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Modeling relation among implementing AI-based drones and sustainable construction project success

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Project failure is a persistent challenge in the construction industry, rendering it one of the most demanding sectors. Many obstacles, including safety concerns, quality management issues, environmental preservation challenges, economic sustainability, privacy constraints, and legal regulations, weigh heavily on construction projects. However, a beacon of hope emerges in AI-powered drones capable of surmounting these challenges and paving the path to resounding project success. This study employed diverse methodologies, engaging subject-matter experts through interviews and conducting pilot and primary surveys. Our analytical arsenal featured Exploratory Factor Analysis (EFA) for the pilot survey and Structural Equation Modelling (SEM) for the primary survey. Our research revolves around a singular mission: elevating building project success by dismantling the barriers that have impeded the widespread adoption of AI-driven drones in construction. The study's verdict is clear: privacy and legal constraints, coupled with economic and sustainability challenges, alongside human resource management dilemmas, constitute the formidable triumvirate obstructing the ubiquitous embrace of drones in construction. Yet, the impact of breaching these barriers reverberates far beyond overcoming these hurdles. It cascades into public health and safety, environmental conservation, quality management, and economic sustainability, culminating in an amalgam of enhanced Building Project Success. The implications of our findings are profound for the construction industry. They beckon the sector to confront and surmount the legal and regulatory barriers to adopting AI-based drones. A clarion call to invest in human resources to empower technology integration resounds. And, perhaps most importantly, it beckons the industry to embrace the profound economic and sustainability advantages of embracing these cutting-edge technologies. Furthermore, our study underscores that adopting AI-powered drones in construction is not merely about project success; it catalyzes fostering public health, safeguarding the environment, ensuring top-tier quality management, and fortifying economic sustainability. These interwoven facets illuminate the broader canvas of drone technology's transformative role in construction.

KEYWORDS

AI-based drone, construction industry, construction project success, sustainable construction, modelling

1 Introduction

The drone, a crewless aerial vehicle, has attracted extensive interest in the construction sector owing to its potential to enhance safety, cut costs, and boost efficiency. According to a survey by market analysts, the worldwide drone services market size in construction was estimated at USD 4.4 billion in 2019 and is predicted to rise at a CAGR of 20.6% to reach USD 11.2 billion by 2024 (Alsamarraie et al., 2022). The report finds many significant drivers pushing the use of drones in construction, including their capacity to conduct various jobs such as surveying, mapping, inspections, and monitoring building progress (Yang et al., 2021). Drones are especially valuable for surveying big or complicated building sites, where they may swiftly and correctly record data that would otherwise be difficult or time-consuming to acquire. In addition, drones outfitted with thermal imaging cameras may be used to discover possible risks, such as heat leaks or electrical issues, that would not be apparent to the human eye. In light of global sustainability concerns, there is an increasing need to transform building practices to conform to ecological and social goals. In this particular setting, incorporating drones that use artificial intelligence (AI) into building procedures presents a potentially revolutionary resolution. The drones have been specifically engineered to carry out various duties independently, such as gathering data, conducting analysis, and making decisions using artificial intelligence algorithms and sensors (Feng et al., 2013; Goessens et al., 2018a).

The concept of sustainable construction entails a comprehensive perspective on the construction and development of buildings and infrastructure, considering various environmental, social, and economic considerations. The construction industry significantly contributes to global resource consumption and environmental degradation, responsible for around 36% of worldwide energy consumption and 39% of carbon emissions (Kubo and Okoso, 2019; Lahmeri et al., 2021; Kim et al., 2022). Using drones with artificial intelligence presents a promising opportunity to tackle these difficulties effectively (Ganesan et al., 2020; Gibbin et al., 2023). The use of AI in uncrewed aerial vehicles holds promise for substantial improvements in the efficiency of building projects. Modern techniques enable them to efficiently carry out site surveys, monitor project progress, and conduct inspections at a significantly accelerated pace compared to conventional ways.

Even with these advantages, the deployment of drones in construction is challenging, including regulatory and legal limits, lack of knowledge and skills among construction professionals, and budgetary constraints (Li and Liu, 2019). In the United States, for instance, the Federal Aviation Agency (FAA) has established restrictions for the use of drones, including commercial usage guidelines and registration, pilot certification, and flight operations criteria. In addition, many experts in the construction industry may need more expertise and skills to operate drones and evaluate the data they gather. Financial limitations may also prevent construction companies from investing in drone technology (Pawar, 2020).

These drones can offer many benefits, including enhancing safety and quality management, bolstering environmental protection, and improving economic sustainability. Drones equipped with AI capabilities have the potential to redefine the landscape of construction project management (Yang et al., 2021; Alsamarraie et al., 2022). They provide real-time data, conduct aerial surveys, and offer precise monitoring capabilities, enabling construction professionals to make informed decisions and optimize project outcomes (Loveless, 2018; Li and Liu, 2019). However, this promising trajectory has its challenges. The construction industry grapples with multifarious obstacles, including technical and functional constraints, privacy and legal restrictions, economic sustainability considerations, and organizational resistance to change (Ateya et al., 2022; Ichimura et al., 2022). These challenges hinder the widespread adoption of drones and impact critical facets like public health and safety, environmental preservation, quality management, and economic sustainability.

Despite the increased interest in using drones in the construction sector, there still needs to be more knowledge on overcoming the obstacles to their acceptance and ensuring their success in the business. While there have been some studies on the advantages and disadvantages of employing drones in construction, only some have explored the correlation between the obstacles to their adoption and the success of the technology in the sector (Loveless, 2018). This information gap is a substantial challenge for construction industry professionals, policymakers, and academics interested in adopting innovative technology (Ateya et al., 2022; Ichimura et al., 2022). Consequently, this expeditious approach results in diminished project durations and cost reductions. The potential advantages of using AI-based drones in sustainable building are readily apparent (Greene and Myers, 2013; Gupta et al., 2021). However, there needs to be a more in-depth investigation into the extent to which these drones affect the overall success of construction projects. Previous research often focuses on specific elements of either AI implementation in the building industry or the adoption of sustainable construction practices. A significant research gap needs to be addressed to establish a connection between these two areas and explore the potential synergistic effects that may arise from their integration.

In addition, extant research tends to emphasize individual obstacles or success factors over their interrelation. A more thorough knowledge of the link between barriers and success factors is required to find the most effective techniques for eliminating obstacles and guaranteeing the success of drones in the industry (Alsamarraie et al., 2022). This is especially crucial since the use of drones in buildings continues to increase, and construction companies are under growing pressure to embrace more sustainable and efficient techniques.

The present article seeks to fill this knowledge gap by realizing the full potential of drones in the construction industry. It is essential to comprehend the connection between overcoming these obstacles and the success of drones in business (Wazid et al., 2020). This study intended to provide an intelligent Partial Least Square (PLS) regression model to investigate the link between drone adoption hurdles and their industrial success. The approach is built on two orders, with the first level consisting of adoption obstacles and the second order consisting of success characteristics, including quality, safety, and environmental effects. The data-driven approach enables us to identify the most significant hurdles to the adoption of drones in construction and the elements that contribute to their success, offering a more excellent knowledge of how the barriers affect the success of the technology in building (Lawani et al., 2022).

While facing substantial challenges, the construction industry has shown a growing interest in adopting AI-powered drones. However, the comprehensive examination of the interconnected barriers hindering their widespread integration remains notably limited in the existing literature. Moreover, the extent to which addressing these barriers can significantly impact project success and critical areas like public health and safety, environmental conservation, quality management, and economic sustainability requires deeper investigation. This research seeks to bridge this notable gap by conducting an in-depth analysis that identifies these challenges and elucidates their multifaceted impact on the construction landscape. In doing so, we aim to contribute to a more comprehensive understanding of the potential and challenges associated with AI-based drones in construction while offering practical insights for industry stakeholders and policymakers.

This is, to the best of our knowledge, the first study to develop an intelligent structural equation model to explore the relationship between the barriers to the adoption of drones in construction and their success in the industry, utilizing a comprehensive set of success factors that includes quality, safety, and environmental factors. The model enables us to identify the most critical hurdles to adopting drones in the construction industry and the characteristics contributing to their success. It offers valuable information on overcoming these barriers and guarantees the effective integration of drones into the sector. This unique method for examining the link between obstacles to adoption and the success characteristics of drones in the building will interest construction professionals, policymakers, and scholars. The intended audience for this article consists of building industry specialists with extensive expertise. This study's results may be of considerable use to construction industry experts, legislators, and scholars interested in adopting developing technology. This research offers a significant road map for enhancing the acceptance and integration of drone technology in construction by identifying the hurdles to drone adoption and the elements that contribute to their success. Using AI-based drones in building projects may result in significant cost reductions, hence offering considerable benefits at a time characterised by limited financial resources and economic instability. The results of this study will provide valuable insights to construction firms and policymakers on the potential of AI-enabled drones, hence facilitating their integration and utilisation within the sector. The research aims to provide a strategic framework for harmonising building practises with sustainability objectives, fostering sustainable development and conscientious resource stewardship.

2 Related works

Many studies have examined the challenges of using drones in construction and the crucial success elements that may assist in overcoming these barriers (Golpîra, 2021; Kim et al., 2022). For instance, it was discovered that a lack of knowledge, legal constraints, and data processing difficulties were the most significant obstacles to drone adoption in the construction business (Yi and Sutrisna, 2021). One study observed comparable constraints, such as privacy and security concerns, lack of technical competence, and investment return uncertainty (Lee and Kwon, 2020; Woo et al., 2021). Cost and a lack of industry standards were also significant hurdles to adoption by one examination. One study identified regulatory restrictions, restricted drone capabilities, and expensive equipment and maintenance costs as the primary obstacles to the deployment of drones in the construction industry (Feder, 2020; To et al., 2021). It was revealed that inadequate awareness and understanding of drone technology, privacy and data security concerns, and drone durability were significant obstacles. It is also identified that the availability of experienced personnel, the price of drone technology, and the aversion to change were significant hurdles to adoption. It is realized that in India, a need for more awareness and expertise regarding drone technology, high prices, and regulatory difficulties were significant obstacles (Amicone et al., 2021; Mahajan, 2021). Sawhney et al. (2020) did a thorough literature analysis. They found that the primary hurdles were the absence of clear laws, high expenses, and a lack of knowledge and awareness (Sawhney et al., 2020).

The use of drones within the construction sector has seen substantial expansion in recent years. It is important to comprehend the many aspects that contribute to this acceptance, with a particular focus on the level of maturity in terms of age (Lee and Kwon, 2020; Wazid et al., 2020). The construction industry, often seen as conservative, has experienced a growing acceptance of drone technology due to its capacity to potentially transform several facets of project management (Charlesraj and Rakshith, 2020; Kim et al., 2022). Nevertheless, the pace of adoption often exhibits variability across people and organizations, with age potentially serving as a relevant element within this context. The available research suggests that individuals belonging to younger professional cohorts, especially those raised in digital advancements, have a greater inclination towards embracing drone technology within the construction industry (Charlesraj and Rakshith, 2020; Feder, 2020). Frequently, individuals of this demographic have a higher level of proficiency in assimilating new technical instruments and are more inclined to see drones as beneficial resources for their endeavours. On the other hand, it is worth noting that older professionals may want further training and assistance to effectively adopt and integrate these advancements (Li and Liu, 2019; Alsamarraie et al., 2022). Moreover, the extent of expertise within the construction sector significantly influences the impression of crewless aerial vehicles. Experienced individuals who have seen the sector's progression may possess a heightened understanding of the capabilities of drones, whilst others who are new to the field may need further persuasion (Loveless, 2018; Pawar, 2020). The occupation of people also has a significant influence in shaping their perceptions and acceptance of drone technology (Ateya et al., 2022; Ichimura et al., 2022). For example, project managers may see drones as instruments for enhancing project efficiency and ensuring quality control, while surveyors may prioritize their capacity for precise data collection.

In a study in Pakistan, the high cost of drone technology and the lack of training and experience were significant obstacles. Agapiou (2020) cited the absence of a regulatory framework, increased expenses, and opposition to change as significant barriers (Agapiou, 2020). It is revealed that the absence of clear rules and policies, the high cost of drones, and a lack of experienced workers were significant impediments to adoption. Kubo and Okoso (2019) researched the challenges and drivers of drone adoption in Saudi Arabia and found that low awareness and understanding, the absence of a regulatory framework, and high prices were the most significant impediments to adoption (Kubo and Okoso, 2019). Kim et al. (2017) indicate similar challenges to using drones in the construction industry, including high prices, a lack of awareness and comprehension, regulatory impediments, and a need for more knowledge and competence (Kim et al., 2017). It highlights the absence of rules and norms, high equipment prices, and technological constraints as the primary obstacles to implementing drones in construction. In the Korean construction business, it was discovered that a lack of competent workers and an inadequate understanding of drone technology were major obstacles (Goessens et al., 2018a; Rovira-Sugranes et al., 2022). Umar (2021) cited legal hurdles, cost concerns, and a lack of integration with existing processes as the main obstacles to drone adoption in the United Arab Emirates construction sector (Umar, 2021). Mahajan (2021) researched India and discovered that there needed to be a legal framework, high prices, and low awareness and understanding were the primary obstacles to using drones in the construction industry (Mahajan, 2021).

It is also important that the absence of rules, privacy concerns, and the restricted range of drones were the most significant obstacles to adoption in the Middle East. A study in China found the lack of laws, high prices, and lack of knowledge and comprehension of drone technology as the primary impediments (Li 2019). Chung et al. (2020) found that there needed to be a regulatory framework, high prices, and a lack of training and education were the primary obstacles to drone adoption in China (Chung et al., 2020). Research done in the United Kingdom highlighted the lack of standards, the difficulty of integrating drone data with BIM, and the lack of appropriate software tools as the primary obstacles to adoption (Golpîra, 2021; Gibbin et al., 2023). Following the research gap, this study has two objectives. The first objective is to identify the barriers to implementing drones in the construction industry. The second objective is to identify the impact of overcoming obstacles of drone implementation on Construction Project Success in the construction industry.

The measurement of environmental advantages is a crucial element in sustainable building. While several research studies have recognised the potential of AI-driven crewless aerial vehicles to mitigate energy consumption and carbon emissions, only a few studies have presented quantifiable data. Nevertheless, this domain needs to be more adequately investigated since a dearth of research provides thorough quantitative evaluations of the environmental consequences (Albeaino et al., 2022; Alsamarraie et al., 2022). There is a need for research endeavours that include project-specific variables, including geographical place, magnitude, and intricacy, to provide a complete comprehension of enhancements in efficiency. However, most studies conclude by highlighting these difficulties without providing specific answers or techniques for their reduction (Beiki and Mosavi, 2020; Bera et al., 2022). The potential of AI-powered drones to gather extensive quantities of data in construction presents a promising opportunity for decision-making informed by data. Numerous studies have shown the potential of this technology to better project management and optimise resource allocation. One notable deficiency in the existing body of literature is the lack of comprehensive frameworks that guide the incorporation of AI-enabled drones into sustainable building methodologies (Charlesraj and Rakshith, 2020; Chen et al., 2021). Most research endeavours concentrate on sure facets, such as efficiency or environmental effect, without presenting a holistic framework for sustainable building. Previous research has put forward a conceptual framework aimed at the seamless integration of drones often called drones, into construction project management. Nevertheless, it is worth noting that this framework needs to improve its emphasis on sustainability, creating an avenue for more investigation in this specific domain (Ciampa et al., 2019; Chung et al., 2020).

To assess their sustainability contributions, it is essential to thoroughly understand these technologies' life cycle effects on building projects. The prevailing body of literature mainly comprises research undertaken in developed areas characterised by established regulatory frameworks and infrastructure. This bias imposes constraints on how the results may be applied to places characterised by distinct socio-economic situations and building practices (Dillow, 2016; Entrop and Vasenev, 2017; Elghaish et al., 2021). Future studies should include a wide range of scenarios to enhance the comprehensiveness of our knowledge about the worldwide application of AI-based drones in sustainable building. The existing body of research recognises the potential impact of AI-based drones in transforming sustainable building; nevertheless, significant gaps still need to be addressed. The identified gaps encompass various areas that require attention in the academic realm (Feng et al., 2013; Firth, 2018; Feder, 2020). These gaps pertain to the necessity for thorough quantitative evaluations of environmental impact, a more extensive examination of efficiency improvements and cost reductions, the formulation of feasible strategies to address implementation obstacles, the incorporation of data generated by drones into decision support systems, the establishment of comprehensive sustainability frameworks, and the ongoing monitoring of project performance over an extended period (Goessens et al., 2018a; Ganesan et al., 2020; Gibbin et al., 2023). Rectifying these shortcomings will significantly expand existing knowledge and enhance the seamless incorporation of artificial intelligence-powered uncrewed aerial vehicles into sustainable building methodologies.

Overall, these studies highlight the need for a holistic approach to addressing the barriers to drone adoption in the construction industry, which includes not only addressing regulatory and financial issues but also increasing awareness and knowledge about drone technology and developing the infrastructure and resources required to support its integration into construction workflows. The central hypothesis for the study is H1: Overcoming barriers to implementing AI-based drones has a positive effect on construction project success. This study concentrates on building more precise frameworks and suggestions for overcoming the unique challenges mentioned in different situations and examining the potential advantages of drone adoption in construction beyond cost savings and productivity increases.

3 Identification of model barriers

In the research, 16 semi-structured interviews were used to determine the obstacles to using drones and the success criteria for AI technology in the construction industry. The interviews were conducted to get a more excellent knowledge of the problems and possibilities related to deploying drones and AI technology in the construction sector, as assessed by industry experts.

The semi-structured interview method was selected because it permitted freedom of questions and allowed for prompts and probes. The interviews with construction businesses and stakeholders aimed to get insight into their perspectives and experiences regarding employing drones and AI technologies (Lee et al., 2019; Gupta et al., 2021).

The interview data were examined to discover common themes on the obstacles to using drones and the success criteria for AI technology in the construction industry. The data were then utilized to design a Smart PLS model to investigate the association between overcoming obstacles to drone adoption and the effectiveness of drones in construction.

Overall, semi-structured interviews offered a wealth of data that enabled a detailed examination of the obstacles and success factors associated with deploying drones and AI technologies in the construction industry (Lee et al., 2020). This information may be used to guide future industry research and policy choices.

The respondents in the study's semi-structured interviews noted that environmental protection, public health, and quality management are three crucial elements that must be addressed to guarantee the success of AI technology in buildings (Mishra, 2019; Ullo and Sinha, 2021).

By maximizing resource utilization, decreasing waste and emissions, and encouraging green building materials and processes, applying AI technology in construction may facilitate more environmentally friendly and sustainable building practices (Irizarry et al., 2012; Kitjacharoenchai et al., 2020). Furthermore, AI technology may improve public health and safety by allowing higher precision and accuracy in project management and delivery, minimizing the likelihood of accidents and injuries on construction sites.

Furthermore, using AI technology may enhance the overall quality of construction projects by allowing higher efficiency and accuracy, minimizing mistakes and delays, and improving project results (Lee et al., 2021; Albeaino et al., 2022). Table 1 presents the identified model barriers and Table 2 indicates the factors of project success along with their identified constructs. These success elements are crucial to guaranteeing the broad acceptance and deployment of AI technology in the construction sector, and industry experts and policymakers should prioritize their consideration.

4 Methodology

Based on the studied literature, 18 hurdles to implementing drones were identified along with nine success factors under three constructs and judged relevant. Figure 1 further demonstrates it. Subsequently, a questionnaire survey was undertaken by distributing a list of obstacles to implementing drones to building industry professionals with relevant construction experience. It was conducted to assess the appropriateness and clarity of drone innovation hurdles that inhibit its adoption and to analyze these barriers and their kinds using exploratory analysis of factors (EFA).

4.1 Data collection

Using a questionnaire, Malaysian stakeholders in the prospective construction sector were contacted during data collection to analyze the hurdles to drones and associated success factors with their implementation (Feng et al., 2013; Duda et al., 2019; Beiki and Mosavi, 2020). The survey instrument was separated into four primary components: 1) the respondents' demographic profile, 2) the drone adoption hurdles, 3) success factors for overcoming the drone implementation barriers, and 4) open-ended questions that allowed experts to add any relevant barriers identified by stakeholders. There were three primary groups questioned. They include customers, consultants, and independent contractors.

They are classified further depending on occupation: mechanical, electrical, structural engineers, architects, and quantity surveyors. Using a five-point Linkert scale, the study population assessed the drone's adoption hurdles and success based on their experience and knowledge (5 = very high, 4 = high, 3 = average, 2 = low, and 1 = very low). This metric has been widely used in the literature. The drone is a recent development in Malaysia. Hence, a stratified sampling strategy of a particular subgroup has been evaluated [85]. In addition, the sample size selection for this investigation was based on examining the procedural goal [86,87]. Figure 1 presents the stages of the research. According to Kline [88], a multidimensional route model requires at least 200 samples.

In contrast, Yin [89] asserts that at least 100 examples are sufficient for SEM. Due to the use of SEM in this research, 248 respondents were obtained from 335 found initially. The 257 individuals were reached through a self-administered questionnaire with a response rate of 71.81%. It was determined that the rate of return was appropriate for this sort of study [90,91].

4.2 Data analysis

SEM-PLS (Structural Equation Modeling-Partial Least Square) has attracted interest from several fields, particularly the social and economic sciences [59]. Popular SSCI Publications [60–62] have published more studies using the SEM-PLS methodology. The most current edition of the SMART-PLS 4 version was utilized to analyze the collected data and estimate the importance of implementation hurdles and success factors for drones using SEM. The SEM-PLS was initially recognized for its solid predictive capabilities when compared to covariance-based CB(SEM)-structural equation modelling (Yıldız et al., 2021), even though the discrepancy between the two techniques is relatively tiny (Duda et al., 2019). This research's mathematical analysis comprises analytical and structural modelling evaluation techniques.

4.2.1 Common method variance

Common Method Bias (CMB) results from the standard method variance (CMV). The CMB assists in explaining the mistake (or variance) in the outcomes of an analysis, which is associated with the analytical approach as opposed to the ideas represented by the methodologies [65]. It may be defined as the overlap in variance across ideas (Yang et al., 2021; Alsamarraie et al., 2022). Similarly, the CMV is complex whenever data from a specific source, such as self-collected data via a questionnaire, are available [66,67]. In some circumstances, self-collected data might overestimate or misrepresent the number of perceived associations, causing issues

TABLE 1 Identified barriers to drone implementation.

Code	Barriers	Method	References
C1	Drones' technology may need to be more scalable for significant construction projects or require substantial modification in larger applications, making its widespread adoption challenging	Literature	Elghaish et al. (2021), Islam et al. (2021)
C2	Integrating with current drone technology systems may require more work with existing construction systems, posing a hurdle for businesses seeking to embrace this technology	Interview	-
C3	Concerns remain over the safety and privacy of drones on building sites, mainly when operating near humans	Literature	Höche et al. (2021), Bera et al. (2022)
C4	The availability of drone technology may be restricted in some countries or for specific applications, posing a substantial obstacle for businesses operating in those regions or seeking to employ the technology for those purposes	Literature	Firth, (2018); Rohan et al. (2019)
C5	To maintain dependability, drone technology may be delicate and require regular maintenance. This may be a substantial obstacle for certain businesses, especially those with minimal resources	Literature	Ganesan et al. (2020), Umar (2021)
C6	Some in the construction sector may believe that drone technology is not suited to the specific problems and requirements of construction operations. This impression might make it challenging for certain businesses to implement this technology	Literature	Anunciado, (2016); Lin (2017)
C7	Some construction projects may need more drone technology usage due to environmental limitations, such as noise or pollution	Interview	-
C8	There may be regulatory and legal obstacles to employing drone technology in the construction industry, notably with safety and liability concerns	Literature	Ganesan et al. (2020), Umar (2021)
C9	The high initial cost of drone technology might be an impediment, especially for smaller construction firms	Interview	-
C10	Using drone technology in construction may be met with opposition from human employees who fear being inspected by drones or are uncomfortable working alongside AI technology	Literature	Lin (2017), Yigitcanlar et al. (2020)
C11	The absence of standardization in drone technology might make it difficult for businesses to analyze and compare various technologies and choose the best solution for their specific requirements	Interview	-
C12	The present variety of uses for drone technology in the construction industry still needs to be expanded, making it difficult for certain businesses to justify the investment	Literature	Anunciado (2016)
C13	Some businesses may resist change and slowly accept new technology, primarily if they have long relied on conventional building techniques	Literature	Lahmeri et al. (2021)
C14	Drone technology operation and maintenance drone technology operation and maintenance may be complex and need specialist skills. Building businesses need to be more confident with this intricacy	Literature	Ciampa et al. (2019), Zhang et al. (2021)
C15	Some firms may be reluctant to invest in drone technology if they lack the specialized staff to operate and maintain drones	Literature	Zaychenko et al. (2018)
C16	The existing spectrum of drone technology in construction may need to be sufficiently adaptable to satisfy the unique requirements of certain businesses or projects, which may be a substantial obstacle to adoption	Interview	-
C17	Some businesses may need to be made aware of drone technology's advantages or comprehend how it may be used in the construction industry	Interview	-
C18	For certain businesses, the return on investment for drone technology in construction may take time to justify the cost	Interview	-

TABLE 2 Construction project success factors with their constructs.

Environmental protection	E1	It regularly scans the building site to discover and monitor environmental hazards, such as soil erosion, water runoff, and other pollution sources	Entrop and Vasenev (2017), Goessens et al. (2018b), MT Hardjo et al. (2020), Ikeda et al. (2021), Pereira da Silva and Eloy (2021)
	E2	Providing thermal imaging and other forms of non-destructive testing to identify possible environmental dangers, such as chemical spills, that might negatively impact the health of local people	
	E3	I monitor the construction process to guarantee compliance with environmental requirements, such as waste disposal and environmentally friendly building materials	
Public Health and Safety	H1	Real-time monitoring of the construction site to guarantee compliance with safety rules and processes and rapid identification and mitigation of any safety concerns or events	Greene and Myers (2013), Urgessa and Esfandiari (2018), Li et al. (2019), Liu et al. (2021)
	H2	Providing precise 3D models and maps of the building site may aid personnel's rapid location and evacuation in an emergency	
	H3	Improving communication and cooperation between project stakeholders may aid in identifying and resolving any possible safety concerns or problems before they become a problem	
Quality Management	Q1	For building projects, drones may offer aerial surveys, site management, and progress monitoring, ensuring quality management	Dillow (2016), Scher et al. (2019), Chung et al. (2020), Khalid et al. (2021)
	Q2	Drones may assist in uncovering possible potential concerns and design defects, assuring compliance with construction norms and codes	
	Q3	Drones may gather data about building supplies and equipment, such as measurements, weight, and dimensions, to ensure that the proper materials are utilized in the right proportions	

[67,68]. That may be crucial, especially for this study, since all data sets are self-collected, unique, and drawn from a single source. Thus, it is vital to address these problems to detect any potential CMV. A valid single-factor test was conducted following the studies undertaken by Harman et al. [69] [70]. Factor analysis yields a single factor that explains most of the variance (Duda et al., 2019; Lewandowski, 2021; Yıldız et al., 2021).

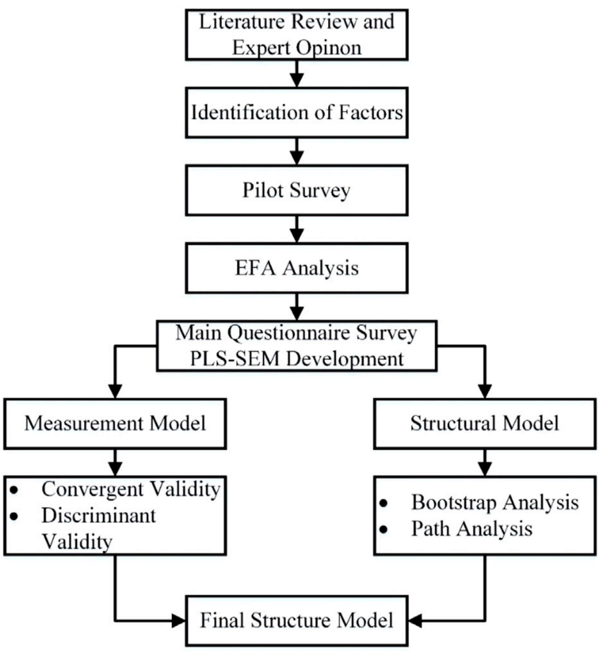

FIGURE 1
Flow chart of the work.

4.2.2 Analytical model

The analytical model reveals the existing link and underlying structure between variables [71]. The next part evaluated the analytical model's discriminant and convergent validity.

4.2.2.1 Convergent validity

CV exemplifies the degree of agreement between two or more binary variables (or obstacles) of the same notion or constructs. It is considered a subset of the validity of the concept. The CV of the calculated constructs in PLS may be determined using three tests. I composite reliability ratings (Pc), Cronbach's alpha, and estimated average variance (AVE). There is a suitable mixed reliability level of 0.70 (Pc). For any research, scores above 0.60 and 0.70 for exploratory studies are considered acceptable. The last test is the AVE, which is regarded as a typical calculation used to assess the CV of the model's structures. My results are more than 0.50, suggesting an excellent CV.

The following calculations were used for concurrent validity exploration:

$$Average\,Variance\,Extracted = AVE = \frac{\sum\lambda^2}{\sum\lambda^2 + \sum\varepsilon} \tag{1}$$

$$Composite\,Reliability = CR = \frac{(\sum\lambda)^2}{(\sum\lambda)^2 + \sum\varepsilon} \tag{2}$$

$$Cronbach\,Alpha = CA = \alpha = \left[\frac{k}{(k-1)} \times \left(1 - \frac{\sum\varepsilon}{\sum x^2}\right)\right] \tag{3}$$

where: λ = the factor loading of each indicator on its corresponding construct.ε = the indicator's unique error variance.where: k = the number of indicators in the construct.ε = the indicator's unique error variance.ΣX^2 = the total variance of the construct, equal to the sum of the squared factor loadings and error variances of the indicators.

4.2.2.2 Discriminant validity

Discriminant validity (DV) stipulates that the concerns under study are experientially unique and proposes that no dimensions define the construct under investigation in SEM. If the DV is to be determined, the degree of similarity across dispersed measurements must not be excessive. The Fornell-Larcker criteria compare the square root of the AVE for each construct to the construct's correlations with other constructs in the model (Feng et al., 2013). When the square root of the AVE for a particular construct is more prominent than its correlation with other constructs in the model, it is argued that the construct has discriminant validity (Makadsi, 2019; Kisi et al., 2020; Chen et al., 2021). The AVE for each structure is computed as follows:

$$AVE\ for\ each\ structure = \frac{\sum \lambda^2}{\sum \theta} \tag{4}$$

where λ^2 is the factor loading squared, θ is the construct's error variance.

The correlation between two constructs, i and j, is calculated as:

$$Correlation(i, j) = \frac{\sum \lambda i \times \lambda j}{\sqrt{\sum \lambda i^2} \times \sqrt{\sum \lambda j^2}} \tag{5}$$

The square root of the AVE for each construct is then compared to the construct's correlation with other model constructs. The discriminant validity is established if the square root of the AVE is larger than the correlation with any different concept (Urgessa and Esfandiari, 2018; Beiki and Mosavi, 2020). The Heterotrait-Monotrait (HTMT) ratio of correlations is determined by dividing the correlation between two constructs (hetero-trait) by the average correlation of each construct with itself (monotrait). Following is the algorithm for calculating HTMT:

$$HTMT = \sqrt{\frac{r_{ij}{}^2}{AVE(r_i, r_j)}} \tag{6}$$

Where r_ij is the correlation between constructs i and j, and ave (r_ i,r_j) is the average of the correlations of constructs i and j with themselves. The HTMT threshold value is generally set at 0.9 or less, suggesting that the constructs are sufficiently dissimilar from one another to have discriminant validity (Li et al., 2019; Liu et al., 2021). The cross-loading of an item on a structure may be described mathematically as follows: For construct j, the loading of item λ_ ij gives me, and the residual variance of item ξ_i gives me. Then, the cross-loading of article i on construct k (k ≠ j) is provided by:

$$\lambda_{ik} = \frac{COV(i, k)}{\sqrt{var(i)}} \tag{7}$$

Where cov (i, k) is the covariance between item I and construct k.Var(i) is the variance of item i.

4.2.3 Structural model analysis

This research attempted to demonstrate, using the SEM, the main hurdles to drone implementation in construction projects and its success factors. It may be accomplished by first determining the route coefficients. Hence, a one-way causal link or route relation has been postulated between the concepts of drone's obstacles (£) and drone's success adoption barriers (μ) (Kardasz and Doskocz, 2016; Oudjehane et al., 2019; Hatfield et al., 2020). Thus, the functional relationship between £, μ, and ∈ 1 principle in the structural equation model has been identified as an inner connection that a linear model may represent:

$$\mu = \beta £ + \in 1 \tag{8}$$

When the route coefficient linking drone, conceptions is β, and it is believed that ∈1 represents the residual correction at the operational level. Hence, the standardized regression load would be identical to the weight of the multiple regression model. Its signals must correspond to the model's predictions and be statistically significant (Makadsi, 2019; Kisi et al., 2020; Chen et al., 2021). The issue arises in determining the significance (β) of the route coefficients. For the CFA, the bootstrap approach available in the SmartPLS 4 program was used to estimate the standard errors of the route coefficients. Five thousand subsamples were used for this. Hence, the t-statistics of testing the hypothesis have been defined. Three functional formulas for drone ideas were created using the PLS model. It illustrates the underlying connections between ideas and Eq. 8

Using the SmartPLS 4.0 software, a structural equation modelling (SEM) study was undertaken to explore the links between the research model's components. The bootstrap approach was used to assess the relevance and robustness of the parameter estimations of the model. Bootstrapping entails obtaining random subsamples from the data set and creating a distribution of parameter estimates for each model route (Greene and Myers, 2013; Duda et al., 2019). The t-value and *p*-value show the significance and strength of the association between the constructs for each path coefficient, provided as the results of the bootstrap analysis (Kardasz and Doskocz, 2016; Oudjehane et al., 2019; Hatfield et al., 2020). A *p*-value of less than 0.05 was statistically significant. In addition, the coefficient of determination (R-squared) was used to assess how much variation the model explained. R-squared values over 0.3 were regarded as acceptable.

4.2.4 Predictive relevance analysis

After determining the relevance of the route variables, the structural model's prediction ability was evaluated. The model's predictive power was assessed using the cross-validated R-squared (Q2) value. The Q2 value represents the amount of predicted variation in the dependent variable. A Q2 value over 0.25 suggests excellent predictive ability, while a Q2 value below 0.1 shows poor predictive power. SmartPLS 4.0's structural model analysis comprehensively examines the model's element connections. The structural model is reliable and valid owing to the use of advanced statistical techniques, such as bootstrapping, and the evaluation of its predictive capability.

5 Results

5.1 EFA analysis

The exploratory factor analysis (EFA) findings suggest that the 18 obstacles to using drones with AI in the construction sector may be broken down into three constructs or components that account

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TABLE 3 Exploratory factor analysis output.

Variables	1	2	3	Cronbach alpha
C2	.735			0.810
C15	.705			
C14	.703			
C13	.645			
C11	.644			
C16		.791		0.811
C10		.768		
C8		.683		
C4		.676		
C3		.650		
C6		.643		
C9			.762	0.876
C12			.753	
C5			.704	
C1			.682	
C7			.641	
Eigenvalue	4.126	4.041	3.921	
% Variance	27.112	20.131	12.116	
Extracted Factors	B2 and B6 were extracted due to loading less than 0.6			

for 59.259% of the total variation. Table 3 presents the rotated component matrix from EFA, along with Cronbach Alpha values for each construct.

The first part, "Technical and Functional Barriers," is made up of 5 barriers with high factor loadings, meaning they are highly correlated with each other and can be thought of as obstacles relating to the integration and compatibility of AI-based drone technology with existing construction systems, safety and privacy concerns, regulatory and legal barriers, and a lack of standardization in the technology (Yıldızel and Calış, 2019; Khalid et al., 2021).

The second part, titled "Privacy and Legal Barriers," is comprised of six barriers with high factor loadings; this means that they are highly correlated with each other and can be thought of as barriers relating to the high price of the technology, the need for routine maintenance and specialized skills, the resistance to change, and the lack of technical staff to operate and maintain the drones.

Thirdly, the "Economic and Sustainability" factor includes six obstacles that have high factor loadings, indicating that they are highly correlated with each other and can be thought of as obstacles related to the environmental limitations of using drone technology in construction, employee opposition, and discomfort with AI technology, the difficulty and complexity of operating and maintaining the drones, and the limited variety of uses and awareness of the tec. The strong Cronbach's alpha values for all three subscales suggest that the individual barriers used to evaluate each subscale are valid and trustworthy indicators of the construct they are meant to assess.

The findings as a whole indicate that there are several obstacles to the successful use of drones powered by artificial intelligence in the construction business. These barriers may be broken down into three categories. The findings of this EFA may guide future studies and practitioners in overcoming obstacles to the widespread use of intelligent drones in the building sector.

The final categorized barriers to AI-based drones in construction are according to EFA results. Businesses may face technical and functional hurdles when trying to embrace and integrate drone technology into their operations, which is what the Technical and Functional Barriers category is all about (Dillow, 2016; Scher et al., 2019; Chung et al., 2020). Difficulties in integrating drone technology with existing systems, a shortage of specialized staff to operate and maintain the technology, aversion to change and new technology, a lack of standardization in drone technology, and the misconception that drone technology is not suited to the unique demands of construction projects are all obstacles to overcome. Concerns about personal privacy, workplace safety, and legal implications are all factors that might slow down the widespread use of drones in the building. These include the belief that drone technology is not suited for construction operations, the dedication that drones cannot be adapted to meet the unique requirements of certain businesses or projects, opposition from human employees who fear being replaced by drones or working alongside AI technology, and regulatory and legal obstacles. Economic and sustainability concern the potential financial and environmental costs companies may incur using drone technology (Yıldızel and Calış, 2019; Khalid et al., 2021). Drone technology has several obstacles, including its high upfront cost, restricted range of applications in construction, its fragile nature and the need for routine maintenance, its inability to scale to more significant building projects, and environmental constraints like noise or pollution. These three frameworks illustrate the many potential challenges companies may face while embracing and using drone technology within the building sector (Kardasz and Doskocz, 2016; Oudjehane et al., 2019; Hatfield et al., 2020). The EFA findings imply that these obstacles may be broken down into three broad groups, which can guide the development of specific treatments and methods to overcome them.

The components that emerged from the EFA were technological and functional limitations, privacy and legal restrictions, and economic and sustainability concerns. Possible roadblocks to the widespread use of drones powered by artificial intelligence in the building sector include the structures mentioned earlier. Using this data, hypotheses "H2: Technical and functional Barriers have a positive impact on Implementation of AI-Based Drones in the construction industry," "H3: Privacy and legal barriers have a positive impact on Implementation of AI-Based Drones in the construction industry," and "H4: Economic and sustainability barriers have a positive impact on Implementation of AI-Based Drones in the construction industry," were developed. All these show that removing these roadblocks to using AI-powered drones might benefit the construction sector. Figure 2 presents the hypothesized framework of formative constructs and reflective constructs. In particular, organizations looking to embrace this technology may need help combining drone technology with current construction processes. Similar privacy and legal constraints, including safety and liability worries, may slow down

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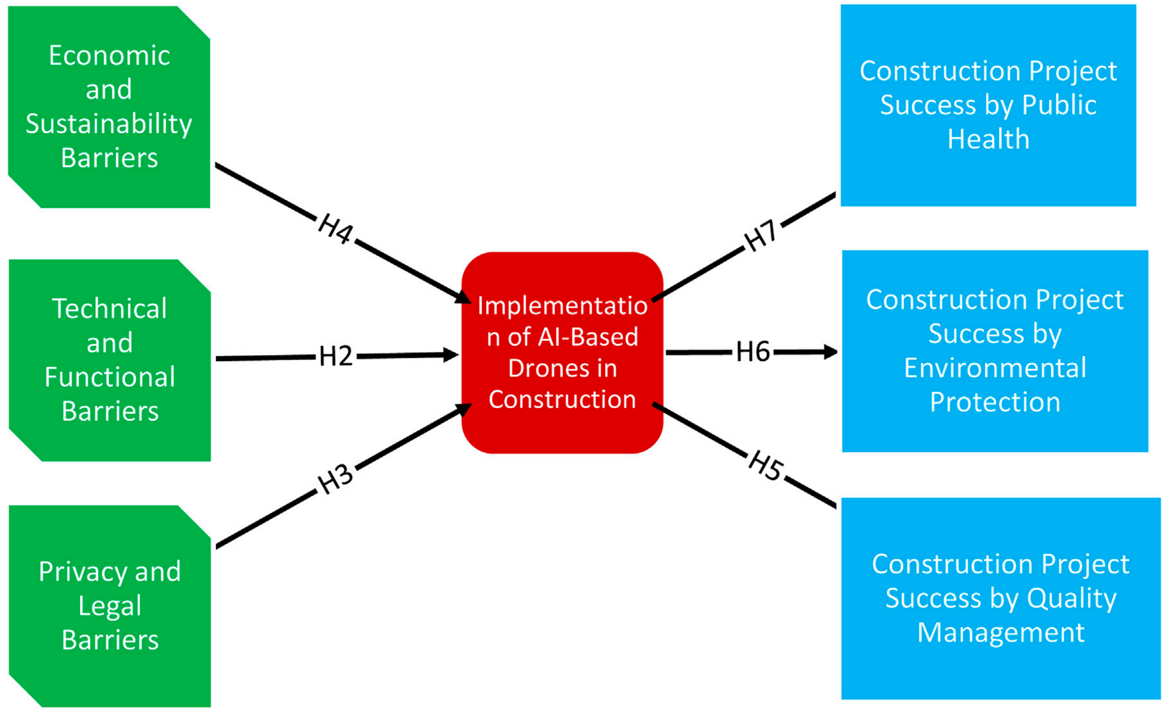

FIGURE 2
Formative constructs with their hypotheses.

the widespread use of drones. Lastly, firms may find the high initial cost and maintenance needs of AI-based drones to hinder their use in construction. After reviewing the available literature and conducting interviews, the authors developed three further hypotheses about the usefulness of drones powered by artificial intelligence in the building industry. The hypotheses were, "H5: Implementation of AI-based drones in construction industry positively impact Construction Project Success by Quality Management," "H6: Implementation of AI-based drones in construction industry positively impact Construction Project Success by environment protection" and "H7: Implementation of AI-based drones in construction industry positively impact Construction Project Success by public health and safety." Using AI-powered drones in the construction industry might improve quality control, safeguard the environment, and boost public health and safety. In sum, we utilized the EFA findings to create the six hypotheses about the adoption and effect of AI-based drones in the construction sector, considering the possible challenges and opportunities presented by this emerging technology.

5.1.1 Demographics

The results of the demographics of the primary questionnaire survey are indicated in Figure 3. Most have a Master's degree (43%), whereas just 32% have a Bachelor's degree. The proportion of those with a Ph.D. is lower (14%), while the "Others" group includes 10%. The largest demographic of responders (43%) is comprised of those aged 31–35, followed by those aged 26–30 (22%) and those aged 36–40 (15%). Just 7 per cent of those who answered the survey were 40 or older. In terms of years of experience, the largest share of respondents had worked in the field between 11 and 15 years (44%), followed by those with 5–10 years of experience (21%) and those with 16–20 years of experience (15%). Just seven percent of those polled had more than 20 years of experience. Most responders (74%) are civil engineers; the subsequent most common occupation is the project manager (18%) and safety manager (4%). Architects and those who answered "Other" comprise a smaller sample fraction (3% and 1%, respectively). When taken as a whole, the survey's respondent pool represents a cross-section of the construction industry's age, education, experience, and occupational spectrum.

5.2 Structure equation modelling (SEM) and analysis

Cronbach's alpha is often used to quantify a measure's reliability, which is the extent to which it maintains consistent and stable results over time. Internal consistency of items inside a concept is measured by the composite reliability (rho-a and rho-c), with rho-c being the more robust measure of reliability. Figure 4 presents the trend of composite reliability in formative and reflective constructs. With a more considerable value representing more convergent validity, the average variance extracted (AVE) quantifies how well the items in a construct capture the latent variable.

Cronbach's alpha coefficients for each construct range from 0.701 to 0.902, indicating excellent reliability. The rho-a and rho-c values, which comprise the composite reliability, are relatively high, ranging from 0.805% to 0.936% and 0.852%–0.932%, respectively. Figure 5 presents the trend of composite reliability in formative and reflective constructs. It shows that the components inside each construct are very consistent and trustworthy.

FIGURE 3
Demographic details.

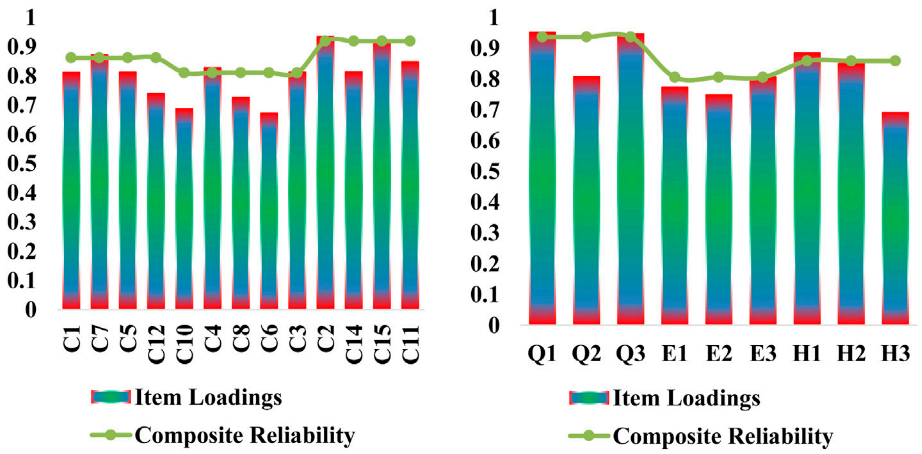

FIGURE 4
Item loadings with composite reliability for formative and reflective constructs items.

In addition, the AVE values range from 0.558 to 0.817, much over the minimally acceptable criterion of 0.5. Hence, it can be concluded that the items within each construct have strong convergent validity and are substantially linked with the underlying concept (Hatfield et al., 2020). Figure 6 presents the trend of composite reliability in formative and reflective constructs.

This suggests that the constructs used in the study are reliable and valid, which means they can be used to measure the intended constructs of economic and sustainability barriers, environmental protection, privacy and legal barriers, public health and safety, quality management, and technical and functional barriers. The relationship significance is indicated between constructs and latent variables. Figure 7 demonstrates the path coefficients.

5.2.1 Second order analysis

Table 4 presents the evaluation results for six fundamental constructs (Economic and sustainability Barriers, Privacy and legal Barriers, Public Health and safety, and Technological and functional Barriers) using the Fornell-Larcker criteria. These criteria are essential for assessing the discriminative capability of these constructs effectively. Examining the table's diagonal reveals each construct's square roots of the AVE. The AVE quantifies how much a particular concept can account for variance within its indicators. Generally, an AVE value of 0.5 or greater signifies robust convergent validity, indicating the construct adeptly captures the shared variance among its indicators (Loveless, 2018; Li and Liu, 2019). Moving on to the off-diagonal values in the table, they depict correlations between different constructs. According to the Fornell-Larcker criteria, for constructs to demonstrate high discriminant validity, the sum of squared correlations between any two constructs should be smaller than the AVE of each concept. This signifies that the constructs should remain distinct, and the shared variance between them should be less than what each construct can explain independently. The findings in Table 4 confirm that all constructs meet the criteria for convergent validity, with AVE values greater than 0.5. Additionally, the AVE

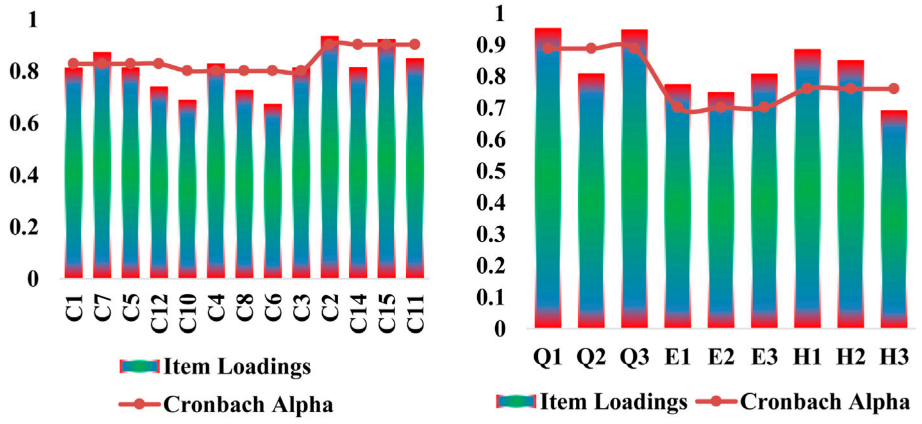

FIGURE 5
Item loadings vs. Cronbach alpha for formative and reflective construct items.

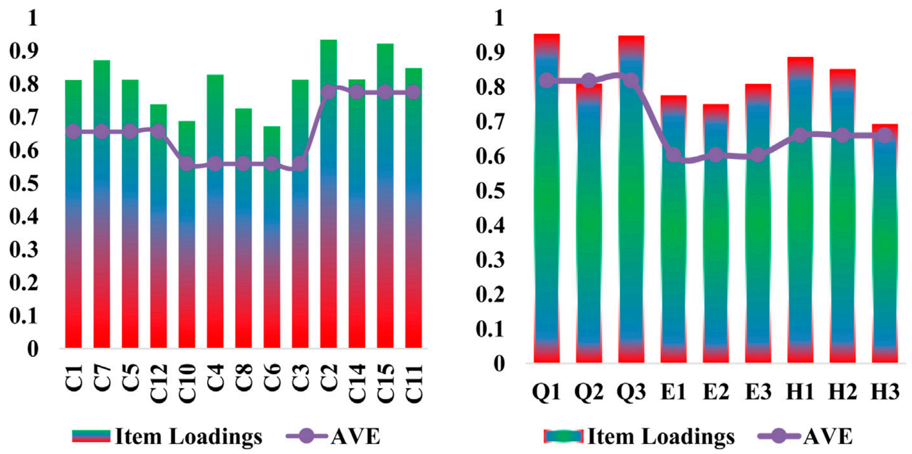

FIGURE 6
Item loadings vs. AVE for formative and reflective constructs items.

values off-diagonal are consistently lower than the AVE values on-diagonal for each concept, indicating robust discriminant validity. This provides strong evidence that the constructs effectively measure separate dimensions of the phenomena under investigation and substantiates the credibility of our study's construct usage.

Table 5 provides the HTMT (Heterotrait-Monotrait) ratio data, a commonly used method for assessing the discriminant validity of a measurement model. This analysis is vital to ensure that the constructs within the model are distinct. The table's diagonal displays the square root of the AVE for each construct, while the numbers below the diagonal represent the HTMT ratios. The HTMT ratio is a crucial metric that must be below 0.90 to confirm discriminant validity. In essence, this metric assesses whether constructs are sufficiently different. In our analysis, all HTMT values are well below the 0.90 threshold, indicating discriminant validity among the constructs (Wazid et al., 2020; Ateya et al., 2022). Each construct effectively captures unique aspects of the phenomena under investigation. To further confirm discriminant validity, we compare the square roots of the AVEs with the HTMT values in the relevant rows and columns. The fact that the AVEs are consistently more significant than the HTMT values reinforces that our model accurately distinguishes between various latent variables (Lee and Kwon, 2020; Lawani et al., 2022). The HTMT analysis supports the notion that the model's components are distinct and effectively measure different aspects of the constructs. This demonstrates the model's accuracy in discerning between various groups and confirms the discriminant validity of our measurement model.

Table 6 illustrates the relationships between individual items and their respective constructs, which are essential for assessing construct validity within our measurement model. It offers insights into the alignment of each item with its intended construct and the potential for capturing unintended aspects. The goal is for items to exhibit strong loadings on their designated constructs and minimal loadings on others (Li and Liu, 2019; Charlesraj and Rakshith, 2020). Reviewing the table, it becomes clear that most items demonstrate substantial loadings on their intended constructs. For instance, items associated with the

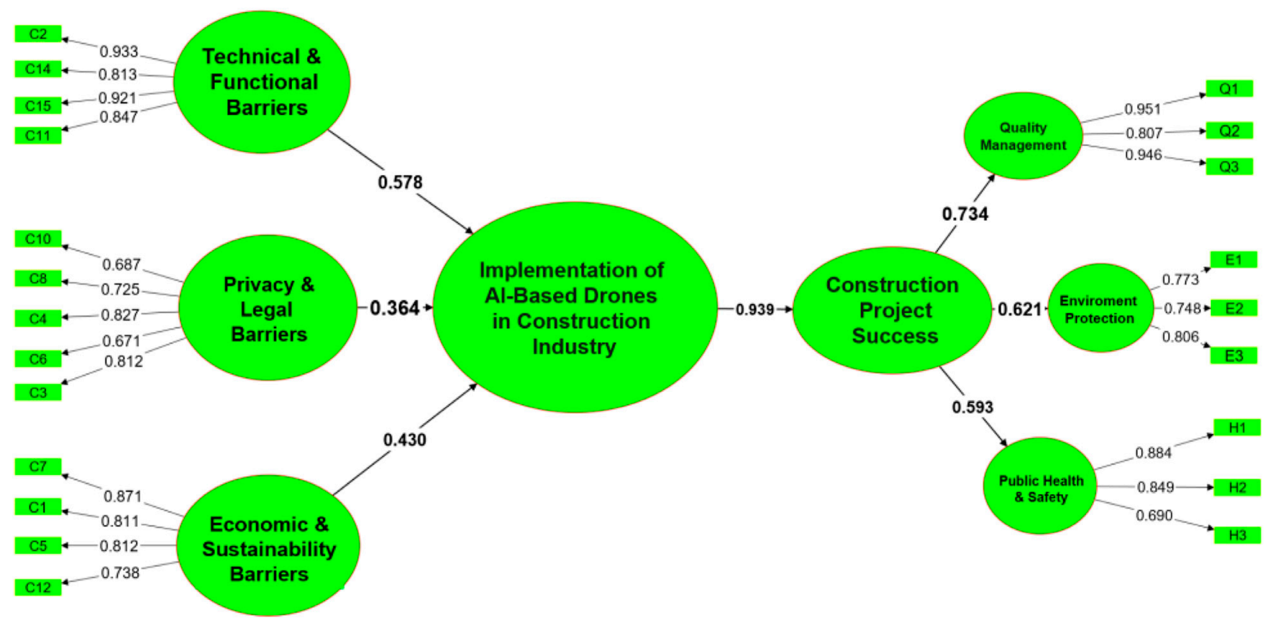

FIGURE 7
Model with items, item loadings, and path coefficients.

TABLE 4 Fornell Larker criteria results.

Constructs	ESB	EPB	PLB	PHS	QM	TFB
Economic and Sustainability Barriers = ESB						
Environment Protection Barriers = EPB	0.298					
Privacy and Legal Barriers = PLB	0.245	0.14				
Public Health and Safety = PHS	0.23	0.335	0.256			
Quality Management = QM	0.22	0.436	0.477	0.27		
Technical and Functional Barriers = TFB	0.221	0.435	0.476	0.265	0.097	

TABLE 5 HTMT analysis results.

Constructs	ESB	EPB	PLB	PHS	QM	TFB
Economic and Sustainability Barriers = ESB	0.81					
Environment Protection Barriers = EPB	0.189	0.776				
Privacy and Legal Barriers = PLB	0.162	0.234	0.747			
Public Health and Safety = PHS	0.188	0.208	0.191	0.812		
Management = QM	0.18	0.332	0.398	0.225	0.904	
Technical and Functional Barriers = TFB	0.173	0.335	0.4	0.221	0.284	0.88

Economic and Sustainability Barriers construct show loadings of 0.811, 0.871, 0.812, and 0.738 for C1, C7, C5, and C12, respectively.

Similarly, items E1, E2, and E3 display loadings of 0.773, 0.748, and 0.806 on the Environmental Protection Barriers construct precisely as intended. However, some exceptions exist where items exhibit significant loadings on additional constructs. For instance, item C2 from the Quality Management construct displays a loading of 0.951 on the Technical and Functional Barriers construct, suggesting it may inadvertently capture aspects of that construct as well. Additionally, item C11 exhibits strong loadings on both the Privacy and legal Barriers and Technical and functional Barriers despite its intended placement in the Quality Management construct. The cross-loadings analysis indicates that, with some notable exceptions, the items effectively measure the targeted constructs rather than unintended ones. These findings inform potential refinements to the measurement scale, ensuring accurate capture of the intended characteristics.

TABLE 6 Cross loadings of items.

Variables	Economic and sustainability barriers (formative group impact rank 2)	Environment protection barriers (reflective group impact rank 3)	Privacy and legal barriers (formative group impact rank 3)	Public health and safety (reflective group impact rank 2)	Quality management (reflective group impact rank 1)	Technical and functional barriers (formative group impact rank 1)
C1	**0.811**	0.194	0.232	0.256	0.301	0.307
C7	**0.871**	0.235	0.15	0.343	0.121	0.112
C5	**0.812**	0.135	0.027	0.348	−0.057	−0.073
C12	**0.738**	−0.023	0.048	0.234	0.147	0.136
E1	0.18	**0.773**	0.194	0.203	0.343	0.34
E2	0.232	**0.748**	0.235	0.255	0.256	0.255
E3	0.064	**0.806**	0.473	0.068	0.198	0.205
C10	−0.055	0.417	**0.687**	−0.029	0.327	0.332
C4	0.232	0.307	**0.827**	0.255	0.256	0.255
C8	0.18	0.136	**0.725**	0.203	0.343	0.34
C6	−0.014	0.39	**0.671**	0.011	0.348	0.353
C3	0.196	0.02	**0.812**	0.21	0.234	0.235
H1	0.271	0.235	0.15	**0.884**	0.121	0.112
H2	0.111	0.194	0.232	**0.849**	0.301	0.307
H3	0.038	−0.023	0.048	**0.69**	0.147	0.136
Q1	0.229	0.318	0.369	0.27	0.251	**0.933**
Q2	0.09	0.259	0.307	0.13	0.107	**0.813**
Q3	0.144	0.319	0.399	0.186	0.046	**0.921**
C2	0.229	0.318	0.369	0.27	0.951	0.933
C14	0.09	0.259	0.307	0.13	0.807	0.813
C15	0.144	0.319	0.399	0.186	0.946	0.921
C11	0.127	0.276	0.326	0.172	0.74	0.847

Bold values are showing significant loadings.

In this scenario, the dependent variable is the frequency with which intelligent drones are used in building projects; hence, the group impact ranking indicates the relative relevance of each construct in making this prediction. Quality Management was shown to have the most significant collective influence, with a grade of 1 (Oudjehane et al., 2019; Hatfield et al., 2020). Quality Management is the most influential factor in using drones with artificial intelligence in the building business. Q1 and Q3 have enormous outer weights in the Quality Management construct, suggesting a stronger connection to the construct. With a group effect value of 1, the Technological and Functional Barriers construct similarly significant in foreseeing the use of AI-based drones in the building sector. C2, C15, and C14 are the heaviest outside elements in this framework. With a group effect value of 2, the Economic and Sustainability construct is relatively significant in foreseeing the widespread use of AI-powered drones in the building sector. Items C7 and C5 have the most ideal outside weights in this structure. With a group effect value of 3, the Privacy and Legal Barriers construct is the least relevant in forecasting the adoption of AI-based drones in the construction business. Also, C16 has been eliminated from this construct, suggesting that it did not play a role in the measurement and may need to be included in future studies (Khalid et al., 2021). Lastly, the group impact score of 3 for Environmental Protection and Public Health and Safety indicates that these concepts are relatively relevant in forecasting the use of AI-based drones in the construction business. Items with outer weights of H1 and H2 are the most important to public health and safety, whereas things with outside consequences of E1 and E2 are the most important to the environment.

5.2.2 Path analysis

The results of the route analysis for the formative constructs are listed in Table 7. Each path's t-value, *p*-value, VIF (variance inflation factor), and SE (standard error) are included in the table. Economic and sustainability Barriers, Privacy and legal Barriers, and Technical and functional Barriers all reveal favourable outcomes for deploying AI-based Drones in the Construction Sector. In particular, the *p*-values for the route coefficients between these three constructs are all less than

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TABLE 7 Path analysis results of formative constructs.

Path	β	SE	t-values	*p*-values	VIF
Economic and Sustainability Barriers	0.430	0.067	7.532	<0.001	1.042
- > Implementation of AI-based Drones in the Construction Industry					
Privacy and Legal Barriers	0.364	0.044	4.516	<0.001	1.203
- > Implementation of AI-based Drones in the Construction Industry					
Technical and Functional Barriers	0.578	0.056	11.394	<0.001	1.208
- > Implementation of AI-based Drones in the Construction Industry					
Overcoming the Barriers to Implementation of Drones in the Construction Industry - > Construction Project Success	0.93	0.004	54.4	<0.001	-
Construction Project Success - > Environment Protection	0.621	0.062	9.885	<0.001	-
Construction Project success - > Public Health and Safety	0.593	0.071	8.552	<0.001	-
Construction Project Success - > Quality Management	0.734	0.034	21.663	<0.001	-

0.001, coming in at 0.430, 0.364, and 0.578, respectively. These three elements are crucial to effectively using drones powered by artificial intelligence in the building sector. It is also important to note that the VIF values for all three constructions are less than 1.5, which is the cutoff number for finding multicollinearity (Feng et al., 2013; Duda et al., 2019; Beiki and Mosavi, 2020). This indicates little correlation between the formative components, suggesting that each adds something novel to the model. Results from the route analysis show that removing economic, sustainability, privacy, legal, technological, and functional hurdles is crucial to expanding the use of drones powered by artificial intelligence in the building sector.

As seen by the high beta coefficient (β = 0.93) and the low *p*-value (0.001), the findings suggest a positive and significant link between the two variables. This indicates that companies are likely to build projects more successfully as they overcome the obstacles of deploying AI-based drones (Urgessa and Esfandiari, 2018; Li et al., 2019; Liu et al., 2021). Taken as a whole, these findings underline the significance of addressing and removing the many barriers that stand in the way of the widespread use of drones powered by artificial intelligence in the building sector. The reflecting constructions' route analysis findings illustrate the connection between environmental preservation, public health and safety, and quality management in successful building projects. Path coefficients reveal the nature and direction of the association between the variables. All three route coefficients are positive and statistically significant (p 0.001), demonstrating that a successful building project significantly improves all three reflective constructs. Success in a building project is most strongly correlated to quality management (β = 0.734), environmental protection (β = 0.621), and public health and safety (β = 0.593). These findings point to a beneficial relationship between environmental protection, public health and safety, quality management, and the success of building projects. The significance of this result in ensuring these goals are attained in the construction sector cannot be overstated. The model with bootstrapping results indicating *p*-values is presented in Figure 8.

The total squares for the Construction Project Success construct are shown in the SS0 column. The sum of squares the model cannot explain is demonstrated in the SSE column. The predicted Construction Project Success value is shown in the Predict-Q^2 column. With an SS0 of 849.000, the model adequately explains a significant fraction of the observed variation in Construction Project Success. With an SSE of 529.479, there is some mystery around the success rate of building projects. Success on a Construction Project is anticipated to be 0.376, as seen in the Predict-Q^2 column. This means the model forecasts a modest degree of Construction Project Success based on the facts. Table 4 shows that the model is a good match for the data and that the other constructs in the model can provide a fair prediction of Construction Project Success (Greene and Myers, 2013). The unaccounted-for variation in Construction Project Success may call for additional research to determine what elements contribute to this concept.

$$Endogenous\,latent\ variable\ (Continous\ Project\ Success)\ SSO = 894.000$$

$$Endogenous\,latent\ variable\ (Continous\ Project\ Success)\ SSE = 529.479$$

$$Endogenous\,latent\ variable\ (Continous\ Project\ Success)\ Predict\ Q^2 = 0.376$$

An R2 of 0.881 shows that the model explains 88.1% of the variation in Construction Project Success. Because the model can present a considerable amount of the observed variation in the dependent variable, it increases its predictive power. Adjusted R2 = 0.881 is near the R2 value; hence, the model is probably not overfitting the data. Model fit is supported by an "excellent" explained size and a "highly predictive" prediction of Construction Project Success using the model's predictors.

$$Endogenous\,latent\ variable\ (Continous\ Project\ Success)\ R^2 = 0.881$$

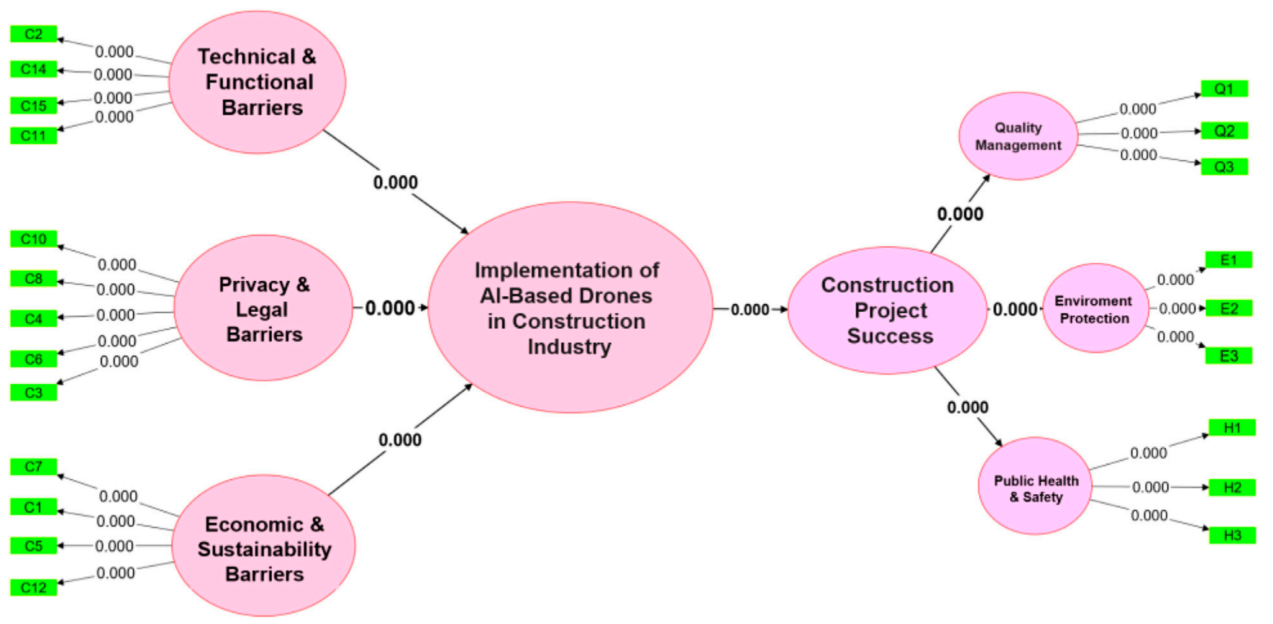

FIGURE 8
Path significance results after bootstrapping analysis.

$$Endogenous\,latent\,variable\ (Continous\ Project\ Success)\ Adjusted\ R^2 = 0.881$$

$$Endogenous\,latent\,variable\ (Continous\ Project\ Success)\ Explained\ Size = Highly\ Predictive$$

The Importance and Performance Index (IPI) of the predictor variable "Overcoming the Barriers to Deployment of AI-based Drones in Construction Industry" is determined from SEM. Respondents placed a high value on this predictor, as demonstrated by its Importance score of 1.810. Respondents with a Performance score of 53.23 think this predictor performs adequately but might need work. The IPI rating is helpful for pinpointing problem spots. With such a high relevance rating, it is clear that removing the obstacles to using drones with artificial intelligence in the building business is crucial. As shown by the score of "moderate," more effort is required to enhance the performance of this predictor, which might be accomplished by more efficient techniques to overcome the obstacles.

$$Predictor\ (\text{Overcoming the Barriers to the Implementation of AI} \\ -\text{based Drones in the Construction Industry) Importance} = 1.810$$

$$Predictor\ (\text{Overcoming the Barriers to the Implementation of AI} \\ -\text{based Drones in the Construction Industry) Performance Index} \\ = 53.23$$

6 Discussion

Technical and Functional Barriers to formative construction include C2 "Integration with current systems drones technology may be difficult to integrate with existing construction systems, posing a hurdle for businesses seeking to embrace this technology," C15 "Some firms may be reluctant to invest in drones technology if they lack the specialized staff required to operate and maintain the drones. C14 "Drone technology operation and maintenance may be difficult and need specialist skills. Some building businesses may be intimidated by this degree of intricacy," and C11, "The absence of standardization in drone technology might make it difficult for businesses to analyze and compare various technologies and choose the best solution for their specific requirements." Four things make up the Technological and Functional Barriers to formative construct, each describing a possible difficulty construction companies may have while attempting to use drones powered by artificial intelligence. Difficulty integrating the technology with preexisting systems, a shortage of qualified personnel to run and maintain the drones, complicated operation and maintenance, and a lack of standardization are all obstacles. The findings support the acceptance of H2: The Deployment of AI-Based Drones in the Construction Industry is Favored by Technological and Functional Barriers. A positive correlation of $\beta = 0.578$ (p 0.001) was found between the constructs of Technical and Functional Barriers and the Implementation of AI-Based Drones in the Construction Industry (Anunciado, 2016; Zaychenko et al., 2018; Ciampa et al., 2019). This suggests that organizations with more technical and functional hurdles to overcome will have difficulty integrating drones powered by artificial intelligence.

Privacy and Legal Barriers formative construct includes C10 "The use of drones technology in construction may be met with opposition from human employees who fear being inspected by drones or who are uncomfortable working alongside AI technology," C8 "There may be regulatory and legal obstacles to the employment of drones technology in the construction industry, notably with safety and liability concerns," C4 "The availability of drones technology may be restricted in some countries or for certain applications, posing a substantial obstacle for businesses operating in those regions or seeking to employ the technology for those purposes," C3 "Concerns remain over the safety and privacy of drones on building sites, especially when operating near humans," and C6 "Some in the construction sector may believe that drones technology is not suited to the specific problems and requirements of construction operations. This impression might make it challenging for certain businesses to implement this technology. The Privacy and Legal Barriers framework highlights potential difficulties for construction companies utilizing AI-based drones. Items in this framework indicate worries about legal and regulatory hurdles, safety and privacy issues, and human workers" reluctance to use this technology. These issues may discourage companies from making the first financial investment necessary to use drones in the building sector. According to the data collected and analyzed for this pathway, the Privacy and Legal Barriers construct positively affects the adoption of AI-Based Drones in the Building Sector. This data shows that companies are more likely to adopt drone technology for construction activities in jurisdictions with lower privacy and regulatory restrictions. Politicians and business leaders must thus address these concerns and lay forth precise rules and regulations for the use of drone technology in the building industry. The empirical findings show that the privacy and Legal Barriers construct a favourable influence on the deployment process of AI-based drones in the construction business (Latteur et al., 2016; Charlesraj and Rakshith, 2020; Çetin et al., 2020). Because of this, we can confidently accept H3, which states that privacy and regulatory restrictions contribute to using AI-based drones in the building business.

Economic and sustainability formative construct include C12: "The present variety of uses for drone technology in the construction industry is still restricted, making it difficult for certain businesses to justify the investment," C5 "To maintain dependability, drone technology may be delicate and requires regular maintenance. This may be a substantial obstacle for certain businesses, especially those with minimal resources," C1 "Drones technology may not be scalable for major construction projects or may need substantial modification to be employed in larger applications, making its widespread adoption challenging," and C7 "Some construction projects may be limited in their usage of drones" technology due to environmental limitations, such as noise or pollution." Information supplied suggests that constraints on usage, maintenance sensitivity, scalability, and environmental issues all figure into the Economic and Sustainability formative construct. These considerations raise concerns about the widespread use of artificial intelligence (AI) drones in the building sector. Economic and sustainability hurdles substantially influence the adoption of AI-based drones in the construction sector, as the path analysis findings show. As a result, we can confidently believe H4, which claims that the Economic and Sustainability hurdles have a beneficial influence on the application of AI-based drones in the construction business (Agapiou, 2020; Sawhney et al., 2020). This indicates that to overcome the constraints and effectively use AI-based drone technology, organizations must consider the economic and sustainability factors, such as the cost-benefit analysis, maintenance needs, scalability, and environmental consequences.

Quality Management reflective construct includes Q1 "For building projects, and drones may offer aerial surveys, site management, and progress monitoring, ensuring quality management," Q2 "Drones may assist in uncovering possible potential concerns and design defects, assuring compliance with construction norms and codes" and Q3 "Drones may be used to gather data about building supplies and equipment, such as measurements, weight, and dimensions, to ensure that the proper materials are utilized in the proper proportions." Three indicators make up the Quality Management reflection construct and show how using AI-based drones in the construction sector may improve the overall quality of projects. The first indication, Q1, describes how quality management may be ensured using drones by conducting aerial inspections, managing the site, and monitoring progress (Goessens et al., 2018a; Rovira-Sugranes et al., 2022). The second indication, Q2, highlights the value of drones in detecting issues and flaws in the design, which is essential for maintaining adherence to building standards and regulations. Q3 demonstrates how drones may collect information on materials and tools in the construction industry, which can then be used to guarantee that the proper resources are utilized. The findings of path analysis support the hypothesis that H5 (Construction Project Success as Influenced by Quality Management) is true when AI-based drones are used in the construction sector. With a beta value of 0.734, the three Quality Management indicators positively and substantially affect the success of construction projects. This indicates that drones equipped with artificial intelligence may be used to enhance quality control and boost the overall success of building projects.

Environmental Protection reflective construct includes E1, "Regularly scanning the building site to discover and monitor any environmental hazards, such as soil erosion, water runoff, and other pollution sources," E2, "Providing thermal imaging and other forms of non-destructive testing to identify possible environmental dangers, such as chemical spills, that might negatively impact the health of local people," and E3 "Monitoring the construction process to guarantee compliance with environmental requirements, such as waste disposal and the use of environmentally friendly building materials." According to the examination of causal relationships, environmental protection is critical in completing construction projects that use reflective constructs. Mainly, it has been established that the three ecological protection indicators of frequent scanning of the construction site, non-destructive testing, and monitoring compliance with environmental regulations all contribute to the success of construction projects (DeYoung, 2018; Li 2019). Using drones powered by artificial intelligence in the construction sector might assist in guaranteeing that projects are carried out in an ecologically friendly way, which in turn can lead to better project outcomes. The research results strongly support hypothesis H6, which states that using AI-powered drones improves the likelihood of a building project's success due to better environmental safeguards.

Public Health and Safety reflective construct include H1, "Real-time monitoring of the construction site to guarantee compliance with safety rules and processes, as well as rapid identification and mitigation of any safety concerns or events," H2, "Providing precise 3D models and maps of the building site, which may aid in the rapid location and evacuation of personnel in the event of an emergency" and H3 "Improving communication and cooperation between project stakeholders may aid in identifying and resolving any possible safety concerns or problems before they become a problem." Three indicators are included in the Public Health and Safety reflective construct to show how intelligent drones in the building have contributed to improved public health and safety. The first indication, H1, emphasizes continuous work site monitoring to check for adherence to safety protocols and prompt detection and resolution of potential problems. H2 is the second indication, and its primary goal is to facilitate the speedy location and evacuation of workers in an emergency by giving accurate 3D models and maps of the construction site. The third indication, H3, stresses increased coordination and communication among project participants to foresee and address potential safety issues. The study's findings support H7, which hypothesizes that using drones equipped with artificial intelligence would improve the success of building projects from the perspective of public health and safety (Kubo and Okoso, 2019; Sawhney et al., 2020). Real-time monitoring of the construction site, accurate 3D models and maps of the building site, and enhanced communication and cooperation between project stakeholders are just some of how the study found that using AI-based drones in construction positively affects public health and safety. These elements work together to make for a better construction site in terms of health and safety, making for a more successful project overall.

Technical and functional constraints, privacy and legal barriers, economic and sustainability barriers, and organizational barriers were all noted in the research as obstacles to the widespread use of AI-based drones in the construction sector. According to the findings, clearing these hurdles is beneficial for introducing intelligent drones into the building sector. The research also concluded that public health and safety, environmental protection, quality control, and economic and sustainability benefit from using AI-based drones in the construction sector, contributing to the success of building projects. Consequently, if obstacles to using drones with artificial intelligence were removed, building projects would be more likely to be successful. Thus, it is reasonable to accept H1 as a whole, which asserts that the success of a building project improves when obstacles to the use of AI-based drones are removed.

6.1 Implications

Two basic types of ramifications may be drawn from the findings of this study: practical and theoretical. With the study's findings in hand, construction companies may better plan for the successful introduction of AI-based drones into their operations. The research's results may be used to inform the development of policies that promote and enable the usage of drones in the construction sector. The study offers a framework for construction companies to evaluate the costs and advantages of using drones equipped with artificial intelligence. The research emphasizes the need to tackle the numerous challenges of implementing AI-based drone deployment to boost public safety, environmental protection, and project quality and efficiency. By examining the effects of AI-based drone deployment across several facets of construction project management, the research gives a holistic knowledge of the influence of such implementation on project success. This research adds to our understanding of the challenges inherent in introducing drones powered by artificial intelligence to the building sector. The study shows the significance of thinking about technological, functional, legal, economic, environmental, and public safety considerations that may affect the success of AI-based drone applications in the construction business (DeYoung, 2018; Li 2019; Rovira-Sugranes et al., 2022). The research offers complex data on how removing roadblocks to using AI-based drones may improve the success rate of building projects. In sum, this research sheds light on the possible upsides and downsides of using drones equipped with AI in the building business. Construction companies and politicians may use the results of this research to develop more efficient strategies for using AI-based drones, which can increase project efficiency, quality, safety, and environmental sustainability.

6.2 Managerial recommendations

This research provides evidence that using drones equipped with artificial intelligence may improve the outcome of building projects. Managers in the construction business should consider investing in this technology to enhance the quality of their projects. Legal and privacy issues, economic and sustainability problems, and scepticism about the technology are all highlighted in the research as potential roadblocks to adoption. Managers must endeavour to remove these obstacles using education and training, communication with stakeholders, and collaboration with technology vendors. The research concludes that drones powered by artificial intelligence may aid in quality control by doing airborne inspections, spotting possible issues and design faults, and compiling information about construction materials and machinery. While looking for ways to improve the quality of their projects, managers should consider deploying drones equipped with artificial intelligence for these tasks. The research concludes that drones powered by artificial intelligence may help ensure the public's wellbeing by keeping tabs on building sites in real time, creating accurate 3D models and maps, and facilitating better communication and collaboration among the project's many parties. Management should prioritize public health and safety by implementing safety rules and deploying AI-based drones for these tasks. The research concludes that drones powered by artificial intelligence may help safeguard the environment by looking for dangers on construction sites, taking thermal images, doing non-destructive tests, and checking for regulatory compliance. While planning a project, managers should think about how it will affect the environment and how they may deploy intelligent drones to lessen the damage. In conclusion, this research provides strong evidence that drones powered by artificial intelligence may significantly improve the outcome of building projects. Managers in the construction sector may set their businesses up for future success by investing in this technology, removing roadblocks to its adoption, and placing a premium on quality management, public health and safety, and environmental impact.

6.3 Limitations and future direction

Although the results are significant, it is essential to note the study's limitations. First, this research is limited to discussing the challenges and opportunities of using drones powered by artificial intelligence in the building sector. More attention should be paid to other aspects that, including company culture and preparation, might impact the success of drone adoption. Second, the research was limited in scope since it only polled construction workers in a single nation; thus, its results cannot be extrapolated to the broader construction sector or other countries. Finally, the survey only looked at how experts felt about using drones with AI, and it did not look at how actual technology users felt about incorporating it into their projects.

Even with the earlier constructs, this work points toward some exciting avenues for further investigation. The construction sector might benefit from more studies into how company culture and preparedness affect the use of artificial intelligence-based drones. Second, the implications of AI-based drones in industries other than military and police operations, such as agriculture and shipping, might be the subject of future research. Finally, comparison research comparing construction industry experts with people who have used drones with artificial intelligence in building projects will illuminate the perception gap. Fourth, the impact of rules and laws on intelligent drones in a building might be studied. Lastly, further study might be done on the ethical and legal ramifications of using AI-powered drones in the building sector.

7 Conclusion

This research aimed to determine what was holding back the construction sector from adopting drones powered by artificial intelligence and what effect doing so would have on the success of building projects. The study's goals were realized using a mixed-methods approach, which included a literature review, in-depth interviews, a pilot survey, and a substantial questionnaire. Barriers to the use of AI drones in construction were highlighted in the research. These included technical and functional hurdles, privacy and legal barriers, and economic and sustainability constraints. The analysis also indicated that construction projects are more likely to be successful if these obstacles can be removed. The study's findings provide a complete model showing how the success of construction projects may be improved by eliminating barriers to using artificial intelligence-based drones in the industry. Public health and safety, quality management, environmental preservation, and the overall effectiveness of building projects were all shown to benefit from removing these obstacles. The research emphasizes the need to resolve the impediments to using AI-based drones in construction and the potential advantages that may be realized. Construction firms may boost their operations, productivity, and the likelihood of a successful project by identifying and eliminating these obstacles.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary materials, further inquiries can be directed to the corresponding author.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the participants was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

Conceptualization, AW and HRA; methodology, AW, HRA, and IO; software, OB, BA, MA, and AB; validation, FA, SH, MAA, NHS, and OB; formal analysis, IO, AW, and OB; investigation, AW and HRA; resources, IO, SH, and MAA; data curation, AW and BA; writing–original draft preparation, AW, AA, and NFS; writing–review and editing, IO, AW, MA, FA, NHS, SA, and AB; visualization, IO, OB, BA, AA, and SA; supervision, IO; project administration, AW. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

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