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Evaluation of success factors of utilizing AI in digital transformation of health and safety management systems in modern construction projects

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ABSTRACT

In the construction industry, managing health and safety concerns is paramount to preventing accidents, injuries, and project delays. The integration of Artificial Intelligence (AI) into existing health and safety management systems holds the potential for significantly improving risk detection, mitigation, and overall management [1,2,3]. However, despite the evident benefits of AI in this domain, there remains a notable gap in the literature concerning the essential factors for successful implementation [4,5]. This study aims to address this gap by meticulously analyzing the key elements that contribute to the success of AI integration into the digital transformation of health and safety management systems within cutting-edge construction projects. Our methodology involved the identification of 25 factors, drawn from prior research and industry consensus. These factors were subjected to rigorous analysis, including Exploratory Factor Analysis (EFA) following a pilot survey with field experts and Structural Equation Modeling (SEM) using data obtained from a comprehensive questionnaire distributed among a representative sample of construction industry experts. The study's findings underscore the paramount importance of six critical constructs in determining the success of AI implementation in construction health and safety management systems: Adaptability, Operation, Management, Reliability, Integration, and Knowledge. These findings provide valuable insights for enhancing safety measures in the construction industry through AI-driven solutions.

1. Introduction

Health and safety management in current building projects is increasingly being handled digitally. Health and safety management systems for construction projects may benefit significantly from using artificial intelligence (AI). On the other hand, several vital aspects will determine how effective the use of AI in health and safety management systems will be [6,7]. This study's overarching goal is to assess the criteria necessary to successfully use artificial intelligence in the digital transformation of current health and safety management systems in cutting-edge building projects. The term "digital transformation" describes the widespread adoption of digital technology throughout an organization, which leads to significant shifts in how organizations function and provide value to their consumers [4]. Managers use health and safety management systems to manage, monitor, and enhance the health and safety performance of a building project.

The term "artificial intelligence" (AI) is used to describe the capacity of computers to carry out activities that would generally need human intellect [5]. There is a central knowledge vacuum in assessing the success aspects of applying AI in the digital transformation of current health and safety management systems, despite the growing use of AI in health and safety management systems on construction projects [8,9]. It is essential to understand the effects of AI on health and safety outcomes in construction projects and the crucial elements influencing its

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successful implementation in health and safety management systems. The construction business has a disproportionately high number of accidents and deaths [10,11]. Health and safety management systems that use artificial intelligence have the potential to enhance safety results significantly and minimize accident and injury risks on construction projects [2].

In recent years, the construction industry has witnessed a growing interest in the potential applications of Artificial Intelligence (AI) to enhance health and safety management. Several studies have delved into the integration of AI technologies to mitigate risks and improve safety outcomes on construction sites. Notable research in this area has focused on the utilization of AI for risk prediction, hazard recognition, and real-time monitoring. These studies have contributed valuable insights into the feasibility and potential benefits of AI-driven solutions in construction safety. While previous research has laid the groundwork, this study seeks to make distinctive contributions by thoroughly examining the critical factors that underpin the success of AI implementation in construction health and safety management systems. By conducting comprehensive analyses, including Exploratory Factor Analysis (EFA) and Structural Equation Modeling (SEM), we aim to provide a deeper understanding of the key determinants that influence the effectiveness of AI applications in this domain. Through this research, we aim to bridge the gap in the literature and offer practical insights that can inform decision-makers and practitioners in the construction industry as they embark on the digital transformation journey for health and safety management.

Thus, this study aims to contribute to the creation of efficient digital transformation strategies for construction projects by shedding light on the aspects that contribute to the success of using AI in health and safety management systems [12]. The main goal of this study is to determine what elements contribute to the effective use of artificial intelligence in the digital transformation of current health and safety management systems in cutting-edge building projects. Better health and safety results and lower accident and injury risks on construction projects may result from this study's influence on establishing a complete framework for the appropriate application of AI in health and safety management systems. More widespread adoption of AI in the construction industry's health and safety management systems may be facilitated by this study's findings for policymakers and industry stakeholders.

In the following sections, we presented literature review, methodology, data collection procedures, and the statistical techniques employed in our analysis. We then presented the key findings, discuss their implications, and conclude with implications for industry practitioners and future research directions. Our approach to developing this study is rooted in a combination of comprehensive literature review, expert consultation, and rigorous data analysis. We have leveraged insights from previous research and industry consensus to identify the 25 factors central to AI implementation in construction health and safety management. These factors were subjected to statistical scrutiny, involving both Exploratory Factor Analysis and Structural Equation Modeling, to extract meaningful constructs and relationships. This approach ensures that our findings are firmly grounded in both existing knowledge and empirical evidence.

2. Background

The construction industry's interest in Artificial Intelligence (AI) has increased in recent years owing to the field's optimistic outlook on AI's ability to enhance worker health and safety. Stakeholders, including workers, managers, and other relevant parties who may offer input on the system's design and execution, must be included if AI is to be adopted successfully [13,14]. Better health and safety results, fewer accidents, and higher productivity are just a few examples of how the cost of adopting AI systems may be offset if done well [1,15]. When integrating AI into health and safety management systems, it is crucial to examine ethical factors such as the potential for discrimination and the need to operate fairly and justly. Deploying AI technologies in the construction sector requires close cooperation across IT, safety, and operations departments [16]. Artificial intelligence systems need to be built to detect and manage health and safety issues, which includes spotting dangers, determining the likelihood and severity of those risks, and coming up with solutions to those problems [17,18]. In addition, construction companies should encourage research into novel data gathering and analysis techniques or the use of AI to uncover new dangers to improve health and safety management systems [19,20]. In order for AI systems to become more valuable over time, they should be built with the capacity to learn and develop on their own via the incorporation of user input, the tracking of performance, and the application of appropriate modifications [21,22]. Moreover, AI systems must be constructed to be reliable and capable of handling unexpected events and producing correct results by developing the system to manage missing data or mistakes and verifying the system before deployment [3].

A wide range of people, including workers, supervisors, and employers, must work together and provide feedback for AI to be successfully used in health and safety management systems [23,24]. Their participation from the get-go is essential to provide helpful criticism of the system's design and implementation [25,26,27]. Implementing an AI system should be affordable and reasonable in light of the possible health, safety, and productivity gains that may result from doing so. Potential sources of prejudice or discrimination should be eliminated, and the system should be built to treat all users relatively [28]. The system has to be set up to detect dangers, evaluate the likelihood and severity of those hazards, and come up with plans to lessen those risks [29,30]. The construction industry has to adopt a more progressive mindset and investigate novel applications of AI in health and safety management [31,32,33]. AI or other novel data-gathering and analysis techniques may uncover such hidden dangers. Employees and managers need proper training and instruction to make the most of the AI system [34].

This can entail teaching users how to use the system's functions, analyze data, and draw conclusions. The AI system must grow with the project, process massive amounts of data, and provide precise, real-time results. All system operation aspects should be tracked in real-time to quickly identify and fix any problems to keep the system running smoothly [35]. Transparency in the AI system's decision-making process includes thoroughly explaining the algorithms used, the data used, and the results obtained [36,37,38]. The results produced by the system must be reliable and applicable, built on accurate and high-quality data, and flexible enough to account for changes in the scope of the project or the data sources used [39,40]. There should be a way to monitor and correct any omissions or inaccuracies in the AI system's choices and activities [41,42]. Last but not least, successful AI adoption requires clear and concise communication of the system's benefits to all relevant parties and their understanding of the system's functioning and impact [43,44].

In addition to handling massive volumes of data and providing precise results in real time, the AI system must be designed to grow with the size and complexity of the project [5,45]. The system should be constantly monitored to ensure it is operating correctly and accomplishing its objectives, and its decision-making process should be made public by explaining the system's algorithms, data inputs, and final results [46]. The AI system's ability to learn from new data and adapt to environmental changes is essential for accurate and helpful results [47,48]. Changes in regulations, project scope, or data sources, as well as other external factors, must be able to be reflected in the system with little effort [49,50,51]. Ultimately, accounting for the AI system's decisions and actions is crucial to keeping an audit trail of those decisions and holding the system responsible for its mistakes [4,52]. To ensure the system runs appropriately and ethically, evaluating factors like the potential for prejudice or discrimination is essential. Companies in the construction industry should promote experimentation with AI to improve health and safety management systems [53,54,55]. This might include exploring new data gathering and analysis techniques or utilizing AI to discover new hazards or threats. Following Table 1 summarizes all success factors identified from the literature review and expert opinion.

3. Methodology

This study used a qualitative literature review approach to identify 25 contributors to success. Thereafter, professional opinion corroborated these elements. The 25 success criteria were tested in a pilot study with 192 individuals from the construction sector of Tabuk, Saudi Arabia, and exploratory factor analysis (EFA) was used to analyze the data. After collecting data from the pilot group, a more extensive survey questionnaire was sent to 258 people again from the construction sector of Tabuk, Saudi Arabia. The primary survey data was then subjected to structural equation modeling (SEM) analysis to determine which aspects and constructs of AI adoption in health and safety management systems strongly correlated with survey respondents' perceptions of success. The overall goal of this study was to identify and assess success criteria for deploying AI in health and safety management systems using qualitative and quantitative approaches. Because of the pilot survey and the complete questionnaire survey, we were able to incorporate a vast sample size and a variety of views in our research. The data were statistically analyzed with precision using EFA and SEM. Fig. 1 presents the methodology of this research.

3.1. Exploratory factor analysis

To further understand the relationship between the 25 success variables uncovered in the literature research, an exploratory factor analysis (EFA) was carried out. Each of the 6 components in the solution found by the EFA has an eigenvalue more extensive than one [7]. Success factors were shortened by including only those that had factor loadings of 0.40 or higher in the associated element. The interpretability of the factors was improved by using the Varimax rotation technique, which maximized the variance of the factor loadings. The EFA analysis helped reveal the success factors' underlying factor structure and condensed them into four key components [56].

3.2. Development of SEM model

3.2.1. Demographics

The presented demographics (Fig. 2) of main questionnaire survey reveal how the respondents are dispersed geographically, educationally, experientially, and professionally. Sixty-five percent of respondents have a master's degree, with another sixteen percent holding a doctorate. Just 5 % of respondents are between the ages of 21 and 25, while 41 % are between the ages of 31 and 35. Most responders (37 %) have experience ranging from 5 to 10 years, while 29 % have experience spanning 11–15 years. When broken down by occupation, 41 % of respondents are safety managers, 33 % are civil engineers, and 13 % are project managers. Statistics show that most responders have at least a master's degree and are employed in fields like safety management, civil engineering, or project management, indicating they are likely to have extensive relevant expertise. The study was performed among a select group of professionals; thus, their responses may need to be more indicative of the public.

Structural equation modeling (SEM) aims to examine how observable variables are connected to latent components. Construct convergent validity and discriminant validity, as well as item loadings on those constructs, were used to evaluate the measurement model. Factor loadings, average variance extracted (AVE), and composite reliability (CR) were analyzed to determine convergent validity [83]. In order to test for discriminant validity, we computed the average squared correlations between each construct to compare with the AVE of each

Table 1
Identified success factors of AI.

Sr. #	Success Factors	References
1	To guarantee the effective adoption of AI, stakeholders must be included in the process from the outset. These may include employees, managers, and other stakeholders who can give insightful feedback on the system's design and execution.	[48,56]
2	The expense of deploying an AI system must be fair and justified. This may include assessing the cost savings and advantages that the system will bring to the project through enhanced health and safety, fewer accidents, and higher productivity.	[57,58]
3	The use of artificial intelligence in health and safety management systems should examine ethical issues, such as the possibility of prejudice or discrimination, and ensure that the system runs honestly and fairly.	[59,60]
4	Collaboration between IT, safety, and operations departments.	[61]
5	The AI system should be developed to detect and manage health and safety concerns associated with detecting possible dangers, assessing the probability and severity of risks, and devising risk mitigation methods.	[57,59]
6	construction firms should support innovation in the use of AI to enhance health and safety management systems. This may include investigating new data collection and analysis methods or using AI to uncover new dangers or threats.	[62,63]
7	AI systems should be created with the capacity for ongoing improvement over time. This may include integrating user input, monitoring the system's performance, and making necessary improvements to enhance the system's efficacy.	[57,60]
8	Artificial intelligence (AI) systems should be built to be robust and dependable so that they can manage unforeseen scenarios and provide correct results. This may include designing the system to accommodate missing data or data mistakes and testing and validating the system before deployment.	[64,65]
9	Employees and supervisors must be educated on utilizing the AI system. Training may involve training on the system's features, data processing, and how to interpret the findings.	[59,61]
10	The AI system must be built to scale with the size and complexity of the project. It should be capable of handling a high amount of data and delivering accurate findings in real-time.	[66,67]
11	The AI system should be continually monitored to verify that it operates as intended. This may include monitoring the system's correctness, identifying and resolving any flaws, and ensuring the system achieves its goals.	[68,69]
12	The AI system's decision-making process should be visible. This may include detailed descriptions of the system's algorithms, data inputs, and outcomes.	[6,70]
13	The artificial intelligence system should depend on precise and high-quality data to deliver trustworthy and relevant outcomes.	[62,63]
14	The artificial intelligence system should be built to learn from new data and adapt to environmental changes. This may include integrating worker and management input to enhance the system's efficacy.	[61,67]
15	The AI system should be adaptable enough to accommodate project and environment changes. Changes in rules, project scope, or data sources are examples.	[59,71]
16	The AI system's choices and actions should be accounted for. This may involve establishing an audit record of the system's preferences and ensuring the system is accountable for any omissions or mistakes.	[57,60]
17	The effectiveness of AI adoption in health and safety management systems is contingent on the quality and precision of the data. Data from diverse sources must be trustworthy, consistent, and current.	[58]
18	AI systems should have an interface that is user-friendly, simple to use, and accessible to all stakeholders. The interface should be user-friendly and deliver relevant information.	[72,73]
19	The AI system should be built to provide quantifiable, trackable, and evaluable outputs. This may include decreasing accidents, enhancing worker productivity, or lowering project expenses.	[74,75]
20	To leverage the advantages of AI, it is necessary to link the system with current health and safety management systems. This may include data exchange, system interoperability, and	[76,77]

(*continued on next page*)

Table 1 (*continued*)

Sr. #	Success Factors	References
	interaction with other construction industry-related technologies.	
21	The AI system should relate to current health and safety management systems and procedures to guarantee smooth operation and data exchange.	[78,79]
22	AI can analyze vast quantities of data to detect patterns and tendencies, which may assist in foreseeing possible dangers and avoiding mishaps. To get the finest outcomes from artificial intelligence, it is essential to guarantee that the algorithms are appropriately constructed, and the data is accurately processed.	[80,81]
23	The AI system shall adhere to all applicable health and safety norms and standards. These include data privacy, security, and worker safety standards.	[64,82]
24	The efficacy of the AI system should be determined by measuring its performance against established criteria. This may include assessing the system's precision, timeliness, and effect on health and safety outcomes.	[65,83]
25	Good communication is essential for successfully adopting AI in health and safety management systems. This may include conveying the system's advantages to stakeholders and ensuring they comprehend how it operates.	[7,56]

construct. The connections between the formative and reflective components were then analyzed using the structural model. Convergent and discriminant validity analyses of the measuring model were conducted, and the direct and indirect impacts of the formative constructs on the reflective construct were examined in the structural model [65].

3.2.2. Fornell and lacker criteria

While doing structural equation modeling, the Fornell and Larcker criteria are often used to evaluate the constructs' discriminant validity. As criteria, we looked at the ratio of the variation captured by the construct's components to the variance attributable to measurement error, represented by the square root of the AVE of the construct [82]. The criteria additionally consider the square roots of the AVEs of the relevant conceptions in comparison to their respective correlations. For a model to pass the Fornell and Larcker test, the square root of the AVE of each construct must be larger than the correlation of that construct with any other construct in the model. That's evidence of discriminant validity, which means the concept captures more independent variation than variance it shares with other constructs [64].

3.2.3. HTMT ratio

We also used the Heterotrait-Monotrait (HTMT) ratio to evaluate discriminant validity (SEM). It's a standard method for checking whether a model component can be separated from others in the model [81]. The HTMT ratio evaluates the degree of similarity between two constructs regarding the similarity between items within the same construct. To prove that the two constructions are distinct, the HTMT ratio should preferably be smaller than 0.85. If the variances of the two constructs are less than this threshold, then the shared variance is less than the variances of the individual constructs. By calculating the HTMT ratio for each pair of components in the model, researchers may evaluate the model's discriminant validity in SEM. Having an HTMT ratio over 0.85 indicates that the constructs are too connected and aren't distinguishable enough from one another [78].

3.2.4. Predictive relevance

Predictive relevance is a statistical metric for evaluating a model's prognostic accuracy. Since it measures the model's predictive efficacy, it is a vital criterion for evaluating SEM. The Q^2 statistic and the coefficient of determination (R^2) are often used to assess the predictive value of a model. R^2 is a statistical measure of how much of the total variation in the dependent variable can be accounted for by the model's independent variables [64,65]. Extending R^2, Q^2 assesses how well the model can predict data that was not used to estimate it. Q^2 assesses how far the new data deviates from the projected values. If the Q^2 score is high, the model is highly predictive and provides reliable predictions.

3.3. Validation check

A brief survey questionnaire was utilized to verify the generated structural model. The validation survey included contractors, consultants, and clients as the primary participants in this research. The purpose of validation would have been to confirm the practical applicability of the developed structural model so that appropriate actions could be taken to evaluate the success factors of implementing AI in the digital transformation of existing health and safety management systems in contemporary construction projects. Twenty-three invited experts participated in the validation survey. Five crucial questions were developed to determine the model's validity, including,

- Q1: Are the success factors proposed in the model are the correct for utilizing AI in digital transformation of existing health and safety management systems in modern construction projects?
- Q2: Is the model reasonable for identifying the success factors for utilizing AI in digital transformation of existing health and safety management systems in modern construction projects?

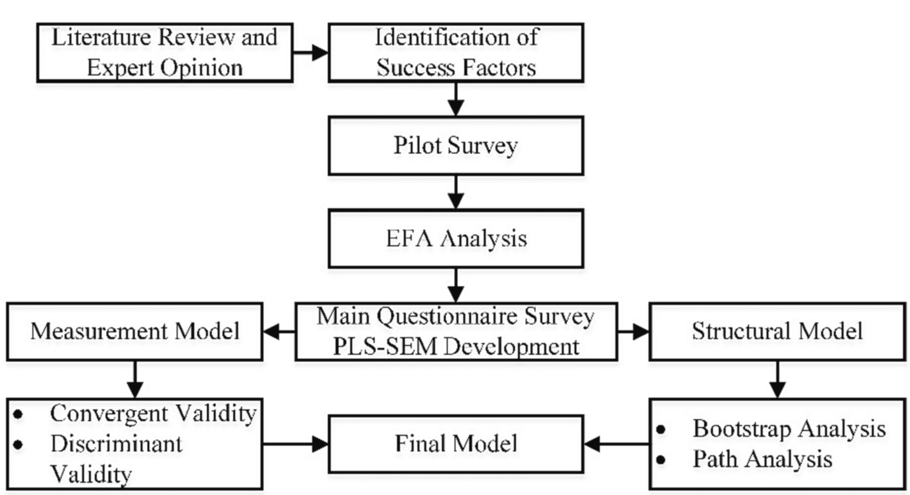

Fig. 1. Flow chart of the work.

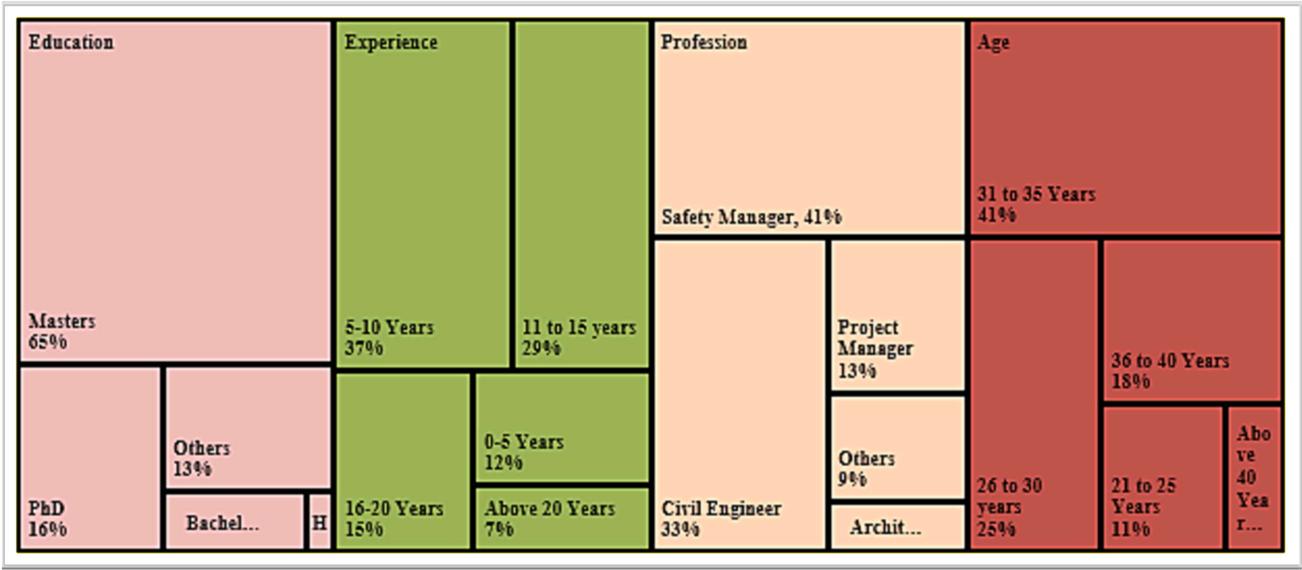

Fig. 2. Demographic details.

- Q3: Can you clearly understand and adopt the factors indicated between constructs of factors and success of utilizing AI in digital transformation of existing health and safety management systems in modern construction projects.?
- Q4: Are the factors presented in the structural model reasonable for becoming the reasons behind success of utilizing AI in digital transformation of existing safety and health management systems in modern construction?
- Q5: Do you find the study results reasonable?

4. Results

4.1. EFA analysis

Results from an EFA indicate that 22 items (variables) were loaded onto six components. Table 2 presents the rotated component matrix of all factors. As the eigenvalues of the components are more than 1, it may be concluded that these six components account for a substantial amount of the observed variation. Component loadings provide information about the strength of the association between a given item and a given component. An item's high loading on a particular component indicates a strong connection. Items with loadings of 0.4 or greater on an element are essential in this study.

Table 2
Exploratory Factor Analysis output.

Variables	1	2	3	4	5	6
AI-SF17	0.843					
AI-SF9	0.814					
AI-SF6	0.802					
AI-SF14	0.790					
AI-SF22		0.767				
AI-SF10		0.725				
AI-SF11		0.713				
AI-SF19		0.698				
AI-SF25		0.654				
AI-SF1			0.712			
AI-SF23			0.701			
AI-SF2			0.695			
AI-SF3			0.684			
AI-SF20				0.823		
AI-SF24				0.794		
AI-SF4				0.705		
AI-SF8					0.807	
AI-SF12					0.777	
AI-SF16					0.709	
AI-SF18						0.824
AI-SF7						0.812
AI-SF15						0.707
Eigen Value	5.61	4.64	4.11	3.26	2.77	2.13
% Variance						
Extraction	AI.SF5, AI. SF21, AI. SF13					

In particular, AI-SF17, AI-SF9, AI-SF6, and AI-SF14 contribute heavily to Component 1 loadings. Since its contents pertain to comprehending machine learning algorithms and programming, this subcomponent may stand in for the idea of "Machine Learning." The factors of AI-SF22, AI-SF10, AI-SF11, and AI-SF19 contribute heavily to Component 2. This component might reflect the notion of "Data Analysis" since these things are connected to analyzing data and creating predictions based on the data. The AI-SF5, AI-SF21, and AI-SF13 all have substantial loadings on component 3, as the contents of this subcomponent pertain to finding patterns and correlations in data. High loadings from AI-SF25, AI-SF1, AI-SF23, AI-SF2, and AI-SF3 may be found in Component 4. As these things are associated with processing and interpreting huge volumes of data, they may stand in for the idea of "Big Data." High loadings from AI-SF20, AI-SF24, and AI-SF4 may be found in Component 5. High loadings are found for AI-SF18, AI-SF7, AI-SF15, AI-SF8, and AI-SF12 on component 6. High loadings on both Component 1 and Component 6 can be seen for the variables AI-SF16 and AI-SF18.

The EFA concludes that the 22 items may be reduced to 6 main categories representing various ideas in the area of AI. Items with the most significant loadings on each component are used to make inferences about the components, and these inferences are subject to variation depending on the specific context and the researcher's background and expertise in the area.

For AI to be successfully implemented in the construction sector's health and safety management systems, the AI Success Phase model lists many essential success elements. Knowledge, operation, management, integration, reliability, and adaptability are the six main classes into which these aspects may be sorted, as indicated in Table 3.

The Knowledge success elements discovered stress the need for trustworthy information for the widespread use of AI. Data gathered by construction companies must be reliable, consistent, and up-to-date [7]. Training workers and managers to make the most of the AI system by analyzing the results and drawing conclusions is also crucial.

The discovered Operation category success characteristics highlight the need for scalable, monitored AI systems that can provide observable

Table 3
Success factors and their categories obtained from EFA.

AI Success Phase	Assigned Code	Success Factor	Description
Knowledge	AI-SF17	Data quality	The effectiveness of AI adoption in health and safety management systems is contingent on the quality and precision of the data. Data from diverse sources must be trustworthy, consistent, and current.
	AI-SF9	Learning	Employees and supervisors must be educated on utilizing the AI system. Training may involve training on the system's features, data processing, and how to interpret the findings.
	AI-SF6	Innovation	Construction firms should support innovation in using AI to enhance health and safety management systems. This may include investigating new data collection and analysis methods or using AI to uncover new dangers or threats.
	AI-SF14	Educating	The artificial intelligence system should be built to learn from new data and adapt to environmental changes. This may include integrating worker and management input to enhance the system's efficacy.
Operation	AI-SF22	Data analysis	AI can analyze vast quantities of data to detect patterns and tendencies, which may assist in foreseeing possible dangers and avoiding mishaps. To get the finest outcomes from artificial intelligence, it is essential to guarantee that the algorithms are appropriately constructed, and the data is accurately processed.
	AI-SF10	Scalability	The AI system must be built to scale with the size and complexity of the project. It should be capable of handling a high amount of data and delivering accurate findings in real-time.
	AI-SF11	Monitoring	The AI system should be continually monitored to verify that it operates as intended. This may include monitoring the system's correctness, identifying and resolving any flaws, and ensuring the system achieves its goals.
	AI-SF19	Measurable	The AI system should be built to provide quantifiable, trackable, and evaluable outputs. This may include decreasing accidents, enhancing worker productivity, or lowering project expenses.
	AI-SF25	Communication	Good communication is essential for successfully adopting AI in health and safety management systems. This may include conveying the system's advantages to stakeholders and ensuring they comprehend how it operates.
Management	AI-SF1	Stakeholder engagement	To guarantee the effective adoption of AI, stakeholders must be included in the process from the outset. These may include employees, managers, and other stakeholders who can give insightful feedback on the system's design and execution.
	AI-SF23	Standards	The AI system shall adhere to all applicable health and safety norms and standards. These include data privacy, security, and worker safety standards.
	AI-SF2	Economic management	The expense of deploying an AI system must be fair and justified. This may include assessing the cost savings and advantages that the system will bring to the project through enhanced health and safety, fewer accidents, and higher productivity.
	AI-SF3	Ethics	The use of artificial intelligence in health and safety management systems should examine ethical issues, such as the possibility of prejudice or discrimination, and ensure that the system runs honestly and fairly.
Integration	AI-SF20	Integration with the existing system	To leverage the advantages of AI, it is necessary to link the system with current health and safety management systems. This may include data exchange, system interoperability, and interaction with other construction industry-related technologies.
	AI-SF24	Precision	The efficacy of the AI system should be determined by measuring its performance against established criteria. This may include assessing the system's precision, timeliness, and effect on health and safety outcomes.
	AI-SF4	Collaboration	Collaboration between IT, safety, and operations departments.
Reliability	AI-SF8	Robustness	Artificial intelligence (AI) systems should be built to be robust and dependable so that they can manage unforeseen scenarios and provide correct results. This may include designing the system to accommodate missing data or data mistakes and testing and validating the system before deployment.
	AI-SF12	Transparency	The AI system's decision-making process should be visible. This may include

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Table 3 (*continued*)

AI Success Phase	Assigned Code	Success Factor	Description
			detailed descriptions of the system's algorithms, data inputs, and outcomes.
	AI-SF16	Accountability	The AI system's choices and actions should be accounted for. This may involve establishing an audit record of the system's options and ensuring the system is accountable for any omissions or mistakes.
Adaptability	AI-SF18	User friendly	AI systems should have an interface that is user-friendly, simple to use, and accessible to all stakeholders. The interface should be user-friendly and deliver relevant information in a simple way.
	AI-SF7	Continuous improvement	AI systems should be created with the capacity for ongoing improvement over time. This may include integrating user input, monitoring the system's performance, and making necessary improvements to enhance the system's efficacy.
	AI-SF15	Compliance	The AI system should be adaptable enough to accommodate project and environment changes. Changes in rules, project scope, or data sources are examples.

results [56]. An excellent artificial intelligence system for the construction industry will be able to process vast amounts of data, be constantly evaluated for its effectiveness, and provide measurable results that can be tracked and analyzed.

Stakeholder involvement, compliance with relevant health and safety rules and standards, sound financial management, and a commitment to ethics are highlighted by the identified success criteria in the Management category [82]. Employees, supervisors, and anyone interested in the construction company's new system and who can provide suggestions for improving it should be included in the adoption process [80].

Integrating the AI system with preexisting health and safety management systems is highlighted by the identified success criteria in the Integration category. The AI system must communicate with other systems already in place, sharing data and working with different technologies used in the building sector [76].

The Reliability category's stated success criteria highlight the significance of trustworthy AI systems. The AI system has to be built to handle unexpected situations and provide reliable results, even if some data is absent or there are some flaws [70].

Lastly, the Adaptability success elements highlight the significance of user-friendliness, continual development, and flexibility to changing project and environmental circumstances. The AI system must have a straightforward interface that provides the necessary data quickly [6]. To top it all off, the system has to be built with continuous development in mind, from gathering user feedback to keeping tabs on how well things are working.

4.2. Structure equation modelling (SEM) and analysis

The results of a structural equation modeling (SEM) study performed on the model's constructs are shown in the table below regarding their reliability and validity. To determine the consistency and validity of the constructs, we calculated Cronbach's alpha values, composite reliability (rho-a and rho-c), and average variance extracted (AVE) [57]. The obtained reliability and validity findings are presented in Table 4. The results suggest that the model's structures are generally reliable and valid. All constructs have Cronbach's alpha values over 0.7, offering excellent internal consistency among the items used to measure them. The trend of Cronbach alpha, composite reliability and AVE is presented in Fig. 3. Good convergent validity may be inferred from the high composite reliability (rho-a and rho-c) values (0.793 to 1.084). The variation explained by the measurements of the concept (AVE values), which range from 0.614 to 0.77, is likewise respectable. The AVE values are higher than the cutoff value of 0.5, suggesting that each concept has sufficient convergent validity [59]. The observed relationship significance of items and their constructs with the latent variable is presented in Fig. 4. Fig. 5 summarizes the intensity of the impact of constructs on the latent variable. The results of the SEM analysis support the validity and reliability of the model's components, suggesting that it may be used effectively to evaluate the variables impacting the implementation of AI in construction sites' health and safety management systems.

The observed relationship significance of items and their constructs with the latent variable is presented in Fig. 4. AI-SF2, AI-SF25, and AI-SF9 were not significant from the analysis because of low loading than 0.6. It is the reason hat these three factors excluded. Thea most critical construct is adaptability with maximum relationship coefficient, while the least one is integration construct. Further the model is presenting the statistical significance which confirms the importance of constructs for the latent variable involved in the model. Fig. 5 summarizes the intensity of the impact of constructs on the latent variable. The high degree impact in this regard is made by the knowledge construct and least one is indicated by reliability construct, which can be considered to be the final model with path coefficients.

The empirical correlation matrix of all success factors is presented in Table 5. Correlation coefficients between each variable and every other variable in the sample are shown in the table. The value of a correlation coefficient between any two variables indicates the closeness of that relationship [35]. The range of correlation coefficients is from −1 to 1, with values closer to −1 suggesting a robust negative association, values more comparable to 1 indicating a strong positive relationship, and values more relative to 0, meaning a weak or no connection. For instance, the weakly positive association between AI-SF1 and AI-SF10 is shown by a correlation value of 0.12.

Similarly, a strong positive link exists between AI-SF12 and AI-SF8, with a correlation value of 0.805. Each variable's correlation with itself is 1, shown along the diagonal of the matrix, which runs from the top left to the bottom right. Research often uses correlation matrices to probe interrelationships and identify trends [42]. By showing the relationships between variables, these matrices may aid in identifying explanatory variables and guide the future investigation.

4.2.1. Second order analysis

The discriminant validity of constructs in a measurement model may be assessed using the Fornell-Larcker criteria, a statistical method. It evaluates the constructs' average variance extracted (AVE) values

Table 4
Model reliability and validity findings.

Constructs	Cronbach's alpha	Composite reliability (rho-a)	Composite reliability (rho-c)	The average variance extracted (AVE)
Adaptability	0.846	0.845	0.909	0.77
Integration	0.815	0.843	0.891	0.732
Knowledge	0.829	0.837	0.898	0.745
Management	0.836	0.902	0.899	0.749
Operation	0.792	0.793	0.864	0.614
Reliability	0.775	1.084	0.865	0.686

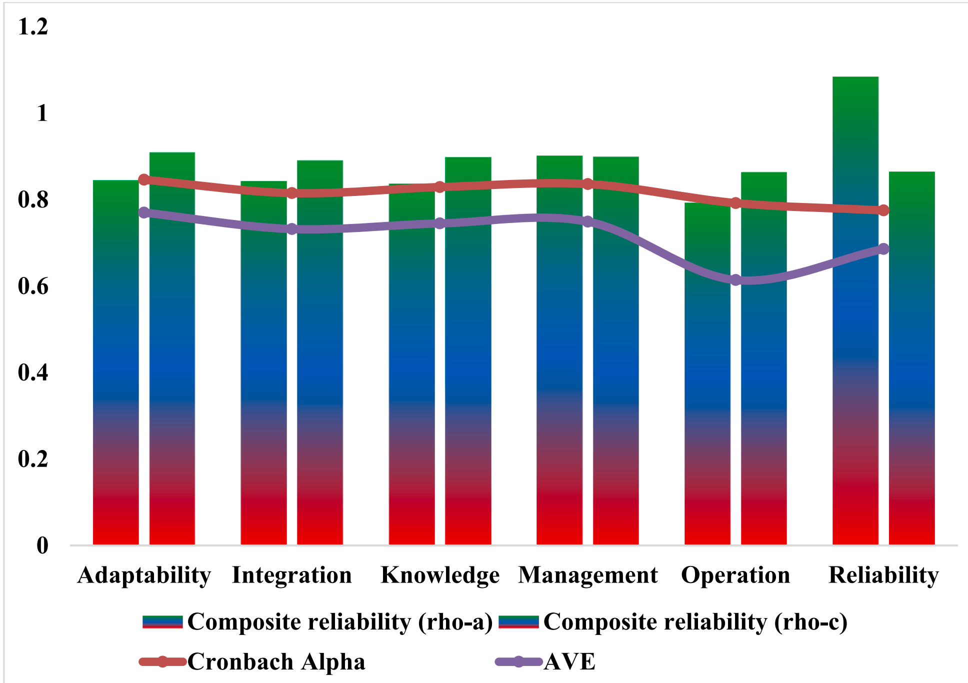

Fig. 3. Trend of reliability statistics.

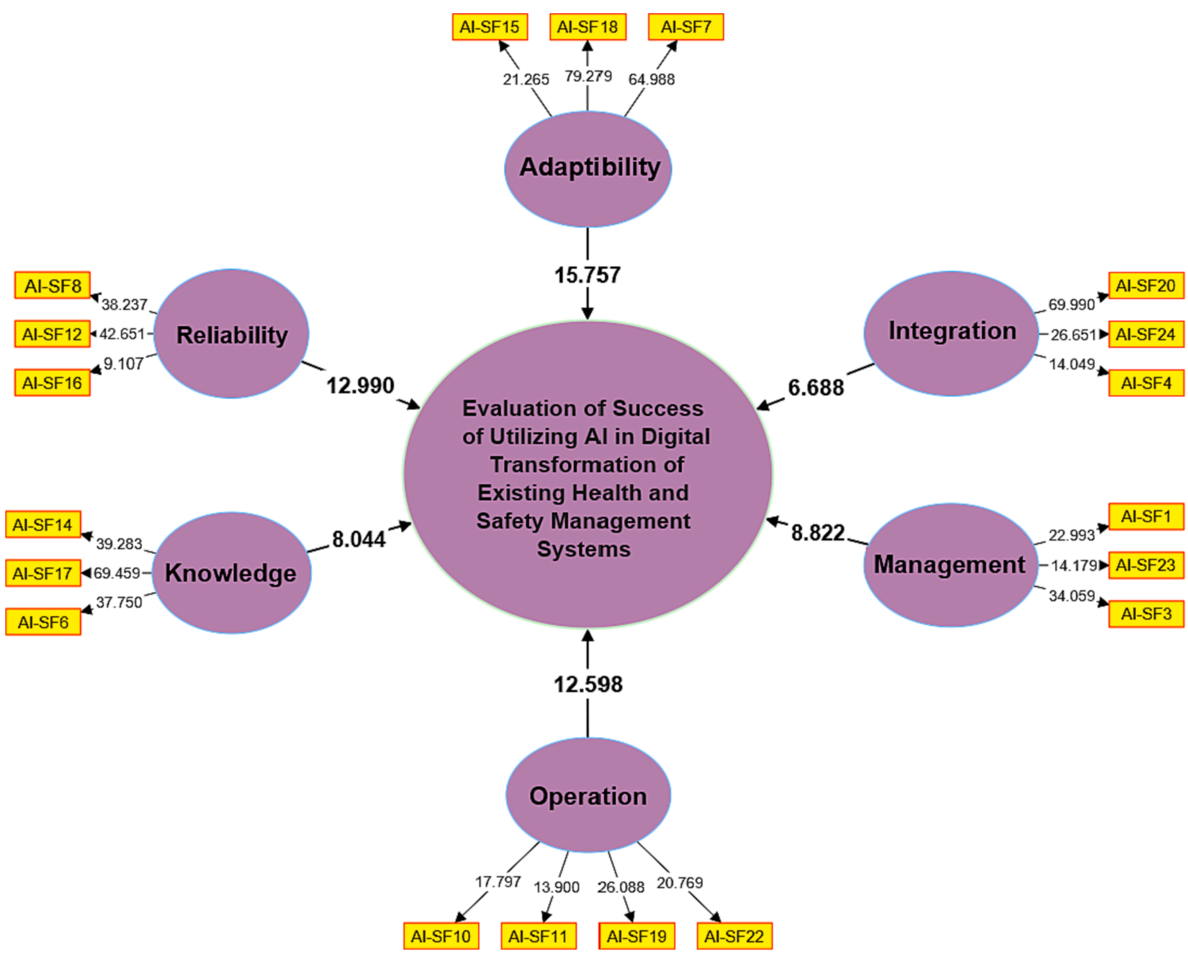

Fig. 4. Structure model indicating relationship significance of success factors.

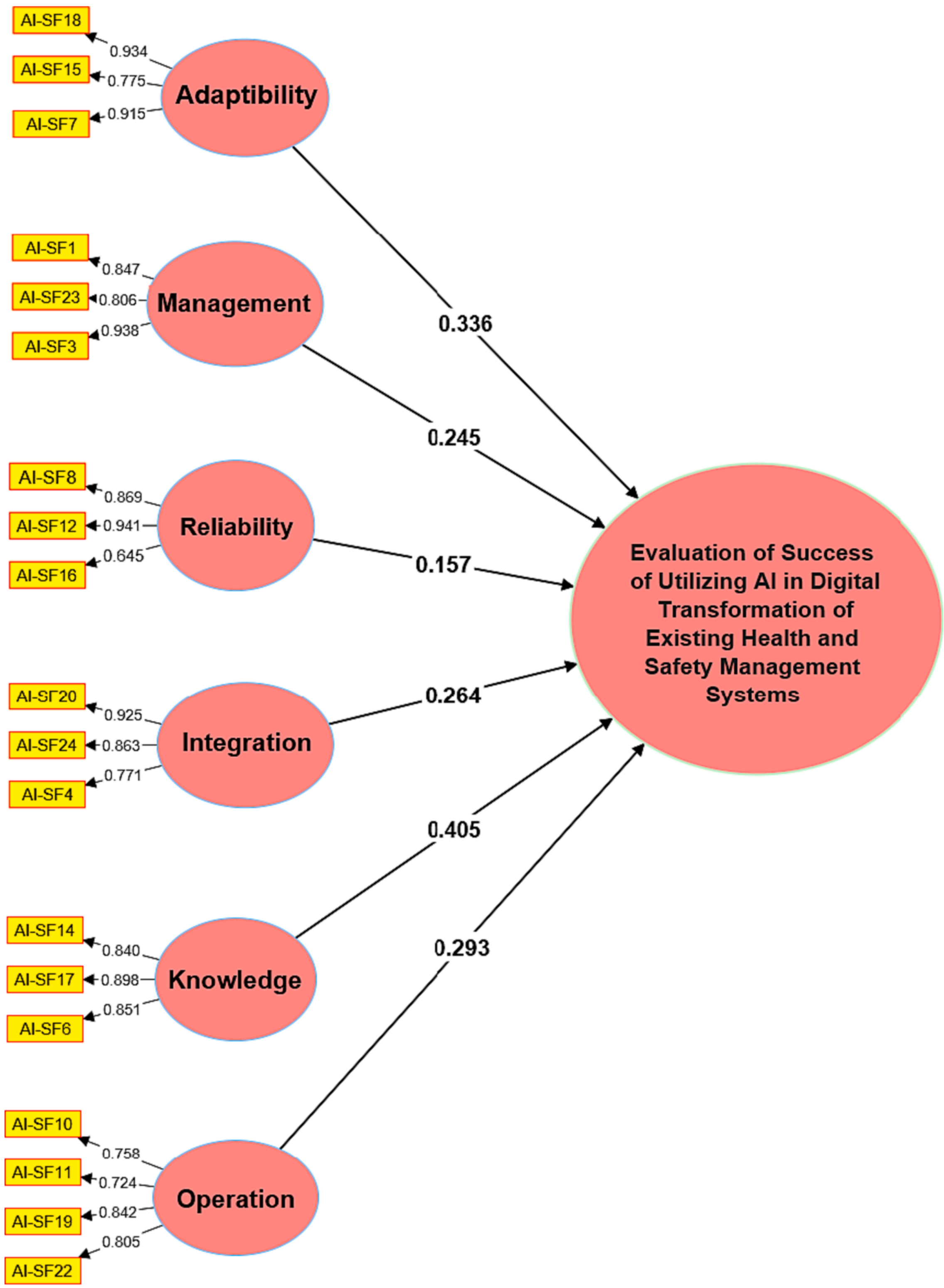

Fig. 5. Model with items, item loadings and path coefficients.

against their squared correlation coefficients. A measure of how much variation a construct accounts for across its pieces, AVE may be seen in Table 6 as diagonal values [5,45]. The table's top triangle contains the squared correlations between the constructions, while the bottom triangle is left blank to avoid unnecessary repetition. According to the Fornell-Larcker criteria, the square root of the AVE for each construct has to be higher than the correlation between that construct and every other construct in the model. A construct may need to be distinguishable enough to be considered unique if it shares more variance with another construct than it explains on its own [4]. When we compare the diagonal values to the correlation coefficients, we find that the diagonal values are always higher. The threashold value was 0.4 considering the correlation. According to the Fornell-Larcker criteria, the notions do have discriminant validity. When looking at the correlations between the

Table 5
Empirical correlation matrix.

Variable	AI-SF1	AI-SF10	AI-SF11	AI-SF12	AI-SF14	AI-SF15	AI-SF16	AI-SF17	AI-SF18	AI-SF19	AI-SF20	AI-SF22	AI-SF23	AI-SF24	AI-SF3	AI-SF4	AI-SF6	AI-SF7	AI-SF8
AI-SF1	1	0.12	0.162	0.057	0.129	0.225	−0.065	0.134	0.203	0.109	0.186	0.094	0.483	0.179	0.659	0.054	−0.04	0.18	−0.017
AI-SF10	0.12	1	0.426	0.02	0.387	0.072	0.055	0.388	0.165	0.429	0.158	0.378	0.052	0.158	0.146	0.085	0.332	0.163	−0.156
AI-SF11	0.162	0.426	1	0.041	0.243	0.242	−0.005	0.223	0.02	0.419	0.229	0.37	0.024	0.229	0.147	0.123	0.195	0.033	−0.088
AI-SF12	0.057	0.02	0.041	1	0.373	0.141	0.373	0.24	0.097	−0.029	0.127	−0.099	0.001	0.147	0.095	−0.002	0.11	0.081	0.805
AI-SF14	0.129	0.387	0.243	0.373	1	0.352	0.053	0.608	0.248	0.189	0.253	0.126	0.135	0.158	0.315	0.179	0.547	0.177	0.062
AI-SF15	0.225	0.072	0.242	0.141	0.352	1	0.133	0.355	0.522	0.181	0.12	0.22	0.015	0.078	0.223	0.086	0.338	0.48	0.041
AI-SF16	−0.065	0.055	−0.005	0.373	0.053	0.133	1	0.046	0.035	0.123	0.1	0.097	−0.101	0.064	−0.1	−0.009	0.048	0.008	0.425
AI-SF17	0.134	0.388	0.223	0.24	0.608	0.355	0.046	1	0.275	0.2	0.263	0.152	0.086	0.202	0.298	0.206	0.701	0.236	0.065
AI-SF18	0.203	0.165	0.02	0.097	0.248	0.522	0.035	0.275	1	0.048	0.145	0.104	0.11	0.152	0.229	0.126	0.211	0.94	0.09
AI-SF19	0.109	0.429	0.419	−0.029	0.189	0.181	0.123	0.2	0.048	1	0.079	0.904	−0.151	−0.023	−0.092	0.061	0.244	0.06	−0.115
AI-SF20	0.186	0.158	0.229	0.127	0.253	0.12	0.1	0.263	0.145	0.079	1	0.074	0.016	0.73	0.144	0.596	0.136	0.095	−0.014
AI-SF22	0.094	0.378	0.37	−0.099	0.126	0.22	0.097	0.152	0.104	0.904	0.074	1	−0.111	−0.012	−0.048	0.04	0.23	0.123	−0.153
AI-SF23	0.483	0.052	0.024	0.001	0.135	0.015	−0.101	0.086	0.11	−0.151	0.016	−0.111	1	0.064	0.745	0.052	0.021	0.062	−0.04
AI-SF24	0.179	0.158	0.229	0.147	0.158	0.078	0.064	0.202	0.152	−0.023	0.73	−0.012	0.064	1	0.12	0.458	0.023	0.13	0.036
AI-SF3	0.659	0.146	0.147	0.095	0.315	0.223	−0.1	0.298	0.229	−0.092	0.144	−0.048	0.745	0.12	1	0.067	0.186	0.184	−0.071
AI-SF4	0.054	0.085	0.123	−0.002	0.179	0.086	−0.009	0.206	0.126	0.061	0.596	0.04	0.052	0.458	0.067	1	0.08	0.114	−0.066
AI-SF6	−0.04	0.332	0.195	0.11	0.547	0.338	0.048	0.701	0.211	0.244	0.136	0.23	0.021	0.023	0.186	0.08	1	0.186	−0.075
AI-SF7	0.18	0.163	0.033	0.081	0.177	0.48	0.008	0.236	0.94	0.06	0.095	0.123	0.062	0.13	0.184	0.114	0.186	1	0.081
AI-SF8	−0.017	−0.156	−0.088	0.805	0.062	0.041	0.425	0.065	0.09	−0.115	−0.014	−0.153	−0.04	0.036	−0.071	−0.066	−0.075	0.081	1

various constructs, the one between Knowledge and Operation has the most excellent value (0.441), followed closely by the one between Integration and Knowledge (0.418). These strong associations imply a possible relationship between the concepts being studied. However, we may still consider them separate images since the Fornell-Larcker criteria bolster their discriminant validity. The findings indicate the measuring model's appropriate discriminant validity and the constructs' independence.

The HTMT (Heterotrait-Monotrait ratio) values are shown in Table 7. This statistical method may evaluate a structural equation model's discriminant validity between constructs. One indication of convergent validity is the square root of the average variance extracted (AVE) for each construct, which is shown on the diagonal [5,46]. All constructs have strong convergent validity, as measured by HTMT, since all diagonal values are more prominent than 0.5. HTMT values, shown as points away from the diagonal, reveal the extent to which specific constructions overlap. It is generally accepted that HTMT values below 0.9 indicate discriminant validity. After looking at Table 8's HTMT values, it is clear that all constructs exhibit evidence of discriminant validity since all off-diagonal values are lower than 0.9 [4]. The HTMT score of 0.214 between the Management and Knowledge domains suggests, however, that there is some overlap between the two. Above all, the results of the HTMT analysis support the uniqueness and validity of the model's components.

Table 8 shows how much each thing loads on top of other structures in addition to its primary target. Correlation coefficients between items and the construct they are designed to measure and between items and other constructs are represented by the numbers in the table cells [74,77]. The findings show that most items exhibit stronger associations with their designated construct than with any other construct. Strong correlations between questions that assess the same concept indicate strong convergent validity [75]. A few items, however, had stronger cross-loadings on other constructs than others, which might point to problems with discriminant validity. Items designed to test one component should have a low correlation with questions designed to measure other constructs to have good discriminant validity [72,73]. For instance, item AI-SF8 may not be a reliable indication of the operation build since it has a stronger cross-loading on the reliability than on the operation construct. It is possible that item AI-SF19 is not a reliable indication of the adaptability construct since it has stronger cross-loadings on the operation and knowledge constructs than on its adaptability construct. Further research and thought may be required to ascertain how these problems undermine the scale's reliability.

Table 9 provides a summary of the factors that were deleted from the analysis. The first column lists the deleted variables (items), and the second column indicates at which investigation stage they were deleted. The third column indicates the status of the deleted factors, whether they were deleted in the EFA (exploratory factor analysis) pilot study or in the SEM (structural equation modelling) main study [58,60]. The items deleted in the EFA pilot study (AI-SF5, AI-SF21, and AI-SF13) were likely removed because they did not show sufficient factor loadings or did not fit well with the other items in their respective constructs. The things that were deleted in the SEM main study (AI-SF14, AI-SF25, and AI-SF2) were likely removed because they did not contribute significantly to their respective constructs or because they had high cross-loadings with other constructs [72,73]. It is important to note that the decision to delete these factors was based on statistical analysis and should be interpreted cautiously. Future research may consider replicating the examination with a larger sample size or a different methodology to confirm the findings.

Each construct's outer loadings, VIF, and ranked order of group effect are shown in Table 10. A more significant external loading indicates a more vital link between the item and the construct. Multicollinearity may be quantified using the VIF (Variance Inflation Factor), where values above five may indicate problems [57,59]. The ranking of groups based on their influence on specific dimensions is a valuable indicator of

Table 6
Fornell larker criteria results.

Constructs	Adaptability	Integration	Knowledge	Management	Operation	Reliability
Adaptability						
Integration	0.187					
Knowledge	0.418	0.275				
Management	0.249	0.16	0.239			
Operation	0.212	0.197	0.441	0.189		
Reliability	0.134	0.111	0.207	0.105	0.16	

Table 7
HTMT analysis results.

	Adaptability	Integration	Knowledge	Management	Operation	Reliability
Adaptability	0.877					
Integration	0.155	0.855				
Knowledge	0.356	0.236	0.863			
Management	0.231	0.146	0.214	0.866		
Operation	0.177	0.165	0.375	0.085	0.784	
Reliability	0.119	0.093	0.212	0.004	−0.018	0.828

Table 8
Cross loadings of items.

Variables	Adaptability	Integration	Knowledge	Management	Operation	Reliability
AI-SF15	**0.775**	0.112	0.404	0.204	0.222	0.142
AI-SF18	**0.934**	0.165	0.286	0.221	0.113	0.094
AI-SF7	**0.915**	0.13	0.232	0.178	0.125	0.073
AI-SF20	0.138	**0.925**	0.257	0.15	0.181	0.112
AI-SF24	0.137	**0.863**	0.155	0.147	0.129	0.124
AI-SF4	0.124	**0.771**	0.185	0.067	0.103	−0.018
AI-SF14	0.301	0.233	**0.84**	0.239	0.321	0.275
AI-SF17	0.333	0.263	**0.898**	0.22	0.325	0.186
AI-SF6	0.284	0.096	**0.851**	0.079	0.327	0.071
AI-SF1	0.233	0.17	0.094	**0.847**	0.158	0.014
AI-SF23	0.071	0.049	0.097	**0.806**	−0.046	−0.039
AI-SF3	0.244	0.133	0.313	**0.938**	0.067	0.016
AI-SF10	0.151	0.16	0.43	0.132	**0.758**	−0.002
AI-SF11	0.116	0.231	0.256	0.143	**0.724**	0.007
AI-SF19	0.113	0.047	0.242	−0.038	**0.842**	−0.005
AI-SF22	0.173	0.042	0.192	−0.012	**0.805**	−0.067
AI-SF12	0.123	0.113	0.287	0.069	−0.014	**0.941**
AI-SF16	0.07	0.067	0.056	−0.1	0.082	**0.645**
AI-SF8	0.08	−0.014	0.026	−0.051	−0.165	**0.869**

Table 9
Summary of deleted factors.

Variables	Stage	Status
AI.SF5	EFA (Pilot)	Deleted
AI. SF21	EFA (Pilot)	Deleted
AI. SF13	EFA (Pilot)	Deleted
AI-SF9	SEM (Main)	Deleted
AI-SF25	SEM (Main)	Deleted
AI-SF2	SEM (Main)	Deleted

their relative importance. Higher values for the product of the outside loading and the VIF indicate a more considerable effect, hence a higher position in the ranking. Rankings determine which aspects of the system need to be worked on first, with the highest group impact scores placed higher. The table shows that AI-SF6 (Knowledge), AI-SF18 (Adaptability), AI-SF19 (Operation), AI-SF24 (Integration), AI-SF1 (Management), and AI-SF12 have the most fantastic group impact rankings (Reliability). Increasing organizational agility should focus on these areas, which are crucial for their respective structures.

4.2.2. *Path analysis*

The findings of the study's route analysis for the formative constructs are listed in Table 11. All of the path coefficients (β), standard errors

Table 10
Outer weights and group impact rank.

Variables	Construct	Outer loadings	VIF	Group Impact Ranking
AI-SF1	Management	0.847	1.77	Rank 5
AI-SF23	Management	0.806	2.252	
AI-SF23	Management	0.806	2.252	
AI-SF12	Reliability	0.941	2.847	Rank 6
AI-SF16	Reliability	0.645	1.225	
AI-SF8	Reliability	0.869	2.992	
AI-SF6	Knowledge	0.851	2.061	Rank 1
AI-SF17	Knowledge	0.898	2.291	
AI-SF14	Knowledge	0.84	1.66	
AI-SF19	Operation	0.842	2.898	Rank 3
AI-SF22	Operation	0.805	2.488	
AI-SF10	Operation	0.758	1.347	
AI-SF11	Operation	0.724	1.334	
AI-SF24	Integration	0.863	2.145	Rank 4
AI-SF20	Integration	0.925	2.629	
AI-SF4	Integration	0.771	1.555	
AI-SF18	Adaptability	0.934	2.028	Rank 2
AI-SF7	Adaptability	0.915	2.54	
AI-SF15	Adaptability	0.775	1.376	

Table 11
Path analysis results of formative constructs.

Path	β	SE	t-values	p-values	VIF
Adaptability -> Evaluation of Success factors of Utilizing AI in Digital Transformation of Existing Health and Safety Management Systems	0.336	0.027	15.757	<0.001	1.19
Integration -> Evaluation of Success factors of Utilizing AI in Digital Transformation of Existing Health and Safety Management Systems	0.264	0.025	6.688	<0.001	1.084
Knowledge -> Evaluation of Success factors of Utilizing AI in Digital Transformation of Existing Health and Safety Management Systems	0.405	0.033	8.044	<0.001	1.406
Management -> Evaluation of Success factors of Utilizing AI in Digital Transformation of Existing Health and Safety Management Systems	0.245	0.025	8.822	<0.001	1.091
Operation -> Evaluation of Success factors of Utilizing AI in Digital Transformation of Existing Health and Safety Management Systems	0.293	0.029	12.598	<0.001	1.19
Reliability -> Evaluation of Success factors of Utilizing AI in Digital Transformation of Existing Health and Safety Management Systems	0.157	0.026	12.99	<0.001	1.069

(SE), t-values, p-values, and VIF values are included in the table. The assessment of the successful aspects of using AI in the digital transformation of current health and safety management systems is positively related to all six formative constructs, as shown by the findings. Each construct contributes to the assessment of success elements to varied degrees, as shown by the route coefficients (which range from 0.157 to 0.405). Each path's VIF value is less than 5. Hence multicollinearity isn't an issue. Fig. 6 presents the frequency histogram of all constructs involved in the model [63,67]. The frequency curve is significantly similar to the standard distribution curve, indicating the acceptability of including these constructs in the model.

Consequently, the findings indicate that the formative constructs play a crucial role in determining how to measure the effectiveness of applying AI to the digital transformation of current health and safety management systems [68,69]. Fig. 7 is finally presenting the path significance of all constructs. They have obtained after bootstrapping analysis. In sum, our results shed light on important considerations for businesses interested in using AI technology within the framework of safety management systems.

The Q^2 value for the endogenous latent variable "Assessment of Success factors of Using AI in Digital Transformation of Current Health and Safety Management Systems" is shown in Table 12 as part of the model's predictive relevance analysis. The model's predictive power, as demonstrated by Q^2, is shown. Higher Q^2 values indicate greater prediction accuracy. With a Q^2 of 0.128, this model's predictive capability is about average when it comes to the "Assessment of Success aspects of Using AI in Digital Transformation of Current Health and Safety Management Systems" construct [45,46]. To put it another way, this suggests that the model accounts for around 12.8 % of the variation in the construct, which is not a lot but is still substantial. The Q^2 result must be understood in light of the particular model and the assessed construct. More analysis and interpretation are required to fully appreciate the

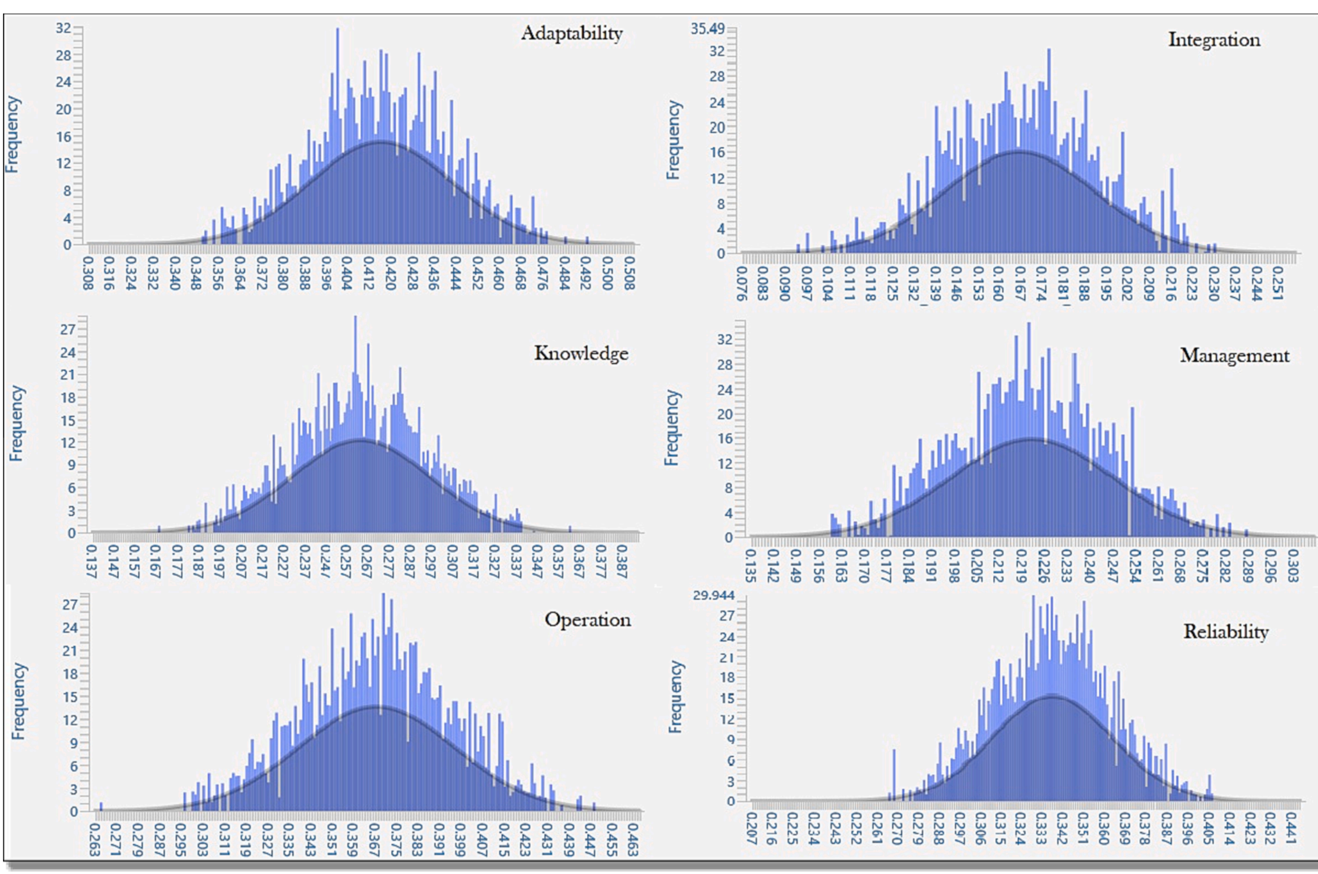

Fig. 6. Frequency histogram of constructs.

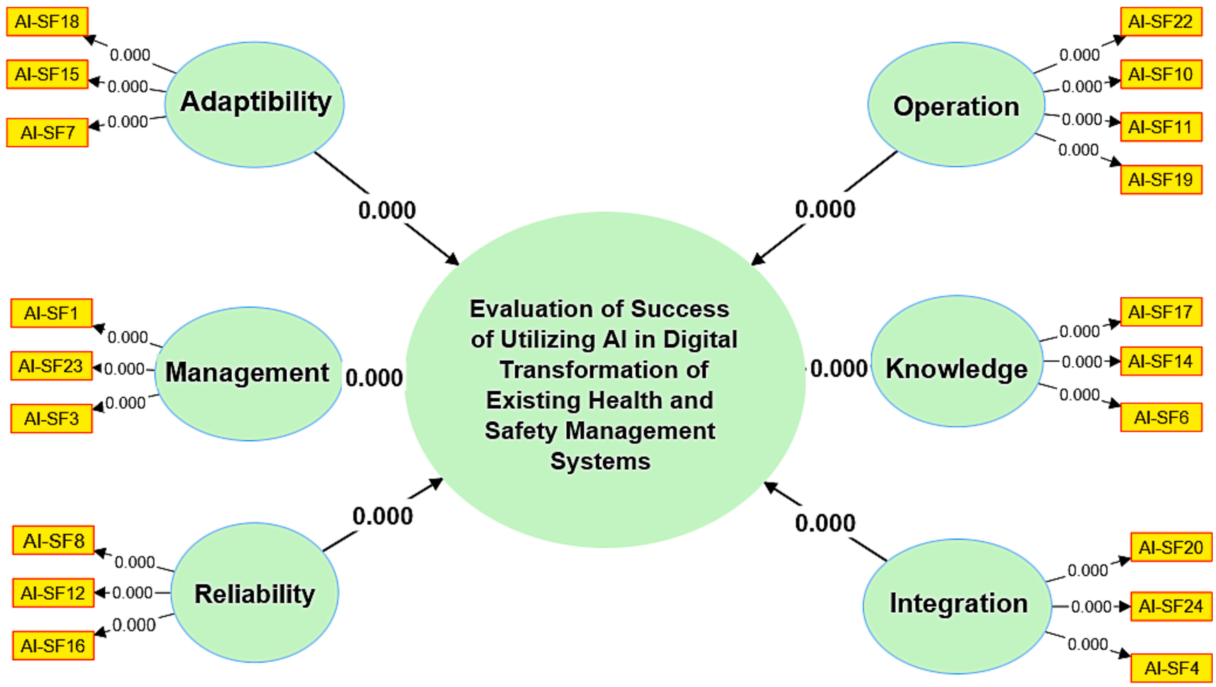

Fig. 7. Path significance results after bootstrapping analysis.

Table 12
Endogenous latent variable Q^2.

Predictive relevance analysis of model	SSO	SSE	Q^2 (=1-SSO/SSE)
Evaluation of Success factors of Utilizing AI in Digital Transformation of Existing Health and Safety Management Systems	14980.000	13065.414	0.128

Table 13
Results of validation.

Respondent	Q1	Q2	Q3	Q4	Q5
1	5	4	4	4	4
2	2	5	4	5	2
3	3	4	5	4	3
4	3	4	5	5	4
5	4	4	4	4	5
6	4	4	4	4	4
7	4	5	4	4	4
8	4	4	5	4	4
9	4	4	4	4	5
10	5	4	5	4	4
11	4	4	5	5	2
12	4	3	4	5	5
13	3	4	4	3	3
14	5	5	4	5	5
15	5	3	5	4	1
16	4	4	4	5	5
17	4	5	5	4	5
18	4	4	4	5	5
19	5	4	4	5	3
20	3	3	4	5	5
21	5	5	4	5	5
22	5	3	4	5	5
23	5	5	4	5	5
	4.09	4.09	4.30	4.48	4.04

significance of this Q^2 number for the study question and aims.

4.3. Validation outcome

The validation findings are shown in Table 13 where the mean value for each respondent answered of 22 participants in the validation survey is more than 4.0. On the basis of the accepted data, the response to each question confirms the model's validity.

5. Discussion

The formative knowledge construct includes AI-SF17, AI-SF6 and AI-SF14. The construct incorporates critical elements for efficient AI use in health and safety management [1,13]. The construct consists of three components that highlight data quality, AI application creativity, and system learnability and adaptability, respectively. The whole knowledge structure reflects the significance of regularly updating and refining artificial intelligence systems to guarantee their efficacy in boosting health and safety management systems. The model emphasizes the need to prioritize data quality, innovation, and flexibility to facilitate the smooth incorporation of AI into health and safety management systems [4,45].

The operation formative construct includes AI-SF22, AI-SF10, and AI-SF11 and AI-SF19. To get the most remarkable results using AI, it is crucial to ensure the algorithms are well-built and the data is handled correctly. This criterion for success emphasizes the need for high-quality data and well-tuned algorithms to get trustworthy outcomes from AI [47,52]. In addition, this highlights the need to assess data sources and processing techniques critically. Thus, the formative framework for operationalizing AI in health and safety management systems is well-built and includes numerous critical success elements. To get dependable and successful results from AI in this setting, paying attention to and improving data quality, flexibility, continuous monitoring and assessment, and quantifiable outcomes is crucial.

The formative management construct includes AI-SF1, AI-SF23 and AI-SF3. "The use of artificial intelligence in health and safety management systems should examine ethical issues, such as the possibility of prejudice or discrimination, and ensure that the system runs ethically and fairly". Members of the target audience are consulted to ensure the system suits their needs and fits in with the organization's overall mission. It's crucial to check that AI abides by all local, national, and international rules, regulations, and ethical considerations [42,46]. Worker safety is vital in construction, making this success element especially pertinent. The moral and equitable functioning of the AI system must be guaranteed [47,52]. This may be done by laying down strict ethical rules for the AI system and keeping a close eye on it to catch any shady behaviour before it does any harm. Generally speaking, the formative management construct stresses the need to include stakeholders, adhere to relevant norms and regulations, and address ethical considerations when integrating AI into health and safety management systems. By focusing on these characteristics, businesses may improve the efficiency of their AI systems and guarantee that they are operating in a secure, fair, and ethical way.

The integration formative construct includes AI-SF20, AI-SF24. and AI-SF4. Also, the framework stresses the need to evaluate the AI system's results in light of predetermined standards. This is crucial since it guarantees that the AI system is effective in its tasks and provides reliable results in real-time. Accuracy, timeliness, and the system's impact on health and safety outcomes assessments may provide light on the system's effectiveness and point to places for improvement [2]. The structure also emphasizes the value of teamwork within the Information Technology, Safety, and Operations divisions. This is crucial for ensuring the AI system serves the corporation and its various parts. The AI system may be better customized to the organization's requirements and current procedures if the team works together to develop it [1,16]. As a whole, the integration formative construct sheds light on why it's crucial to integrate the AI system with preexisting health and safety management systems, how to evaluate the system's efficacy, and how to foster interdepartmental cooperation.

The formative reliability construct includes AI-SF8, AI-SF12, and AI-SF16. Three critical features of successful AI are included in the framework: reliability and sturdiness, transparency in decision-making, and responsibility for outcomes. This is essential to ensuring the system can adapt to new situations while maintaining high accuracy. It's important to remember that the system can only be as trustworthy as the information it receives. Inaccurate conclusions might be drawn from insufficient or inadequate data. It is of the utmost importance to guarantee that the system's decision-making process does not jeopardize the confidentiality or safety of user information. It is crucial to provide an audit trail of the system's choices and hold it accountable for errors or oversights. By doing so, system faults may be found and fixed to avoid future problems.

In conclusion, the formative dependability construct plays a vital role in ensuring that the AI system can be trusted, is open to scrutiny, and is held accountable for its actions [17,18]. Trust in the system may be bolstered in this way, and that's crucial if stakeholders are going to adopt it ultimately. Data privacy, security, and ethical standards must be considered throughout the system's development and rollout.

The formative adaptability construct includes AI-SF18, AI-SF7, and AI-SF15. The capacity of an AI system to adjust to new circumstances is the primary emphasis of the adaptability of formative architecture. The three sub-constructs of this construct stress the significance of meeting user needs, maintaining progress, and adjusting to new circumstances. This is essential to make the system accessible to all stakeholders, regardless of their degree of technical knowledge. Adopting the AI system and its incorporation into current processes might be aided by a straightforward interface. Thus, the system should be built to consider user input and undergo constant monitoring to detect and fix any problems that may occur. If the regulations, the scope of the project, or the data sources change, it will be necessary to modify the algorithms and the data inputs used by the system [21,22]. In general, the adaptability of the formative framework acknowledges the requirement for AI systems to be versatile and responsive to new conditions. For an AI system to be effective in health and safety management over the long term, it must have a straightforward interface, undergo continuous development, and be flexible enough to accommodate changes to the project and surrounding environment.

5.1. Empirical and theoretical contributions

This study contributes to the growing body of literature on the use of AI in the construction industry's health and safety management systems. The survey data collected provides insights into the demographics of professionals involved in the construction industry and their attitudes towards AI. The study identifies five formative constructs (i.e., knowledge, operation, management, integration, reliability, and adaptability) crucial for successful AI adoption in construction industry health and safety management systems. The study highlights specific factors (e.g., data quality, system scalability, ethical considerations, and user-friendliness) that should be considered when designing and implementing AI systems in the construction industry. The study contributes to the theoretical understanding of the factors contributing to successful AI adoption in the construction industry's health and safety management systems. The study builds on existing literature on AI adoption in the construction industry by providing a more nuanced perspective on the crucial factors for successful implementation. The identification of the five formative constructs provides a theoretical framework that can be used to guide future research in this area. The study highlights the importance of considering ethical considerations, such as the risk of bias or discrimination, when designing and implementing AI systems in the construction industry. This contributes to the broader debate on the responsible use of AI in society.

5.2. Managerial suggestions

This investigation provides numerous recommendations for managerial action that construction companies can take to incorporate artificial intelligence into their health and safety management structures. Construction companies that want to integrate AI successfully should start by including key stakeholders, such as workers, managers, and anyone affected by the change. Because of this, they'll be able to make helpful criticism of the system's implementation. It is important to note that the quality and accuracy of the data are crucial to the success of AI adoption in health and safety management systems. There has to be a guarantee of accuracy, consistency, and timeliness in the data collected by construction companies. Building companies should encourage research into how artificial intelligence may be integrated into existing safety management systems to make them more effective. This may include trying out innovative data collection and analysis approaches, such as using artificial intelligence to spot potential hazards.

The AI system needs constant checking to make sure it's doing its job. Checking the system's accuracy, finding bugs and fixing them, and ensuring it's doing its intended tasks might fall under this category. Ethical concerns, such as the potential for bias or discrimination, should be thoroughly investigated before AI is included in health and safety management systems. Measuring the AI system's success against predetermined benchmarks is essential. Accuracy, timeliness, and the system's impact on health and safety outcomes may all be evaluated. An intuitive, straightforward, and easily accessible interface is a must for AI systems.

5.3. Limitations and future implications

The study's reliance on EFA and SEM as primary analysis methods is a significant drawback. While these methods see extensive usage in the academic world, they sometimes need better capture the subtleties and complexity of the data. Using complementary methodologies, such as machine learning algorithms or qualitative data analysis, may improve the results of future investigations. The research was done with a select group of experts from the construction business. Thus its effects may not apply to the field as a whole. Similar studies with diverse populations should be conducted in the future to strengthen the study's external validity. More specifically, this research looked into how experts in the construction sector feel about implementing AI into HSS. To get a more nuanced picture of the issue, future research might account for the viewpoints of many other parties involved, such as employees, regulatory organizations, and insurance providers.

The identified success factors, such as adaptability, operation, management, reliability, integration, and knowledge, are fundamental principles of AI adoption that are not limited to the construction industry. These principles are applicable to any domain seeking to integrate AI technologies effectively. The study emphasizes the importance of ethical considerations, transparency in decision-making, and fairness in AI systems. These principles are universally applicable and are increasingly essential in various industries, including finance, healthcare, and retail, where AI is being used for decision support and customer interactions. The need for collaboration across IT, safety, and operations departments is a key finding that can be extended to other sectors. In any industry, successful AI adoption often requires close cooperation and communication between different functional areas to ensure alignment with business objectives. Training users and employees to effectively utilize AI systems is a common requirement across industries. The study's emphasis on user education can serve as a model for designing training programs in various sectors where AI tools are deployed. Ensuring the accuracy and quality of data, as well as the flexibility to accommodate changes in project scope or data sources, is a challenge faced across industries. These factors are vital for AI systems to produce reliable and actionable insights.

Communication of Benefits: Effectively communicating the benefits of AI to stakeholders is a universal requirement. Industries, such as marketing and sales, can draw insights from the study's emphasis on clear and concise communication of AI advantages.

Notwithstanding the study's limitations, it has significant ramifications for the field. The research shows that while creating and deploying AI in the construction sector's health and safety management systems, it is crucial to consider elements like data quality, system scalability, ethical difficulties, and stakeholder participation. The study lays the groundwork for future studies and interventions in this area. With the study's numerous formative components in mind, construction firms may design and execute AI-based health and safety management systems that are robust enough to withstand the rigours of various projects and environments.

6. Conclusion

Overall, this research aimed to create and verify a thorough model for the efficient use of AI in health and safety management systems in the building trades. The study concluded that six foundational constructs—knowledge, operation, management, integration, dependability, and adaptability—are essential to the widespread use of AI in health and safety management systems. Research shows that each factor significantly affects the rate at which health and safety management systems incorporate AI. A cross-section of experts working in the construction sector participated in the empirical study, and their feedback was essential in understanding how to use AI in health and safety management best. Using EFA and SEM, the researchers were able to determine the connection between the formative constructions and the uptake of AI. The theoretical and practical consequences of this study's conclusions are substantial. This paper makes theoretical contributions by identifying six important foundational characteristics when using AI in health and safety management systems. These models give a roadmap for those responsible for health and safety in the construction sector to follow as they integrate AI into their existing processes. The study's management recommendations may include implications for the construction sector. This advice may help those responsible for health and safety in the construction sector use AI efficiently. Suggestions include integrating stakeholders' early development, following health and safety regulations, creating a user-friendly interface, keeping tabs on the system's progress, and ensuring those responsible for its decisions and actions are held to account. This research had certain drawbacks, despite making some critical contributions: EFA and SEM were the principal analytical techniques used. Future studies may want to investigate other ways of analysis to understand better the connection between the foundational components and the integration of AI into health and safety management systems. Overall, this study lays the groundwork for further investigation into the integration of AI into construction sector health and safety management systems.

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Declaration of Competing Interest

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

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