Heliyon 10 (2024) e37078

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Revolutionizing construction: A cutting-edge decision-making model for artificial intelligence implementation in sustainable building projects

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ARTICLE INFO

Keywords:
Artificial intelligence
Benefits assessment
Construction digitalization
Digital transformation
Health and safety
Project completion
Sustainable construction

ABSTRACT

This study examines how certain artificial intelligence (AI) drivers affect the industry's adoption of this technology in the construction industry. The research methods comprised a comprehensive analysis of previous studies to pinpoint the primary factors influencing AI adoption in the construction industry. Data collection was carried out through a well-structured survey involving relevant stakeholders in the building construction sector. The three main constructs of technological devices, advancement, and knowledge were found from the set of drivers with the technique of exploratory factor analysis. The deployment of AI in construction has the potential to improve health and safety and expedite project completion, as this research has evaluated. To figure out how these factors relate to the adoption of AI in the construction industry, partial least squares structural equation modeling was used. The study's conclusions showed that the influence of AI installation in the construction industry is reasonably significant thanks to the technology, advancement, and knowledge, contributing around 15 % of the effects that have been directly witnessed. The practical implications of AI for policy makers, engineers, and construction stakeholders are extensive and provide valuable insights for customized strategies aimed at using AI's potential to improve projects, promote sustainability, and elevate health and safety standards.

1. Introduction

The global economy is mostly driven by the architectural, engineering, construction, and operation (AECO) sector. By 2028, the

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https://doi.org/10.1016/j.heliyon.2024.e37078
Received 24 February 2024; Received in revised form 23 August 2024; Accepted 27 August 2024
Available online 28 August 2024
2405-8440/

AECO sector is expected to contribute 15 % of the world's gross domestic product, up from its current 13 % share [1,2]. Building projects, the backbone of the AECO sector, are responsible for as much as three percent of the emissions of greenhouse gases and 40 % of world energy consumption [3]. Major cities are essential to accomplishing global sustainability goals because of their increasing population density and economic activity [4]. To this end, the AECO sector is continuously looking for new and creative methods to cut down on resource usage, eliminate waste, and encourage ecologically friendly behaviors across the whole building lifetime [5,6]. Finding the ideal balance between environmental stewardship and economic growth is still a topic of discussion within the industry [7,8].

While the building industry in many wealthy nations has made great strides in adopting sustainable methods and technologies, the situation in poor countries is somewhat different [9]. Inadequate infrastructure, a shortage of competent labor, political unrest, budgetary restrictions, and other resource-related issues are common problems faced by projects in these areas [10–15]. The need for creative solutions that may successfully handle these complex problems is highlighted by these difficulties [16]. Using artificial intelligence (AI) technology strategically is one way to address this. AI's development has opened up new avenues of opportunity for the building industry. AI can boost productivity from 0.8 % to 1.4 % annually, and by 2030, the global construction market is predicted to have risen by 85 % to reach USD 15.5 trillion [17]. AI technologies, including automation, machine learning, and predictive analytics, have the potential to completely transform the construction industry by increasing project efficiency, cutting waste, and improving resource allocation [18]. Additionally, AI can offer reasonably priced ways to lessen financial limitations, which will support environmentally friendly building practices and sustainability [19]. Nevertheless, in contrast to other industries, the construction sector has proven slower to adopt new technologies. The probable future of the construction industry's labor force and the possible effects of AI have both been hot topics of discussion. Particularly in repetitive and manual jobs, some contend that automation and artificial intelligence could result in job displacement [20]. Nonetheless, advocates of AI stress that AI may supplement human labor by managing hazardous and repetitive jobs, improving worker safety, and freeing up staff members to concentrate on more intricate and strategic work [19].

Despite these concerns, the construction industry risks lagging if it does not commence the adoption of transformational technologies like AI [21]. Because AI technology has not been sufficiently adopted by the construction sector globally over the past few decades, the industry's annual output has only increased by 1 % on average [17]. Only 8 % of construction organizations are categorized as highly imaginative, with the remaining 92 % being classified as moderate or low innovators, according to a recent study [22]. Utilizing AI and other cutting-edge technologies, the construction industry must embrace innovation to be competitive in today's quickly changing world [23]. Adopting AI-driven solutions can help construction organizations complete projects more quickly and affordably while upholding the highest safety and quality requirements [24]. In addition, maintaining competitiveness requires luring and keeping top talent, as skilled laborers and young professionals are pulled more and more to tech-forward sectors that provide chances for skill advancement in AI domains [25]. By implementing AI technologies, the construction industry may cultivate a culture of innovation and continual improvement and attract a younger workforce.

While AI has become a widely adopted tool for addressing construction challenges in many industrialized countries [26], The fact that most emerging nations have not given it the same amount of attention is notable. In the case of the Nigerian construction industry, traditional construction methods continue to be the norm, despite persistent recommendations that the introduction and full utilization of AI could simplify professional tasks. This may stem from the belief that AI offers the most viable solution to some of the efficiency problems that are particularly acute in the Nigerian construction sector [27]. Blanco et al. [24] further pointed out that the prospects and challenges of AI adoption have not been fully examined within the sector. Although the industry is gradually transitioning towards digitizing the construction process, Abdirad and Mathur [28] suggested that firms are increasingly interested in AI-powered algorithms and analytics once they realize the benefits. Even so, there are not many in-depth analyses of this subject in the global literature, and even fewer that do so in the framework of Nigeria's building sector is rare. Considering its ability to automate several tasks and improve construction productivity, AI in construction is still a relatively unexplored field [29]. Furthermore, it is important to comprehend how the automated technology used by the construction sector achieves sustainable results, possibly making traditional jobs redundant [21]. Thus, the purpose of this study is to address the issues that follow.

1) To what extent might AI aid Nigeria's modern building sector?
2) In the construction industry, what are the essential conditions and motivators for effective AI integration?

The results of this study will offer important new perspectives on how the deployment of AI could change the Nigerian construction sector. These results can help stakeholders, industry experts, and legislators create strategies and laws that will maximize AI's capabilities to advance sustainability, improve health and safety regulations, and improve construction projects [30]. This study offers insights into the advantages and difficulties of using AI in the construction industry to meet effectiveness, safety, and sustainability goals. It can also be used as a reference for comparable initiatives in other developing countries. To evaluate the complex links between the drivers and the adoption of AI in the construction industry, this study uses the partial least squares-structural equation modeling (PLS-SEM) approach. The goal is to provide a thorough knowledge of how various elements engage. Through this approach, the research aims to provide empirical data and practical insights that can guide policy development, industry practices, and strategic decision-making, ultimately promoting the development of construction methods in Nigeria and abroad.

The article is structured as follows: The material that has already been written about the use of AI in the construction industry is examined in Section 2. Additionally, it clarifies the research within pre-existing frameworks and provides information about the model development. Section 3 offers more information on the analytical methods applied in the study, including exploratory factor analysis and structural equation modeling. The comprehensive study in Section 4 covers the following topics: path analysis, SEM model supremacy exploration, model construct classification, common method bias, multicollinearity and outlier analysis, measurement model description, and predictive relevance evaluation. Comprehensive analyses and explanations of the acquired data are given in Section 5. Using the data gathered from the study, Section 6 makes broad conclusions. In Section 7, the shortcomings of the study are evaluated and potential lines of inquiry for further research are proposed.

2. AI in the construction industry

The greatest project teams are used on big projects, however most of them run over budget [19]. Predicting cost overruns based on variables like project size, contract type, and project managers' skill level is done using artificial neural networks [31]. Predictive models envisage plausible schedules for future projects based on historical data, including anticipated start and end dates. To improve skills and knowledge, AI also makes it possible for people to obtain online training materials, which speeds up project completion [32]. A 3D model-based method called building information modeling provides insights to experts in engineering, construction, and architectural fields on how to effectively plan, design, build, and manage infrastructure and buildings [19]. To reduce the amount of rework required, the industry is investigating the implementation of machine learning methods to detect and resolve conflicts between the many models built by all of the teams throughout the design and planning phase [24]. To find the best solution, it uses machine learning to generate 3D models of the plumbing, electrical, and mechanical systems that do not conflict with the design of the structure. Every construction project carries some risk in terms of cost, schedule, quality, and safety. Because several subcontractors operate on different trades simultaneously at job sites, the larger the project, the greater the risk [33]. General contractors employ modern AI and machine learning systems to follow and assess risk on the construction site. This helps the project team concentrate their scarce resources and time on high-risk issues [22].

To help construction managers reduce risk, subcontractors are assessed according to a risk score. An AI business that was founded in 2018 employs robots to take 3D pictures of construction sites on their own. The data is then fed through an advanced neural network that determines the status of several sub-projects [28]. The management team has the authority to intervene if things appear out of control to address minor concerns before they worsen [34]. Algorithms in the future will make use of "reinforcement learning," which enables learning through trial and error. To outperform human workers in repetitive jobs like pouring concrete, laying bricks, welding, and demolishing, some companies are beginning to provide self-driving construction machinery [23]. Self-contained or partially self-governing bulldozers are utilized for excavation and site preparation. These machines can be programmed by a human worker to precisely design a project site [17]. In addition to shortening the time needed to finish the project overall, it frees up human resources for the building phase. To monitor worker productivity and adherence to protocols, project supervisors can also use onsite cameras, facial recognition software, and other comparable technology to monitor work in progress. Construction workers lose their lives five times more frequently than other laborers do, according to safety statistics. Aziz [35] reports that falls were the most common cause of private sector fatalities in the construction industry (apart from crashes on the highway), followed by being struck by an object, electrocutions, and being caught in/between. A $3 billion-a-year general contractor in Boston is creating an algorithm that examines job site photos, looks for safety risks, and compares the photos to accident reports. Construction companies are being forced to engage in data science and artificial intelligence activities due to labor scarcity and a need to increase the low productivity of the sector. According to a 2017 McKinsey report, real-time data analysis might increase construction companies' efficiency by up to 50 % [21]. AI and machine learning are being utilized by construction organizations to optimize manpower and equipment allocation among various tasks. By monitoring task progress continuously, a robot helps project managers identify which job places have sufficient staff and tools to finish the project on time and others might be running behind schedule and could benefit from additional manpower. Construction robots are predicted by experts to use AI approaches to become more autonomous and intelligent [23]. Building corporations are depending more and more on outside factories where indestructible robots create building components, which are then connected on-site by human personnel [31]. An informational pool has been created using data from several sources, including photos, films taken by drones, security sensors, building information modeling, and others [21]. With the aid of AI and machine learning technologies, this offers clients and professionals in the construction sector the chance to evaluate and profit from the insights derived from the data [36].

3. Research methods

3.1. Research background and model development

Robots are used to carry out jobs that are normally completed by humans, according to the theory underpinning automation and artificial intelligence [37,38]. Fundamentally, AI is the ability of a computer program to reason and learn. Any task that a program performs that would normally need human intelligence qualifies as AI [19]. Bricklaying is one of the repetitious on-site operations that AI is starting to streamline and change, along with the way structures are designed and built. One of the key advantages of AI adoption is the reduction in human error. The term "human error" exists because humans are occasionally prone to making mistakes [21,39]. Conversely, computers do not make such errors when they are programmed correctly. AI relies on decisions based on previously gathered information and specific algorithms, thereby reducing errors and increasing the likelihood of achieving precise outcomes [24,40]. In addition, some of the riskiest jobs can be done by robots because engineering and construction might be intrinsically dangerous fields [34]. These robots, if properly developed, can function in hazardous conditions and learn from their surroundings, which will ultimately reduce workplace accidents. Automation is now showing signs of improving worker safety, even though it was first implemented to increase efficiency on building sites [21,41].

Intelligent robots possess the capability to tackle perilous construction tasks [23,40], such as lifting heavy equipment, delving into hazardous materials, engaging in space exploration, and addressing challenges that could jeopardize or endanger human lives. Robots never decline a task, get distracted by colleagues, or experience fatigue [35]. Additionally, machines equipped with AI excel at completing repetitive, monotonous, or risky tasks. They can work continuously, around the clock, without becoming bored or fatigued, and they are faster and stronger than humans [42]. Robots can maintain a constant level of focus and stamina, in contrast to the human brain, which can get exhausted as well as less focused with continuous effort, increasing the risk of workplace mishaps [43]. Moreover, robots do not need lunch breaks, vacations, sick days, or pay breaks [36]. Unless instructed otherwise, they can be programmed to run in a continuous loop. Robotic technologies can operate continuously as long as they are programmed and maintained correctly [24]. This skill enables companies to fulfill strict timeframes with round-the-clock production, enabling human operators to focus on more skill-intensive tasks that demand expertise. According to Pan and Zhang [32], AI robots can address various limitations and hazards associated with human work, Whether it is mining for coal and oil, traveling to Mars, disarming a bomb, or penetrating the ocean's depths. To put it simply, they can be used in circumstances where it would be dangerous for humans to intervene [41].

Furthermore, the average human typically works for 4–6 h a day, excluding breaks. Humans are designed to take time off for refreshment and to prepare for another working day to balance work and personal life [29,44]. In contrast, AI-driven machines can operate 24/7 without breaks and without experiencing boredom, unlike humans [22]. By utilizing AI, humans can efficiently automate routine tasks, relieving humans of monotonous duties and allowing them to channel their creativity more effectively [45]. More and more cutting-edge companies are using digital assistants to communicate with people to minimize the need for human labor. Additionally, these digital assistants are frequently included in webpages to offer consumers information and assistance. Users can engage in conversations with these chatbots to find the necessary information [46]. Some chatbots are so well-designed that it becomes challenging to distinguish whether one is conversing with a chatbot or a human being. For instance, many organizations have customer

Table 1
The drivers behind the AI application in construction projects.

Code	Variables	[45]	[37]	[49]	[25]	[23]	[21]	[34]	[50]	[28]	[33]	[24]	[29]	[17]
D1	The use of AI in boosting its overall adoption			*		*		*						*
D2	AI's role in the quickly expanding field of AI applications in the construction industry		*		*	*			*		*		*	*
D3	The application of AI in the improvement of clients' experience and expectations					*			*			*		*
D4	Development in construction is a driver of AI adoption					*					*			*
D5	Enhanced cyber security in construction technologies as a promotion of the use of AI		*	*		*							*	*
D6	The use of AI is influenced by major investment in its application by the big players in the construction industry			*		*		*			*		*	
D7	The rapid advancement of technology in the construction sector serves as a boost for the use of AI		*			*				*	*			
D8	The vast opportunities inherent in the industry as a result of technological advancement are a driver of AI adoption					*						*		*
D9	The incorporation of smarter software into the construction sector is a means of improving the adoption of AI					*		*				*		*
D10	Rapid development of the use of AI influencing the use of AI	*	*			*			*		*		*	
D11	The potential of AI to overcome information challenges serves as a huge influence on its use		*			*								*
D12	The ability of AI to monitor and observe construction proceedings influences its utilization	*		*				*					*	*
D13	The potential of AI having a considerable relative advantage over other forms of technologies in construction is a good driver for its use				*				*		*			*
D14	The fact that AI is compatible with other technologies is being pointed to as an influencer in its adoption		*	*	*						*			*
D15	The interface of AI even at the experimental stages of construction gives it an edge and improves its likelihood of adoption		*	*			*		*			*		*

support teams responsible for addressing customer inquiries and concerns [47]. By utilizing AI, organizations can deploy voicebots or chatbots that assist customers with their queries. Many organizations have already implemented these AI-powered assistants on their websites and mobile applications. AI, when combined with other technologies, enables machines to make decisions faster than humans and carry out actions more swiftly [27]. When making decisions, people consider a range of practical and emotional variables; in contrast, AI-driven machines follow preprogrammed instructions and provide outcomes more quickly.

Companies worldwide are increasingly embracing AI implementation to streamline their business operations [23]. AI technology proves highly beneficial in handling complex and cumbersome tasks, thereby enhancing employee productivity [28]. Moreover, AI can assist enterprises in mitigating cyber security risks and preventing potential data breaches. Given the expanding capabilities of AI across various business functions, it presents key drivers, restraints, and opportunities [48]. AI has become a driving force behind numerous innovations across various domains, aiding humans in solving complex problems [46]. This generation is witnessing rapid technological advancement, with innovations such as robots, fuzzy systems, and spacecraft, and AI plays a significant role in these developments [34]. However, human intervention remains essential, even in the face of advancing technology. Humans continue to control machines and software, ensuring they perform as intended. Nevertheless, the integration of AI is reducing the reliance on human labor in construction [31]. AI applications are automating many tasks, potentially leading to decreased human involvement and, in some cases, human dependency on technology [48]. Table 1 summarizes the drivers of AI adoption, whereas a summary of the advantages is given in Table 2. This study adds to the existing body of knowledge on how AI is transforming industries, particularly the construction sector. While previous research has often used methods like factor analysis, regression analysis, and literature reviews to understand these transformations [18,23], this study employs PLS-SEM which allows for a more comprehensive examination of the drivers and benefits of AI adoption. Consequently, this study hypothesizes a significant relationship between AI implementation drivers and AI implementation (Fig. 1).

Table 2
Benefits incurred while adopting AI for construction projects.

S/N	Variables	[27]	[47]	[36]	[32]	[23]	[21]	[34]	[48]	[28]	[33]	[24]	[29]	[19]
B1	Reduction in human error in carrying out construction projects			*		*		*						*
B2	Reduction of the risk of accidents in the construction sites and laboratories		*		*	*			*		*		*	
B3	The ability of AI to adapt to very hostile environments without any considerable compromise		*			*			*			*		*
B4	The ability of AI to function in the place of humans in some construction activities										*			
B5	AI or any other technologies are immune to fatigue and tiredness serving as a huge benefit in construction		*	*		*							*	
B6	The benefit of AI in continuing to turn out results without delay or stops is huge			*		*		*			*		*	*
B7	A benefit of AI is that it takes construction risks instead of humans, hence, promoting construction safety		*			*				*	*			*
B8	Can be used in executing repetitive construction works					*			*			*		*
B9	AI helps to foster digital assistance in the work process and procedures					*		*				*		
B10	The fast pace of function of AI is beneficial in making faster decisions	*							*		*		*	*
B11	The use of AI helps to foster more ingenuity in construction techniques among construction contractors		*			*			*					
B12	The use of AI can serve as a bedrock for the development of new inventions in construction technologies	*		*				*					*	*
B13	Helps ensure humans are better secured for more critical construction requirements				*				*		*			
B14	The use of AI helps to reduce unemployment in the society		*		*									
B15	The ability of AI to work perfectly to detail is a huge benefit towards its adoption		*	*			*		*			*		
B16	The use of AI helps to foster better subsequent improvement in its use for construction projects			*		*		*			*	*		*

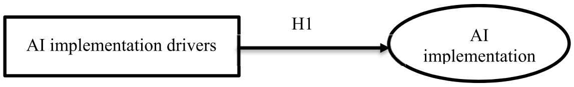

Fig. 1. Conceptual model.

3.2. Research design and methodology

The conceptual modeling process for this study encompassed three essential stages: identifying the model's constructs, categorizing these constructs, and delineating the relationships between them [51,52]. Fig. 2 visually represents the research design, adapted from prior studies conducted by Schia [21] and Kineber et al. [53]. Given the novelty of AI in Nigeria, this research used stratified sampling to focus on a certain subgroup of the population. [54], a method chosen to ensure the acquisition of exceptionally reliable and precise data, particularly considering the survey's emphasis on AI. Respondents provided insights into AI drivers and adoption benefits based on their experiences and knowledge, using the Likert five-point scale. The scale ranges from "5 = very high, 4 = high, 3 = moderate, 2 = low, and 1 = very low" [15,55–57]. This approach aimed to offer stakeholders a comprehensive range of insights rooted in practical experiences within the domain of construction projects. Experts were chosen based on their direct participation in numerous construction projects around Lagos State, Nigeria. Their data was gathered from the following annual reports: the Nigerian Institute of Architects/Architects Registration Council of Nigeria; the Council of Registered Builders of Nigeria/Nigerian Institute of Building; the

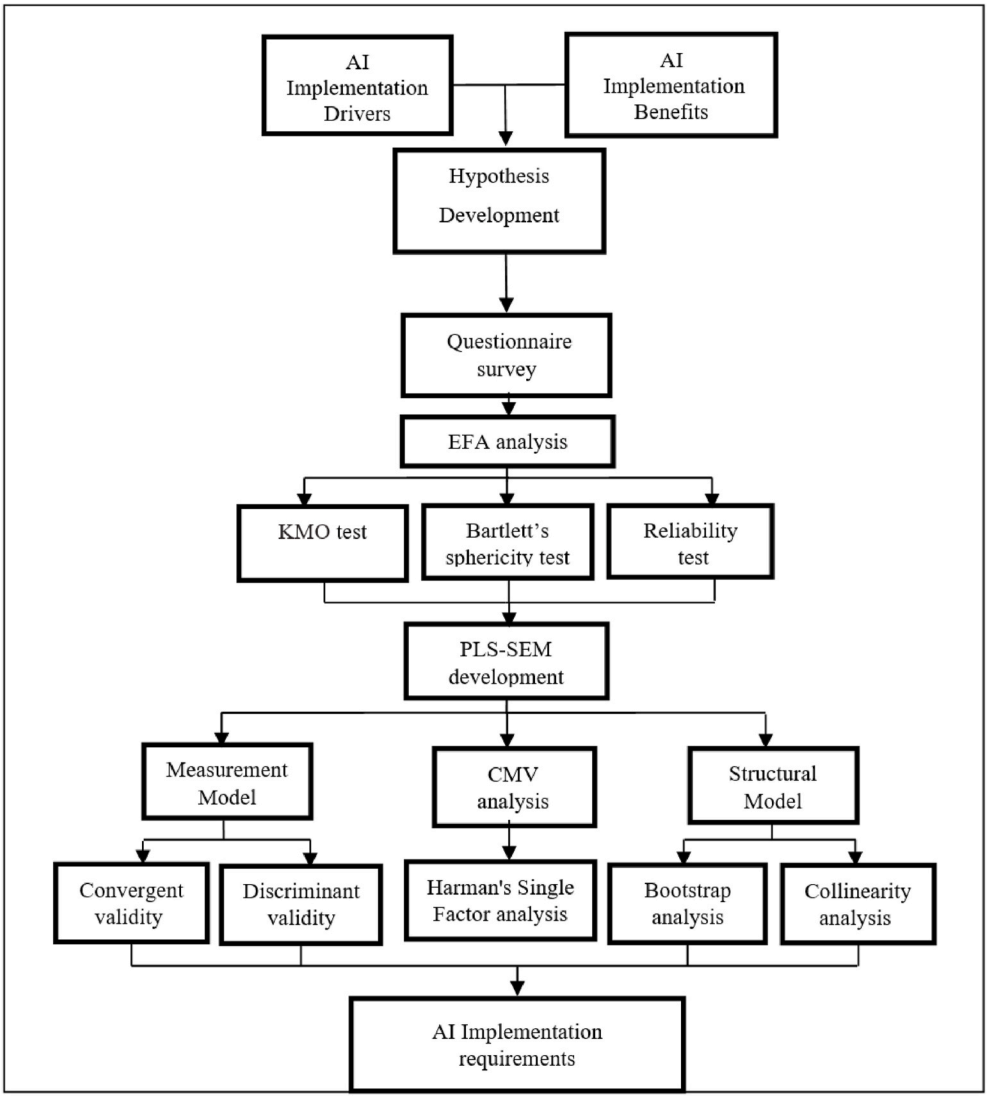

Fig. 2. Research design.

Council for the Regulation of Engineering in Nigeria/Nigerian Society of Engineers; and the Quantity Surveyors Registration Board of Nigeria/Nigerian Institute of Quantity Surveyors.

The study's objectives guided the determination of the sample size [58]. Typically, a sample size of over thirty cases is deemed sufficient for a comprehensive examination, including statistical measures such as a normal distribution curve's mean, median, and mode [59]. However, it should be noted that Harris and Schaubroeck [60] argued that a minimum sample size of 200 is essential for a robust SEM analysis. Additionally, Kline [61] suggested that a very complex path model may require a sample size of 200 or more. Nevertheless, Yin [62] considered a sample size greater than 100 to be acceptable. Given that this analysis employed the SEM method, 224 questionnaires were distributed to the respondents for the study. Out of these, 150 questionnaires were returned as valid and suitable for the study, representing a response rate of 66.96 % [63,64]. The completed questionnaires were distributed through a combination of Google Forms, chosen for its user-friendliness and a secure survey platform to ensure data privacy. The appendix provides a detailed overview of the questions pertaining to the prioritization of drivers and benefits associated with AI adoption in construction project delivery.

3.3. Exploratory factor analysis

Because it makes it possible to examine intricate linkages and patterns within the dataset, exploratory factor analysis (EFA) was used in this study. EFA is a robust statistical technique that is particularly suited for exploring the underlying constructs or factors that may not be immediately evident, thus providing valuable insights into the multifaceted aspects of the research [65–67]. EFA typically requires a sample size of at least 150 to 300 observations [66]. However, there is some disagreement among researchers regarding the optimal sample size for factor analysis. Pallant [68] suggested that researchers have varying opinions on the matter, but using larger sample sizes is recommended when dealing with a higher number of variables [69]. Factor analysis may benefit from possessing twenty to fifty variables or parameters, according to Shen [70]. A reduced amount of variables may be employed when the amount of data collected is very big, according to certain research, but if the total quantity of variables surpasses this limit, it can be difficult for researchers to identify individual aspects efficiently [12,71]. Therefore, it was decided that the 150 respondents chosen and the ten important factors identified would be appropriate for factor analysis [66].

3.4. Structural equation modeling

Because it completely fits the objectives of the investigation, the SEM technique was carefully chosen for this study. With its strong foundation for analyzing both direct and indirect consequences inside an all-encompassing research model, SEM is especially well-suited for analyzing intricate interactions between numerous quantitative and non-observable variables [72–74]. Additional evidence that SEM is a suitable option for this research comes from Amaratunga et al. [75], who emphasized its capacity to handle errors within variables. A study [76] states that SEM offers a rigorous way to test and improve theoretical constructs inside the research framework [73,76,77]. It also facilitates the study of complicated interactions by evaluating the match within the suggested framework and the observed data. Because the PLS-SEM provides a strong and flexible analytical framework that is precisely matched with the complexities and subtleties of the study, it was used to evaluate the links between AI drivers and AI implementation [53,78]. The sample size was a crucial determinant in the PLS-SEM selection. Since PLS-SEM does not require the enormous datasets that traditional SEM may, it is especially helpful when working with lower sample numbers. This study demonstrated the applicability and efficacy of PLS-SEM in assessing the available data by focusing on a particular subgroup within the construction industry [79].

Table 3
Demographic information.

Profession	Frequency	Percentage (%)
Architects	48	32.0
Quantity surveyor	48	32.0
Builders	24	16.0
Engineer	30	20.0
Total	150	100.0
Academic qualification	Frequency	Percentage (%)
ND	32	21.3
HND	41	27.3
BSC/BTECH	24	16.0
MSC/MTECH	27	18.0
PhD	26	17.3
Total	150	100.0
Years of experience	Frequency	Percentage (%)
Less than 5 years	34	22.7
6–10 years	41	27.3
11–15 years	29	19.3
16–20 years	23	15.3
Above 20 years	23	15.3
Total	150	100.0

PLS-SEM was chosen in part because of the characteristics of the variables that were used in the investigation. A mix of manifest (observable) variables and latent (unobservable) components were used in the development of AI drivers and implementation. Modeling these components efficiently was made possible by PLS-SEM's adaptability in handling both kinds of variables [80]. Furthermore, in keeping with the goals of the research, PLS-SEM was selected because it made it possible to evaluate how AI drivers affected the application of AI while also investigating the basic processes and connections between these constructs [81]. Furthermore, PLS-SEM is well-known for its adaptability to multivariate normality deviations and non-normally distributed data. In the construction business, where real-world data may not always align with ideal statistical assumptions, this flexibility is very helpful [82,83].

4. Results

4.1. Characteristics of the respondents

The study surveyed professionals across various key roles in the construction industry. The data reveals that 32.0 % of the respondents are architects, another 32.0 % are quantity surveyors, 16.0 % are builders, and 20.0 % are engineers (see Table 3). This diverse representation ensures that the information gathered is credible and reflective of the industry's core professions.

The academic qualifications of the respondents are also noteworthy. Among them, 16.0 % hold BSc/BTech degrees, 27.3 % hold HNDs, 18.0 % possess MSc/MTech degrees, 21.3 % hold ND qualifications, and 17.3 % have earned PhD degrees. This high level of educational attainment underscores their expertise and relevance for the research. Moreover, the respondents' years of experience highlight their familiarity with the construction industry. Approximately 22.7 % have less than 5 years of experience, 27.3 % have 6–10 years, 19.3 % have 11–15 years, and 15.3 % each have 16–20 years and more than 20 years of experience. This extensive experience indicates their deep understanding and adeptness in using technology within the industry.

4.2. Classification of the model constructs

An extensive evaluation of their factor structures was conducted using EFA for the 15 AI drivers and the 16 AI implementation advantages. This study used Bartlett's test of sphericity (BTS) and the Kaiser-Meyer-Olkin (KMO) test as two statistical tests to assess the data's appropriateness for factor analysis [84]. If there was enough data in the dataset to move forward with factor analysis, the KMO test offered an estimate of sampling adequacy [85–87]. A high KMO score (usually in the range of 0–1) demonstrates that all the variables in the dataset are good candidates for factor analysis [66,67]. It evaluates the degree of interdependence and suitability of variables for factorization. Values nearer to 1 indicate strong intercorrelations between variables, supporting the argument for factor analysis, and values above 0.7 are typically seen as suggestive of an appropriate set of variables for factor analysis. BTS, on the other hand, assessed whether the correlation matrix of the variables significantly deviated from an identity matrix [88]. The KMO values for the AI drivers and benefits were 0.630 and 0.782, respectively. These values fall within the range of 0–1, where a higher KMO value generally indicates better suitability for factor analysis. The BTS yielded results for both sets of variables that were below the commonly used significance threshold of 0.05.

The communalities, with values exceeding 0.4, further affirm the suitability of the variables for factor analysis. Table 4 demonstrates that, with varimax rotation, the analysis of the 15 AI drivers unveiled the presence of three distinct factors, each possessing eigenvalues greater than 1. These three factors collectively accounted for a substantial portion of the total variance, totaling approximately 52.86 %. Similarly, when examining the 16 AI benefits of implementation, the analysis identified two factors with eigenvalues exceeding 1. These two factors collectively explained a significant proportion of the total variance, amounting to approximately 50.37 %. The statistical dependability of the components that were retrieved was also assessed using Cronbach's alpha.

Table 4
Factor loadings of AI drivers and benefits.

Drivers	Components			Benefits	Components	
	Technology	Knowledge	Advancement		Speed up the project	Improve health and safety
D1	–		0.568	B1		0.65
D2		0.532	–	B2		0.75
D3	0.567		–	B3	0.691	.
D4		0.652	–	B4	0.540	
D5	0.611		–	B5	0.664	
D6	–	0.674	–	B 6	0.569	
D7	–	–	0.767	B7	–	0.56
D8	–	–	0.774	B8	–	0.55
D9	0.751	–	–	B 9	0.505	
D10	0.863	–	–	B10	0.721	–
D11	–	0.65	–	B 11	0.566	–
D12	0.540	–	–	B12	0.643	–
D13	–	0.75	–	B13	–	0.56
D14	–	–	0.65	B14	–	0.65
D15	–	0.60	–	B15	0.56	–
				B16	0.66	–

The reliability or internal consistency of each factor's elements is evaluated using this generally accepted metric. The validity and reliability of the factor structure discovered by factor analysis are improved when it is ensured that the items inside a particular factor are consistently testing the same underlying construct. The derived components exhibited a high degree of internal consistency and dependability, as evidenced by the values obtained for both studies surpassing the 0.7 threshold [89,90].

4.3. Common method bias

General process bias, also referred to as systematic variance error, is the statistical assessment of the variance that influences the validity of sampled data. It encapsulates the statistical discrepancies between observed and expected variables [91]. Harman's single-factor model operates on the premise that if common method bias is prevalent, a single factor should emerge during factor analysis when all survey items are considered together. This single factor represents the variance attributed to common method bias, which can systematically affect responses across various items [92]. If the single factor accounts for a substantial portion of the total variance, it signals the presence of common method bias that needs to be addressed to ensure research validity. Conversely, if the single factor explains only a minor portion of the variance, it suggests that common method bias is less likely to exert a substantial influence [92,93]. The initial set of variables explained 47.9 % of the overall variance, which implies that a significant portion of the observed variation in the data can be attributed to these variables. This finding underscores the importance and relevance of the factors and variables under investigation, suggesting that they hold substantial explanatory power within the context of the study [94].

4.4. Multicollinearity

Multicollinearity, when analyzed through SEM within a group of predictor variables, arises when certain predictors, although observable, are not distinguishable. This phenomenon poses challenges in deciphering the individual impact of each independent variable due to their intertwined variation. As a general guideline, it is advisable to avoid employing two variables with a bivariate correlation of 0.7 or higher, as this could exacerbate issues related to multicollinearity [66,95]. Variance inflation factors (VIFs) assess multicollinearity effects for second-order constructs during the preparatory phase. In this study, the examined endogenous variable was AI implementation. Findings revealed that the highest VIF for the endogenous variable was 1.476, significantly below the threshold of 10 and even below the more stringent threshold of 3.5 [9,15,53]. Findings revealed that the highest VIF for the endogenous variable was 1.476 (Table 5), significantly below the threshold of 10 and even below the more stringent threshold of 3.5.

4.5. Outliers

An observation that differs significantly from the rest of the population is called an outlier, and it is usually identified by a score that is abnormally high or low [96]. Data sets' normalcy may be impacted by the existence of outliers [97]. When the Z score (standard score) is greater than ± 4, outliers could appear [66]. The range (Min-Max) of Z-scores for each research construct fell within the allowed range, which was between -3.19 and 2.25 after the outlier test carried out for this study.

4.6. First-order construct measurement model

Because the study was exploratory and had theoretical underpinnings, the first-order construct was structured as reflecting measurement models. Using EFA analysis and the construct validation procedure from the literature review, the measuring items of first-order constructs were identified and verified. Because it allows the measurement items to be eliminated without affecting the meaning or intent of the construct, it makes more sense to select the reflecting relation between the things and the reasonable constructs. The interchange ability of the construct to the measurement items serves as the explanatory objective in reflective measurement models. Furthermore, this study is exploratory and predictive, to generate a reflective relationship and forecasting observed measurements or measuring items.

Fig. 3 displays an SEM designed to replicate the theoretical framework within the context of this research. The model evaluation process involved assessing indicator reliability and composite reliability, extracting average variance, and evaluating discriminant ability [98]. To ensure a robust and comprehensive assessment of the model's performance and stability in the PLS analysis, 300 iterations were conducted each incorporating a varied weighing scheme, weighing path, and matrix of data [99,100]. Generally, indicators displaying external loadings falling within the range of 0.40–0.70 often merit consideration for removal if their exclusion significantly enhances the composite's reliability and the average variance extracted (AVE) [101]. Variables with external loadings below 0.60 often fail to meet this criterion and are, therefore, omitted from further analysis, aligning with the guidance provided by

Table 5
Collinearity assessment based on VIF for project success.

Constructs	VIF
Technology	1.24
Knowledge	135
Advancement	1.476

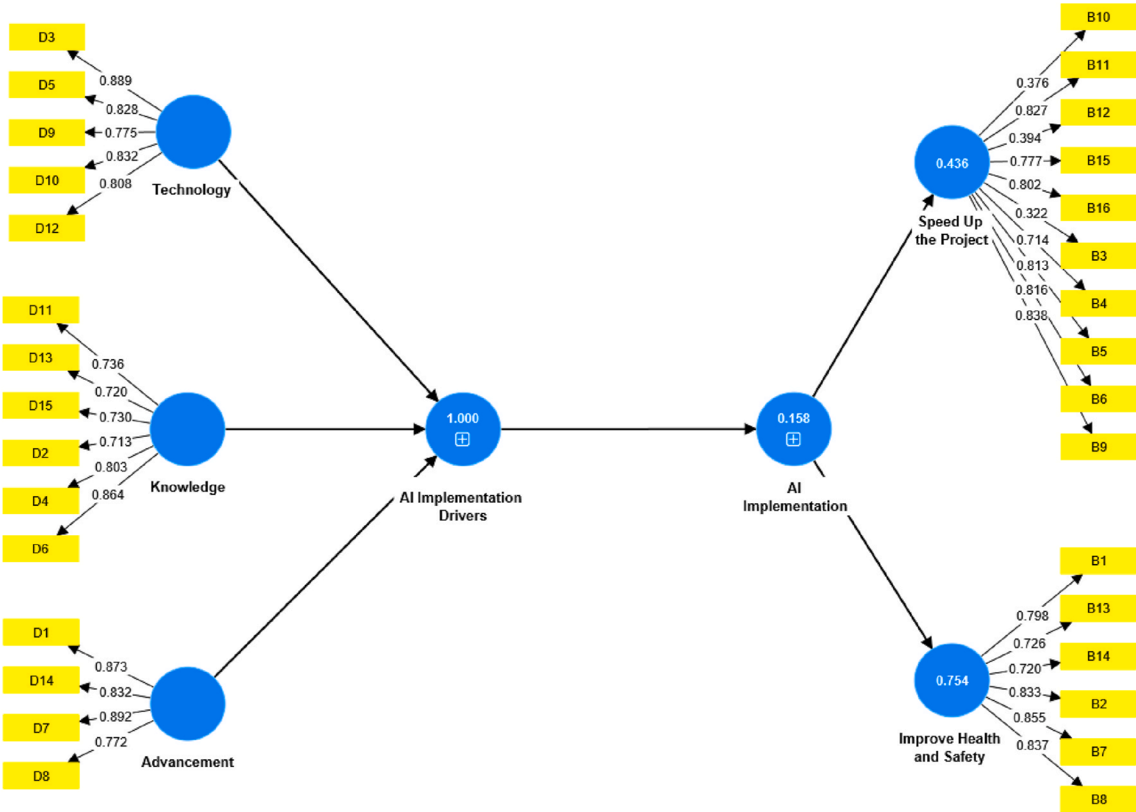

Fig. 3. SEM model with R^2 values and path coefficient.

Ref. [98]. In such instances, it is noteworthy that roughly 50 % of an indicator's variance can be accounted for by its constituent elements. It is crucial to ensure that the variance explained surpasses the variance's associated error. Fig. 4 illustrates the external loadings for all variables within the measurement model, and it is worth noting that all of these exceeded the threshold of 0.60, signifying their acceptability. Since Cronbach's alpha is sensitive to the number of variables considered, composite reliability (CR) was evaluated for the core consistency of all models, following the guidelines of [98,100]. Table 6 summarizes the acceptability of the model, with a CR above the 0.70 threshold which suggests their acceptability. The AVE is a statistic used to assess the convergent validity of a measurement model. If AVE is greater than 0.5, it is generally considered acceptable, indicating that more than 50 % of the variance in the indicators is explained by the latent construct after accounting for measurement error. All constructs in the study passed this test and exhibited good convergent validity [100,102,103].

Discriminant validity is established when different latent constructs in a model are shown to be distinct and not highly correlated with each other. In other words, it confirms that the measures or indicators associated with one construct do not measure the same underlying concept as another construct. Discriminant validity is crucial in SEM because it helps ensure that the model accurately represents distinct constructs rather than just one overarching construct [104]. Assessing discriminant validity can be carried out by using two primary methods: the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio of correlations. The squared correlations between construct pairs and the average variance of each construct are compared in the Fornell-Larcker criterion. According to the criteria, two constructs may have discriminant validity if their squared correlation is less than the AVE values for each of those constructs. The measurement model's discriminant validity is displayed in Table 7, and the findings show that the model's constructs are separate and free of overlap and multicollinearity problems [105,106]. Conversely, the correlation between constructs is directly compared using the HTMT ratio of correlations, which is sometimes referred to as the cross-loadings ratio approach. It requires computing the square root of the product of the two constructions' AVE values and the correlation ratio between them. This ratio offers proof of discriminant validity if it drops below a given cutoff (often 0.85; see Table 7).

4.7. Measurement model (second-order construct)

Second-order static variables were used to classify both the independent and dependent variables since this categorization makes sense given the nature of the study and the underlying theoretical framework. The first-order latent variables, such as factor loadings, path coefficients, and model fit statistics, were resampled and analyzed using the bootstrap method to evaluate their robustness and stability and comprehend the reliability and confidence intervals of parameter estimations [104]. Every predictor variable in the

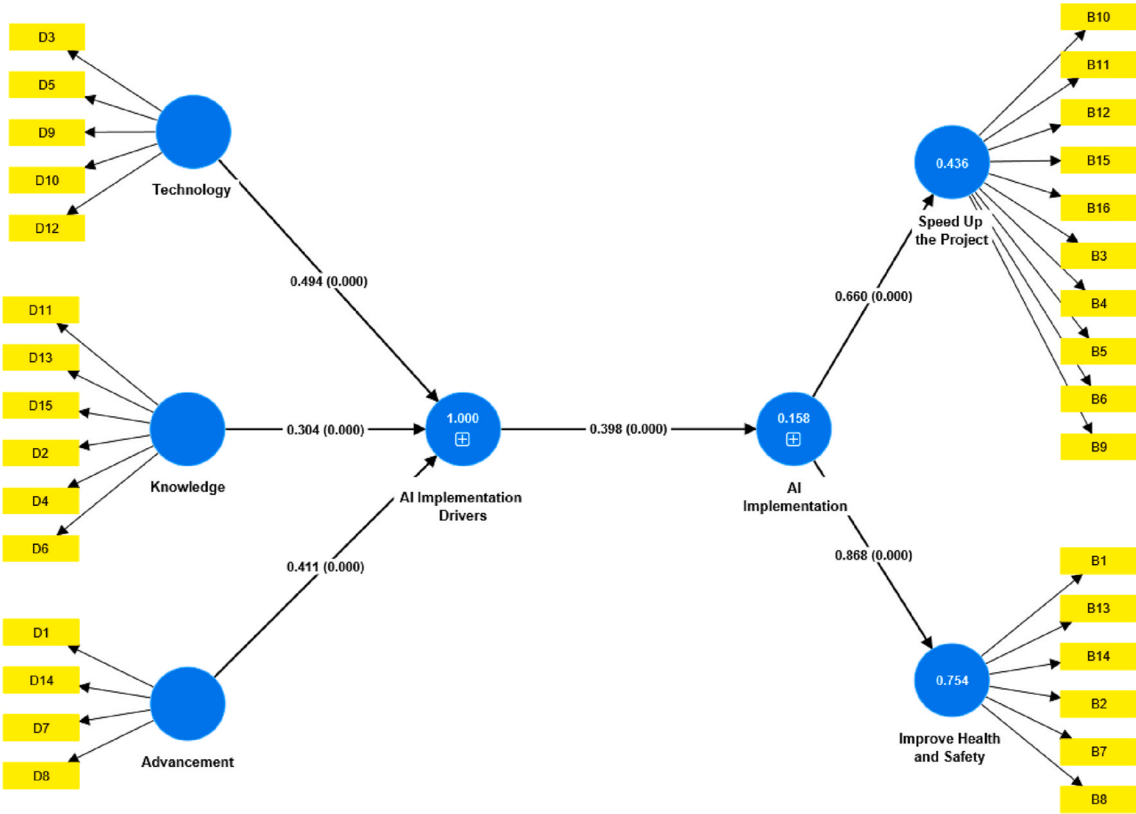

Fig. 4. Performing bootstrapping analysis.

Table 6
Result of the convergent validity.

Constructs	Cronbach's alpha	Composite reliability	Average variance extracted
Advancement	0.864	0.869	0.712
Improve health and safety	0.884	0.891	0.635
Knowledge	0.856	0.878	0.582
Speed up the project	0.866	0.891	0.587
Technology	0.884	0.887	0.685

Table 7
Discriminant validity results.

Constructs	Advancement	Improve health and safety	Knowledge	Speed up the project	Technology
	Fornell-Larcker				
Advancement	**0.844**				
Improve health and safety	0.319	**0.797**			
Knowledge	0.257	0.209	**0.763**		
Speed up the project	0.213	0.218	0.395	**0.698**	
Technology	0.879	0.304	0.244	0.207	**0.828**
	HTMT				
Advancement					
Improve health and safety	0.363				
Knowledge	0.285	0.134			
Speed up the project	0.258	0.251	0.448		
Technology	0.6	0.346	0.265	0.248	

model had its VIF determined to take care of the collinearity problem. Predictor variable multicollinearity in a regression model may not be a serious problem if the VIF value is less than 3.5, which is typically seen as falling within an acceptable range. With respect to multicollinearity, this result implied that the model's assumptions were satisfied therefore the findings could be believed.

4.8. Path analysis

Path analysis (PA) is a useful linear statistical technique with a wide range of applications in management and social sciences domains. It provides a useful way to analyze intricate interactions between several variables at once [66]. PA plays a crucial role in the SEM framework in helping to comprehend these complex relationships inside the model. PA is used in the first stage of SEM analysis to help assess the connections between the concepts in the study. SEM becomes the next main stage in SEM analysis after the model's fit has been determined. SEM is an effective method for identifying and comprehending the connections between different variables. Based on actual data, it offers a thorough representation of the relationships between exogenous (or independent) and endogenous (or dependent) factors [96,107]. The process of evaluating SEM involves determining the model's overall fit, which includes estimating the correlations between postulated variables and analyzing their size, direction, and significance. To learn more about the underlying dynamics and interactions between the variables in the model, as well as the impact of AI drivers on AI implementation, the PLS-SEM was utilized. The robustness and reproducibility of the results regarding the pathways (β) and corresponding p-values of the standardized coefficients were evaluated by bootstrapping. The model's routes are provided by the bootstrapping method's results. According to the evaluation of the relative routes in the model, the impact of AI drivers on the application of AI was discovered to be both favorably significant ($\beta = 0.398$) and statistically significant ($p < 0.001$).

4.9. Exploratory supremacy of the SEM model

Following the verification of each item's reliability and the model's convergent and discriminant validity, the model's exploratory power was evaluated. In order to do this, one can compute the R^2, the statistic that expresses how much of the diversity in the dependent variable that is included in a regression model is clarified by the independent factors [81]. Greater R^2 values suggest that the variables that are not included in a regression model account for a greater percentage of the variance in the dependent variable's value. The model's dependent variable, the application of AI, had an R^2 value of 0.15. While this value is below the commonly accepted threshold of 0.25 for a weak effect, it still provided valuable insight. AI implementation is a complex process influenced by a multitude of factors, not all of which were included in this study. The 15 % variability explained by the AI drivers indicated a significant portion of the influence on AI adoption in the construction sector. Given the complex nature of AI adoption, it is not uncommon to observe lower R^2 values in studies of this kind, as argued by Ref. [97].

4.10. Structural model's predictive relevance

Moreover, a blindfolding protocol was executed to evaluate the model's performance and to gauge its predictive significance. The Q^2 statistic was utilized for this purpose. As observed in this study, the Q^2 value, which amounted to 0.057, surpassed zero, signifying that the model holds predictive power. This also implied that the model possessed a degree of predictive capability, suggesting its relevance and usefulness in making informed predictions in a given context [108].

5. Discussion

Construction sites make use of a variety of equipment [109]. However, selecting the most suitable building life cycle variant from a multitude of alternatives is a significant challenge in project management [110]. Additionally, various aspects within the construction industry, including productivity, quality, and product functionality tend to lag behind other industries [111]. Construction firms operate in an increasingly complex and dynamic global environment [112]. A digital revolution is occurring, and the industry is finding it difficult to keep up with the rapid advancements in digital development, claim Harty et al. [42]. Because different researchers have found different things about how AI can be used, it is still debatable how quickly AI is developing in underdeveloped nations like Nigeria. Unfortunately, most developing countries do not subscribe to the adoption of these contemporary concepts in carrying out construction activities [113]. Despite the persistent emphasis on the potential benefits of introducing and fully implementing AI and related information communication technologies in the Nigerian construction industry, traditional construction methods continue to be prevalent. This may stem from the belief that AI offers solutions to some of the challenges associated with human inefficiency, as highlighted by Pistorius [27], which are particularly severe in the Nigerian construction sector. The fact that there are so few studies examining the opportunities and barriers to AI adoption in the construction industry, despite the growing significance of AI for the sector, was also mentioned by Blanco et al. [24]. According to Abdirad and Mathur [28], companies are becoming more interested in using AI-powered algorithms and analytics as they become aware of the advantages, even if the construction sector is gradually changing to digitize the process. However, the number of research documented in the worldwide literature on this topic is still small, even though it is expanding, and very few of them examine the problem in the larger context of Nigeria's building industry. That being said, the application of AI technology under the direction of knowledgeable professionals and purposeful actions could greatly improve the way building projects are carried out. For the AECO sector and the building business, automated systems and AI have many benefits [114,115]. Utilizing SEM models and the statistical values produced by model assessments, this work offers a strong basis for investigating the connections between AI drivers and their advantages within the suggested model.

Certain interesting conclusions were drawn from this investigation. Technological innovation, knowledge, and advancement are the three primary categories into which the drivers of AI deployment may be divided, according to the EFA study. Technology drivers had an external path coefficient of 0.494, according to the PLS-SEM data, making it the category having the biggest influence on AI drivers. With external path coefficients of 0.304 and 0.411, respectively, the knowledge and advancement drivers came next. Additionally, the external path coefficients of 0.868 and 0.660, respectively, indicated that the environment and resources were the two major categories into which the categorization for the application of AI could be divided. It was determined how AI drivers affected the execution of the technology by analyzing the link between the independent and dependent variables. It was found that the application of AI in the building sector was facilitated by drivers of AI, to the tune of 15 %. The study's β value of 0.398 indicated a substantial link between AI drivers and AI deployment. This implied that if a corporation or organization makes a single AI driver upgrade, it may result in a comparable advancement in AI technology of 0.398, especially in areas like speed, safety, and health. The participants in the study attested to the several advantages of implementing AI, including less human error, elimination of weariness, risk mitigation, consistency, decreased unemployment, and higher productivity. This is consistent with other studies, as Schia [21] pointed out that automation increases worker and process productivity and safety. Parallel to this, Abdirad and Mathur [28] highlighted how AI may improve accuracy and productivity while cutting down on labor-intensive jobs in big building projects. The construction sector's rapid technological advancements are a major driver of AI adoption in the research area. According to Salehi and Burgueño [29], a lot of enterprises are using AI technologies in the construction industry to change their operations. This is consistent with their viewpoint. The results of the study showed that respondents strongly agreed on these motivators, indicating that more people are interested in examining AI's potential in the study area's construction business. Other drivers, such as improving customer experience, the rapid growth of AI applications, the ability to overcome information challenges, and compatibility with other technologies, were also identified as factors promoting AI adoption. Elshawi et al. [37] similarly recognized the vast opportunities that AI offers in construction activities. Therefore, the drivers identified in this study seemed to be effective strategies for fostering AI adoption in the study area.

6. Conclusion

AI technology plays a significant role in the construction industry worldwide, but its adoption remains uncertain, especially in third-world nations. Nigeria, like many developing countries, has faced numerous challenges related to construction quality and project management, particularly in large-scale projects. To address these issues, there is a pressing need to implement AI technologies in the construction sector. To establish and validate the relationships between AI drivers and the actual implementation of AI, this study employed the PLS-SEM method. Through data collected from 150 building experts, the study identified one direct path and eight indirect paths crucial for constructing the structural model. Furthermore, it confirmed the connections among various factors, both directly and indirectly, involving AI drivers and indicators related to AI implementation. The study's results strongly support the idea that the adoption of AI, facilitated by the identified drivers proposed in the model, can significantly enhance the sustainability of construction projects, particularly in terms of environmental impact and efficient resource utilization. These findings have substantial implications for the construction industry and its stakeholders.

The findings of this investigation have important ramifications for professionals working in the construction sector, such as project owners and contractors who want to successfully implement AI. Project stakeholders can increase the overall success and efficacy of their projects by coordinating their project goals with resource and environmental requirements. Furthermore, this study emphasizes how critical it is to adopt new technologies, particularly in emerging nations like Nigeria. Construction stakeholders may ensure their success in a dynamic and competitive business by adopting AI technologies and comprehending the motivations for their application. The results of this study may potentially be useful to regulatory agencies and policymakers in the building industry. With the use of this data, they may develop policies and rewards that promote the ethical application of AI, stimulating new ideas and raising industry standards.

Limitations and future directions

The scope of this study is limited to the evaluation of AI applications in construction project performance in Lagos state, Nigeria. To achieve this, the awareness level of AI in the construction industry is determined among construction professionals, its contributions to construction processes are examined, and the drivers and barriers to its incorporation in Lagos state are assessed. This is because the study area is home to prominent and technologically compliant construction companies in Nigeria, making it a suitable location for obtaining credible responses to the research. However, a limitation of the research is its specificity to a particular state of the country (Lagos state), and therefore, the findings may not be generalizable to other regions. Given the study's scope, future researchers may consider conducting additional research on the influence of culture in the construction industry on the adoption of AI for project management. Additionally, future studies might focus on enhancing and solidifying knowledge of the interactions between AI technologies and the major players in the construction sector. As a final recommendation, it is suggested that future studies examine how AI is being adapted based on the needs of users, gather more empirical data, and explore how other businesses have successfully handled similar situations. This would contribute to a deeper understanding of AI adoption in the construction industry.

Ethics statement

For this research, informed permission was not needed.

Funding

The authors express their gratitude to the Middle East University in Jordan for providing financial support to cover the publication fees associated with this research article.

Data availability statement

If you make a legitimate request, the relevant author will provide you with the data supporting the results of this study.

CRediT authorship contribution statement

Ahmed Farouk Kineber: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nehal Elshaboury:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ayodeji Emmanuel Oke:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **John Aliu:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ziyad Abunada:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mohammad Alhusban:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e37078.

References

[1] O. Olanrewaju, J. Idiake, L. Oyewobi, Global economic recession: causes and effects on Nigeria building construction industry, Journal of Surveying, Construction & Property 9 (1) (2018) 9–18.
[2] O.I. Olanrewaju, S.A. Babarinde, N. Chileshe, M. Sandanayake, Drivers for implementation of building information modeling (BIM) within the Nigerian construction industry, Journal of Financial Management of Property and Construction 26 (3) (2021) 366–386.
[3] U. Sbci, Buildings and climate change: Summary for decision-makers, United Nations Environmental Programme, Sustainable Buildings and Climate Initiative, Paris, 2009, pp. 1–62.
[4] A. Sharifi, A. Dawodu, A. Cheshmehzangi, Limitations in assessment methodologies of neighborhood sustainability assessment tools: a literature review, Sustainable Cities and Society 67 (2021) 102739.
[5] S. Durdyev, S. Ismail, A. Ihtiyar, N.F.S.A. Bakar, A. Darko, A partial least squares structural equation modeling (PLS-SEM) of barriers to sustainable construction in Malaysia, Journal of Cleaner Production 204 (2018) 564–572.
[6] M. Heide, K.M. Dudka, M.Z. Hauschild, Absolute sustainable CO2-limits for buildings should reflect their function. A case study of four building typologies, Developments in the Built Environment 15 (2023) 100175.
[7] X. Gan, J. Zuo, P. Wu, J. Wang, R. Chang, T. Wen, How affordable housing becomes more sustainable? A stakeholder study, Journal of Cleaner Production 162 (2017) 427–437.
[8] M. Scherz, H. Kreiner, A. Passer, Sustainable procurement for carbon neutrality of buildings: A life cycle assessment (LCA)-based bonus/malus system to consider external cost in the bid price, Developments in the Built Environment 14 (2023) 100161.
[9] I. Othman, A. Kineber, A. Oke, T. Zayed, M. Buniya, Barriers of value management implementation for building projects in Egyptian construction industry, Ain Shams Engineering Journal 12 (1) (2021) 21–30.
[10] E. Kissi, E. Boateng, T. Adjei-Kumi, Strategies for implementing value management in the construction industry of Ghana, in: Proceedings of the DII-2015 Conference on Infrastructure Development and Investment Strategies for Africa, 2015, pp. 255–267.
[11] L.A. Adeyemi, M. Idoko, Developing local capacity for project management–Key to social and business transformation in developing countries, Project Management Institute, 2008.
[12] S.-Y. Kim, Y.-S. Lee, V.T. Nguyen, Barriers to applying value management in the Vietnamese construction industry, Journal of Construction in Developing Countries 21 (2) (2016) 55.
[13] W. Jekale, Performance for public construction projects in developing countries: Federal road and educational building projects in Ethiopia, Norwegian University of Science & Technology, 2004.
[14] L. Manman, P. Goswami, P. Mukherjee, A. Mukherjee, L. Yang, U. Ghosh, V.G. Menon, Y. Qi, L. Nkenyereye, Distributed artificial intelligence empowered sustainable cognitive radio sensor networks: a smart city on-demand perspective, Sustainable Cities and Society 75 (2021) 103265.
[15] A.F. Kineber, I. Othman, A.E. Oke, N. Chileshe, M.K. Buniya, Identifying and assessing sustainable value management implementation activities in developing countries: the case of Egypt, Sustainability 12 (21) (2020) 9143.
[16] S.V. Russell-Smith, M.D. Lepech, Cradle-to-gate sustainable target value design: integrating life cycle assessment and construction management for buildings, Journal of Cleaner Production 100 (2015) 107–115.

[17] M. Regona, T. Yigitcanlar, B. Xia, R.Y.M. Li, Opportunities and adoption challenges of AI in the construction industry: a PRISMA review, Journal of Open Innovation: Technology, Market, and Complexity 8 (1) (2022) 45.
[18] A. Darko, A.P. Chan, M.A. Adabre, D.J. Edwards, M.R. Hosseini, E.E. Ameyaw, Artificial intelligence in the AEC industry: Scientometric analysis and visualization of research activities, Automation in Construction 112 (2020) 103081.
[19] M. Regona, T. Yigitcanlar, B. Xia, R.Y.M. Li, Artificial intelligent technologies for the construction industry: how are they perceived and utilized in Australia? Journal of Open Innovation: Technology, Market, and Complexity 8 (1) (2022) 16.
[20] G.J. Hwang, H. Xie, B.W. Wah, D. Gašević, Vision, challenges, roles and research issues of artificial intelligence in education, Computers and Education: Artificial Intelligence 1 (2020) 100001.
[21] M.H. Schia. The introduction of AI in the construction industry and its impact on human behavior, 2019. Dublin, Ireland.
[22] T.D. Akinosho, L.O. Oyedele, M. Bilal, A.O. Ajayi, M.D. Delgado, O.O. Akinade, A.A. Ahmed, Deep learning in the construction industry: A review of present status and future innovations, Journal of Building Engineering 32 (2020) 101827.
[23] S.O. Abioye, L.O. Oyedele, L. Akanbi, A. Ajayi, J.M.D. Delgado, M. Bilal, O.O. Akinade, A. Ahmed, Artificial intelligence in the construction industry: a review of present status, opportunities and future challenges, Journal of Building Engineering 44 (2021) 103299.
[24] J.L. Blanco, S. Fuchs, M. Parsons, M.J. Ribeirinho, Artificial intelligence: Construction technology's next frontier, Building Economist, The (2018) 7–13.
[25] Y. Yao, Z. Xiao, B. Wang, B. Viswanath, H. Zheng, B.Y. Zhao, Complexity vs. performance: empirical analysis of machine learning as a service, in: Proceedings of the 2017 Internet Measurement Conference, 2017, pp. 384–397.
[26] J.G. Everett, H. Saito, Construction automation: demands and satisfiers in the United States and Japan, Journal of Construction Engineering and Management 122 (2) (1996) 147–151.
[27] C. Pistorius, The impact of emerging technologies on the construction industry, Innovation Insight 4 (17) (2017).
[28] H. Abdirad, P. Mathur, Artificial intelligence for BIM content management and delivery: Case study of association rule mining for construction detailing, Advanced Engineering Informatics 50 101414 (2021).
[29] H. Salehi, R. Burgueño, Emerging artificial intelligence methods in structural engineering, Engineering Structures 171 (2018) 170–189.
[30] D.O. Aghimien, A.E. Oke, C.O. Aigbavboa, Barriers to the adoption of value management in developing countries, Engineering, Construction and Architectural Management 25 (7) (2018) 818–834.
[31] G.F. Bigham, S. Adamtey, L. Onsarigo, N. Jha, Artificial intelligence for construction safety: mitigation of the risk of fall, in: Intelligent Systems and Applications: Proceedings of the 2018 Intelligent Systems Conference (IntelliSys), vol. 2, Springer, 2019, pp. 1024–1037.
[32] Y. Pan, L. Zhang, Roles of artificial intelligence in construction engineering and management: A critical review and future trends, Automation in Construction 122 (2021) 103517.
[33] A.A. Basaif, A.M. Alashwal, F.A. Mohd-Rahim, S. Karim, S.-C. Loo, Technology awareness of artificial intelligence (AI) application for risk analysis in construction projects, Malaysian Construction Research Journal 9 (1) (2020) 182–195.
[34] B.G. Kang, M.A. Fazlie, B.H. Goh, M.K. Song, C. Zhang, Current practice of risk management in the Malaysia construction industry-the process and tools/techniques, International Journal of Structural and Civil Engineering Research 4 (4) (2015) 371–377.
[35] R.F. Aziz, Ranking of delay factors in construction projects after Egyptian revolution, Alexandria Engineering Journal 52 (3) (2013) 387–406.
[36] R.H. Ansah, S. Sorooshian, S.B. Mustafa, G. Duvvuru, Assessment of environmental risks in construction projects: a case of Malaysia, in: Proceedings of the 2016 International Conference on Industrial Engineering and Operations Management Detroit, vol. 23, 2016, pp. 752–763. Michigan, USA.
[37] R. Elshawi, S. Sakr, D. Talia, P. Trunfio, Big data systems meet machine learning challenges: towards big data science as a service, Big Data Research 14 (2018) 1–11.
[38] R. Sacks, M. Girolami, I. Brilakis, Building information modelling, artificial intelligence and construction tech, Developments in the Built Environment 4 (2020) 100011.
[39] D.W. Chan, A.B. Baghbaderani, H. Sarvari, An empirical study of the human error-related factors leading to site accidents in the Iranian urban construction industry, Buildings 12 (11) (2022) 1858.
[40] Y. Xu, Y. Zhou, P. Sekula, L. Ding, Machine learning in construction: from shallow to deep learning, Developments in the Built Environment 6 (2021) 100045.
[41] K. Karyono, B.M. Abdullah, A.J. Cotgrave, A. Bras, The adaptive thermal comfort review from the 1920s, the present, and the future, Developments in the Built Environment 4 (2020) 100032.
[42] J. Harty, T. Kouider, G. Paterson, Getting to grips with BIM: a guide for small and medium-sized architecture, engineering and construction firms, Routledge, 2015.
[43] P. Atanasov, A. Gauthier, R. Lopes, Applications of artificial intelligence technologies in healthcare: a systematic literature review, Value in Health 21 (2018) S84.
[44] M. Khayatazad, Pue L. De, W. De Waele, Detection of corrosion on steel structures using automated image processing, Developments in the Built Environment 3 (2020) 100022.
[45] Z.P. Jiang, T. Bian, W. Gao, Learning-based control: A tutorial and some recent results, Foundations and Trends® in Systems and Control 8 (3) (2020) 176–284.
[46] I. Motawa, Spoken dialogue BIM systems–an application of big data in construction, Facilities 35 (13/14) (2017) 787–800.
[47] J. Hangl, V.J. Behrens, S. Krause, Barriers, drivers, and social considerations for AI adoption in supply chain management: a tertiary study, Logistics 6 (3) (2022) 63.
[48] G. Patil, Recent aspects on digitalization in construction industry, in: Proceedings of the 3rd International Conference on Construction, Real Estate, Infrastructure & Project Management, vol. 3, 2018, p. 12.
[49] L. Zhang, J. Tan, D. Han, H. Zhu, From machine learning to deep learning: progress in machine intelligence for rational drug discovery, Drug Discovery Today 22 (11) (2017) 1680–1685.
[50] A. Kaplan, M. Haenlein, Rulers of the world, unite! The challenges and opportunities of artificial intelligence, Business Horizons 63 (1) (2020) 37–50.
[51] C.M. Christensen, The ongoing process of building a theory of disruption, Journal of Product Innovation Management 23 (1) (2006) 39–55.
[52] A. Oyedele, H.A. Owolabi, L.O. Oyedele, O.A. Olawale, Big data innovation and diffusion in projects teams: towards a conflict prevention culture, Developments in the Built Environment 3 (2020) 100016.
[53] A.F. Kineber, I. Othman, A.E. Oke, N. Chileshe, M.K. Buniya, Impact of value management on building projects success: structural equation modeling approach, Journal of Construction Engineering and Management 147 (4) (2021) 04021011.
[54] Z. Mohamad Ramly, G.Q. Shen, A.T. Yu, Critical success factors for value management workshops in Malaysia, Journal of Management in Engineering 31 (2) (2015) 05014015.
[55] A.E. Oke, A.F. Kineber, I. Albukhari, I. Othman, C. Kingsley, Assessment of cloud computing success factors for sustainable construction industry: the case of Nigeria, Buildings 11 (2) (2021) 36.
[56] A.F. Kineber, I. Othman, A.E. Oke, N. Chileshe, B. Alsolami, Critical value management activities in building projects: a case of Egypt, Buildings 10 (12) (2020) 239.
[57] L. Zeng, R.Y.M. Li, X. Huang, Sustainable mountain-based health and wellness tourist destinations: The interrelationships between tourists' satisfaction, behavioral intentions, and competitiveness, Sustainability 13 (23) (2021) 13314.
[58] Badewi A., Investigating benefits realisation process for enterprise resource planning systems, 2016, PhD thesis, Cranfield University, England.
[59] A. Field, Discovering statistics using IBM SPSS statistics, sage, 2013.
[60] M.M. Harris, J. Schaubroeck, Confirmatory modeling in organizational behavior/human resource management: issues and applications, Journal of Management 16 (2) (1990) 337–360.
[61] R. Kline, in: Edition 3. Principles and practice of structural equation modeling, The Guilford Press, New York, 2010.
[62] R.K. Yin, in: fourth editionCase study research: Design and methods, vol. 5, Applied Social Research Methods Series, 2009.
[63] C. Kothari, Research methodology methods and techniques 2nd revised edition, vol. 20, New Age International publishers, 2009.

[64] D. Wahyuni, The research design maze: understanding paradigms, cases, methods and methodologies, Journal of Applied Management Accounting Research 10 (1) (2012) 69–80.
[65] S.A. Ganiyu, L.O. Oyedele, O. Akinade, H. Owolabi, L. Akanbi, A. Gbadamosi. BIM competencies for delivering waste-efficient building projects in a circular economy, Developments in the Built Environment 4, 2020, p. 100036.
[66] B.G. Tabachnick, L.S. Fidell, J.B. Ullman, Using multivariate statistics, Pearson, Boston, MA, 2007.
[67] T. Yigitcanlar, R.Y.M. Li, P.B. Beeramoole, A. Paz, Artificial intelligence in local government services: Public perceptions from Australia and Hong Kong, Government Information Quarterly 40 (3) (2023) 101833.
[68] J. Pallant, SPSS survival guide, *Crow's Nest*, Allen & Unwin, NSW, 2005.
[69] J.F. Hair, R.E. Anderson, R.L. Tatham, W.C. Black, Multivariate data analysis, fifth edition, Printice-Hall, New Jersey, NJ, 1998.
[70] Q. Shen, Value management in Hong Kong's construction industry: lessons learned, Proceedings of the SAVE International Conference (1997) 260–265.
[71] D. Ahadzie, D. Proverbs, P. Olomolaiye, Critical success criteria for mass house building projects in developing countries, International Journal of Project Management 26 (6) (2008) 675–687.
[72] S.A. Raza, W. Qazi, N. Shah, M.A. Qureshi, S. Qaiser, R. Ali, Drivers of intensive Facebook usage among university students: an implications of U&G and TPB theories, Technology in Society 62 (2020) 101331.
[73] L. Li, Z. Yi, F. Jiang, S. Zhang, J. Zhou, Exploring the mechanism of digital transformation empowering green innovation in construction enterprises, Developments in the Built Environment 15 (2023) 100199.
[74] R.Y.M. Li, B. Tang, K.W. Chau, Sustainable construction safety knowledge sharing: A partial least square-structural equation modeling and a feedforward neural network approach, Sustainability 11 (20) (2019) 5831.
[75] E.C. Hui, X. Zheng, Measuring customer satisfaction of FM service in housing sector: A structural equation model approach, Facilities 28 (5/6) (2010) 306–320.
[76] C.M. Ringle, M. Sarstedt, D.W. Straub, Editor's comments: a critical look at the use of PLS-SEM in" MIS Quarterly, MIS Quarterly (2012) iii–xiv.
[77] K.H. Yuan, R. Wu, P.M. Bentler, Ridge structural equation modelling with correlation matrices for ordinal and continuous data, British Journal of Mathematical and Statistical Psychology 64 (1) (2011) 107–133.
[78] A.F. Kineber, I. Othman, A.E. Oke, N. Chileshe, T. Zayed, Exploring the value management critical success factors for sustainable residential building – a structural equation modelling approach, Journal of Cleaner Production 293 (2021) 126115.
[79] S. Bag, L.C. Wood, L. Xu, P. Dhamija, Y. Kayikci, Big data analytics as an operational excellence approach to enhance sustainable supply chain performance, Resources, Conservation and Recycling 153 (2020) 104559.
[80] M. Al-Emran, V. Mezhuyev, A. Kamaludin, Towards a conceptual model for examining the impact of knowledge management factors on mobile learning acceptance, Technology in Society 61 (2020) 101247.
[81] D. Chandra, D. Kumar, Evaluating the effect of key performance indicators of vaccine supply chain on sustainable development of mission indradhanush: a structural equation modeling approach, Omega 101 (2021) 102258.
[82] M. Sarstedt, C.M. Ringle, D. Smith, R. Reams, J.F. Hair Jr, Partial least squares structural equation modeling (PLS-SEM): a useful tool for family business researchers, Journal of Family Business Strategy 5 (1) (2014) 105–115.
[83] M.A. Camilleri, A.C. Camilleri, Remote learning via video conferencing technologies: implications for research and practice, Technology in Society 68 (2022) 101881.
[84] N.F. Arenas, M. Shafique, Recent progress on BIM-based sustainable buildings: State of the art review, Developments in the Built Environment 15 (2023) 100176.
[85] J.R.C. Vargas, C.E.M. Mantilla, A.B.L. de Sousa Jabbour, Enablers of sustainable supply chain management and its effect on competitive advantage in the Colombian context, Resources, Conservation and Recycling 139 (2018) 237–250.
[86] S. Sharma. Applied multivariate techniques, John Wiley and Sons Inc, New York, 1996, p. 512.
[87] M.Z. Alam, W. Hu, M.A. Kaium, M.R. Hoque, M.M.D. Alam, Understanding the determinants of mHealth apps adoption in Bangladesh: a SEM-Neural network approach, Technology in Society 61 (2020) 101255.
[88] J. Pallant, SPSS survival manual, 3rd edition, vol. 15, McGrath Hill, 2007.
[89] J.C. Nunnally, Psychometric theory 3E, Tata McGraw-Hill Education, 1994.
[90] A. Field, Discovering statistics using SPSS (3. Baskı), Sage Publications, NY, 2009.
[91] S.B. MacKenzie, P.M. Podsakoff, Common method bias in marketing: causes, mechanisms, and procedural remedies, Journal of Retailing 88 (4) (2012) 542–555.
[92] P.M. Podsakoff, D.W. Organ, Self-reports in organizational research: problems and prospects, Journal of Management 12 (4) (1986) 531–544.
[93] R. Akhtar, S. Sultana, M.M. Masud, N. Jafrin, A. Al-Mamun, Consumers' environmental ethics, willingness, and green consumerism between lower and higher income groups, Resources, Conservation and Recycling 168 (2021) 105274.
[94] X. Zhang, C. Liu, W. Li, S. Evans, Y. Yin, Effects of key enabling technologies for seru production on sustainable performance, Omega 66 (2017) 290–307.
[95] L.S. Meyers, G. Gamst, A. Guarino, Applied multivariate research: Design and interpretation, Sage Publications, Inc., Thousand Oaks, CA, 2006.
[96] J.F. Hair, W.C. Black, B.J. Babin, R.E. Anderson, R.L. Tatham, Multivariate data analysis, vol. 6, Pearson Prentice Hall, Upper Saddle River, NJ, 2006.
[97] R.B. Kline, Principles and practice of structural equation modeling, Guilford publications, 2015.
[98] J.F. Hair Jr., G.T.M. Hult, C. Ringle, M. Sarstedt, A primer on partial least squares structural equation modeling (PLS-SEM), Sage Publications, 2016.
[99] O. Khan, T. Daddi, H. Slabbinck, K. Kleinhans, D. Vazquez-Brust, S. De Meester, Assessing the determinants of intentions and behaviors of organizations towards a circular economy for plastics, Resources, Conservation and Recycling 163 (2020) 105069.
[100] K.K.K. Wong, Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS, Marketing Bulletin 24 (1) (2013) 1–32.
[101] J. Henseler, C.M. Ringle, R.R. Sinkovics, The use of partial least squares path modeling in international marketing, in: New Challenges to International Marketing, Emerald Group Publishing Limited, 2009, pp. 277–319.
[102] S. Bag, L.C. Wood, S.K. Mangla, S. Luthra, Procurement 4.0 and its implications on business process performance in a circular economy, Resources, Conservation and Recycling 152 (2020) 104502.
[103] X. Zhu, P. Zhang, Y. Wei, Y. Li, H. Zhao, Measuring the efficiency and driving factors of urban land use based on the DEA method and the PLS-SEM model—a case study of 35 large and medium-sized cities in China, Sustainable Cities and Society 50 (2019) 101646.
[104] J.F. Hair, C.M. Ringle, M. Sarstedt, Partial least squares structural equation modeling: rigorous applications, better results and higher acceptance, Long Range Planning 46 (1–2) (2013) 1–12.
[105] C. Fornell, D.F. Larcker, Evaluating structural equation models with unobservable variables and measurement error, Journal of Marketing Research 18 (1) (1981) 39–50.
[106] W.W. Chin, P.R. Newsted, Structural equation modeling analysis with small samples using partial least squares, Statistical Strategies for Small Sample Research 1 (1) (1999) 307–341.
[107] Y.S. Ho, Review of second-order models for adsorption systems, Journal of Hazardous Materials 136 (3) (2006) 681–689.
[108] J.F. Hair, C.M. Ringle, M. Sarstedt, PLS-SEM: indeed a silver bullet, Journal of Marketing Theory and Practice 19 (2) (2011) 139–152.
[109] D. Briskorn, M. Dienstknecht, Covering polygons with discs: the problem of crane selection and location on construction sites, Omega 97 (2020) 102114.
[110] N. Banaitiene, A. Banaitis, A. Kaklauskas, E.K. Zavadskas, Evaluating the life cycle of a building: a multivariant and multiple criteria approach, Omega 36 (3) (2008) 429–441.
[111] A. AfsharGhotli, A. Rezaei, Value management in building construction industry of northern Cyprus: addressing a theory and practice gap, in: AEI 2013: Building Solutions for Architectural Engineering, 2013, pp. 84–93.
[112] S. Kusi-Sarpong, I.J. Orji, H. Gupta, M. Kunc, Risks associated with the implementation of big data analytics in sustainable supply chains, Omega 105 (2021) 102502.

[113] G. Patil, Recent aspects on digitalization in construction industry, Construction Real Estate Infrastructure & Construction Management 3 (2018) 12.
[114] B.G. De Soto, I. Agustí-Juan, J. Hunhevicz, S. Joss, K. Graser, G. Habert, B.T. Adey, Productivity of digital fabrication in construction: cost and time analysis of a robotically built wall, Automation in Construction 92 (2018) 297–311.
[115] V. Gerling, S. Von Mammen, Robotics for self-organised construction, in: 2016 IEEE 1st International Workshops on Foundations and Applications of Self* Systems (FAS* W), IEEE, 2016, pp. 162–167.