frontiers in Built Environment

ORIGINAL RESEARCH
published: 24 March 2022
doi: 10.3389/fbuil.2022.823998

Organisational Factors of Artificial Intelligence Adoption in the South African Construction Industry

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The innovation of technology, particularly Artificial Intelligence (AI), has rapidly changed the world. It is currently at a nascent stage worldwide in the construction industry throughout the lifecycle of projects. However, construction organisations of developing countries such as South Africa are still lagging in recognising the need to adopt emerging digital innovations such as AI to improve the built sector's performance. This study aims to identify organisational factors imperative to driving the adoption of AI in construction organisations. The study uses a quantitative survey approach to collect data through snowball sampling of industry experts on factors associated with AI adoption. With data from 169 respondents, exploratory factor analysis was adopted to identify critical organisational factors to ease AI adoption in the industry. Furthermore, confirmatory factor analysis was employed to demonstrate the relationship among the constructs. The study proposes 17 factors to drive organisational AI, categorised into four components; innovative organisational culture, competence-based development, collaborative decision-making, and strategic analysis. However, previous studies have identified organisational factors of AI in the construction and allied industries. This study presented the organisational factors of AI in the construction industry using EFA and CFA, a method not used in articles presented in the SLR identified. The use of CFA improves the measurement of the constructs. It thus enhances understanding of the underlying components of a construct and its relationship with AI in the construction industry.

Keywords: artificial intelligence, confirmatory factor analysis, construction industry, exploratory factor analysis, organisational factors, South Africa

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Edited by:
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Specialty section:
This article was submitted to Construction Management, a section of the journal Frontiers in Built Environment

Received: *28 November 2021*
Accepted: *21 February 2022*
Published: *24 March 2022*

Citation:
Tjebane MM, Musonda I and Okoro C (2022) Organisational Factors of Artificial Intelligence Adoption in the South African Construction Industry. Front. Built Environ. 8:823998. doi: 10.3389/fbuil.2022.823998

INTRODUCTION

Various productivity problems characterise the construction industry of developing countries. These include a shortage of skilled labour, low productivity, excessive material waste, and unsafe working conditions, primarily caused by repetitive and labour-intensive tasks (Pradhananga et al., 2021). Windapo and Cattell (2013) noted challenges of the construction industry of developing countries to include public sector capacity, lack of required skills, globalisation and technology, among others. These constraints reduce the efficiency of the construction process and provide difficult conditions for the country's construction development (Ivanov and Aldeen, 2018). The construction industry is found to play a crucial role in developing economies worldwide (Isa et al., 2013). The government can laudably leverage it as a platform to stimulate the national economic transformation toward developed country status (Yap et al., 2019). The construction industry needs to adopt an efficient and effective solution to promote infrastructure development, develop the local economy, reduce costs, and increase construction efficiencies (Pheng and Hou, 2019). Moreover, the industry needs to improve service quality and expertise and attract increasing interest from policymakers, researchers, and industry practitioners (Alinaitwe and Ayesiga, 2013). This addresses the construction industry's dealings with important data from diverse disciplines throughout a project's life cycle (Yousif et al., 2021).

It is now a reality to develop construction processes and systems aimed at technological innovations that can successfully contribute to a building's construction process (Diniz Fonseca, 2021). According to Sun et al. (2020), technology development drives the continuous transformation of the construction industry. The industry's issues put it under greater pressure to shift from a sector that has rejected emerging technology to one that embraces it (El Jazzar et al., 2021). Olanipekun and Sutrisna (2021) noted that construction professionals, companies, and government agencies worldwide declared their preference for digital technologies in construction. Adopting technology such as AI comes with many advantages for the construction industry. These include visualisation, clear communication, site planning, logistics, health and safety management (Swallow and Zulu, 2019). However, the construction industry is lethargic in adopting technology that can address the challenges holistically (Nadhim et al., 2016; Delgado et al., 2019). Most technologies in the construction industry focus on a single task. Drones/UAVs are efficient and effective means of remotely conducting safety inspections in construction projects (Nnaji et al., 2019). 3D Concrete Printing technologies create objects by depositing concrete layer-by-layer using materials such as polymers or metals (Adaloudis and Bonnin Roca, 2021). Building Information Modelling (BIM) is used for design preparation, 3D modelling, simulation, risk assessment, environmental analysis, site control, project control, identification, and collision detection (Shehzad et al., 2021). These technologies provide part solutions to the problems of the construction industry. With this comes the usage of AI.

Artificial Intelligence has completely changed conventional design, manufacturing, and construction technologies (Manzoor et al., 2021). In construction, AI helps with operations on-site such as automated welding bricklaying and alerts an operator with a warning message, thereby minimising risks (Chakkravarthy, 2019). AI also automatically adds explicit information to models produced from algorithms trained to recognise and infer pre-defined groups of target concepts from building patterns (Sacks et al., 2020). It has ramifications in economics, geopolitics, sociology, the environment, demographics, and security, among other fields and disciplines (Yeh and Chen, 2018). AI has enabled rapid computing capabilities such as natural language processing, voice recognition, and machine learning (Sohn and Kwon, 2020). Natural language AI is used to cluster construction schedules (Hong et al., 2021). Voice recognition is used in building quantities software using text to speech (Olanrewaju et al., 2020). The application of machine learning in construction is in site supervision, automatic detection, and intelligent maintenance, among others (Xu et al., 2021). AI is defined as being the oldest field of computer science and very broad, dealing with all aspects of mimicking cognitive functions for real-world problem solving and building systems that learn and think like people (Holzinger et al., 2019). AI plays a significant role in the construction industry in terms of digitisation and intelligence (Abioye et al., 2021). It enables significant automation, performance, and reliability improvements and directly links physical and digital in other industries (Manzoor et al., 2021). On the other hand, construction organisations have yet to establish common AI adoption infrastructures (Mahroof, 2019). Furthermore, stakeholders in the construction industry are apprehensive of AI technology's market worth (Merschbrock and Munkvold, 2015). The application of AI can improve construction development competence by facilitating data exchange (Lekan et al., 2018).

The need to use digital technologies is to improve the productivity and performance of the built environment in developing countries such as South Africa (Windapo, 2021). South Africa needs infrastructure to drive economic growth, but this depends on the built environment performing optimally and being productive (Li et al., 2019). AI has been at the forefront of research for operations and supply chain management (Dubey et al., 2019). However, organisations are limited in resources and capabilities (Girginkaya Akdag and Maqsood, 2019). This is because organisations play an important role in external shocks like pandemics or geopolitical situations; adapting to market changes or responding to customer demands is critical in AI adoption (Paul et al., 2020). According to Mabad et al. (2021), organisations are not considering technological advancement and AI implementation to diminish their capabilities and efficiencies in service provision in the current digitalisation age.

The construction industry's productivity depends on the smooth integration of applicable AI technology. This is because it restructured organisations by making their business processes more productive and efficient than ever before (Lakhwani et al., 2020). According to Miranda et al. (2016), organisations frequently overlook the development of learning and innovation, despite these two qualities being critical in the search for long-term sustainability in the construction industry and market. Moreover, organisations in the construction industry undergo many changes such as merging and acquisition, cultural and structural, procedural (Sarala et al., 2019; Boadu et al., 2020). Organisational adoption is critical because it involves technology infrastructure, expertise (human) resources, and organisational commitment to change (Saghafian et al., 2021). While organisational perspectives are not often ignored or even denied in the technological factors. The results are a major factor that causes swing from either to or from the technology imperative of considering the organisation (Metcalf and Benn, 2012). In a changing context, AI adoption in organisations is dynamically and jointly created, affecting the intra-organisational legitimacy of technology in the adoptive organisation and, as a result, affecting the periodic adoption results (Ren, 2019). Moreover, construction organisations come in different sizes, either large or SMEs. This portends that there could be disenfranchisement in the process; hence an inclusive strategy can examine how all these concerns can be easily resolved.

Previous studies have looked at AI adoption in the construction industry. For instance, Mohamed et al. (2021) looked at the implementation of AI in the Malaysian construction industry. The study looked at AI to improve project quality while reducing project duration, cost, and design by utilizing technologies in the construction sector. Furthermore, Nikolaeva and Nikolenko's research, 2021) aimed to analyse and pick ready-made solutions for the use of AI technology to improve a construction company's productivity in the chosen AI activity. Similarly, Karan et al. (2020) investigated the use of AI as a tool in the AEC business, with decisions made on data input. Hooda et al. (2021) focused on how AI and its many concepts can be integrated with developing fields of structural engineering and how it influences the construction industry by employing in the primary areas of structural health assessment damages and construction management. Consequently, it becomes difficult for construction organisations to adopt AI as they are not driven or prohibited by any factor.

Systematic literature review conducted for providing literature evidence for organisational factors in the construction and allied industries. Jöhnk et al. (2020) looked at AI readiness factors in organisations using the qualitative interview research method. Chatterjee et al. (2020) looked at the adoption of AI in Indian organisations using partial least square (PLS)—structural equation modelling (SEM). García de Soto et al. (2019) looked at AI-related technologies' implications on construction organisational structures. The study used a case study to address the implications. Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were not used in the review to derive estimates of factor structure when there was *a priori* information available that could help identify factors (Faragher, 2005). A valuable analysis for validating data structure is combining the experimental methods such as EFA and CFA (Hyett and Parker, 2014).

To date, there are no empirical studies on AI in the construction industry of South Africa. As a result, the current situation of AI adoption factors in South African construction organisations remains unclear. For this reason, the research question concerning organisational factors of AI adoption in the South African construction industry remains unclear. Thus, posing the research question "What are the organisational factors of AI in the South African construction industry?' aims to fill the research gap. This research question should provide South African construction organisations with practical assistance in AI implementation. Further, this study aims to identify the AI constructs and then test the relationship between the constructs.

The paper starts with an introduction and background to the study's structure. This is followed by a literature review of the definition and scope of AI in the construction industry. After the presentation on the research method, the results are discussed before conclusions are made, and recommendations are proposed.

LITERATURE REVIEW

Definition and Scope of Artificial Intelligence

Scholars define AI as the ability to make sense of data gathered from previous experiences and deal with the uncertainty of future actions. AI simulates human-like cognitive activities more transparently (Trocin et al., 2021). In recent years, AI has been broadly defined as the study and design of intelligent agents, with the ultimate objective of making computers capable of thinking and acting (Smith, 2016; Shneiderman, 2020). AI aims to solve jobs that are difficult to formalise but relatively simple for humans with intuitive abilities (Shi et al., 2020). Advances in AI and big data analytics have made it possible to use numerous forms of data, make data-driven decisions, and improve operational efficiency. IT-enabled data collection and analysis skills have improved the management of organisations (Cho and Wang, 2021).

Artificial Intelligence in Construction Organisations

AI is a swiftly developing field with robots impacting how organisations are run and managed. It has attracted an important place in recent years. With the help of the technologies such as machine learning (ML), autonomous tools can promote their concert by deriving from the data over time (Dhanabalan and Sathish, 2018). According to Dhamija and Bag (2020), AI is the key to achieving persuasive operational transformations in most current organisational set-ups. According to Arrotéia et al. (2021), AI has become a common process tool for managing construction projects and organisations. This is because it consists of all aspects, disciplines, and systems of a facility within a model, with which all stakeholders can collaborate more accurately and efficiently than traditional processes (Azhar et al., 2015). Organisations view AI as capable of performing jobs that formerly required the human mind. In terms of application, adoption, processing speed, and capacities, AI-based systems quickly evolve (Haefner et al., 2021). AI has brought about capabilities within the construction sector through technical skills and social skills to deliver project outcomes (Sima et al., 2020). These capabilities result from the organisation's AI investments in staffing, training, compensation, communication, and other human resource areas (Ahuja et al., 2018). The machines are increasingly capable of taking on less-routine tasks (Ghosh et al., 2018). Digital technologies, such as AI cause major changes in the features of an organisation, a process known as digital transformation. As a result, AI has become a topic of interest in strategic information research and industrial business practice (Wu et al., 2021). However, human intellect does not rule out the possibility of making a perfect decision at the right time. AI is simply about 'choosing' the best option at the right time.

Factors that could influence the adoption of AI in organisations have been identified in various studies. Ghobakhloo and Ching (2019) study identified that knowledge and competency and information processing management are the factors of organisational AI adoption. Automation, the creation of networks of connected and intelligent machines and materials, and the integration of real and virtual worlds are all associated with AI. Employees must therefore be knowledgeable and competent in the disciplines of IDT, cybernetics, and data analytics, implying that skilled employees must also undergo skill evolution. In the construction sector, AI plays a vital role as a major enabler of information processing capability to process increased data. As a result, organisations with a greater demand for information processing are projected to be more open to AI adoption. Turner et al. (2020) indicated that performance, cost, government pressure and knowledge are key organisational factors influencing AI adoption. AI can customise part production and utilise it to enable new cost-effective building methods. It reduces workers' exposure to risks encountered in conventional construction projects and overall reduces construction costs. Likewsie, Mabad et al., 2021) study showed that productivity, government pressure and firm size are important. Governments can use their regulatory frameworks to favour or inhibit AI adoption. When deciding whether to implement new technology, construction organisations consider various regulations, norms, and guidelines. Governments can use their regulatory frameworks to favour or inhibit AI adoption. When deciding whether to implement new technology, construction organisations consider various regulations, norms, and guidelines.

Jöhnk et al. (2020) found organisational readiness, top management support, decision making support, cost, skills, and attitude to innovation. An informed decision regarding an organisation's readiness increases the probability of successful AI adoption and is important to successfully leverage AI's business value. Instead of depending on "gut feeling or business instinct," decision-making is the technique of employing insights based on data analytics to make decisions. AI-assisted decision-making not only improves organisational performance but also raises AI readiness because it serves as a warm-up for AI-driven decision-making. As a result, organisations should promote decision-making as an organisational practice and prepare employees to work in a culture where AI provides complementary insights to help organisations make better judgements. The willingness of top management to start AI efforts from the top down and express support for bottom-up initiatives is referred to as top management support. Top management support is critical for successful AI adoption, given the vast range of organisational requirements connected with AI implementation. Experts underlined that a firm could only commit to AI adoption if top management has given the green light. Integrating AI adoption into strategy and cultivating AI expertise and awareness are strong top management support indications. Moreover, organisations recognise needs, become aware of innovation, form an attitude toward it, and create a proposal for adoption. García de Soto et al. (2019) looked at the implications of AI in the construction industry, workforce and organisations. They revealed that time-saving, cost, competitive pressure and collaboration influence AI adoption. Currently, construction organisations and roles need to be transformed in many aspects. These include reducing lead times and improved quality and cost by integrating design and construction activities and maximising parallelism in AI technologies' working practices. Moreover, constructions adopt AI to ensure competitiveness. The construction industry must adopt a new organisation involving collaboration and interaction between the different construction professionals.

McAleenan (2020) further identified risk, standards and decision making support. Government, industry bodies and organisations develop are among many who are researching and producing guidelines for system designers and developers. This is to recognise that technological developments occur faster than philosophical and ethical considerations can keep up. Unlimited risks such as corruption, fragmented structures, inefficient design, and insufficient planning time drive organisations to adopt AI. While Chatterjee et al. (2020) pointed out cost, work culture, staff relationship, and attitude towards innovation. The AI system causes organisations to shift their attention away from traditional thinking about cutting operation costs and increasing profit. It is extremely difficult for humans to manage and evaluate such a large of data cost-effectively, necessitating the use of AI technology. Users, who are employees of organisations, wish to utilise a system if it is useful and believes that utilising it would provide them with delight and beauty. This is how they feel about the organisation's innovation.

Olawumi and Chan (2020) and Pan and Pan (2020) added that collaboration, government pressure, standards, top management support, firm size and organisational readiness are key influencers on an organisation's AI adoption. Organisations need to secure project stakeholders' collaboration and coordination and early involvement in construction projects. As a result, construction organisations must avoid using traditional procedures. Regulatory policies and standards could facilitate innovation adoption by reward schemes or mandatory regulations. In construction organisations, the government's role is critical for innovation adoption to formulate regulation and guidance for the largest client. **Table 1** below shows the summary of organisational factors.

RESEARCH METHOD

The research techniques chosen for this study were a literature review accompanied by a quantitative survey to achieve the study's objectives. A quantitative research approach tests objective theories, formulating facts, uncovering patterns, examining the relationship between statistically measured variables and analysing them using statistical techniques (Apuke, 2017). A quantitative approach was adopted as it enables the development of quantitative valuation indicators (Basias and Pollalis, 2018). The questionnaire technique was chosen for this survey because it was rapid, allowed for broad geographic coverage, and provided adequate opportunity for respondents to check facts and provide accurate replies (Jones

TABLE 1 | Summary of organisational factors.

Organisational factor	Reference
Information Processing Management	Ghobakhloo and Ching (2019:4)
knowledge and competency	Ghobakhloo and Ching (2019 : 5), Turner et al. (2020: 746), Jöhnk et al. (2020:11)
Improve performance	Turner et al. (2020: 746), Mabad et al. (2021:43)
Cost to organisation	Chatterjee et al. (2020:2), Pan and Pan (2020:6) Olawumi and Chan (2020:1259), Turner et al. (2020:746), Jöhnk et al. (2020:11)
Organisational Culture	Jöhnk et al. (2020:7) Olawumi and Chan (2020:1270), Ghobakhloo and Ching (2019:5)
Government pressure	Olawumi and Chan (2020:1259), Turner et al. (2020:746), Mabad et al. (2021:43)
Collaboration	De Soto et al. (2019: 2), Olawumi and Chan (2020:1259), Turner et al. (2020:751), Jöhnk et al. (2020:11)
Firm size	Mabad et al. (2021:43), Pan and Pan (2020:6)
Organisational readiness	Jöhnk et al. (2020:10), Pan and Pan (2020:6)
Top Management support	Jöhnk et al. (2020:11), Olawumi and Chan (2020:1259), Pan and Pan (2020:6)
Attitude to innovation	Chatterjee et al. (2020:5), Jöhnk et al. (2020:11)
Time-saving	De Soto et al. (2019: 2)
Competitive pressure	De Soto et al. (2019: 2)
Risk involved in using AI technologies	McAleenan (2020:166)
Standards	McAleenan (2020:166), Olawumi and Chan (2020:1259)
Reputation	De Soto et al. (2019: 1)
Decision making support	McAleenan (2020:167), Turner et al. (2020:755), Jöhnk et al. (2020:11)
Work culture	Chatterjee et al. (2020 p 3), Olawumi and Chan (2020 p1259)
Workplace relationship of staff	Chatterjee et al. (2020 p3)

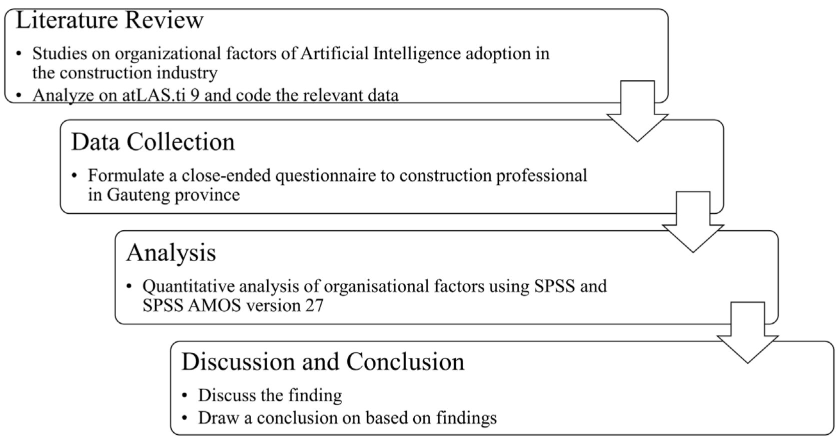

FIGURE 1 | The research process of the study.

et al., 2013). In addition, questionnaires are cost-effective. They can provide a significant number of research data for a relatively low cost in terms of materials, money, and time, and they are reasonably simple to set up (Datti et al., 2019). The research followed the process depicted in **Figure 1**—literature review, questionnaire survey, data analysis using SPSS 27 (mean item score (MIS), exploratory factor analysis (EFA)) and SPSS AMOS 27 of all the constructs that emerged during the study.

Literature Review

The first step was to perform a literature review to identify key factors affecting the construction industry's AI Organisational factors. A systematic literature review (SLR) was conducted. This literature method was chosen as its systematic literature review provides transparent and explicit protocols. Researchers use the search for and assess the field of studies relevant to a specific research topic, in this case being organisational factors of AI in the construction industry (Tian et al., 2018).

Review Protocol

The first stage of SLR is to establish a review protocol. This entails formulating good and comprehensive research questions, strategising systematic searching efforts, selecting appropriate inclusion criteria, implementing a rigorous quality appraisal process, strategising data extraction and synthesis, and demonstrating the best data from their review. A review protocol can help guide and ensure that the researcher stays on course while also increasing the review's methodological transparency (Shaffril et al., 2020).

The following research question was proposed in this paper: What are the organisational factors of AI adoption in the construction industry?

Various steps were undertaken to ensure the research question was answered. The established protocol comprised information on the research question, sample articles, search strategy and selecting relevant keywords to characterise the scope of the study (de Carvalho et al., 2017). This includes the assessment of inclusion and exclusion criteria (de Melo et al., 2020).

Defining an Inclusion and Exclusion Criteria

This review's inclusion criteria were empirical studies based on the relevant research topic, organisational factors of AI adoption in the construction and allied industries, written in English and published between 2011 and 2021. Only papers published in journals and peer-reviewed conferences were included. Ensuring the correct data was being extracted and avoiding any effort at biased results of any specific type is extremely important (Wager and Wiffen, 2011). To eliminate this risk and increase the validity of the findings, the exclusion criteria eliminated papers, not in the scope of the industries, years, language, and publication type.

Search for Studies

When searching for the relevant documents, various search terms were used. These search terms include 4IR, Adoption, Artificial Intelligence, Automation, Construction industry, Construction Innovation Construction 4.0, Digitalisation, Factors, Machine Learning, Organisations, Organisations, Organisational, Robotics, Fourth industrial revolution. Furthermore, Boolean and database-specific operators such as AND, OR and special characters such as truncation (*) or (?) were associated with the search terms were used (Madigan et al., 2014).

Select Studies for Inclusion Based on Pre-Defined Criteria

Studies were discovered through searching these electronic databases: ASCE Journals, Emerald Insight, Elsevier ScienceDirect, Engineering Village, Google Scholar, ICE virtual library, IOPscience, IEEE Xplore, Elsevier ScienceDirect, Elsevier Scopus, SpringerLink and Taylor and Francis

Extract Data From Studies Included

Relevant information was screened after the article extraction, eliminating the need to read all the papers thoroughly. The ATLAS. ti 9 was utilised to systematically sort and conduct the theme analysis review of the final articles (Samsudin et al., 2022). The findings were used to develop a questionnaire for the South African Construction professionals to get primary data. **Table 1** presents a list of seventeen organisational aspects of AI adoption in the construction industry culled from the literature review.

Data Collection

A questionnaire was designed to solicit the perceptions of construction professionals in the Gauteng Province of South Africa. The purpose of selecting the province of Gauteng is that it is the Republic of South Africa's economic powerhouse and makes the largest contribution to almost 38 per cent, KwaZulu-Natal (KZN) at 14.9 per cent compared to second place. Although it is the smallest province, with 12.2 million people, it is the most highly populated, representing nearly 25 per cent of the national total. It is also the fastest-growing province in the country, with a population growth of more than 33% between 1996 and 2011 (Hove and Banjo, 2018).

Questionnaires have become a vital tool for declarations about specific groups or individuals or entire populations when properly constructed and responsibly administered (Roopa and Rani, 2012). This is a valuable method of gathering a wide range of information from many individuals, often called respondents. An online questionnaire using Google form was administered between December 2020 and January 2021. The questionnaire looked at respondents' demographics and organisational factors of AI adoption. It used a five-point Likert scale from 1 ("strongly disagree") to 5 ("strongly agree"), with three being classed as 'neutral'. The scale was adopted due to its ability to detect respondents' feelings about their attitudes (Munyasya and Chileshe, 2018).

Judgemental and snowball sampling methods targeted professionals from professional networks such as industry practitioners. It was also incorporated on social messaging platforms such as LinkedIn and mails to reach out to participants within the study area. The social media platforms comprise communication websites that facilitate relationship forming between users from diverse backgrounds, resulting in a rich social structure of construction professionals (Kapoor et al., 2017).

The judgemental sampling technique does not allow the researcher to generalise to the population because it does not randomly sample research participants. To have the necessary information and be willing to share it, the research needs to concentrate on those individuals with the same opinion (Etikan and Bala, 2017). Snowball sampling is a non-random method of selection that uses a few cases to encourage the participation of other cases in the study, thus increasing the sample size (Taherdoost, 2016). Initial contacts between the initial respondents and the researcher are done with a small group of individuals relevant to the research topic and then used to establish connections with others. It is a helpful way to build networks and increase participants' numbers by asking each participant to suggest more potential participants. The non-probability sampling methods were appropriate as a random sampling method could not be used to select respondents from the population identified from LinkedIn (Lehdonvirta et al., 2020). The respondents can rather be selected based on their willingness to participate in the research study and their knowledge of construction processes (Darko and Chan, 2018).

A total of 150 respondents were targeted for this study, three times above the minimum requirement based on de Winter et al. (2009) and Pearson and Mundform (2010). One hundred sixty-nine 169) completed questionnaires were received and used for analysis at the end of the data collection period. The respondents comprised Architects, Quantity Surveyors, Civil Engineers, Construction Managers, and Construction Project Managers.

Data Analysis

The data were analysed using descriptive and inferential statistics. The outputs were mean and principal components. The analyses were conducted using the Statistical Package for the Social Sciences (SPSS) version 27 and SPSS AMOS (Analysis of a Moment Structures) version 27.

Mean Item Score

The primary responses from participants were analysed using the Mean Item Score (MIS). The average agreement among respondents about the organisational elements influencing AI adoption in the South African construction industry is represented by MIS (Sarhan et al., 2018). To summarise the characteristics of the respondents and the current status of AI applications in construction sector organisations, descriptive statistics were employed to measure central tendency and dispersion (Nasila and Cloete, 2018). The arithmetic mean is a measure of central tendency that represents the average values of a group of numbers. Standard deviation (SD) is a quantitative measure of how much each result deviates from the mean. It is a metric for determining something is (Evans et al., 2021). A low SD suggests that the values are close to the mean, whereas a high SD indicates that the data points span a wide range of values. To rank the highest to lowest mean, the MIS was employed (Ejohwomu et al., 2017). The Likert scale is used to determine the rankings.

Exploratory Factor Analysis

Exploratory factor analysis (EFA) is a computational technique for determining the structure that underpins many variables (Ngowtanasuwan 2019:6). EFA filters out the variables that are not important, leaving just the description variables. Before the EFA, Kaiser-Meyer-Olkin (KMO) and Bartlett's sphericity tests were used to assess sampling adequacy. This is needed to check the case-to-variable ratio and thus the factorability of the data. Bartlett's test of sphericity should be significant at ($p < 0.05$) for the factor analysis to be appropriate (Ul Hadia et al., 2016). The KMO scale runs from 0 to 1, but anything above 0.45 is considered appropriate (Zeray et al., 2021). The total variance explained was also examined as an extraction process of items to reduce them into a manageable number before further analysis (Effendi et al., 2020). Objects with eigenvalues greater than 1.0 are separated into different components using this method (Matsunaga, 2010). The rotated variable matrix was also analysed, and only objects with a factor loading of greater than 0.5 were held for further analysis (Maskey et al., 2018).

Confirmatory Factor Analysis

This research uses the Confirmatory Factor Analysis (CFA) to test for convergent validity and to measure the measurement model's adequacy (Maletičet al., 2013). It also demonstrated the relationship among the constructs. The results from the EFA were used in the CFA to verify the validity of the latent variables and the measurement variables using the SPSS AMOS 27 statistical program (Kim et al., 2015). According to Zahoor et al. (2017), a sample size of 200 can guarantee reliable results if the data set is analysed using confirmatory factor analysis (CFA). However, Kyriazos (2018) claims that for a CFA model with 3–4 indicators per component, a sample size of more than 100 is required. The many fit indices in CFA should be reported since distinct fit indices indicate different aspects of fit. Numerous goodness-of-fit indices typically used in CFA and suggested literature were applied (Chan et al., 2017). As stated in **Table 2**, the study used the fit indices adopted by Chan et al. (2014), Molwus et al. (2017), Tanko et al. (2017), Zahoor et al. (2017), and Puiu (2020).

TABLE 2 | Model fit indices.

Fit indices	Recommended measure
CMIN/df	Good <3, acceptable <5
Root mean sq. error of approx. (RMSEA)	0.05 (very good)-0.1 (threshold)
Root mean sq. residual (RMR)	0–1 (smaller values = better fit)
Goodness-of-fit index (GFI)	0 (no fit)-1 (perfect fit)
Comparative fit index (CFI)	0 (no fit)-1 (perfect fit)
Incremental fit index (IFI)	0 (no fit)-1 (perfect fit)
Tucker-Lewis index (TLI)	0 (no fit)-1 (perfect fit)

Validity and Reliability

Reliability means that the score of an instrument is stable and coherent. When the instrument is repeatedly administered at different times, the scores should remain the same and remain consistent (Creswell and Guetterman, 2019). The Likert scale was reliable for this study as the little variance is specific to particular items. On the other hand, validity implies that individual instrument scores are meaningful and allow the researcher to draw reasonable conclusions from the studied sample population. Internal validity was used to see how accurately the measures obtained from the research quantified what it was designed to measure. The internal reliability was measured using the most common internal consistency measure being measured is Cronbach's alpha (α) (Mohajan, 2017). Cronbach's alpha measures the internal consistency of items, that is, how closely related a set of items are as a group, usually interpreted as the mean of all possible split-half coefficients. (Sileyew, 2019). It is viewed as the most appropriate measure of reliability when using Likert scales. If Cronbach's alpha coefficient is close to 1, the construct is considered internally consistent and highly reliable (Liu et al., 2021). However, most scholars agree that the minimum Cronbach Alpha coefficient is 0.70 (Nair et al., 2019).

Ethical Considerations

In addition to choosing the right research methodology and procedures, ethical considerations should be considered when performing the research. It is critical to think about the fundamentals of ethical human-participant research in more depth (Fleming and Zegwaard, 2018). The University of Johannesburg granted ethical approval for this research. The research ethics addressed beneficence, nonmaleficence, autonomy and justice. Under the principle of beneficence, researchers must also protect participants from exploitation. Any information provided by participants through their study involvement must be protected (Barrow et al., 2021). The study's benefit was also explained as AI can reduce human errors and increase productivity on construction

TABLE 3 | Respondents' profile summary.

Profile	Description	Frequency	Percentage (%)
Qualification	Matric/Grade12	7	4.1
	National Diploma	19	11.2
	Bachelor's/Honours' Degree	114	67.5
	Master's Degree	27	16
	Doctorate	2	1.2
Profession	Architect	9	5.3
	Quantity Surveyors	82	48.5
	Civil Engineer	42	24.9
	Construction Manager	21	12.4
	Construction Project Manager	15	8.9
Organisation	Public Client	22	13
	Private Client	41	24.3
	Contracting Organisation	59	34.9
	Consulting Organisation	47	27.8
Experience	1–5 years	103	60.9
	6–10 years	31	18.3
	11–15 years	13	7.7
	More than 20 years	8	4.7

projects. Autonomy also referred to as respect for persons, is a fundamental ethical principle that guides the research on construction professionals. The principle obligates the researcher to allow participants the freedom to decide whether to take part in the research or not (Singh and Hylton, 2015). In the research context, nonmaleficence compels the researcher to avoid the accidental or intentional infliction of harm and to minimise the risk of harm or discomfort for research subjects (Sobočan et al., 2018). Justice demands an equitable selection of research participants. This means avoiding research participant populations that may be unfairly coerced into participating (Žydžiūnaitė, 2018). The study participants were construction professionals, including project managers, quantity surveyors, architects, and civil engineers working in construction projects from public and private organisations in Gauteng, South Africa. All races and groups were involved in the study; no single race will be the target and the other left out of the survey.

RESULTS

Respondents Profile

The 169 respondents' profiles can be seen in **Table 3**. Based on the frequency of occurrence, most of the respondents had a bachelor's/Honours' Degree (67.5%) as their highest educational qualifications this was followed by master's degree (16%), the majority of the respondents were Quantity Surveyors by profession (48.5%) this was followed by civil engineers (24.9%). For organisations, most participants work for contracting (34.9%). This was followed by consulting organisations (27.8%). In terms of experience, the vast majority have experience of between 1 and 5 years (60.9%). This was closely followed by 6–10 years (18.3%).

Organisational Factors Influencing AI Adoption

Descriptive Results

A descriptive analysis of the study participants' responses to the questionnaire items is presented below in **Table 4** on organisational factors of AI adoption in the South African construction industry. Overall, all the 17 identified organisational factors to AI adoption have MIS >3.50. The organisational factor with the highest MIS is top management skills (M = 4.02), followed by decision making support (M = 3.09) and cost to the organisation (MIS = 3.98). The lowest MIS scores came from risks involved in using innovative technologies (MIS = 3.61), the reputation of the organisation (MIS = 3.60) and firm size (M = 3.57), an important factor in AI adoption.

Exploratory Factor Analysis

The KMO measure of sampling adequacy was at the value of 0.895. This is greater than the adequate value of 0.70. This result indicates that multicollinearity structures among the variables were sufficient to justify aggregating the organisational factors. This is into the related sets for extraction of exploratory factor

TABLE 4 | MIS analysis of organisational factors of AI adoption in the South African construction industry.

	Mean	Std. Deviation	Inter-quartile range
Top management Skills	4.02	0.92	4.00
Decision Making support	3.99	0.81	4.00
Cost to Organisation	3.98	0.99	4.00
Improved performance	3.95	0.87	4.00
attitude to innovation	3.88	0.97	4.00
Organisation's work culture	3.85	0.92	4.00
collaboration	3.83	0.90	4.00
Organisational readiness	3.83	0.91	4.00
Time-saving	3.83	1.07	4.00
Knowledge and Competency	3.82	1.03	4.00
Standards	3.75	0.95	4.00
Information Processing Management	3.69	0.99	4.00
Governmental pressure	3.64	1.01	4.00
The workplace relationship among staff	3.62	1.01	4.00
Risks involved in using innovative technologies	3.61	1.10	4.00
The reputation of the organisation	3.60	1.08	4.00
Firm size	3.57	1.11	4.00

TABLE 5 | KMO and Bartlett's test.

Kaiser-meyer-olkin measure of sampling adequacy		0.895
Bartlett's Test of Sphericity	Approx. Chi-Square	1298.571
	df	136
	Sig	0.000

analysis Bartlett's Test of Sphericity was significant at $p < 0.001$. This indicates that the data on organisational factors of AI adoption can be used for factor analysis. This is shown in **Table 5** below.

As shown in **Table 6**, principal components were extracted using initial eigenvalues greater than 1. The analysis revealed four components as the number of factors for this particular EFA, with the explained variance percentage value of 62.43%. Component one was 41.747%, component 2 was 7.760%, component 3 was 6.852%, and component 4 was 6.070%. This is shown in **Table 6** below.

Table 7 presents the results of EFA for the organisational factors identified for the adoption of AI by South African construction professionals, separated into four principal component groups. The organisation's work culture explains component one, the workplace relationship among staff, cost to organisation, organisational readiness, standards and organisation attitude to innovation. Component 2 is explained by competitive pressure, information Processing Management, firm size knowledge and competency and government pressure. Component three is explained by top management skills, decision making support and collaboration. Lastly, component four is explained by improved performance, risks involved in using AI technologies and time-saving.

Confirmatory Factor Analysis

In the confirmatory factor analysis, the output revealed slightly good scores for a good fit in terms of fit indices. The Chi-square value is at 311.47 at a $p < 0.001$. The degree of freedom is 91 ratios of CMIN/df 3.42. The Root Means Square Error of Approximation (RMSEA) value of 0.12 and Root mean sq. residual (RMR) value of 0.072 indicates that the model cannot be rejected at a high confidence level. Furthermore, all other essential indices such as goodness-of-fit index (GFI =), comparative fit index (CFI = 0.766), Tucker-Lewis index (TLI = 0.781), and incremental fit index (IFI = 0.838) values provide evidence that the fit between the measurement model and the data is certainly acceptable. This is shown in **Table 8** below.

The performed model revealed that the four components positively influence organisational AI adoption and that the influence is statistically significant. This is shown in **table 9** below.

TABLE 6 | Total variance explained.

Component	Initial eigenvalues			Rotation sums of squared loadings		
	Total	% Of variance	Cumulative %	Total	% Of variance	Cumulative %
1	7.097	41.747	41.747	3.609	21.228	21.228
2	1.319	7.760	49.506	2.924	17.200	38.428
3	1.165	6.852	56.359	2.315	13.617	52.045
4	1.032	6.070	62.429	1.765	10.383	62.429

TABLE 7 | Rotated component matrix and Cronbach Alpha.

		Factor loading	Cronbach alpha	
Component No.1	Organisation's work culture	0.781	0.835	0.909
	The workplace relationship among staff	0.704		
	Cost to organisation	0.697		
	Organisational Readiness	0.681		
	Standards	0.515		
	attitude to innovation	0.488		
Component No.2	Competitive pressure	0.726	0.807	
	Information Processing Management	0.709		
	Firm size	0.627		
	Knowledge and competency	0.510		
	Government pressure	0.543		
Component No.3	Top management skills	0.763	0.770	
	Decision making support	0.762		
	Collaboration	0.710		
Component No.4	Improved performance	0.67	0.667	
	Risks involved in using AI technologies	0.629		
	Time-saving	0.623		

TABLE 8 | Fit indices.

Fit indices	Recommended measure	Value
Chi-square	Tabled x^2 value	311.47
Significance value		<0.001
Degrees of Freedom		91
CMIN/df	Good <3, acceptable <5	3.42
Root mean sq. error of approx. (RMSEA)	0.05 (very good)-0.1 (threshold)	0.12
Root mean sq. residual (RMR)	0–1 (smaller values = better fit)	0.072
Goodness-of-fit index (GFI)	0 (no fit)-1 (perfect fit)	0.812
Comparative fit index (CFI)	0 (no fit)-1 (perfect fit)	0.834
Incremental fit index (IFI)	0 (no fit)-1 (perfect fit)	0.838
Tucker-Lewis index (TLI)	0 (no fit)-1 (perfect fit)	0.781

TABLE 9 | Regression coefficients.

Factor	Path-coefficient	Standard error	t-value	Significance (p)
Innovative Organisational Culture	0.239	0.069	3.448	0.001
Competence Based Development	0.304	0.082	3.713	0.001
Collaborative decision making	0.161	0.056	2.897	0.004
Strategic Analysis	0.291	0.095	3.07	0.002

DISCUSSION

Descriptive Results

From the descriptive statistics, top management skills ($\bar{x}$ = 4.02, SD = 0.92, IQR = 4.00), decision making support ($\bar{x}$ = 3.99, SD = 0.81, IQR = 4.00) and cost to organisation ($\bar{x}$ = 3.98, SD = 0.99, IQR = 4.00) are the top three highest-ranked in the descriptive analysis ranked highest in the descriptive analysis. However, risks involved in using innovative technologies ($\bar{x}$ = 3.61, SD = 1.10, IQR = 4.00), the reputation of the organisation ($\bar{x}$ = 3.60, SD = 1.08, IQR = 4.00) and firm size ($\bar{x}$ = 3.57, SD = 1.11, IQR = 4.00) were the least ranked variables.

This supports the findings of Jöhnk et al. (2020). Top management support is a priority in implementing AI in organisations. Managers who gain the essential knowledge and abilities create a favourable environment for adopting and executing innovation. Managers are required, in particular, to be able to gather information on the best competition and learn how they succeed in adopting innovation. Competitive intelligence can assist managers in making decisions about whether innovations are less risky or difficult and will have the greatest influence on the company's industry reputation and profitability (Yusof et al., 2014). This also supports the findings of McAleenan (2020) when it comes to decision making support. Much time is spent on risk management techniques, as the consequences of making a poor decision and replacing a poor technology may be significant, resulting in a significant delay and huge additional costs to the organisation (Sepasgozar et al., 2018). The findings also support Chatterjee et al. (2020) and Pan and Pan (2020) regarding cost. However, the findings do not support Olawumi and Chan (2020). This is because the initial cost of AI set up in the organisation is expensive. According to Bello et al. (2020), AI technologies have provided construction organisations with access to high-end computing infrastructure and applications that could cost a fortune to acquire. However, it will result in a lower total cost of project delivery, in the long run, offering construction businesses a competitive and operational advantage.

The findings do not support McAleenan's (2020) when it comes to risks. In Africa, the more diffused a certain technology in the construction industry, the less risky it is to implement. That can influence industrial practitioners' interest in the technology (Darko et al., 2017). Furthermore, the findings on reputation do not collaborate with those of García de Soto et al. (2019). Construction organisations need to preserve the image and reputation they have. The adoption of AI not only helps with the record-keeping of information. It also avoids bad publicity, which may strain the relationship with stakeholders (van Heerden et al., 2018). The findings for firm size support those of Pan and Pan (2020). Because both small and large organisations have certain innovation generation and adoption advantages, firm size has no bearing on innovation orientation. As a result, the size of an organisation is a poor predictor of AI activities (Kamal et al., 2016).

In order to understand the organisational factors of AI in the South African construction industry, exploratory factor analysis was undertaken. The 17 variables were factored into four clusters, which then underwent confirmatory factor analysis to demonstrate the relationship among the constructs. **Figure 2** below shows the diagrammatic representation of the organisational factors according to EFA.

Component 1 - Innovative Organisational Culture

This component has six sub-components, mainly the organisation's work culture (0.781), the workplace relationship among staff (0.704), the cost to the organisation (0.697), organisational readiness (0.681), standards (0.515) and organisation attitude to innovation

FIGURE 2 | Diagrammatic representation of the organisational factors.

(0488). This cluster accounts for 41.747% of the variance, as shown in Table. This component was significant at a p-value of 0.001 at a path coefficient of 0.239.

The findings do not support Olawumi and Chan's (2020). The findings suggest that innovation can flow in organisations when organisational culture supports it. Focus shifts from traditional processes to AI technology created through organisational routines, practices, norms, and cultures. It suggests that organisational culture changes are needed before AI can be successfully embedded within construction practices (Yap and Toh, 2019). However, many organisations do not have available capital to experiment with innovation. There is a failure to learn and evolve successful innovations that limit adaptability and the attitude towards innovation (Mark et al., 2021). AI brings a new tool and process that changes people, processes, communication, and unavoidable work culture (Enegbuma et al., 2015). The findings also support those of Chatterjee et al. (2020), Olawumi and Chan (2020) and Pan and Pan (2020). It implies that effective leadership in organisations should take holistic to shape the attitude of employees toward intending to adopt the new system. Organisational readiness reflects the need for financial and human resources in construction AI adoption. Organisational readiness also gives the organisation understanding of the AI maturity measurements of performance, reliability, durability, and operational experience in the expected environment (Salazar and Russi-Vigoya, 2021). Stakeholders in the construction industry play a critical role in adopting innovation by defining rules and standards and giving direction and assistance, decreasing the risk of AI technology adoption significantly (Yuan et al., 2021).

Component 2 - Competence-Based Development

This component has five sub-components, mainly competitive pressure (0.726), information processing management (0.709), firm size (0.627), knowledge and competency (0.510) and government pressure (0.543). This cluster accounts for 7.760% of the variance, as shown in **Table 4**. This component was significant at a p-value of 0.001 at a path coefficient of 0.304.

The findings support those of Olawumi and Chan (2020). Human knowledge capacities facilitate information required, which can take up AI in organisations. Competence-based development is more than just putting learning into action. The manager must integrate several areas of knowledge and abilities in a relevant and opportunistic manner for each circumstance and setting they must deal with. As a result, the only way to succeed is to exercise decision-making about external pressure, business size, and the ability to comprehend information. As a result, stakeholders can develop their competencies by addressing various problematic situations (Lantelme et al., 2017). Competitive pressure operates as a prompt for organisations to adopt AI-based innovations to remain competitive. Moreover, competitive pressure drives organisations in all industries to seek competitive advantages by adopting new technologies (Pan and Pan, 2020). Organisations in the construction industry have realised that their competitiveness is dependent on the speed with which innovation and knowledge transfer. The value of innovation as a source of long-term competitive advantage for project-based businesses is becoming increasingly apparent. Businesses constantly use AI to produce new knowledge and abilities (Sergeeva and Duryan, 2021). This outcome shows that building a digital strategy is a strong requirement for organisations operating in competitive environments (Trocin et al., 2021). According to Ghobakhloo and Ching (2019), developing information management capabilities is associated with higher AI innovation diffusion in the construction industry. AI provides a construction organisation's optimisation strategy and opportunities to apply relevant information management approaches and a collaboration platform to help the team get involved in the process much earlier. This information includes several resource flows that need to be aligned, including the workforce, building information, plant and equipment hire, and the procurement and delivery of materials and components (Alwan et al., 2017). Mabad et al. (2021) noted small size construction organisations based in remote areas are likely to struggle in search of the expertise necessary to execute any necessary support in AI adoption. Lack of a comprehensive. The lack of government support in AI strategy for construction in infrastructure restricts the use of AI. So much so that the benefits are often not recognised or understood by decision-makers, and as a result, the focus is on more day-to-day activities (Bolpagni and Bartoletti, 2021).

Component 3 - Collaborative Decision Making

This component has three sub-components, mainly top management skills (0.763), decision making support (0.762) and collaboration (0.710). This cluster accounts for 6.852% of the variance, as shown in **Table 4**. This component was found not to be significant at a p-value of 0.004 at a path coefficient of 0.161.

The findings support McAleenan (2020) and Olawumi and Chan (2020). Collaborative decision making is an integrated process that employs digital technology like AI in a virtual and shared environment, anchored by people, processes, and procedures, to enable collective stakeholders to assess, plan, and execute a project at any stage of its life cycle. Efficient, effective, and transparent information transfer is crucial to eliminate errors and cost overruns, increase the quality of exchanges between multiple stakeholders, and take advantage of toolsets, innovations, and better governance processes (Pidgeon and Dawood, 2021). This finding suggests that the best opinion comes from combining people's input with technology in making organisations sustainable. It was emphasised that top management of construction firms train their staff and increase their knowledge and awareness of AI. Top management is important to the construction industry's continued and effective implementation of these novel technologies. Additionally, the firm's leadership support can take several forms, including decision-making assistance, restructuring the firm's structure and policies to accommodate the new concept and training assistance. When making the right adoption decisions, top management should consider the potential benefits and drawbacks of the available construction robots. AI assists in making decisions in response to barriers, disagreements, and abnormalities discovered throughout the scheduled production. AI is equipped with methods for capturing and reusing knowledge to improve decision-making, weighted according to the project's features and needs and the external environment (Yap and Toh, 2019). Moreover, AI functions through a single source of information for a project and plays a supporting role in decision-making during its life cycle (Moshood et al., 2020). The ability of an organisation's employees to collaborate in developing AI-based systems boosts the possibility of the organisation adopting AI technologies (Mabad et al., 2021). The nature of construction organisations is project-oriented, necessitating collaboration and interaction among diverse stakeholders and specialists throughout the project life cycle, posing significant challenges for agreement on innovation adoption among various groups (Pan and Pan, 2020).

Component 4 - Strategic Analysis

This component had three sub-components improved performance (0.67), risks involved in using AI technologies (0.629) and time-saving (0.623). This cluster accounts for 6.070% of the variance, as shown in **Table 4**. This component was found not to be significant at a p-value of 0.002 at a path coefficient of 0.291.

The findings support that of Turner et al. (2020) and Mabad et al. (2021). Strategic analysis is a key component in establishing a company's effective strategy. It provides a realistic appraisal of a company's resources, time, and capabilities regarding the situation of the external environment. The rational choice of strategies from a possible set of options should occur due to this analysis (Makovetskaya and Yuzikhanova, 2018). These findings suggest that organisations weigh the advantages and disadvantages of adopting AI. It may be advantageous in the long run. However, there will be challenges and sacrifice required as adoption is still in its infancy in South Africa. According to Mabad et al. (2021), the value of AI technology lies in its performance. AI tools improve prediction, modelling performance, and accuracy in construction organisations and project aspects. Organisations can use AI to establish digital processes and service innovation, which can help them perform better in terms of perceived fairness, less biased decision-making, transparent feedback, and greater communication, among other things (Trocin et al., 2021). Communities of practice can grow into risk-free, loosely coupled operating systems that foster organisational innovation and learning across functional and project boundaries while increasing creativity and problem-solving effectiveness (Sergeeva and Duryan, 2021).

IMPLICATIONS

Implications for Research

While studies on AI in the construction industry do not look at the adoption of AI and related technologies. These studies also do not look at the relationships of the construct organisational factors. Therefore, the research contributes to AI adoption literature by providing a clearer understanding of related organisational factors of AI adoption in the South African construction industry and their relationship. Subsequently, identifying adoption factors enabled an important knowledge foundation with suggestions for successfully adopting AI techniques in the construction industry. This study also presents empirical data to guide researchers on drafting roadmaps for the South African construction industry and other developing countries. This should be through a clear research design of how the adoption of AI in the construction industry organisations will provide effective and efficient running.

Implications for Practice

Adopting AI in business operations and functions could enhance effective organisational management. AI adoption can ensure improvement in business products and services and save organisations huge costs on investment. To remain competitive, organisations need to constantly measure productivity and attend to the factors identified in this study. This will provide an edge to leverage AI adoption in setting and monitoring targets, business processes, construction, accountability, and other engagements. Knowledge management strategies will also be enhanced as storing, sharing and gaining of knowledge can be facilitated through AI adoption.

In addition, organisations' management and leadership can emphasise greater pressure to increase awareness and perception of the strategic value of adopting AI technologies in their organisations. This is because it will bring profits for improving productivity, efficiency, quality and collaboration. The adoption can help to ensure effectiveness, safety, and sustainability, thus improving the poor image of the construction industry in the long run.

Further, many unsolved issues are to be addressed, such as the lack of standards for many technologies, the increased demand for AI, and the growing need for improved stakeholder engagement and partnership collaboration. Other considerations include regulatory compliance, legal, and contractual uncertainties. Given this, it is evident that construction organisations must be encouraged to adopt through government regulations and industry bodies. This can also be done through demonstration pilot projects and workshops. The approach could be based on the factors presented in this study.

In addition, the government and industry bodies should promote the use of AI through human capital development of training programs. This promotion can help change worker attitudes and behavioural intentions, thus enabling a favourable disposition to use AI in the construction industry.

CONCLUSION

The adoption of AI in the construction industry is still uncertain, especially in developing countries' organisations. The benefits among these nations are yet to be seen. This study contributes to academic research on AI adoption in developing countries. It points out the fundamental factors confronting the construction industry in South Africa to have it in their organisations. While many previous studies have provided in-depth evidence of AI adoption factors in developing countries' construction and allied industries, none has used EFA and CFA to measure the constructs. In filling this research gap, this study, through literature review and empirical investigation, has identified characteristics of AI in the construction industry organisations in developing countries. The Systematic literature found 17 factors contributing to AI adoption. The study conducted a factor analysis in organisational factors among South African construction professionals. A total of 169 online questionnaires were completed.

However, previous studies have identified organisational factors of AI in the construction and allied industries. This study presented the organisational factors of AI in the construction industry using EFA and CFA, a method not used in articles presented in the SLR identified. The use of CFA improves the measurement of the constructs. It thus enhances understanding of the underlying components of a construct and its relationship with AI in the construction industry. EFA yielded a four-component cluster: innovative organisational culture, competent-based development, collaborative decision-making, and strategic analysis. The CFA tested for convergent validity and measured the measurement model's adequacy. Innovative organisational culture and competence-based development were significant at a p-value of 0.001.

Future research should address the research limitation of geographic and systematic literature review. Future research should also adopt a Delphi technique to collect expert based judgement to get consensus on the identified organisational factors of AI in the construction industry.

Limitations

Although the objective of this study was achieved, there are limitations to conclusions derived from the results. The study only covered the opinions of construction professionals in South Africa. Therefore the results can only be interpreted in the South African context. Furthermore, the study limited the literature review to certain databases, years and publication types.

Recommendations

Based on the study findings, the following are recommended.

Industry Recommendation

- Organisations should change traditional work culture in order to foster AI adoption. This is because of the value capabilities it brings in achieving efficiency, sustainability and productivity within the construction organisations and projects
- Organisations should look at introducing learning tools and skills to develop employees on AI knowledge
- Top management should include employees when working on AI adoption strategies

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

Conceptualisation, MT, IM, CO. Methodology, MT, IM, and CO. Formal analysis, MT. Investigation, MT resources. MT, IM, and CO. writing—original draft preparation, MT. Writing—review and editing, IM and CO. Visualisation, MT. Supervision, IM and CO. Funding acquisition, MT.

FUNDING

This research was funded by National Research Foundation, grant number 123120. Opinions and conclusions are those of the authors and are not necessarily attributable to the NRF.

REFERENCES

Abioye, S. O., Oyedele, L. O., Akanbi, L., Ajayi, A., Davila Delgado, J. M., Bilal, M., et al. (2021). Artificial Intelligence in the Construction Industry: A Review of Present Status, Opportunities and Future Challenges. *J. Building Eng.* 44, 103299. doi:10.1016/j.jobe.2021.103299

Adaloudis, M., and Bonnin Roca, J. (2021). Sustainability Tradeoffs in the Adoption of 3D Concrete Printing in the Construction Industry. *J. Clean. Prod.* 307, 127201. doi:10.1016/j.jclepro.2021.127201

Ahuja, R., Sawhney, A., and Arif, M. (2018). Developing Organizational Capabilities to Deliver Lean and green Project Outcomes Using BIM. *Ecam* 25 (10), 1255–1276. doi:10.1108/ecam-08-2017-0175

Alinaitwe, H., and Ayesiga, R. (2013). Success Factors for the Implementation of Public-Private Partnerships in the Construction Industry in Uganda. *J. Construction Developing Countries* 18 (2), 1–14.

Alwan, Z., Jones, P., and Holgate, P. (2017). Strategic Sustainable Development in the UK Construction Industry, through the Framework for Strategic Sustainable Development, Using Building Information Modelling. *J. Clean. Prod.* 140, 349–358. doi:10.1016/j.jclepro.2015.12.085

Apuke, O. D. (2017). Quantitative Research Methods : a Synopsis Approach. *Kcajbmr* 6 (10), 40–47. doi:10.12816/0040336

Arrotéia, A. V., Freitas, R. C., and Melhado, S. B. (2021). Barriers to BIM Adoption in Brazil. *Front. Built Environ.* 7. doi:10.3389/fbuil.2021.520154

Azhar, S., Khalfan, M., and Maqsood, T. (2015). Building Information Modelling (BIM): Now and beyond. *Ceb* 12 (4), 15–28. doi:10.5130/ajceb.v12i4.3032

Barrow, J. M., Brannan, G. D., and Khandhar, P. B. (2021). Research Ethics. *Nih. Gov*. Treasure Island, FL: StatPearls Publishing. Available at: https://www.ncbi.nlm.nih.gov/books/NBK459281/.

Basias, N., and Pollalis, Y. (2018). Quantitative and Qualitative Research in Business & Technology: Justifying a Suitable Research Methodology. *Rev. Integr. Business Econ. Res.* 7 (1), 91–105.

Bello, S. A., Oyedele, L. O., Akinade, O. O., Bilal, M., Davila Delgado, J. M., Akanbi, L. A., et al. (2021). Cloud Computing in Construction Industry: Use Cases, Benefits and Challenges. *Automation in Construction* 122, 103441. doi:10.1016/j.autcon.2020.103441

Boadu, E. F., Wang, C. C., and Sunindijo, R. Y. (2020). Characteristics of the Construction Industry in Developing Countries and its Implications for Health and Safety: An Exploratory Study in Ghana. *Ijerph* 17 (11), 4110. doi:10.3390/ijerph17114110

Bolpagni, M., and Bartoletti, I. (2021). Artificial Intelligence in the Construction Industry: Adoption, Benefits and Risks. *CIB* W78, 11–15.

Chakkravarthy, R. (2019). Artificial Intelligence for Construction Safety - ProQuest.Availableat: www.proquest.com/scholarly-journals/artificial-intelligence-construction-safety/docview/2165604383/se-2?accountid=48944.

Chan, A. P. C., Wong, F. K. W., Hon, C. K. H., Lyu, S., and Javed, A. A. (2017). Investigating Ethnic Minorities' Perceptions of Safety Climate in the Construction Industry. *J. Saf. Res.* 63, 9–19. doi:10.1016/j.jsr.2017.08.006

Chan, I. Y. S., Liu, A. M. M., and Fellows, R. (2014). Role of Leadership in Fostering an Innovation Climate in Construction Firms. *J. Manage. Eng.* 30 (6), 06014003. doi:10.1061/(asce)me.1943-5479.0000271

Chatterjee, S., Nguyen, B., Ghosh, S. K., Bhattacharjee, K. K., and Chaudhuri, S. (2020). Adoption of Artificial Intelligence Integrated CRM System: an Empirical Study of Indian Organizations. *Bl* 33 (4), 359–375. doi:10.1108/bl-08-2020-0057

Cho, Y. K., and Wang, C. (2021). Information Technology and the Built Environment. *J. Constr. Eng. Manage.* 147 (11), 02021001. doi:10.1061/(asce)co.1943-7862.0002191

Creswell, J. W., and Guetterman, T. C. (2019). *Educational Research: Planning, Conducting, and Evaluating Quantitative and Qualitative Research*. Tel: 800-848-; Web Site. 6th Edition. One Lake Street, Upper Saddle River, New Jersey 8: Pearson. Availableat: Http://Www.Pearsoned.com/-00-00.

Darko, A., Chan, A. P. C., Gyamfi, S., Olanipekun, A. O., He, B.-J., and Yu, Y. (2017). Driving Forces for green Building Technologies Adoption in the Construction Industry: Ghanaian Perspective. *Building Environ.* 125, 206–215. doi:10.1016/j.buildenv.2017.08.053

Darko, A., and Chan, A. P. C. (2018). Strategies to Promote green Building Technologies Adoption in Developing Countries: The Case of Ghana. *Building Environ.* 130, 74–84. doi:10.1016/j.buildenv.2017.12.022

Datti, Y. U., Dahiru, A., and Olamilokun, O. (2019). Assessment of Information Technology Adoption in Project Information Exchange in Nigerian Construction Industry. *ARID ZONE JOURNAL ENGINEERING, TECHNOLOGY ENVIRONMENT* 15 (2), 226–236. Availableat: https://www.azojete.com.ng/index.php/azojete/article/view/65.

Davila Delgado, J. M., Oyedele, L., Ajayi, A., Akanbi, L., Akinade, O., Bilal, M., et al. (2019). Robotics and Automated Systems in Construction: Understanding Industry-specific Challenges for Adoption. *J. Building Eng.* 26, 100868. doi:10.1016/j.jobe.2019.100868

de Carvalho, A., Granja, A., and da Silva, V. (2017). A Systematic Literature Review on Integrative Lean and Sustainability Synergies over a Building's Lifecycle. *Sustainability* 9 (7), 1156. doi:10.3390/su9071156

de Melo, A. L. O., Kaewunruen, S., Papaelias, M., Bernucci, L. L. B., and Motta, R. (2020). Methods to Monitor and Evaluate the Deterioration of Track and its Components in a Railway In-Service: A Systemic Review. *Front. Built Environ.* 6. doi:10.3389/fbuil.2020.00118

de Winter*, J. C. F., Dodou*, D., and Wieringa, P. A. (2009). Exploratory Factor Analysis with Small Sample Sizes. *Multivariate Behav. Res.* 44 (2), 147–181. doi:10.1080/00273170902794206

Dhamija, P., and Bag, S. (2020). Role of Artificial Intelligence in Operations Environment: a Review and Bibliometric Analysis. *Tqm* 32 (4), 869–896. doi:10.1108/tqm-10-2019-0243

Dhanabalan, T., and Sathish, A. (2018). Transforming Indian Industries through Artificial Intelligence and Robotics in Industry 4.0. *Int. J. Mech. Eng. Technology* 9 (10), 835–845.

Diniz Fonseca, E. (2021). Accident and Innovation in Construction Industry: Learning by Doing to Prevent Accidents and Improve the Production. *Saf. Sci.* 142, 105389. doi:10.1016/j.ssci.2021.105389

Dubey, R., Gunasekavan, A., Childe, S., Roubaud, D., Foropon, C., Bryde, D., et al. (2019). Big Data Analytics and Artificial Intelligence Pathway to Operational Performance under the Effects of Entrepreneurial Orientation and Environmental Dynamism: A Study of Manufacturing Organisations. *Int. J. Prod. Econ.* 226, 107599. doi:10.1016/j.ijpe.2019.107599

Effendi, M., Matore, E., Firdaus, M., Noh, M., Zainal, M., Rina, E., et al. (2020). Establishing Factorial Validity in Raven Advanced Progressive Matrices (RAPM) in Measuring IQ from Polytechnic Students' Ability Using Exploratory Factor Analysis (EFA). *Proc. Mech. Eng. Res.*, 248–250.

Ejohwomu, O. A., Oshodi, O. S., and Lam, K. C. (2017). Nigeria's Construction Industry: Barriers to Effective Communication. *Ecam* 24 (4), 652–667. doi:10.1108/ecam-01-2016-0003

El Jazzar, M., Schranz, C., Urban, H., and Nassereddine, H. (2021). Integrating Construction 4.0 Technologies: A Four-Layer Implementation Plan. *Front. Built Environ.* 7. doi:10.3389/fbuil.2021.671408

Enegbuma, W. I., Aliagha, G. U., and Ali, K. N. (2015). Effects of Perceptions on bim Adoption in Malaysian Construction Industry. *Jt* 77 (15). doi:10.11113/jt.v77.6532

Etikan, I., and Bala, K. (2017). Sampling and Sampling Methods. *Bbij* 5 (6). doi:10.15406/bbij.2017.05.00149

Evans, M., Farrell, P., Elbeltagi, E., and Dion, H. (2021). Barriers to Integrating Lean Construction and Integrated Project Delivery (IPD) on Construction Megaprojects towards the Global Integrated Delivery (GID) in Multinational Organisations: Lean IPD&GID Transformative Initiatives. *Jedt* ahead-of-print. doi:10.1108/jedt-02-2021-0070

Faragher, E. B. (2005). The Relationship between Job Satisfaction and Health: a Meta-Analysis. *Occup. Environ. Med.* 62 (2), 105–112. doi:10.1136/oem.2002.006734

Fleming, J., and Zegwaard, K. (2018). Methodologies, Methods and Ethical Considerations for Conducting Research in Work-Integrated Learning. *Int. J. Work-Integrated Learn. Spec. Issue.* 19 (3), 205–213.

García de Soto, B., Agustí-Juan, I., Joss, S., and Hunhevicz, J. (2019). Implications of Construction 4.0 to the Workforce and Organizational Structures. *Int. J. Construction Management*, 1–13. doi:10.1080/15623599.2019.1616414

Ghobakhloo, M., and Ching, N. T. (2019). Adoption of Digital Technologies of Smart Manufacturing in SMEs. *J. Ind. Inf. Integration* 16, 100107. doi:10.1016/j.jii.2019.100107

Ghosh, A., Chakraborty, D., and Law, A. (2018). Artificial Intelligence in Internet of Things. *CAAI Trans. Intelligence Technology* 3 (4), 208–218. doi:10.1049/trit.2018.1008

Girginkaya Akdag, S., and Maqsood, U. (2019). A Roadmap for BIM Adoption and Implementation in Developing Countries: the Pakistan Case. *Arch* 14 (1), 112–132. doi:10.1108/arch-04-2019-0081

Haefner, N., Wincent, J., Parida, V., and Gassmann, O. (2021). Artificial Intelligence and Innovation Management: A Review, Framework, and Research Agenda✰✰. *Technol. Forecast. Soc. Change* 162, 120392. doi:10.1016/j.techfore.2020.120392

Holzinger, A., Langs, G., Denk, H., Zatloukal, K., and Müller, H. (2019). Causability and Explainability of Artificial Intelligence in Medicine. *Wires Data Mining Knowl Discov.* 9 (4). doi:10.1002/widm.1312

Hong, Y., Xie, H., Bhumbra, G., and Brilakis, I. (2021). Comparing Natural Language Processing Methods to Cluster Construction Schedules. *J. Construction Eng. Management* 147 (10). doi:10.1061/(asce)co.1943-7862.0002165

Hooda, Y., Kuhar, P., Sharma, K., and Verma, N. K. (2021). Emerging Applications of Artificial Intelligence in Structural Engineering and Construction Industry. *J. Phys. Conf. Ser.* 1950 (1), 012062. doi:10.1088/1742-6596/1950/1/012062

Hove, G., and Banjo, A. (2018). Perceptions of Small Business Executives on Determinants of Performance in the Construction Industry in Gauteng, South Africa. *Acta commer.* 18 (1). doi:10.4102/ac.v18i1.528

Hyett, M. P., and Parker, G. B. (2014). Further Examination of the Properties of the Workplace Well-Being Questionnaire (WWQ). *Soc. Indic Res.* 124 (2), 683–692. doi:10.1007/s11205-014-0805-5

Isa, R. B., Jimoh, R., and Achuenu, E. (2013). An Overview of the Contribution of Construction Sector to Sustainable Development in Nigeria. Futminna.edu.Ng. Availableat: http://repository.futminna.edu.ng:8080/jspui/handle/123456789/8093.

Ivanov, N., and Aldeen, A. M.-A. S. (2018). Construction in the Republic of Yemen: Problems of Development and Solutions. *IOP Conf. Ser. Mater. Sci. Eng.* 365, 062015. doi:10.1088/1757-899x/365/6/062015

Jilcha Sileyew, K. (2019). *Research Design and Methodology.* Text Mining - Analysis, Programming And Application [Working Title. doi:10.5772/intechopen.85731

Jöhnk, J., Weißert, M., and Wyrtki, K. (2020). Ready or Not, AI Comes- an Interview Study of Organizational AI Readiness Factors. *Bus Inf. Syst. Eng.* 63 (1), 5–20. doi:10.1007/s12599-020-00676-7

Jones, T., Baxter, M., and Khanduja, V. (2013). A Quick Guide to Survey Research. *annals* 95 (1), 5–7. doi:10.1308/003588413x13511609956372

Kamal, E. M., Yusof, N. A., and Iranmanesh, M. (2016). Innovation Creation, Innovation Adoption, and Firm Characteristics in the Construction Industry. *J. Sci. Technology Pol. Management* 7 (1), 43–57. doi:10.1108/jstpm-03-2015-0011

Kapoor, K. K., Tamilmani, K., Rana, N. P., Patil, P., Dwivedi, Y. K., and Nerur, S. (2017). Advances in Social Media Research: Past, Present and Future. *Inf. Syst. Front.* 20 (3), 531–558. doi:10.1007/s10796-017-9810-y

Karan, E., Asgari, S., and Mohammadpour, A. (2020). Applying Artificial Intelligence within the AEC Industry: Collecting and Interpreting Data. *Construction Res. Congress* 2020. doi:10.1061/9780784482865.084

Kim, S., Park, C. H., and Chin, S. (2015). Assessment of BIM Acceptance Degree of Korean AEC Participants. *KSCE J. Civ Eng.* 20 (4), 1163–1177. doi:10.1007/s12205-015-0647-y

Kyriazos, T. A. (2018). Applied Psychometrics: Sample Size and Sample Power Considerations in Factor Analysis (EFA, CFA) and SEM in General. *Psych* 09 (08), 2207–2230. doi:10.4236/psych.2018.98126

Lakhwani, M., Dastane, O., Dastane, O., Satar, N. S. M., and Johari, Z. (2020). The Impact of Technology Adoption on Organizational Productivity. *Jidb* 11 (4), 7–18. doi:10.13106/jidb.2020.vol11.no4.7

Lantelme, E. M. V., Formoso, C. T., and Powell, J. A. (2017). Integrating Technical and Social Competencies of Construction Managers. *J. Prof. Issues Eng. Educ. Pract.* 143 (4), 04017004. doi:10.1061/(asce)ei.1943-5541.0000332

Lehdonvirta, V., Oksanen, A., Räsänen, P., and Blank, G. (2020). Social Media, Web, and Panel Surveys: Using Non-Probability Samples in Social and Policy Research. *Policy & Internet* 13, 134–155. doi:10.1002/poi3.238

Lekan, A., Leke, O., Mariam, A., Adebisi, M., Farayola, N.-P., and Osawaru, F. (2018). Adopting Information and Communication Technology in Construction Industry. *Int. J. Mech. Eng. Technology (IJMET* 9 (1), 739–746.

Li, J., Greenwood, D., and Kassem, M. (2019). Blockchain in the Built Environment and Construction Industry: A Systematic Review, Conceptual Models and Practical Use Cases. *Automation in Construction* 102, 288–307. doi:10.1016/j.autcon.2019.02.005

Liu, Z., Lu, Y., Nath, T., Wang, Q., Tiong, R. L. K., and Peh, L. L. C. (2021). Critical success Factors for BIM Adoption during Construction Phase: a Singapore Case Study, *Ecam*. doi:10.1108/ecam-12-2020-1072

Mabad, T., Ali, O., Ally, M., Wamba, S. F., and Chan, K. C. (2021). Making Investment Decisions on RFID Technology: An Evaluation of Key Adoption Factors in Construction Firms. *IEEE Access* 9, 36937–36954. doi:10.1109/access.2021.3063301

Madigan, S., Wade, M., Tarabulsy, G., Jenkins, J. M., and Shouldice, M. (2014). Association between Abuse History and Adolescent Pregnancy: A Meta-Analysis. *J. Adolesc. Health* 55 (2), 151–159. doi:10.1016/j.jadohealth.2014.05.002

Mahroof, K. (2019). A Human-Centric Perspective Exploring the Readiness towards Smart Warehousing: The Case of a Large Retail Distribution Warehouse. *Int. J. Inf. Management* 45, 176–190. doi:10.1016/j.ijinfomgt.2018.11.008

Makovetskaya, E. G., and Yuzikhanova, E. G. (2018). Strategic Analysis as a Tool for Development of a Transport Company (On the Example of the Company from the Tyumen City). *MATEC Web Conf.* 239, 04026. doi:10.1051/matecconf/201823904026

Maletič, D., Maletič, M., and Gomišček, B. (2013). The Impact of Quality Management Orientation on Maintenance Performance. *Int. J. Prod. Res.* 52 (6), 1744–1754. doi:10.1080/00207543.2013.848480

Manzoor, B., Othman, I., Durdyev, S., Ismail, S., and Wahab, M. H. (2021). Influence of Artificial Intelligence in Civil Engineering toward Sustainable Development-A Systematic Literature Review. *Asi* 4 (3), 52. doi:10.3390/asi4030052

Maskey, R., Fei, J., and Nguyen, H.-O. (2018). Use of Exploratory Factor Analysis in Maritime Research. *The Asian J. Shipping Logistics* 34 (2), 91–111. doi:10.1016/j.ajsl.2018.06.006

Matsunaga, M. (2010). How to Factor-Analyze Your Data Right: Do's, Don'ts, and How-To's. *Int. J. Psychol. Res.* 3 (1), 97–110. doi:10.21500/20112084.854

McAleenan, P. (2020). Moral Responsibility and Action in the Use of Artificial Intelligence in Construction. *Proc. Inst. Civil Eng. - Manag. Procurement L.* 173 (4), 166–174. doi:10.1680/jmapl.19.00056

Merschbrock, C., and Munkvold, B. E. (2015). Effective Digital Collaboration in the Construction Industry - A Case Study of BIM Deployment in a Hospital Construction Project. *Comput. Industry* 73, 1–7. doi:10.1016/j.compind.2015.07.003

Metcalf, L., and Benn, S. (2012). The Corporation Is Ailing Social Technology: Creating a 'Fit for Purpose' Design for Sustainability. *J. Bus Ethics* 111 (2), 195–210. doi:10.1007/s10551-012-1201-1

Miranda, M. Q., Farias, J. S., de Araújo Schwartz, C., and de Almeida, J. P. L. (2016). Technology Adoption in Diffusion of Innovations Perspective: Introduction of an ERP System in a Non-profit Organization. *RAI Revista de Administração e Inovação* 13 (1), 48–57. doi:10.1016/j.rai.2016.02.002

Mohajan, H. K. (2017). Two Criteria for Good Measurements in Research: Validity and Reliability. *Ashu- Es* 17 (4), 59–82. doi:10.26458/1746

Mohamed, M. A., Ahmad, A. b., and Mohamad, D. (2021). The Implementation of Artificial Intelligence (AI) in the Malaysia Construction Industry. *PROCEEDINGS GREEN. DESIGN MANUFACTURE* 2020. doi:10.1063/5.0044597

Mohamed Shaffril, H. A., Samsuddin, S. F., and Abu Samah, A. (2020). The ABC of Systematic Literature Review: the Basic Methodological Guidance for Beginners. *Qual. Quant* 55, 1319–1346. doi:10.1007/s11135-020-01059-6

Molwus, J. J., Erdogan, B., and Ogunlana, S. (2017). Using Structural Equation Modelling (SEM) to Understand the Relationships Among Critical success Factors (CSFs) for Stakeholder Management in Construction. *Ecam* 24 (3), 426–450. doi:10.1108/ecam-10-2015-0161

Moshood, T. D., Nawanir, G., Sorooshian, S., Mahmud, F., and Adeleke, A. Q. (2020). Barriers and Benefits of ICT Adoption in the Nigerian Construction Industry. A Comprehensive Literature Review. *Asi* 3 (4), 46. doi:10.3390/asi3040046

Munyasya, B., and Chileshe, N. (2018). Towards Sustainable Infrastructure Development: Drivers, Barriers, Strategies, and Coping Mechanisms. *Sustainability* 10 (12), 4341. doi:10.3390/su10124341

Nadhim, E., Hon, C., Xia, B., Stewart, I., and Fang, D. (2016). Falls from Height in the Construction Industry: A Critical Review of the Scientific Literature. *Ijerph* 13 (7), 638. doi:10.3390/ijerph13070638

Nair, J., Chellasamy, A., and Singh, B. N. B. (2019). Readiness Factors for Information Technology Adoption in SMEs: Testing an Exploratory Model in an Indian Context. *Jabs* 13 (4), 694–718. doi:10.1108/jabs-09-2018-0254

Nasila, M., Cloete, C., and Cloete, C. (2018). Adoption of Building Information Modelling in the Construction Industry in Kenya. *As* 25 (2), 1–38. doi:10.18820/24150487/as25i2.1

Ngowtanasuwan, G. (2019). Strategic Factor Analysis of Innovation Adoption in Thai Architects: A Case Study of Building Information Modeling. *IOP Conf. Ser. Mater. Sci. Eng.* 650, 012002. doi:10.1088/1757-899x/650/1/012002

Nikolaeva, D. R., and Nikolenko, T. A. (2021). Methodological Basis for Using Artificial Intelligence Technologies in a Construction Company. *IOP Conf. Ser. Earth Environ. Sci.* 751 (1), 012106. doi:10.1088/1755-1315/751/1/012106

Nnaji, C., Gambatese, J., Karakhan, A., and Eseonu, C. (2019). Influential Safety Technology Adoption Predictors in Construction. *Ecam* 26 (11), 2655–2681. doi:10.1108/ecam-09-2018-0381

Olanipekun, A. O., and Sutrisna, M. (2021). Facilitating Digital Transformation in Construction-A Systematic Review of the Current State of the Art. *Front. Built Environ.* 7. doi:10.3389/fbuil.2021.660758

Olanrewaju, O. I., Sandanayake, M., and Babarinde, S. A. (2020). Voice Assisted Key-In Building Quantities Estimation System. *J. Eng. Project, Prod. Management* 10 (2), 114–122. doi:10.2478/jeppm-2020-0014

Olawumi, T. O., and Chan, D. W. M. (2020). Key Drivers for Smart and Sustainable Practices in the Built Environment. *Ecam* 27 (6), 1257–1281. doi:10.1108/ecam-06-2019-0305

Pan, M., and Pan, W. (2020). Understanding the Determinants of Construction Robot Adoption: Perspective of Building Contractors. *J. Constr. Eng. Manage.* 146 (5), 04020040. doi:10.1061/(asce)co.1943-7862.0001821

Paul, S. K., Riaz, S., and Das, S. (2020). Organizational Adoption of Artificial Intelligence in Supply Chain Risk Management. *Re-Imagining Diffusion Adoption Inf. Technology Syst. A Continuing Conversation* 617, 10–15. doi:10.1007/978-3-030-64849-7_2

Pearson, R. H., and Mundform, D. J. (2010). Recommended Sample Size for Conducting Exploratory Factor Analysis on Dichotomous Data. *J. Mod. App. Stat. Meth.* 9 (2), 359–368. doi:10.22237/jmasm/1288584240

Pheng, L. S., and Hou, L. S. (2019). "The Economy and the Construction Industry," in *Construction Quality and the Economy*, 21–54. doi:10.1007/978-981-13-5847-0_2

Pidgeon, A., and Dawood, N. (2021). Bridging the gap between Theory and Practice for Adopting Meaningful Collaborative BIM Processes in Infrastructure Projects, Utilising Multi-Criteria Decision Making (MCDM). *ITcon* 26, 783–811. doi:10.36680/j.itcon.2021.043

Pradhananga, P., ElZomor, M., and Santi Kasabdji, G. (2021). Identifying the Challenges to Adopting Robotics in the US Construction Industry. *J. Constr. Eng. Manage.* 147 (5), 05021003. doi:10.1061/(asce)co.1943-7862.0002007

Puiu, A.-I. (2020). "An Exploratory Analysis of the Consumer Resistance Determinants Regarding the Usage of Nanotechnology in Fashion Industry," in Proceedings of the International Conference on Economics and Social Sciences, 738–748. doi:10.2478/9788395815072-073

Ren, M. (2019). Why Technology Adoption Succeeds or Fails: an Exploration from the Perspective of Intra-organizational Legitimacy. *J. Chin. Sociol.* 6 (1). doi:10.1186/s40711-019-0109-x

Roopa, S., and Rani, M. (2012). Questionnaire Designing for a Survey. *Jios* 46 (4), 273–277. doi:10.5005/jp-journals-10021-1104

Sacks, R., Girolami, M., and Brilakis, I. (2020). Building Information Modelling, Artificial Intelligence and Construction Tech. *Dev. Built Environ.* 4, 100011. doi:10.1016/j.dibe.2020.100011

Saghafian, M., Laumann, K., and Skogstad, M. R. (2021). Stagewise Overview of Issues Influencing Organizational Technology Adoption and Use. *Front. Psychol.* 12. doi:10.3389/fpsyg.2021.630145

Salazar, G., and Russi-Vigoya, M. N. (2021). Technology Readiness Level as the Foundation of Human Readiness Level. *Ergon. Des.* 29, 25–29. doi:10.1177/10648046211020527

Samsudin, N. S., Mohammad, M. Z., Khalil, N., Nadzri, N. D., and Izam Che Ibrahim, C. K. (2022). A Thematic Review on Prevention through Design (PtD) Concept Application in the Construction Industry of Developing Countries. *Saf. Sci.* 148, 105640. doi:10.1016/j.ssci.2021.105640

Sarala, R. M., Vaara, E., and Junni, P. (2019). Beyond Merger Syndrome and Cultural Differences: New Avenues for Research on the "human Side" of Global Mergers and Acquisitions (M&As). *J. World Business* 54 (4), 307–321. doi:10.1016/j.jwb.2017.10.001

Sarhan, J., Xia, B., Fawzia, S., Karim, A., and Olanipekun, A. (2018). Barriers to Implementing Lean Construction Practices in the Kingdom of Saudi Arabia (KSA) Construction Industry. *Ci* 18 (2), 246–272. doi:10.1108/ci-04-2017-0033

Sepasgozar, S. M. E., Davis, S., Loosemore, M., and Bernold, L. (2018). An Investigation of Modern Building Equipment Technology Adoption in the Australian Construction Industry. *Ecam* 25 (8), 1075–1091. doi:10.1108/ecam-03-2017-0052

Sergeeva, N., and Duryan, M. (2021). Reflecting on Knowledge Management as an Enabler of Innovation in Project-Based Construction Firms. *Ci* 21, 934–950. doi:10.1108/ci-09-2020-0148

Shehzad, H. M. F., Ibrahim, R. B., Yusof, A. F., Khaidzir, K. A. M., Khurshid, M. M., and Othman, F. Z. (2021). Building Information Modelling Adoption Model for Malaysian Architecture, Engineering and Construction Industry. *Lecture Notes Data Eng. Commun. Tech.* 999, 999–1008. doi:10.1007/978-3-030-70713-2_89

Shi, Z., Yao, W., Li, Z., Zeng, L., Zhao, Y., Zhang, R., et al. (2020). Artificial Intelligence Techniques for Stability Analysis and Control in Smart Grids: Methodologies, Applications, Challenges and Future Directions. *Appl. Energ.* 278, 115733. doi:10.1016/j.apenergy.2020.115733

Shneiderman, B. (2020). Design Lessons from AI's Two Grand Goals: Human Emulation and Useful Applications. *IEEE Trans. Technol. Soc.* 1 (2), 73–82. doi:10.1109/tts.2020.2992669

Sima, V., Gheorghe, I. G., Subić, J., and Nancu, D. (2020). Influences of the Industry 4.0 Revolution on the Human Capital Development and Consumer Behavior: A Systematic Review. *Sustainability* 12 (10), 4035. doi:10.3390/su12104035

Singh, J. P., and Hylton, T. (2015). Autonomy/Respect for Persons. *Encyclopedia Clin. Psychol.* 1, 1–3. doi:10.1002/9781118625392.wbecp014

Smith, I. F. C. (2016). Studies of Sensor Data Interpretation for Asset Management of the Built Environment. *Front. Built Environ.* 2. doi:10.3389/fbuil.2016.00008

Sobočan, A. M., Bertotti, T., and Strom-Gottfried, K. (2018). Ethical Considerations in Social Work Research. *Eur. J. Soc. Work* 22 (5), 805–818. doi:10.1080/13691457.2018.1544117

Sohn, K., and Kwon, O. (2020). Technology Acceptance Theories and Factors Influencing Artificial Intelligence-Based Intelligent Products. *Telematics Inform.* 47, 101324. doi:10.1016/j.tele.2019.101324

Stride, M., Renukappa, S., Suresh, S., and Egbu, C. (2021). The Effects of COVID-19 Pandemic on the UK Construction Industry and the Process of Future-Proofing Business. *Ci.* doi:10.1108/CI-03-2021-0045

Sun, C., Xu, H., and Jiang, S. (2020). Understanding the Risk Factors of BIM Technology Implementation in the Construction Industry: an Interpretive Structural Modeling (ISM) Approach. *Ecam* 27, 3289–3308. doi:10.1108/ecam-09-2019-0508

Swallow, M., and Zulu, S. (2019). Benefits and Barriers to the Adoption of 4D Modeling for Site Health and Safety Management. *Front. Built Environ.* 4. doi:10.3389/fbuil.2018.00086

Taherdoost, H. (2016). Sampling Methods in Research Methodology; How to Choose a Sampling Technique for Research. *SSRN J.* 5 (2), 18–27. doi:10.2139/ssrn.3205035

Tanko, B. L., Abdullah, F., Ramly, Z. M., and Enegbuma, W. I. (2017). Confirmatory Factor Analysis of Value Management Current Practice in the Nigerian Construction Industry. *J. Adv. Res. Appl. Sci. Eng. Technology* 9 (1), 32–41. Availableat: https://www.akademiabaru.com/submit/index.php/araset/article/view/1941.

Tian, M., Deng, P., Zhang, Y., and Salmador, M. P. (2018). How Does Culture Influence Innovation? A Systematic Literature Review. *Md* 56 (5), 1088–1107. doi:10.1108/md-05-2017-0462

Trocin, C., Hovland, I. V., Mikalef, P., and Dremel, C. (2021). How Artificial Intelligence Affords Digital Innovation: A Cross-Case Analysis of Scandinavian Companies. *Technol. Forecast. Soc. Change* 173, 121081. doi:10.1016/j.techfore.2021.121081

Turner, C. J., Oyekan, J., Stergioulas, L., and Griffin, D. (2021). Utilizing Industry 4.0 on the Construction Site: Challenges and Opportunities. *IEEE Trans. Ind. Inf.* 17, 746–756. doi:10.1109/tii.2020.3002197

Ul Hadia, N., Abdullah, N., and Sentosa, I. (2016). An Easy Approach to Exploratory Factor Analysis: Marketing Perspective. *Jesr*, 215–223. doi:10.5901/jesr.2016.v6n1p215

van Heerden, J. H. F., Musonda, I., and Okoro, C. S. (2018). Health and Safety Implementation Motivators in the South African Construction Industry. *Cogent Eng.* 5 (1), 1446253. doi:10.1080/23311916.2018.1446253

Wager, E., and Wiffen, P. J. (2011). Ethical Issues in Preparing and Publishing Systematic Reviews. *J. Evidence-Based Med.* 4 (2), 130–134. doi:10.1111/j.1756-5391.2011.01122.x

Windapo, A., and Cattell, K. (2013). The South African Construction Industry: Perceptions of Key Challenges Facing its Performance, Development and Growth. *J. Construction Developing Countries* 18 (2), 65–79.

Windapo, A. (2021). The Construction Industry Transformation and the Digital divide: Bridging the gap. *S. Afr. J. Sci.* 117 (7/8). doi:10.17159/sajs.2021/10990

Wu, M., Kozanoglu, D. C., Min, C., and Zhang, Y. (2021). Unraveling the Capabilities that Enable Digital Transformation: A Data-Driven Methodology and the Case of Artificial Intelligence. *Adv. Eng. Inform.* 50, 101368. doi:10.1016/j.aei.2021.101368

Xu, Y., Zhou, Y., Sekula, P., and Ding, L. (2021). Machine Learning in Construction: From Shallow to Deep Learning. *Dev. Built Environ.* 6, 100045. doi:10.1016/j.dibe.2021.100045

Yap, J. B. H., Chow, I. N., and Shavarebi, K. (2019). Criticality of Construction Industry Problems in Developing Countries: Analyzing Malaysian Projects. *J. Manage. Eng.* 35 (5), 04019020. doi:10.1061/(asce)me.1943-5479.0000709

Yap, J. B. H., and Toh, H. M. (2019). Investigating the Principal Factors Impacting Knowledge Management Implementation in Construction Organisations. *Jedt* 18 (1), 55–69. doi:10.1108/jedt-03-2019-0069

Yeh, C.-C., and Chen, Y.-F. (2018). Critical success Factors for Adoption of 3D Printing. *Technol. Forecast. Soc. Change* 132, 209–216. doi:10.1016/j.techfore.2018.02.003

Yousif, O. S., Zakaria, R. B., Aminudin, E., Yahya, K., Mohd Sam, A. R., Singaram, L., et al. (2021). Review of Big Data Integration in Construction Industry Digitalization. *Front. Built Environ.* 7. doi:10.3389/fbuil.2021.770496

Yuan, M., Li, Z., Li, X., Luo, X., Yin, X., and Cai, J. (2021). Proposing a Multifaceted Model for Adopting Prefabricated Construction Technology in the Construction Industry. *Ecam*. doi:10.1108/ecam-07-2021-0613

Yusof, N. A., Mustafa Kamal, E., Kong-Seng, L., and Iranmanesh, M. (2014). Are Innovations Being Created or Adopted in the Construction Industry? Exploring Innovation in the Construction Industry. *SAGE Open* 4 (3), 215824401455242. doi:10.1177/2158244014552424

Zahoor, H., Chan, A., Utama, W., Gao, R., and Zafar, I. (2017). Modeling the Relationship between Safety Climate and Safety Performance in a Developing Construction Industry: A Cross-Cultural Validation Study. *Ijerph* 14 (4), 351. doi:10.3390/ijerph14040351

Zeray, M., Mariam, D. H., Sahile, Z., and Hailu, A. (2021). Validity and Reliability of the Amharic Version of the Schwartz Center Compassionate Care Scale. *PLOS ONE* 16 (3), e0248848. doi:10.1371/journal.pone.0248848

Žydžiūnaitė, V. (2018). Implementing Ethical Principles in Social Research: Challenges, Possibilities and Limitations. *Vocational Train. Res. Realities* 29 (1), 19–43.

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