities and is typical from the rest of the model's constructs that are not well described. DV may be calculated using two distinct criteria:

(a) The Fornell and Larcker (1981) criterion and cross-loading and

(b) HTMT criterion

(Every value should be less than 0.90 and below 0.85 is highly recommended). The results of both are indicated in Table 7 and Table 8. In the original method, the correlation between a single construct and any other construct could be tested for discriminant validity by equating the particular construct's AVE's square root. The correlation between the dormant parameters should be smaller than the square root of the AVE, according to Fornell and Larcker. Data in Tables 8 and 9 show how the measurement model is discriminant valid, respectively.

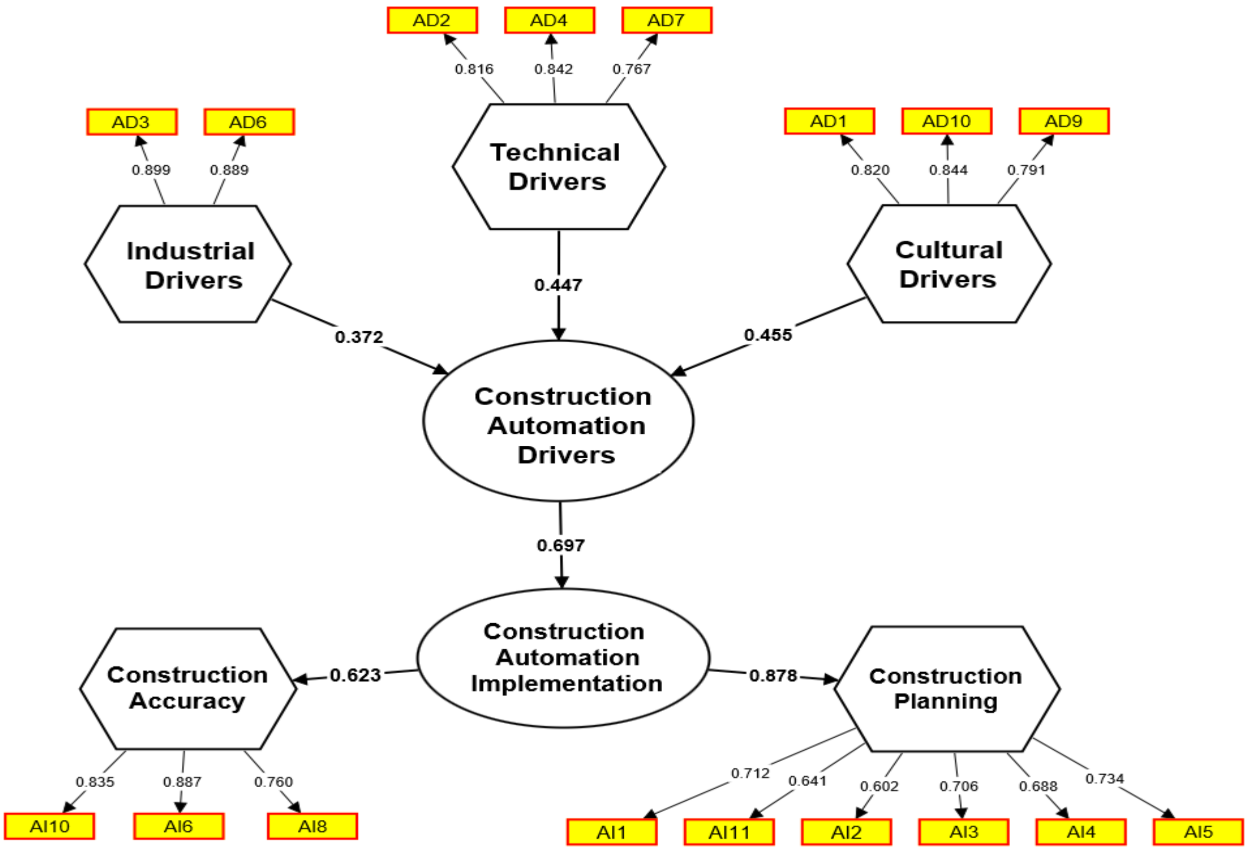

Figure 1. SEM model together with path coefficients and R2 values.

Table 6: The results of Cronbach alpha, composite reliability, and average variance extract with intimal and modified loadings of variables under certain constructs.

Stages	Assigned Code	Loadings		Cronbach Alpha	Composite Reliability	AVE
		Initial	Final			
Cultural Drivers	AD10	0.844	0.844	0.755	0.859	0.67
	AD9	0.791	0.791	-	-	-
	AD1	0.820	0.820	-	-	-
Technical Drivers	AD4	0.842	0.842	0.737	0.85	0.654
	AD7	0.767	0.767	-	-	-
	AD2	0.816	0.816	-	-	-
Industrial Drivers	AD6	0.799	0.889	0.749	0.888	0.799
	AD3	0.814	0.899	-	-	-
	AD8	0.522	Deleted			
Construction Planning	AI2	0.602	0.602	0.77	0.839	0.565
	AI5	0.734	0.734	-	-	-
	AI4	0.688	0.688	-	-	-
	AI3	0.706	0.706	-	-	-
	AI1	0.712	0.712	-	-	-
	AI11	0.641	0.641	-	-	-
Construction Accuracy	AI10	0.835	0.835	0.775	0.868	0.687
	AI6	0.887	0.887	-	-	-
	AI8	0.760	0.760	-	-	-

Table 7: The results of discriminant validity by using correlation of latent of Fornell–Larcker method.

Constructs	Construction Accuracy	Construction Planning	Cultural Drivers	Industrial Drivers	Technical Drivers
Construction Accuracy	0.829				
Construction Planning	0.349	0.682			
Cultural Drivers	0.307	0.484	0.819		
Industrial Drivers	0.316	0.388	0.465	0.894	
Technical Drivers	0.331	0.313	0.417	0.388	0.809

Table 8: The results of discriminant validity by using correlation of latent of HTMT method.

Constructs	Construction Accuracy	Construction Planning	Cultural Drivers	Industrial Drivers	Technical Drivers
Construction Accuracy					
Construction Planning	0.453				
Cultural Drivers	0.395	0.624			
Industrial Drivers	0.413	0.804	0.615		
Technical Drivers	0.443	0.813	0.542	0.512	

Cross-loading was a metric for assessing discriminative validity. This strategy is an attempt to create indicator loadings based on the allegedly inactive construct, which must be higher than the loadings on the following structures [14], [15]. As a result, each construct's indication (item) loadings must be higher than those of other constructions. Table 9 demonstrates that the loading at each point of the selected inactive construct is less than the cross loading of the alternative constructions in a row.

Table 9: Cross loadings of the substitute construct are applied to each point of the designated inactive construct.

Variables	Construction Accuracy	Construction Planning	Cultural Drivers	Industrial Drivers	Technical Drivers
AI6	0.887	0.295	0.25	0.296	0.236
AI8	0.76	0.273	0.221	0.269	0.291
AI10	0.835	0.304	0.295	0.219	0.32
AI11	0.237	0.641	0.284	0.241	0.529
AI2	0.207	0.602	0.262	0.265	0.595
AI3	0.27	0.706	0.294	0.638	0.265
AI4	0.212	0.688	0.4	0.327	0.581
AI5	0.247	0.734	0.414	0.706	0.279
AI1	0.251	0.712	0.316	0.634	0.284
AD1	0.35	0.507	0.82	0.416	0.433
AD10	0.174	0.329	0.844	0.362	0.309
AD9	0.216	0.338	0.791	0.358	0.267
AD6	0.287	0.609	0.398	0.889	0.337
AD3	0.278	0.622	0.432	0.899	0.356
AD2	0.335	0.56	0.423	0.377	0.816
AD4	0.249	0.5	0.3	0.324	0.842
AD7	0.203	0.412	0.272	0.224	0.767

4.5 Second-Order Construct Measurement Model

The bootstrap approach was used to analyze the significant input of all first-order latent variables, and the significant variables (both dependent and independent) were designated as second-order static variables. Construction automation was discovered that execution was a wise construct., and the specific construct of the construction automation drivers was crucial [12], [100]. No frequent and significant correlations between the measure's formative indicators were predicted. Moreover, large correlations between formative variables showing collinearity are considered unacceptable. Collinearity between the construct's formative variables was discovered by the variable inflation factor (VIF) value analysis [7], [71]. For this evaluation, collinearity problems Utilizing the internal VIF values which are the formative-reflective form of second-order constructions was studied. Cultural drivers, technical drivers, and industrial drivers were three subscales of first-order construction automation drivers [8], [102]. As shown in Table 10, external loading was greatest for culture (β = 0.455, p 0.001), followed by technical (β = 0.447, p 0.001) and industrial (β = 0.372, p 0.001). VIF results came smaller than 3.5, indicating that each subdomain independently impacting to upper-order structures.

Planning (β=0.907,p 0.001) and accuracy (β=0.907,p 0.001) second-order static variable significantly improved robotics application; the standardized coefficient paths (external loadings) were > 0.7 and statistically significant, as shown in Table 11.

Table 10: Second-order model testing for basic components via bootstrapping.

Hypothesis	Path	β	SE	t-values	p-values	VIF	Results
H1D-1	Cultural Drivers -> Construction Automation Drivers	0.455	0.027	16.709	<0.001	1.392	Accepted
H1D-2	Industrial Drivers -> Construction Automation Drivers	0.372	0.022	17.005	<0.001	1.354	Accepted
H1D-3	Technical Drivers -> Construction Automation Drivers	0.447	0.028	16.123	<0.001	1.285	Accepted

Table 11: Second-order model testing using bootstrapping for voluminous second order constructions.

Hypothesis	Path	β	SE	t-values	p-values	Results
H1I-1	Construction Automation Implementation-> Accuracy	0.623	0.059	10.637	<0.001	Accepted
H1I-2	Construction Automation Implementation-> Planning	0.878	0.016	17.102	<0.001	Accepted

4.6 Path Analysis

A linear statistical tool used in management and the social sciences is called the structural model path analysis (SMPA) method. SMPA is indispensable instrument for contemporaneous analysis of multidimensional relationships. SEM is required for use in primary phase analysis. This paradigm is helpful for assessing relationships between researched ideas. Within SEM analysis, SEM is the key phase after model fitting [7], [100]. SEM may be used to establish associations between variables. In SEM, the relationship between variables is thoroughly explained. The data reveal the links between exogenous (or dependent) and independent factors. The SEM assessment bases on the model's overall fit, with relevance, magnitude, and direction following theoretical variable estimates. The last step consists of confirming the suggested analytical connection based on the research assumptions stated in Figure 1. Applying SEM to the study idea. Based on the research methodology, PLS-SEM was used to examine the impact of construction automation drivers on construction automation deployment. Figure 4 illustrates the associated research model hypothesis. In the framework of the bootstrapping procedure, the model's hypothesized effect was calculated. Bootstrapping consisted of arbitrarily resampling the fundamental dataset to generate additional samples of equivalent size to the fundamental dataset. This method assesses the consistency of datasets and their statistical consequences, as well as mistake in route of derived coefficient's. Figure 4 shows significance of the route, the path of coefficient of standardization (β), and p-values. Table 12 p-values in model route shows because of the bootstrapping procedure. The impacts of construction automation drivers on construction automation deployment were statistically significant and beneficial (p = < 0.005, β= 0.697).

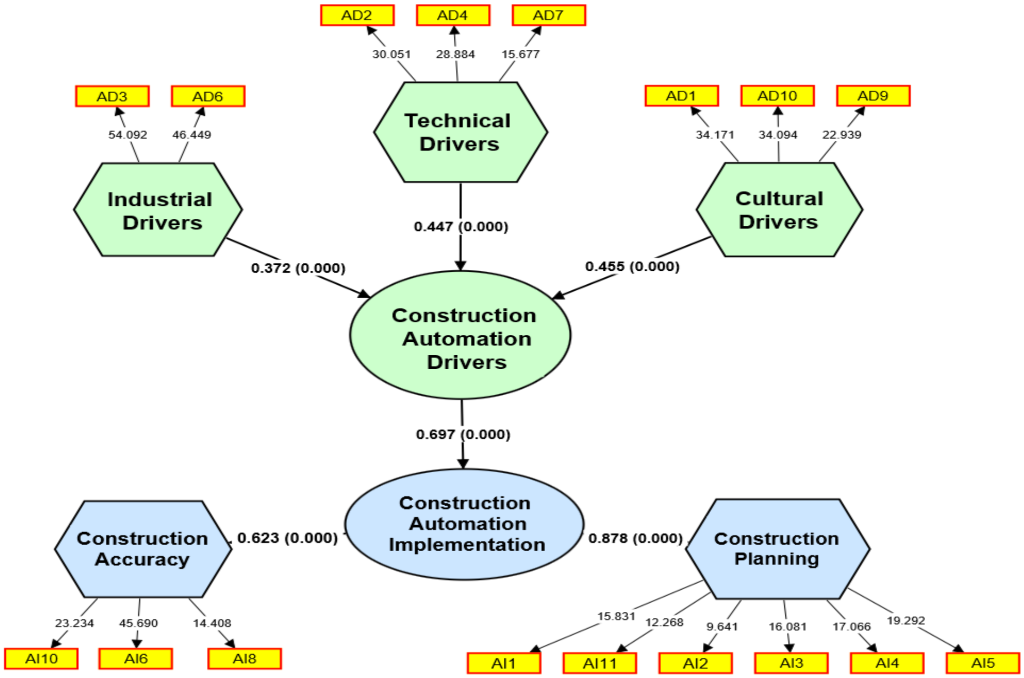

Figure 5. Path coefficients with P values using bootstrapping analysis.

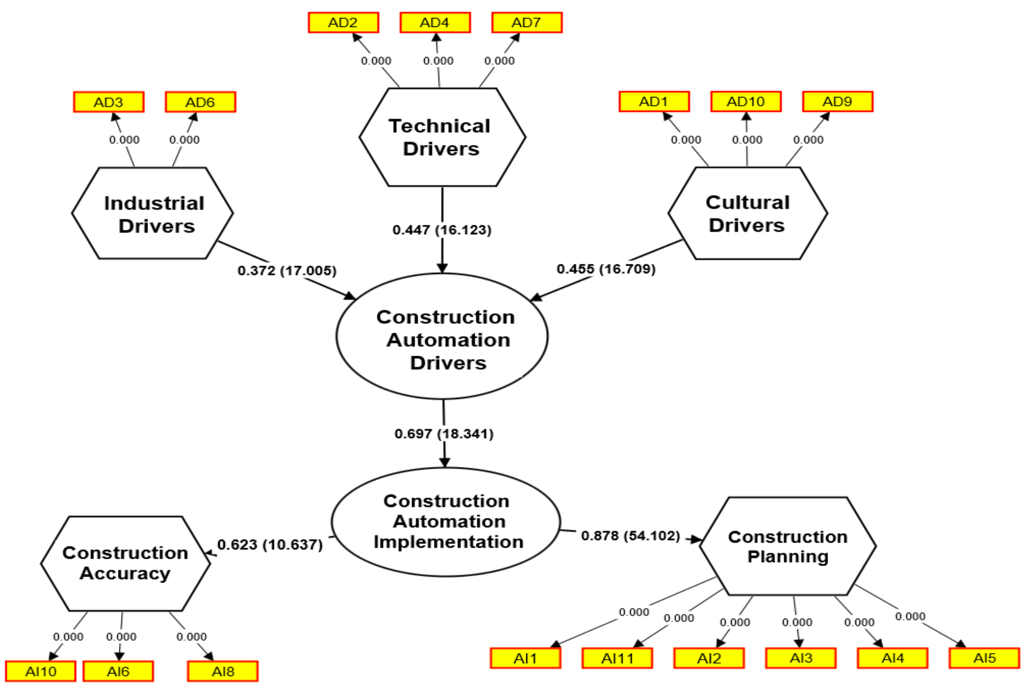

Figure 6. Bootstrapping analysis with T-statistics.

Table 12: Path relative to the mode

Hypothesis	Path	β	SE	t-values	p-values	Results
H1	CA-Drivers -> CA-Implementation	0.697	0.038	18.341	<0.001	Accepted

4.7 Empirical Correlation for Verification of Hypothesis

Every row and column in the table 14 corresponds to a separate variable. Each cell depicts the correlation coefficients between each pair of variables. The values range from -1 to 1, with -1 being a perfect negative correlation, 0 representing no correlation, and 1 representing a perfect positive correlation. The table displays both positive and negative correlations between variables. Some variables are highly connected, whereas others have no correlation whatsoever. Correlation is useful for discovering patterns and correlations between data, which may be advantageous for statistical analysis and modelling.

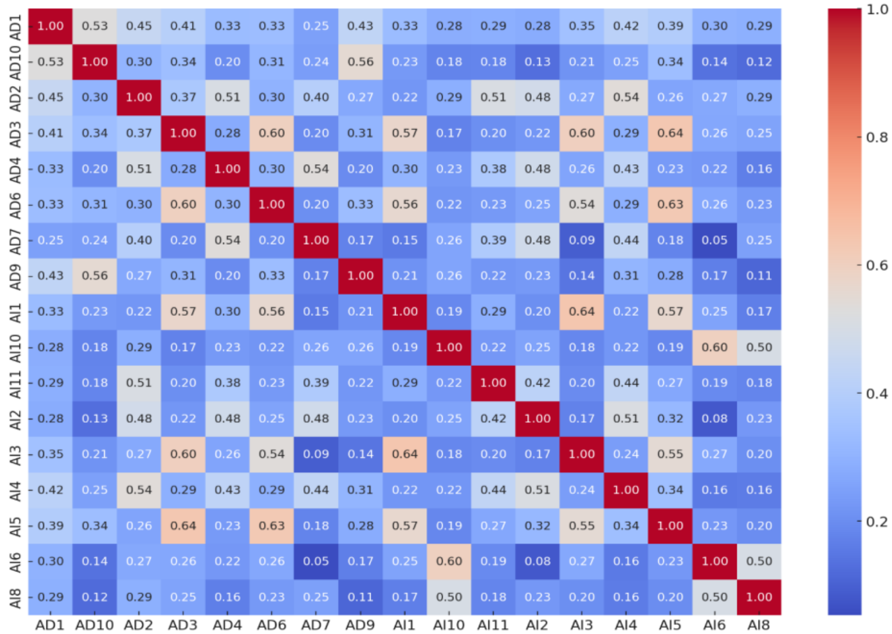

Figure 7. Correlation matrix.

4.8 Exploratory Strength (SEM Model)

The model findings illustrate the measuring model's discriminant and cogent validity, as well as the high dependability of each item. The elaborative superiority that SEM model has is evaluated in addition to the variation within the dependent variable that the model may describe. Regarding dependent model variables, the PLS technique strengthened squared multiple (R2) correlations [3], [10]. The R2 determined by the PLS method is equivalent to the R2 obtained by conventional regression. The value of R2 represents the total variation that may be described utilizing independent elements among the dependent variables. Thus, greater R2 values augment the SEM model's analytical power. As indicated in Table 13, the R2 values in the present study were obtained using the Smart-PLS technique. Construction automation adoption, the main dependent variable in the model, had a modified R2 of 0.486, meaning that automation drivers, an independent (or exogenous) static variable, can explain 48.6% of automation adoption. According to Chea et al. (2020), these findings indicate that the influence of construction automation drivers is moderate [12].

Table 13: Ratio of determination (R^2)

Endogenic dormant variable	**R^2**	**R^2 Adjusted**
Construction Automation Implementation	0.486	0.5

4.9 Predictive Relevance (SM Model)

The suggested model's ability to judge analytical importance is a crucial component. To evaluate the cross-validation's redundancy measures, each dependent variable was covered in blindness. The findings indicated that project completion was larger than 0 for values of Q2 (0.466), demonstrating the predictive significance of the autonomous construct for the provided construct studied in the research. According to Table 14, the value of Q2 exceeds zero. Consequently, it may be inferred that the model has an excellent predictive power.

Table 14: Predictive Relevance output Q^2

Endogenous Latent Variable	**Predict-Q^2**
Construction Automation Implementation	0.466

5. Discussion

On construction sites, a large variety of equipment is employed. Nevertheless, "the adoption of building's life cycle variation from a broad array of choices is a significant difficulty in project management". Overall, the construction sector has fewer elements (productivity, quality, and product functions) than other industries, and businesses compete within a competitive industry getting further complex, vibrant in present period along with international environment. However, green construction initiatives successfully advance social advancement and environmental sustainability. construction automation technology Execution with construction professionals along with the execution of relevant activities may significantly enhance the completion of building projects [7], [71].

Automated systems and robots have the potential to revolutionize the building, architectural, engineering, and construction sectors and provide several advantages. In addition to data obtained by model assessments, a SEM analysis contained a thorough basis for the discovery of correlations between construction automation drivers and their advantages in the proposed model [10], [12]. Revision and analysis led to the discovery of several remarkable findings. EFA study reveals that there are three primary groups of construction automation implementation drivers (cultural, technical, and industrial).

The PLS-SEM results show that Construction automation drivers were most impacted by traditional drivers, which had an exterior path of 0.455, trailed by technological and industrial drivers, which had external paths of 0.447 and 0.372, respectively. Similarly, the EFA findings reveal deployment of construction automation may be categorized into substantial sets: planning and accuracy, with exterior pathways of 0.878 and 0.623, respectively. Variables are evaluated to determine impact of construction automation installation and construction automation drivers. Results indicate the construction automation drivers contribute around above 40% to the application of construction automation in the construction sector [13], [14].

Construction automation drivers also indicate a substantial association with construction automation deployment, as measured by a value of 0.697; this correlation becomes significant once an organization or business adopt a single component of construction automation drivers. Additionally, planning and accuracy factors boost construction automation technology by 0.697. The findings indicate that the deployment of certain construction automation drivers facilitates the implementation of construction automation technology for projects that aim to preserve the client's resources and satisfy environmental responsibilities [7], [12]. With a score of 0.878 for outside loading, the planning factor was deemed the most significant. "planning (labor productivity and safety, Sustainability and design) advantages result from more rational use and decreased exploitation of natural resources, decreased water and energy use, and conscientious and orderly growth".

It has been proposed that construction automation devices may improve the building environment by lowering deaths and relieving workers of dangerous tasks. In this respect, the use of construction automation planning and accuracy is a potential resolution to grow ecological sources and sustainability in a variety of ways, such as by minimizing the waste produced by construction, conserving natural sources, enhancing workplace safety, and promoting a better living environment [10], [100]. Moreover, participants must consider how the risk reduction afforded by construction automation in construction enterprises justifies the more primary money of investment along with enhancement of building environment and planning.

The comparison table 15 provides a detailed analysis of the present study's findings against those of previous research. The total variance explained by the present study (30.96%) aligns well with the typical range of 25% to 50% found in earlier studies, demonstrating a reasonable explanation of variability. Key drivers such as cultural, technical, and industrial factors were identified, consistent with previous studies that also emphasized technical and economic drivers.

The benefits of automation, particularly in planning and accuracy, were in line with prior research, underscoring the positive impact on project management and quality control. Methodologically, the use of PLS-SEM in the present study offers robust validation, matching the advanced analytical methods used in contemporary research. The common method bias impact remains below the critical threshold, ensuring data validity, while the strong predictive relevance ($Q^2 = 0.466$) confirms the model's applicability for future predictions. Finally, the strong positive correlations between drivers and outcomes echo previous findings, with a unique emphasis on cultural drivers reflecting regional influences.

Table 15: Comparison of results with previous studies.

Aspect	Present Study	Previous Studies	Comparison and Analysis
Total Variance Explained	30.96%	Typically ranges from 25% to 50% in similar studies [3],[12].	The total variance explained in the present study falls within the typical range observed in previous studies, indicating a reasonable explanation of variability by the identified components.
Key Drivers	Cultural (0.455), Technical (0.447), Industrial (0.372)	Varies by study; often includes technical, economic, and policy drivers [103]	The key drivers identified in the present study align with those found in previous studies, with cultural drivers also playing a significant role, highlighting regional differences.
Implementation Benefits	Planning (0.878), Accuracy (0.623)	Efficiency, quality, and safety improvements [13].	The benefits observed, such as planning and accuracy, are consistent with previous findings, reinforcing the positive impact of automation on project management and quality control.
Methodological Approach	PLS-SEM for model validation and hypothesis testing	Various methods, including regression analysis and traditional SEM [104]	The use of PLS-SEM in the present study provides robust validation and aligns with contemporary analytical methods, offering detailed insights into the relationships between variables.
Common Method Bias (CMV) Impact	30.96%	Less than 50% in most studies [38]	The CMV impact in the present study is below the critical threshold of 50%, indicating a manageable level of bias similar to previous studies.
Predictive Relevance (Q^2)	0.466	Typically ranges from 0.3 to 0.5 [105].	The Q^2 value indicates strong predictive relevance, comparable to previous studies, confirming the model's applicability for predicting outcomes in the construction industry.
Correlation Between Drivers and Outcomes	Strong positive correlations between drivers (cultural, technical, industrial) and outcomes (planning, accuracy)	Positive correlations often found, though specific drivers vary [31].	The present study's findings of strong correlations are consistent with previous research, though the emphasis on cultural drivers may reflect unique regional influences.

Through a fully integrated 3D AutoCAD interface, various automation design software and tools, such as fundamental 2D drawing kits with parametric laws, can be combined with parametric mechanisms, to improve construction environment (planning and accuracy) during the design phase. The creation of concepts of design however, should be left to a single person. Computers give significant assistance in terms of storage capacity as well as the capacity to analyze and uphold extremely interconnected and complex data designs; Compared to manual methods, the jobs are completed far more swiftly resulting in reliable and predictable efficiency that reduces the oversight burden for management [12], [13].

A basis for evaluating the suitability and user satisfaction, performance and resource accuracy is defined as a combination of characteristics required for services by those involved in the construction project. The planning (labor productivity and safety, Sustainability, and design) and accuracy (error free) factor's outside loading of 0.878 and 0.623 was considered acceptable. One of the usual advantages of integrating construction automation technology is the ability to distinguish the required elements for a project's success, as shown by the results. These results support Leśniak et al. (2021) and M. N. A. Rashid, Abdullah, Ismail, et al. (2019) hypothesis that an image recognition-based independent classification (classification) could help to lessen the labor-intensive nature of recycling tasks [14], [15]. According to Chen et al. (2018) and M. N. A. Rashid, Abdullah, & Ismail (2019), the application of construction automation offers several economic advantages and increases the speed, quality, and productivity of building [29], [75].

Moreover, automation implementation could overcome a number of construction-related obstacles. Automated robots might encourage the construction of off-site projects, enhancing the ability to more precisely design and close the energy usage gap will result in the triple bottom-line benefits (financial, environmental, and societal advantages). Construction automation is divided into three categories by the International Association of Automation and Robotics in Construction (IAARC): those who upgrade current industries and building machinery, enthusiastic automation, and less cognitive (or intelligent) automation [106]. For instance, the Big Canopy system from the Obayashi Corporation lessen the amount of staff needed on the site for concrete-reinforced structures by 75%, and ABCs method shortened the construction period for forty (40) storey buildings by six months. Moreover, the use of automation may facilitate the efficient prefabrication, delivery, and supply of components in accordance with the project schedule.

Cultural Drivers: Four key cultural factors were identified as significant drivers. Innovation Orientation, which emphasizes technological advancements, encourages investment in new automation technologies. A strong Work Ethic and Efficiency culture pushes for productivity improvements, making automation an attractive solution. Risk Tolerance allows organizations to experiment with new technologies despite uncertainties, facilitating the adoption of automation. Lastly, a culture of Collaboration and Communication promotes teamwork and smooth integration of automation technologies into existing workflows.

Technical Drivers: The study found that Advanced Technologies, System Integration, Ease of Use, and Reliability and Performance are critical technical drivers. The availability of cutting-edge tools provides new capabilities, while system integration ensures seamless operation with existing systems. User-friendly interfaces enhance user adoption, and consistent and robust operation builds trust in automation technologies. These factors collectively ensure that automation solutions are not only feasible but also effective and reliable.

Industrial Drivers: Market Demand, Regulatory Environment, Economic Incentives, and Competitive Pressure were identified as the primary industrial drivers. Increasing demand for efficient construction methods pushes for faster adoption of automation. Supportive policies and standards create a conducive regulatory environment, encouraging compliance and adoption. Economic incentives such as cost savings and profitability justify the investment in automation. Finally, competitive pressure drives innovation, compelling companies to adopt automation to maintain a competitive edge in the industry.

Overall, these drivers collectively influence the adoption and implementation of construction automation by addressing various aspects of the organizational, technological, and industrial environment shown in Table 16. Understanding these drivers helps in developing strategies to promote automation in the construction industry effectively.

Due to the fragmented, diverse, and multi-party nature of the construction industry, contractors typically view design, manufacturing, transportation, and installation as challenging tasks that need to be coordinated well throughout the project life cycle. Automation implementation can help with these tasks. The implementation of engineering automated tools has resulted in a widening of profit margins. The introduction of engineering automated tools has increased predictability and production quality, resulting in a rise in profit margins. Under the effect of planning in terms of sustainability and accuracy terms of resources output in factors, the success of the adoption of construction automation technology will be impacted by construction automation drivers, according to the findings provided above [107].

The collected findings regarding the adoption of automation technology using automation drivers supported our study's premise. Therefore, the purpose of the research was met. planning and accuracy issues effect the application of automated construction, and the above stated variables determine the project success. This is supported by our findings, which are consistent with the current literature.

Table 16: Cultural, technical and industrial drivers.

Aspect	Details	Influence on Adoption and Implementation
Cultural Drivers	Innovation Orientation: Emphasis on technological advancements. Work Ethic and Efficiency: Focus on productivity. Risk Tolerance: Acceptance of uncertainties. Collaboration and Communication: Promotes teamwork.	Innovation Orientation: Encourages investment in automation. Work Ethic and Efficiency: Drives productivity improvements. Risk Tolerance: Facilitates tech adoption. Collaboration: Smooths integration.
Technical Drivers	Advanced Technologies: Availability of cutting-edge tools. System Integration: Compatibility with existing systems. Ease of Use: User-friendly interfaces. Reliability and Performance: Consistent and robust operation.	Advanced Technologies: Provides new capabilities. System Integration: Ensures seamless operation. Ease of Use: Enhances user adoption. Reliability: Builds trust in automation.
Industrial Drivers	Market Demand: Increasing demand for efficient construction. Regulatory Environment: Supportive policies and standards. Economic Incentives: Cost savings and profitability. Competitive Pressure: Need to stay competitive.	Market Demand: Pushes for faster adoption. Regulatory Environment: Encourages compliance and adoption. Economic Incentives: Justifies investment. Competitive Pressure: Drives innovation.

Application of Findings Across Different Construction Project Types

The findings of this study, particularly regarding the impact of construction automation drivers, may vary significantly between different types of construction projects, such as residential and industrial projects. Each project type has unique characteristics, priorities, and challenges that influence the relevance and effectiveness of automation technologies.

1. **Residential Projects:** In residential construction, the implementation of automation technologies is often focused on efficiency and precision in repetitive tasks such as bricklaying, prefabrication of building components, and interior finishing. The cultural drivers, such as innovation orientation and work ethic, are particularly important in this context because residential construction tends to rely heavily on manual labor and traditional practices. Automation in residential projects can help reduce labor costs, improve accuracy in repetitive tasks, and ensure quicker project completion. However, due to budget constraints typical of residential projects, the adoption of high-tech automation may be limited unless cost-effective solutions are available. Additionally, technical drivers, such as ease of use and system integration, are crucial to ensure that automation tools can be easily deployed and managed by workers who may have limited technical expertise.

2. **Industrial Projects:** In contrast, industrial construction projects, such as factories, warehouses, or large-scale infrastructure, often have more complex and large-scale requirements. These projects benefit significantly from advanced automation technologies, including robotics for heavy lifting, automated guided vehicles (AGVs), and precision systems for large-scale assembly. Technical drivers, such as system reliability and performance, play a more critical role in industrial projects where automation must handle high loads, complex tasks, and harsh environments. Additionally, industrial drivers, such as regulatory environment and competitive pressure, are more prominent in this context. Industrial projects are often subject to stricter regulations regarding safety and environmental impact, making the use of automation a key factor in ensuring compliance and improving operational efficiency.

Moreover, industrial projects tend to have larger budgets, which allows for greater investment in cutting-edge automation technologies. The findings related to the benefits of construction planning and accuracy are particularly applicable here, as industrial projects require high precision and coordination across various stages to avoid costly delays and ensure safety. The significant planning impact factor of 0.878 identified in this study demonstrates that automation can play a critical role in enhancing project management and coordination in large-scale industrial settings.

3. **Comparative Insights:** While both residential and industrial projects can benefit from automation, the emphasis on specific drivers may vary. For residential projects, cultural and cost-efficiency considerations are more prominent, with a focus on integrating automation in a way that enhances labor productivity and minimizes manual errors. In contrast, industrial projects prioritize technical and industrial drivers, focusing on system integration, scalability, and meeting regulatory requirements.

   In both cases, the study's findings provide valuable insights into how automation can be tailored to meet the unique needs of each project type. Construction professionals can leverage these insights to make informed decisions about which automation technologies to implement, depending on the project scale, complexity, and budgetary constraints.

6. Limitations and Future Implications

We consider research to be a process rather than an outcome. Thus, we advise research in the following fields:

- We investigated the use of automation in construction (building) projects in this study. Robotics can be used in construction projects to conduct further research.
- Assessing the impact of automation on student performance in higher education institutions.

We recommend the following based on the outcomes of our research into the advantages of automation for the building industry:

- Higher education institutions should teach students how to apply new technology and employ them in construction projects. This will help students gain more knowledge that they can use after graduation.
- Construction firms should organize training for industry professionals and educate them on the importance and advantages of using automation in the construction sector, including architects, quantity surveyors, builders, project managers, and engineers.
- To remain updated and maintain their relevance, members should also be encouraged to use automated tools in the construction sector.
- Suppliers need to make sure that the cost of purchasing automation equipment is reduced so that everyone involved in the building sector can easily access it.

7. Conclusion

This study highlights the critical role of cultural, technical, and industrial drivers in shaping the successful implementation of construction automation. Automation offers significant benefits, such as improved efficiency, precision, and sustainability, which can address many of the pressing challenges in the construction industry. However, the adoption of automation technologies remains uneven, with distinct variations between residential and industrial projects. To bridge these gaps and encourage broader adoption of automation, specific recommendations are necessary for both industry practitioners and policymakers.

For practitioners, one of the key areas for improvement is workforce development. Construction companies must prioritize training and upskilling their employees to ensure that they are proficient in operating and managing automation technologies. This will not only increase productivity but also minimize errors and reduce safety risks on construction sites. Additionally, firms should focus on fostering a culture of innovation and collaboration, where employees feel encouraged to embrace new technologies. This cultural shift will be essential in overcoming resistance to automation and creating an environment where technological advancements can thrive.

From a technical perspective, practitioners should ensure that the automation technologies they adopt are compatible with existing systems and workflows. Seamless system integration is crucial for maximizing the benefits of automation, particularly in large-scale industrial projects. Construction companies must also invest in reliable and scalable automation solutions that can handle the complexities of modern construction projects, ensuring consistent performance and long-term value.

For policymakers, there is a need to establish supportive regulatory frameworks that encourage the adoption of automation in the construction industry. Policies should promote innovation by offering incentives, such as tax breaks or subsidies, for companies that invest in automation technologies. Additionally, governments can play a pivotal role by establishing clear standards and guidelines for the safe and efficient use of automation in construction, ensuring that these technologies are used responsibly while maintaining high safety standards.

Finally, collaboration between industry stakeholders and educational institutions should be encouraged to foster the development of future professionals skilled in automation technologies. Integrating automation-related curricula in engineering and construction management programs will equip the next generation of professionals with the knowledge and skills necessary to drive the future of automated construction.

In conclusion, while the benefits of automation in construction are evident, its full potential can only be realized if industry practitioners and policymakers work together to address existing barriers and foster an environment conducive to technological innovation. By investing in workforce development, improving system integration, and implementing supportive policies, the construction industry can unlock the full benefits of automation, leading to more efficient, sustainable, and safer construction practices.

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