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RESEARCH ARTICLE

Intelligent Risk Management in Construction Projects: Systematic Literature Review

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ABSTRACT As digitalization leads to the development of the global economy and artificial intelligence stimulates technological innovation, integrating smart management methods into project management is becoming more and more critical to the development of the construction industry. As an influential branch of engineering management, intelligent risk management in the construction field will be a future research direction. Hence, the aim of this study is to find the gaps and future research trends in intelligent risk management field by Systematic Literature Review. In order to achieve these objectives, 436 articles were selected from the WOS and Scopus databases to be analyzed by CiteSpace scientometric software, and the results were classified into collaborative network analysis, co-citation analysis, and public network analysis. From the analysis, China had the highest number of publications, while the United States was the most influential country in this field. The researchers at different institutions in this field have formed research teams despite the lack of collaboration between the authors and their institutions. In co-cited references, the emphasis was on traditional methods and applications of risk analysis, with fewer citations of novel methods. According to the keywords, the clusters of keywords, and the temporal evolution of the keywords, and combining the conceptual model, 5 research gaps areas were discovered. In order to fulfill these challenges and barriers, this study found the future research trends, including: developing digital management platform for intelligent construction management and risk management; building a decision-making system for risk management to find an optimum solution; refining building digital models which would be the basis of digital management platform; identifying and category the characteristic construction risk factors by using machine learning techniques, just like text mining or knowledge graph; building an API to embed decision making system into digital management platform, and the intelligent risk management system in real-time projects to verify its possibility.

INDEX TERMS Intelligent risk management, construction projects, CiteSpace, bibliometric analysis.

I. INTRODUCTION

The technological revolution has always been a major driver of economic development. In 2021, The global digital economy reached US$45 trillion, accounting for 50% of the global economy, and digital economy growth rate reached at 3.01% while the global GDP growth rate of −2.84% (Global Digital Economy White Paper, 2021). Currently, the fourth revolution (digitalization revolution) is triggering a profound change in the economy and society [1]. With digitalization has been and will continue to be a key engine of global economic growth, it is also necessary for construction industry to move into this revolution [2]. At the same time, the characteristics of construction industry are gradually changing from labor-intensive to technology-intensive, which will surely promote and need the intelligent development in construction industry. It is expected that the continuous emergence of various digital technologies such as Digital Twin, Internet of Things, Big Data, cloud computing and artificial intelligence will lay a solid technical foundation for intelligent construction industry [3]–[5].

Intelligent construction is rapidly developing under the influence of Industrial Revolution 4.0 (Chacón,2021), which develop intelligent science and technology to reshape

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production and management in the whole engineering development lifecycle, so that the construction system possesses various automatic management features comparable to human intelligence, thereby optimizing the construction process, enhancing the quality of construction, and promoting the sustainable development of the construction industry [6], [7]. It is evident that intelligent construction not only emphasizes the application of new information technologies, but also enhances the organization, management, and decision-making capabilities of construction industry [8]. In future, the new construction industry will be based on intelligent construction model, which will promote the intelligent transformation and upgrading of the construction industry by optimizing the various resources in the industrial chain and maximizing their benefits, thus achieving the development goals of high efficiency, high quality, low consumption and low emissions.

Risk management is main part of construction management, and essentially a process of collecting information, analyzing it, and making decisions, and the purpose of risk management for participants is to achieve optimum project performance and maximize profits. From 2010-2021, Figure 1 illustrates the top 250 international contractors by revenue worldwide (Engineering News-Report, 2010-2021). The top 250 international contractors reached 544 billion dollars in revenue in 2013 after rapid growth from 2010 to 2013. Revenues began to decline from 2014 onwards, a trend that continued until 2016, although they began to rise again from 2017, but began to decline significantly with the impact of COVID-19. In response to the continued decline in revenue, Engineering New-Record ENR noted (TOP 250 International Contractors' Revenue Report, 2019) that international contractors are becoming increasingly wary of risk exposure and project management expertise. In this context, contractors are required to focus more on risk management and operational efficiency in order to stay on schedule or ahead of schedule as well as to make a profit.

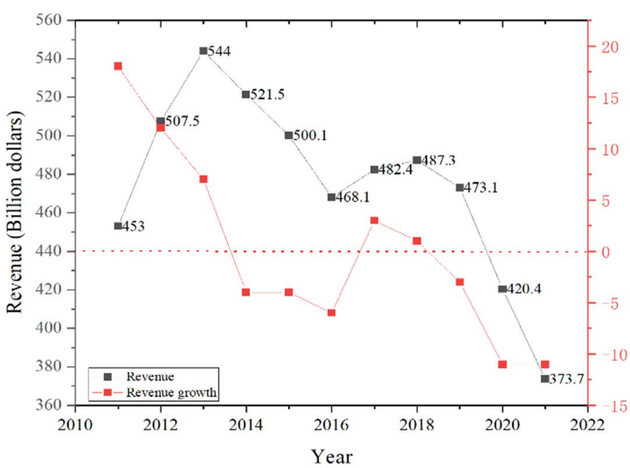


FIGURE 1. Top 250 international contractors' revenue worldwide from 2010-2021 (billion U.S. dollars).

Hence, the participants of construction are urgent to find an effective risk management to achieve the lean project, but there are some obstacles. Traditional risk management in construction industry has been studied in depth and has a solid foundation of results, but the integration of risk management with new management techniques is still in its infancy. With the rapid advances in information technology, artificial intelligence, and big data technologies, novel applications are being created for data, which is causing it to grow exponentially in size. A huge amount of data contains vast amounts of potentially valuable information, which can be used to develop the economy and society. However, obtaining useful information from such diverse and heterogeneous samples of data has become a key issue in knowledge management research [9]. Risk data is often recorded and stored as unstructured data. This is more abstract than structured information and cannot be directly processed by computer software, and therefore cannot be directly substituted into relevant mathematical models for the analysis and prediction of faults or accidents. In order to extract valuable information from this textual data, construction projects management experts with specialized knowledge are often required to manually extract and classify the information. As a result of the high repetition rate, not only does the experts' judgement degrade, but it also allows the subjectivity of their judgement to have an impact on the accident analysis results [10]. The development of technologies related to natural language processing has led to the development of methods for converting structured textual data into structured data that have been applied in a number of fields, providing a methodology as well as a theoretical framework for the study of unstructured risk data [11]. Currently, intelligent risk management research is facing the following main problems:

(1) The traditional risk management approach does not meet the needs of information-based construction management.

Traditionally, risk identification methods have been based on subjective human experience. In the face of a large quantity of risk data and a variety of risk types, human-based risk management methods are prone to problems such as low analysis efficiency and insufficient identification of risk [12]. The majority of risk evaluations make use of probabilistic calculations and mathematical statistics based on small samples, which are suitable for the analysis of risk sources, accident hazards, and risk evaluations of single-dimensional scenarios, but are insufficient for the analysis of an enormous amount of information and data in a multi-dimensional scenario [13]. Currently available risk warning methods are mostly based on single indicators of risk source state parameters, risk development consequence prediction, and causality modelling between risks, but rarely take into account correlations of various risk factors in building information, and the data rate is insufficient [14].

(2) Intelligent risk management techniques are not applicable to construction industry.

Artificial intelligence has become a vital part of industrial reform and a cornerstone of intelligent management [15]. Construction management is currently at the stage of enlightenment as it pertains to intelligent management. However, as industry reform takes place, it will become necessary to conduct research on construction management intelligence. The use of text and data mining in artificial intelligence is one of the main techniques for identifying risks, but existing text mining tools and methods are unable to address the non-standardized representation of risk text data and non-uniform data structure in construction engineering [16]. It is impossible to accurately recognize the professional vocabulary of construction risks, and there is less research in this area [17], [18].

(3) There has been lack of literature about synthesis management platform, such as Digital Twin, BIM-based cloud Platform, with risk management to face the construction digitalization.

Some studies have been conducted on the application of data mining and text mining techniques to risk management, as well as research on the use of APIs to connect them to BIM, however the construction of a digital twin is still in its infancy, and there is little research on risk intelligence management techniques with the objective of creating a digital twin [19]–[21].

In order to address these issues, and achieve thoroughly understanding of recent literature review about construction intelligent risk management, then to find the research gaps. This study is performed to conduct a systematic literature review. Systematic literature review (SLR) has served a variety of important purposes, as it has been a way to maximize the information on how this topic has been researched, what domain has been concerned, and which main journals choose this topic to published [22]. Researchers can identify problems in primary research and correct them in future studies; and they can provide an overview of the state of knowledge in a field that can inform future research priorities, because it typically synthesizes information from original papers in a field of research, assess the degree of consensus or the lack of it concerning the state of the art in the field, and identify opportunities and future work [23].

Based on the above content, the following questions have been identified for discussion in this paper.

Q1. What is intelligent management, how is it applied in risk management, and how does it affect the efficiency of management?

Q2. What are the characteristics of the distribution of scholars in this field, as well as their institutions and countries?

Q3. Which journals do researchers prefer to publish articles in this field and what are their domain-specific impact factors?

Q4. What is the research classification of this field and what are its research priorities?

Q5. What are the research gaps and future research trends in this field?

II. LITERATURE REVIEW

The definition of retrieve keywords is the first step to conduct Systematic Literature Review. Hence, this study described the detailed progress of risk management, categorized Artificial Intelligence techniques used in construction industry. In additional, conceptual model was developed which could elaborate the principal of intelligent risk management.

A. RISK MANAGEMENT

Risk management is one of the core branches of project management and is therefore also a branch of contemporary management that requires digital and logical approaches. Risk management is the scientific method for identifying, assessing, and analyzing risks in order to control them effectively and to address them in an integrated way in the most cost-effective manner in order to meet organizational safety and security goals [24]. The process of risk management involves risk analysis, such as risk identification, risk estimation, and risk evaluation, and also includes risk planning, risk control, and risk monitoring [25]. Furthermore, a risk management cycle consists of the identification of risks, the selection techniques about risk warning and control, and the evaluation of their effectiveness [18]. In the context of a complex system, the implementation and operation of construction projects are subject to a variety of uncertainties arising from society, nature, and a variety of other factors. Hence, construction projects are characterized by long-term, interrelatedness, and complexity, and they typically involve multiple objectives, subjects, and stages. Moreover, advances in science and technology, changes in the social environment, as well as the impact of unexpected events, such as COVID-19 epidemic, have significantly increased the risks and challenges associated with the development of the construction industry. By using effective risk management strategies, construction participants can better predict risks and grasp their timing, improve the science and accuracy of decision-making, and enhance the viability of their operations.

There are three stages in the process of developing a project risk management system in construction industry. Traditionally, risk management was conducted by companies or engineers utilizing their own unique project experience in order to manage projects unilaterally. The second stage was comprehensive risk management, which is a systematic and dynamic approach to controlling risks in order to reduce uncertainty during the project implementation process [26]. It not only enables project managers at all levels to build up risk awareness, pay attention to risk issues and prevent them before they arise, but also implement effective risk control at all stages and in all aspects, forming a coherent management process using methods such as neural networks, Monte Carlo, system dynamics, etc [18], [27] to plan and control the entire risk management process. As the third stage, the integration of information management and supply chain relationship management would occur on the basis of comprehensive risk management, combining information technology platforms for all-round, multi-perspective risk management, including Palisade Corporation's project risk analysis software @RISK Professional for Project [28], and Primavera's Monte Carlo software for their risk management information systems [29].

A growing trend in risk management is moving in the direction of intelligence with the help of big data and digitalization. In the field of financial risk management, for example, customer behavior analysis described in the previous section or market analysis is often used to estimate the probability of risk events and provide early warning of possible financial risks in advance to reduce unnecessary losses. In the construction industry, however, the development of intelligent risk management lags behind, so it is necessary to assess the current state of research in intelligent risk management in the construction industry in order to guide its future development [15].

B. ARTIFICIAL INTELLIGENCE TECHNOLOGIES

As illustrated in Figure 2, some AI technologies have already been integrated into digitalizing the construction industry [15]. Furthermore, the use of BIM in particular has significantly advanced its digital and intelligent management. For example. In order to reduce communication between project participants, Zhang *et al.* [30] suggested the use of a BIM platform on which they could collaborate and manage the project. Zhou *et al.* [14] integrates BIM platform technology with IoT technology to provide online, real-time exchange of information and personalization of products for assembled buildings. Nevertheless, few studies have incorporated BIM platforms with knowledge mapping technology and risk analysis models for dynamic and real-time intelligent risk management.

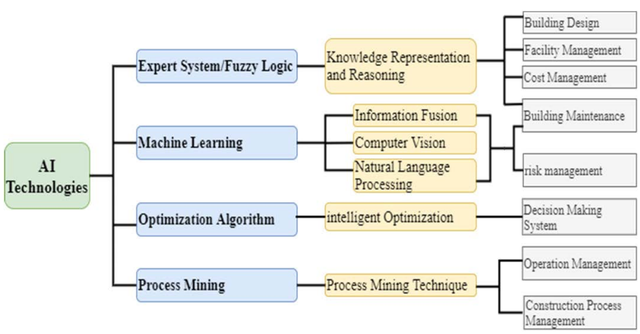


FIGURE 2. AI technologies used in construction industry.

C. INTELLIGENT RISK MANAGEMENT

Intelligent management is a management method that incorporates various disciplines and technologies such as artificial intelligence and management science, knowledge engineering, systems engineering, computing technology, communication technology, software engineering and information technology [7]. In addition, at the heart of intelligent management lies the information receiving device in the front section and the embedded control algorithm [31]–[33], which can also definite as Artificial Intelligence (AI). Intelligent management is already in use in a wide range of industries and sectors. As an example, in industrial production systems, intelligent management is one of the factors that contribute to the development of Industry 4.0, making use of key technologies such as the Internet of Things (IoT), Cyber-Physical Systems (CPS), cloud computing, Big Data Analytics (BDA), and Information and Communication Technologies (ICT) in order to integrate smart management [1]. Moreover, allowing for a greater level of innovation in vehicle driving, intelligent management technologies also enable in-depth analysis and learning of large data sets related to traffic to create intelligent transportation systems [5], [34].

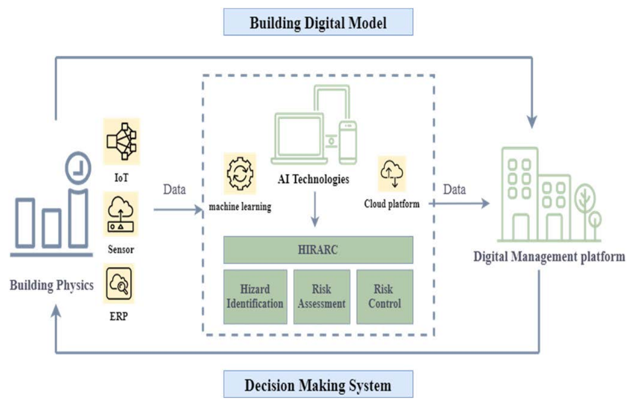


FIGURE 3. Conceptual model of intelligent risk management.

As one core branch of intelligent management, the use of intelligent risk management, that is, by analyzing and mining data, can assist management companies to establish a process of risk quantification enabling automatic identification, automatic evaluation, and automatic provision of response solutions for refined management, thus ensuring scientific, robust and sustainable development of projects in various areas [16], [18]. The conceptual model of risk management is as shown in figure 3. Building construction and operation real-time information would be captured by LoT, Sensors or ERP management system, then to be transferred to Machine Learning progress or uploaded in Cloud Platform. Computer would analyze this information to complete HIRARA progress. Finally, participants of construction would make a decision by the result of Machine Learning via Digital Management platform. Then the Decision-Making System would work in Building Physics.

III. METHDOLOGY AND DATA SOURCES

As part of a systematic literature review, all relevant literature must be systematically searched and eliminated bias. Then this would allow for a comprehensive and integrated evaluation and analysis. This study was conducted by bibliometric software in order to facilitate literature management. It could typically take a set of bibliographic records and produce a general overview of the domain knowledge. Generally, the knowledge domain could be defined as a concept that

TABLE 1. Comparison of different scientific bibliometric software.

Bibliometric software		CiteSpace	Bibiliometrix	VOS viewer	BibExcel
cited article analysis	co-authors	√	√	√	√
	bibliographic coupling	√	√	√	√
	co-citation	√	√	√	√
	citation		√	√	√
	co-word	√	√	√	√
data progress	data pre-process	√	√		√
	data clean	√	√	√	√
analysis method	network analysis	√	√	√	√
	time-series analysis	√	√		
	geospatial analysis	√	√		
	Burst detection	√	√		
	others		√	√	
visualization view	network	√	√	√	
	timeline	√			
	Geography	√		√	
	others	√	√	√	
Convenient operation		No	No	Yes	Yes
		Complicated operator interface	R Programming Language toolkit		

encompass a scientific field or scientific discipline. The graph of knowledge domains involves the systematic development of an accessible and visually appealing graphic, which would accurately represent the information resources accessible. Due to the popularity of information visualization, domain analysis has become one of the hottest research fields. Available as a new research area for information visualization, domain analysis is an advantageous scientometric method for discovering meaning hidden in large amounts of information. It is also an advantageous method for tracking the frontiers of development. Table 1 elaborated the features of 4 main analytical software available in the field of intelligent visual bibliometric knowledge, which are CiteSpace, Bibiliometrix, VOSviewer, and BibExcel. VOSviewer and BibExcel are easier to conduct and the knowledge graphs are clarity. These two analysis tools would help scholars to find co-words quickly and simply, but lack of some advanced functions. Meanwhile, Bibiliometrix and CiteSpace are both more comprehensive including some further function such as timeline analysis, keywords burst analysis, but they are more difficult to use. CiteSpace has much parameter settings and a complex interface. Bibiliometrix needs to be operated with R Programming Language toolkit. Additionally, there are papers that combine multiple software packages in order to conduct a comprehensive analysis [35]. In this study, CiteSpace was selected as the analysis software due to its comprehensiveness, consistency of analysis, and convenience of operation [36], [37].

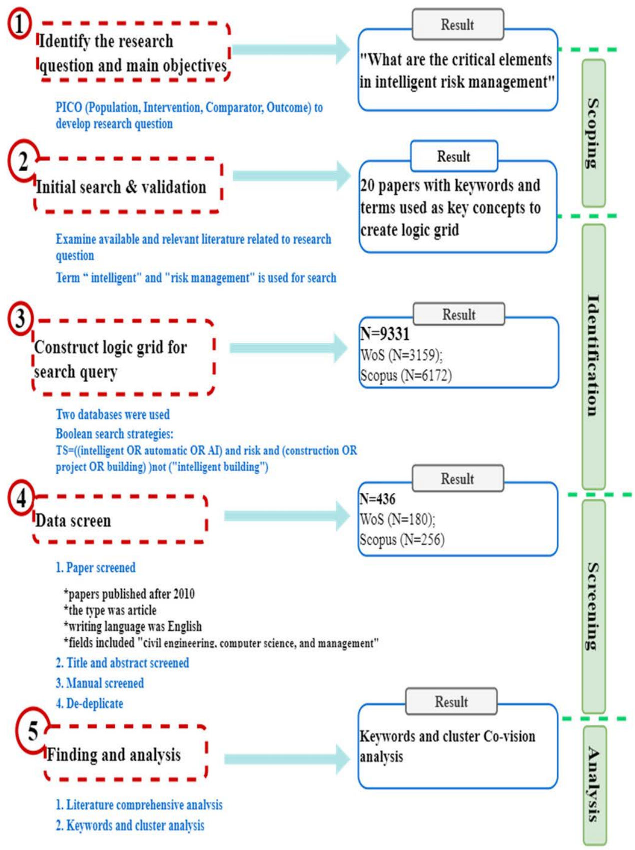


FIGURE 4. The method of SLR about intelligent risk management.

A. METHDOLOGY

According to PRISMA2020 [38], this study firstly identified data sources and retrieval strategies to screen data, then screened and cleaned data to reduce bias. Next, the conceptual and relational analyses were performed via CiteSpace. In the graphs generated by CiteSpace, each node is colored from grey to red to represent its progression through time. The size and clarity of the labels indicate the frequency of occurrence. By examining the thickness of the connections between nodes, additional parameters can be determined regarding the relevance of the information. These parameters include the centrality of the network, cluster size and silhouette, as well as time series analysis. Following the quantitative analysis, a qualitative analysis was conducted. The whole research method of this study displayed in Figure 4.

B. DATA SOURCES

1) DEFINITION OF RETRIEVING KEYWORDS

This study used keyworks "risk management", "intelligent" and "construction industry" to find 20 most relevant literature. After reviewing these papers, especially the detail definition of these words, the logic grid could be built up. As a result, except keywords of "risk" in this study, the keywords of "intelligent" are "automatic", "intelligent", "Artificial Intelligence (AI). And the keyworks of construction industry can be defined as "construction", "project" and "building".

2) STRATEGY OF REVIEW

Firstly, this study defined keywords for intelligent risk management in construction projects. Next, using Web of Science (WOS) and Scopus as the literature source databases, the keywords were linked by Boolean operations as follows: TS = ((intelligent OR automatic OR AI) and risk and (construction OR project OR building))not ("intelligent building"). The search period was set from 2010-01-01 to 2021-12-31, focusing on developments in this academic field over the last 12 years. On the basis of this strategy, 3159 papers from WOS and 6712 papers from SCOPUS were retrieved. To ensure that the data were accurate, the following steps were taken: (1) Filtering the type of literature by selecting Article as the filter; (2) Selecting English as the language of the literature; (3) determining the scope of the research. The field of civil engineering, computer science, and management was chosen as the scope of the literature review. There were again identified keywords related to construction engineering, intelligence, and risk in the Scopus database; (4) The literature was manually screened to eliminate invalid literature; (5) Duplicate literature was eliminated by using CiteSpace. Figure 5 demonstrates the number of studies selected for each process, and a total of 436 studies were found to be relevant to the analysis.

Based on the statistical analysis of the literature retrieval results, there were less than 20 publications from 2010 to 2014, as is shown in figure 4. However, the number of publications significantly increased in 2016 to 2018. In those years, the number of publications remained nearly 50. It should be noted that although the number of studies in 2018 decreased, that number tripled in 2019. Because the revenue of global contractors constantly decreased for these years, more and more researchers has focused on risk management field. The number of papers published in 2019 also increased dramatically, reaching 76. Although the number of articles falls a little in 2020, it rose again to around 70 articles in 2021.And the overall trend has been upward from the trendline, with the development of digital economy, that intelligent risk management in the construction industry would perform a research trend in next years.

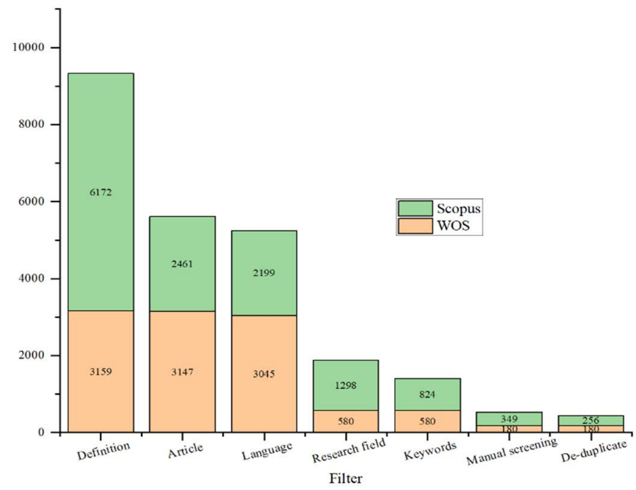


FIGURE 5. The process of data clean.

IV. RESULT

A. COOPERATIVE NETWORK aNALYSIS

1) COUNTRIES

As a result of the cooperative network between the various countries, the size of each node reflects the number of publications in that country. The nodes were colored from grey to red corresponding to the years 2010-2021, with the width of each color representing the number of publications in each year. On the outer circle, the width of the purple node indicated the centrality of that node (its importance in the network). As is shown in Figure 7. USA occupied a central position (centrality is 0.49) and acted as a bridge between the various countries. China was the country with the greatest number of publications (126, 30%), and next in line were USA, Italy and England. For these countries, there shown a wide and strong connections. Moreover, the top five countries by number of publications (284, 62%) were all developed countries with the exception of China. Based on these findings, researchers in developed countries were more likely to research intelligent risk management in construction industry than researchers in developing countries.

2) AUTHORS AND INSTITUTIONS

However, as shown in Figure 8, at the same time only a small number of articles were published by one author, and the number of collaborations between different authors were also low. This indicated that the concentration of authors working on intelligent risk management for construction projects is not close. Combining the network figure of institutional cooperation, we could see that the units of authors with the most publications were similar to the units of research institutions with the most publications, indicating that although there was less cooperation between institutions, the research authors were more concentrated and formed a core research group in their institutions.

B. CO-CITATION ANALYSIS

1) CITED REFERENCE

Analyzing highly cited literature is often helpful in understanding the origins and future directions of research on "intelligent risk management in construction projects". The node type was "Reference", the timeframe was "1 year", the criterion was "Top 10% per slice, up to 100", and the network

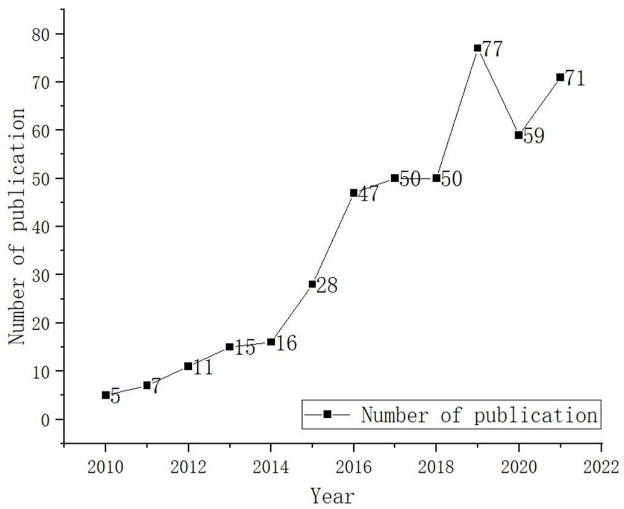


FIGURE 6. The number of publications.

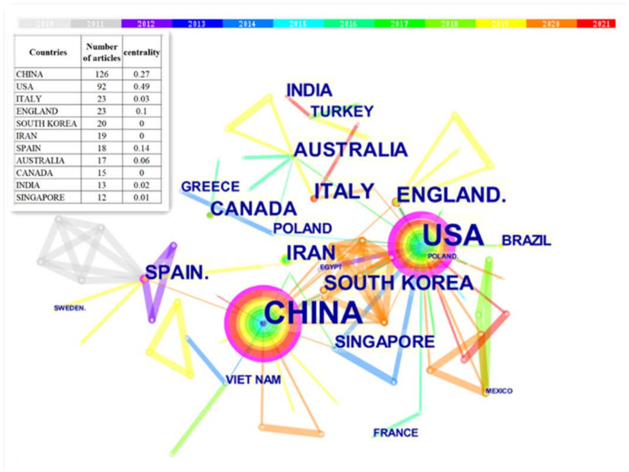


FIGURE 7. The cooperative network of countries.

crop was "Pathfinder". The network culling method was "Pathfinder", and the Log-Likelihood Ratio(LLR)algorithm was used to extract the tagged words from the relevant citation literature for clustering analysis.

The analysis from the CiteSpace illustrated that [39], [40] were cited in four papers with the highest number of co-citations and had a significant impact on this field. (Vose, D.. 2008) [88] provided a guidance framework that focuses on specific methods and steps for quantitative analysis of risk in the field of risk management. Using a survey of recent studies conducted on databases, virtual reality, geographic information systems, 4D CAD, BIM and sensor technologies, Zhou *et al.* [40] found that a variety of digital tools were available to address safety issues during construction, but that there were not many available to support safe design during construction. In addition, new intervention types were proposed, such as the use of digital models to facilitate multiparty collaboration on safety. Zhou *et al.* [39] outlined a weakly supervised migration learning approach that incorporates 2D and 3D labels within a unified deep neutral network with a two-level cascade structure, allowing 3D posed labels to be transferred from a controlled laboratory environment to field images. A further application of this technique will be for behavioral simulation and image analysis of worker safety in the construction industry.

In addition, as is shown in figure 7, the co-citation network of reference map with 7 cluster labels were obtained, and the detail information of each cluster was summarized in table 2. According to Table 2, these findings were grouped into two categories, namely methods versus major applications. The silhouette scores for all clusters were close to 1, indicating high homogeneity within each cluster. This means that the significance and robustness of the clustering results have been confirmed. Using the LLR algorithm, labels were assigned to the clusters to describe their nature. Cluster 0 and Cluster 1 have the largest size of references. In Cluster 0, the average age of the literature is 2001, with references appearing earlier and still being consistently cited in the last 12 years. Note that Cluster 1, in addition to having a higher number of references, also has an average year of 2010 and a more recent reference, indicating an increase in interest in this field in recent years.

2) CITED JOURNALS

Journals with high impact factors and higher relevance in the field of the paper are more likely to be cited by other papers. CiteSpace was configured with the node type "cited journal" and all other settings were left unchanged. After software analysis, Table 3 further summarized the top 10 cited journals, and queried the number of articles published in these journals from 2010 to 2021 in order to calculate the impact factor of the journals in that particular field. As is shown, *journal of construction engineering and management, international journal of project management, journal of computing in civil engineering and automation in construction have got the higher domain-specific impact factors*. In other words, these 4 journals contribute more to high-quality studies on the topic of intelligent risk management in construction and focus more on this area.

C. CO-VISION NETWORK ANALYSIS

1) KEYWORDS CO-VISION NETWORK ANALYSIS

Keywords representing the core content of existing research and describing the topics of research within a given field. The node type was "term", meaning noun words were extracted from the title, abstract, author keywords, and publisher keywords. The time period was "1 year", the criterion was "Top 10% per slice, up to 100" and the web culling method was "Pathfinder". A total of 589 keyword nodes and 4129 relationship lines were analyzed from the data base, as shown in Figure 10. The centrality of a keyword represents its importance within an overall keyword co-network and is indicative of the core body of research at that time. The top 20 keywords

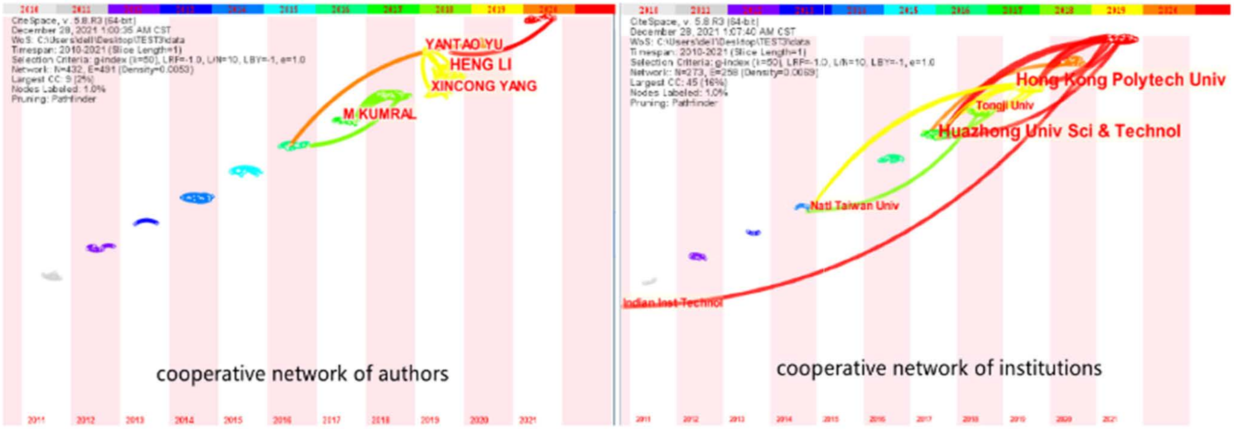


FIGURE 8. The cooperative network of authors and institutions.

TABLE 2. Summary of identified co-citation clusters.

Type	Cluster ID	Cluster label	size	Silhouette	Mean year	Alternative label
method	0	causality constraint	23	1	2001	using Bayesian network; software project risk analysis; application; evaluation
applica tion	1	wearable biosensor	23	1	2010	construction site; assessing worker's stress; application; physical demand
method	2	emergency evacuation	19	1	2007	metro station; deep excavation project; semantic IFC data model; automatic safety risk identification
applica tion	3	construction worker	13	0.996	2012	smart insole; computer vision; joint-level vision-based ergonomic assessment tool; application
method	4	rule extraction	13	1	2001	construction companies; financial risk hedging; predicting derivative use;
applica tion	5	blast fragility	13	1	1988	concrete column; novel reliability technique; performance-based seismic design; structure
method	6	classification method	13	1	2014	Beijing subway; environmental risk; design; emergency evacuation

TABLE 3. Top 10 journals in terms of number of publications and citations (2010-2021).

Journals	Number of publications	Number of citations	Domain-specific impact factors
JOURNAL OF CONSTRUCTION ENGINEERING AND MANAGEMENT	1827	97	5.31%
AUTOMATION IN CONSTRUCTION	2706	86	3.18%
EXPERT SYSTEMS WITH APPLICATIONS	11,278	75	0.67%
INTERNATIONAL JOURNAL OF PROJECT MANAGEMENT	1,184	71	6.00%
SAFETY SCIENCE	3457	50	1.45%
JOURNAL OF COMPUTING IN CIVIL ENGINEERING	969	49	5.06%
ENGINEERING STRUCTURES	9894	37	0.37%
EUROPEAN JOURNAL OF OPERATIONAL RESEARCH	7702	37	0.48%
RELIABILITY ENGINEERING & SYSTEM SAFETY	3478	36	1.04%
BUILDING AND ENVIRONMENT	5617	25	0.45%

Domain-specific impact factors：Impact factor in intelligent risk management of construction (number of citations/Number of publications)

as well as their centrality and occurrence time are shown in Figure 11. From 2010, the year when the analysis began, the keyword "construction industry" was at the core of entire network with the highest centrality of 0.16. In the same year, the terms "risk assessment", and "decision making" appeared, implying that traditional risk management was still the main trend. The keyword "intelligent system" grew rapidly, showing 177 appearances between 2012 and 2021,

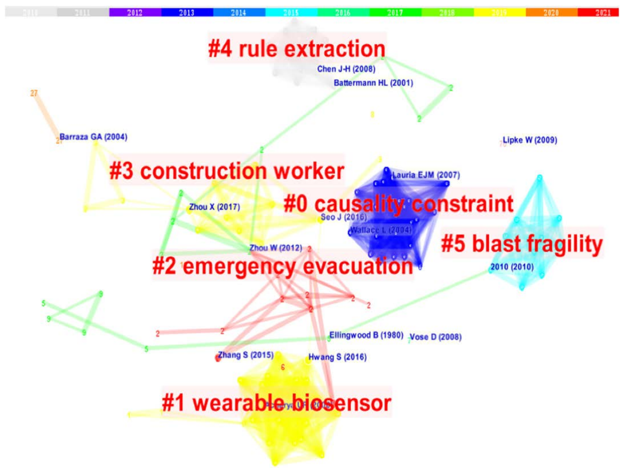


FIGURE 9. Cluster of co-citation.

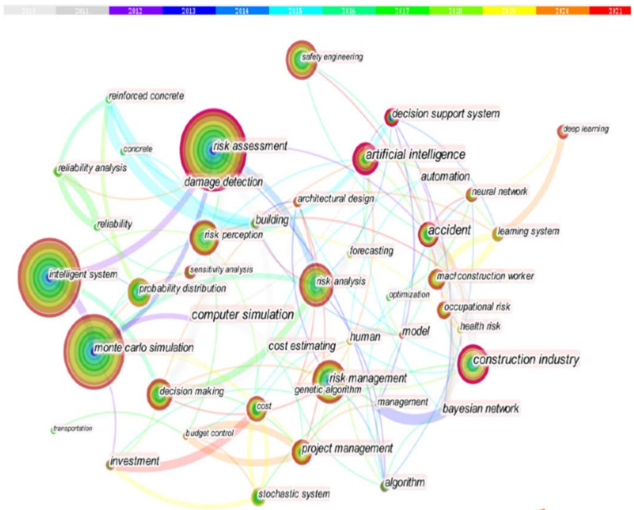


FIGURE 10. The keyword network.

the second highest number of occurrences ever recorded. Following this, the research topics became more segmented, with ''project management'', ''risk perception'' and ''safety engineering'' becoming the main focus of research on intelligent risk management in the construction industry from 2015 onward. Since 2017, AI technologies has become the main trends in this field, such as ''machine learning'' and ''deep learning''

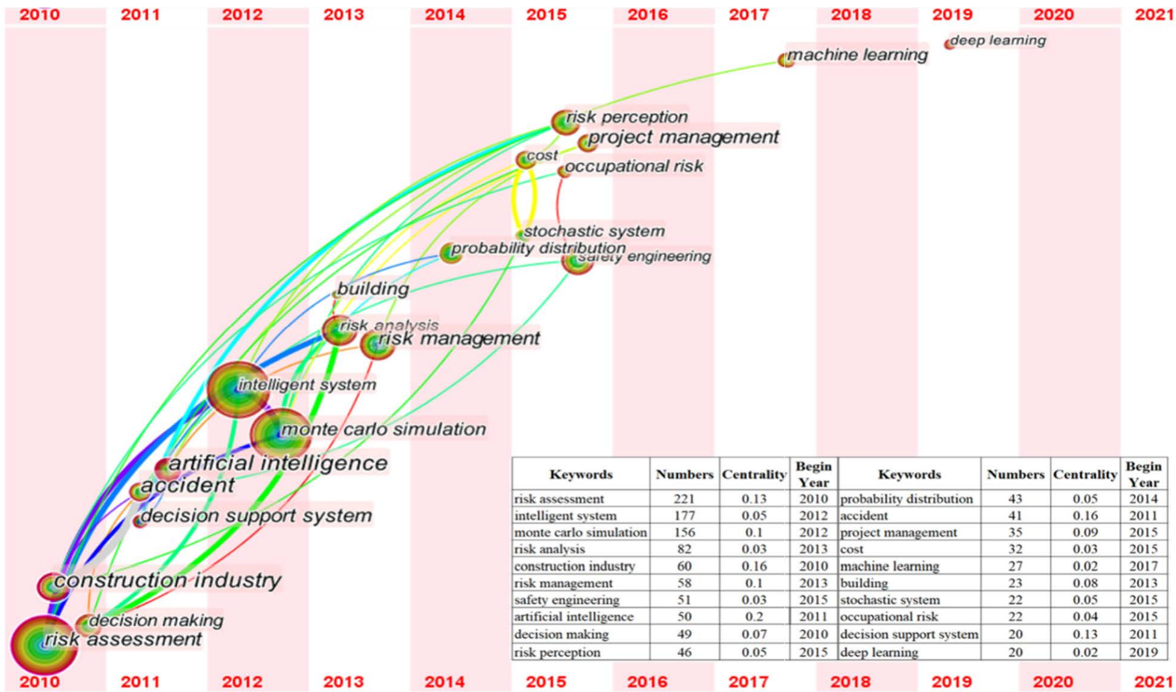
In order to perform cluster analysis of keywords in this research field, CiteSpace software was utilized and the Log-Likelihood Rate algorithm (LLR) was applied. By using the feature words taken by the LLR operator as the cluster names, there were 15 clusters and their timeline graph with keywords were generated, as shown in figure 12. Table 4 summarized information of these 15 clusters, including ID, Cluster label, Size, Silhouette, Occurrence Mean Year, Alternative Label and some Typical papers.

Some detailed clusters information are as follows:

Cluster #0 (workers behavior) has been the cluster that has produced the most literature, with 57 articles. This cluster began in 2016. It is worth noting that this area of interest continued until 2021, with the latest keyword being ''safety management''. Two primary areas of clustering research were explored, the first being a set of analytical computational models derived from computer simulations. As an example, Yu *et al.* [55] presented a novel non-invasive sensor-based fatigue assessment model that utilized computer vision to monitor the whole-body fatigue of construction workers. This method could collect and utilize 3D model data from a motion capture algorithm and biomechanical analysis, which experiments demonstrated the feasibility and potential of this method for promoting intelligent safety in the construction industry. Secondly, the use of risk management software, for example Marefat *et al.* [69] summarized the development of BIM in the field of construction project safety risk management using a qualitative analysis of questionnaires. The risks and barriers to the adoption of BIM were analyzed and solutions were proposed.

Cluster #1, novel reliability technique, which included the keywords ''3D macro model'', ''probabilistic modeling'', ''consideration of multiple dependent uncertainties'', ''embedded system'', and ''monte carlo simulations (mcs)'' with 47 articles. Within this cluster, the central issues include applications of intelligent risk management [70], which combined cost-benefit analysis, Monte Carlo simulation, and decision support systems to provide risk analysis and forecasting. Using Fuzzy Stochastic Monte Carlo Simulation (FR-MCS) [71], this paper established the FR-MCS technique as a hybrid method for risk and uncertainty assessment and compared FR-MCS results to traditional Monte Carlo methods. According to the results, the FR-MCS technique facilitated decision-making by decision-makers in both the public and private sectors that were involved in PPP-BOT projects. Providing greater flexibility to decision makers, this method could be utilized by all parties involved in the project at the negotiation time.

Cluster #2 was included in machine learning techniques cluster, combining 45 articles. In this cluster, the main research questions related to the most recent artificial intelligence techniques, with interchangeable cluster labels including knowledge graph; deep reinforcement; and dynamic pricing demand response. Chen *et al.* [31] built an automated vulnerabilities mining model using knowledge graph technique. First, a knowledge graph was constructed by extracting the basic information of engineering quality results and reasoning these results, resulting in a correlation analysis of information and visualizing the results of information processing. After the creation of the knowledge graph was completed, the corresponding attack graph was then created for the specific network environment to determine the attack path. This data could be used for risk assessment in the future. A number of text mining methods were utilized to automatically identify security incident reports containing corresponding risks [72]. The process of text recognition was followed by the construction of a domain lexicon, the calculation of information entropy weighted word



Keywords	Numbers	Centrality	Begin Year	Keywords	Numbers	Centrality	Begin Year
risk assessment	221	0.13	2010	probability distribution	43	0.05	2014
intelligent system	177	0.05	2012	accident	41	0.16	2011
monte carlo simulation	156	0.1	2012	project management	35	0.09	2015
risk analysis	82	0.03	2013	cost	32	0.03	2015
construction industry	60	0.16	2010	machine learning	27	0.02	2017
risk management	58	0.1	2013	building	23	0.08	2013
safety engineering	51	0.03	2015	stochastic system	22	0.05	2015
artificial intelligence	50	0.2	2011	occupational risk	22	0.04	2015
decision making	49	0.07	2010	decision support system	20	0.13	2011
risk perception	46	0.05	2015	deep learning	20	0.02	2019

FIGURE 11. Top 20 keywords and their information.

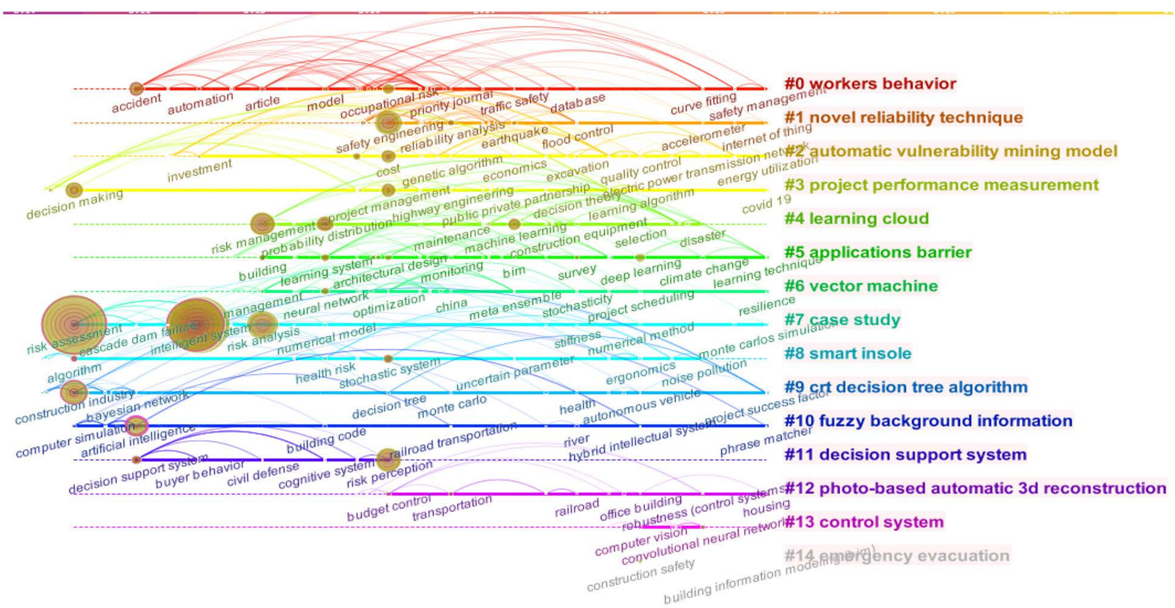


FIGURE 12. The timeline of clusters.

frequencies, and the construction of word vectors. An analysis of 221 metro construction accident reports was conducted to extract 37 safety risk factors and verify their feasibility.

Cluster #3 included ‘‘project performance measurement’’, ‘‘operational safety’’, ‘‘complex projects’’, and ‘‘construction safety risk perception’’, in addition to ‘‘intelligent systems.’’ This cluster focused on the application and performance of intelligent systems in various projects. Accordingly, Zhang *et al.* [73] used intelligent systems to predict risks in engineering safety. Iranmanesh and Hojati [6] focused on the application and evaluation of intelligent systems to project performance management. Choi *et al.* [74] employed artificial intelligence and text mining techniques to develop an EPC contract risk analysis tool for contractors based on critical

TABLE 4. Clusters of keyword co-vision network.

ID	Cluster label	size	Silhouette	Mean year	Alternative Label Name	Typical Papers
0	workers behavior	51	0.778	2016	data-based platform; integrating safety behavior; earthmoving case study; construction planning	(Guo et al., 2016)[41] (Goh & Askar Ali, 2016)[42]
1	novel reliability technique	47	0.824	2016	performance-based seismic design; wall-frame building shear; reliability assessment	(Gaxiola-Camacho et al., 2017)[43] (Tuken et al., 2017)[44]
2	automatic vulnerability mining model	45	0.85	2017	knowledge graph; offshore EPC megaproject; forecast model; linear programming approach	(Z. Chen et al., 2020)[31] (Naderpour et al., 2019)[45]
3	project performance measurement	42	0.854	2015	assessing work; physical demand; project delivery decision; predicting cost variance	(Iranmanesh & Hojati, 2015b)[6] (Salling & Leleur, 2017b)[46]
4	learning cloud	41	0.731	2017	Bayesian network; risk measurement; super-long tunnel; group construction	(C. Chen et al., 2020)[47] (Tong et al., 2018)[48]
5	applications barrier	39	0.823	2016	construction safety; forecasting air temperature; using geographic information; different data-intelligent modeling strategies	(Choi et al., 2021a)[49] (F. Zhang et al., 2019)[50]
6	vector machine	36	0.723	2015	using evolutionary fuzzy least square; risk score inference; bridge maintenance project; artificial intelligence combiner	(J. H. Lee & Yi, 2017)[51] (Cheng & Hoang, 2014)[52]
7	case study	35	0.875	2013	risk management; learning cloud; Bayesian network; risk measurement	(Chou et al., 2017)[53] (J. Han et al., 2017)[54]
8	smart insole	29	0.843	2015	computer vision; stochastic-based noise exposure assessment; off-site construction; vital sign	(Yu et al., 2019)[55] (Wang et al., 2021)[56]
9	CRT decision tree algorithm	28	0.889	2014	no-bid decision-making model; using data-mining technique; predicting workplace accident; lane road construction site	(Gunduz & Al-Ajji, 2021)[57] (Tixier et al., 2017)[58]
10	fuzzy background information	26	0.869	2014	multi-agent system; web-based concession period analysis system; mobility service; smartphone application	(Ahmadi et al., 2017)[59] (Park et al., 2021)[60]
11	decision support system	25	0.905	2013	RC girder bridge superstructure; carbon footprint; independent component ensemble; brain-computer interface	(Hosny et al., 2012)[61] (Sun et al., 2015)[62]
12	photo-based automatic 3d reconstruction	14	0.805	2017	train accident scene; cost contingency management; statistical learning technique; value analysis	(Z. Tang et al., 2016)[63] (Traynor & Mahmoodian, 2019)[64]
13	control system	13	0.899	2019	po engineering safety monitoring; high-risk scenario; building construction; pathology assessment	Nie et al. 2020[65] Dimitrova et al. 2020 [66]
14	emergency evacuation	6	0.956	2020	metro station; case study; risk analysis; risk assessment	(M. Li et al., 2018)[67] (Y. Tang et al., 2021)[68]

risk checks (CRC) and term frequency analysis (TFA) and verified their accuracy. The result has enhanced the precision of engineers' risk analyses and allowed for intelligent risk management.

TABLE 5. Keywords with the strongest citation bursts.

Keywords	Strength	Begin	End	Duration	2010 - 2021
decision support system	3.41	2011	2015	5	
management	2.76	2013	2015	3	
numerical model	3.24	2014	2016	3	
historical data	3.5	2015	2016	2	
concrete	3.36	2015	2017	3	
stochastic model	3	2015	2016	2	
algorithm	2.91	2015	2018	4	
uncertainty analysis	4.03	2016	2017	2	
transportation	4.03	2016	2017	2	
reliability analysis	3.8	2016	2018	3	
reinforced concrete	3.36	2017	2018	2	
survey	2.88	2018	2019	2	
deep learning	6.53	2019	2021	3	
machine learning	3.83	2019	2021	3	
construction worker	3.45	2019	2021	3	
construction site	2.75	2019	2021	3	

Cluster #4 was connected to artificial intelligence and included the tags "learning cloud", "risk measurement", "Bayesian network" and "vulnerability analysis". The cluster was formed in 2013 and was expected to last until 2020. There were 50 papers expected to be published. "Systems engineering", "service life", "diagnosis" and "evolving network" were used as keywords. Cluster research focused on specific applications of specific AI software or models. For example, Chen *et al.* 2020 [75], which combined fuzzy set theory with Bayesian networks to create a Bayesian network cloud model and to use it in the field of risk management. It made use of artificial intelligence, a learning mechanism that automatically discovered structure from data in order to create dynamic networks. This model is then tested through a tunneling project.

It is worth noting that cluster #9 (CRT decision tree algorithm) were the ones that have endured the longest over the study period (2010-2021) and would be the main research trend in the future. A typical paper has been that of [76]. He used automatic machine learning methods to obtain risk information from the physiological signals generated by workers during the course of their daily work activities. In addition to its accuracy of 81.2%, this has been a revolutionary method of intelligently managing risks and making decisions about workers' work in real time. [57] collected qualitative information and used Chi-square Automatic Interaction Detector (CHAID) and Classification and Regression (CRT) decision tree algorithms to develop intelligent decision models that could help bidders make informed decisions about whether to bid. The simplicity and speed of this model could enable engineering decisions to be reached more quickly. This cluster addressed the use of BIM in risk management. Accordingly, [14] designed an automatic identification and classification of environmental risks within a design phase BIM system, integrated risk management with an integrated BIM platform, and validated the risk management platform with the help of a specific project. An approach based on BIM that would identify environmental risks automatically and would facilitate the transfer of information regarding risk during construction in addition to increasing the efficiency of safety risk-specific design. In a paper [30] has proposed a method for quantitative assessment of construction safety risks by integrating safety risk information with BIM through a Revit plug-in. The method was validated through case studies. It has been based on a BIM platform that been built on combining safety risk information with BIM. In the context of the great digital revolution, information, procedures, and automated management will be the new directions in risk management.

2) KEYWORDS BURST ANALYSIS

In order to better identify research frontiers in the field, this study conducted a burst detection of keywords via an algorithm built into software, and results are shown in Table 5. There were 16 burst keywords found, including their burst strength, begin year, end year and duration. A keyword with the longest duration was "decision support system", which lasted for five years from 2011 through 2015. Following this was the keyword "algorithm", which lasted for a period of four years, from 2015 to 2018. The strongest keyword is "deep learning". Additionally, it is associated with the keywords "machine learning", "construction worker", and

TABLE 6. Clusters in fields of conceptual model.

ID	Cluster label	Conceptual model field	Categories
0	workers behavior	Building Physics	Information
1	novel reliability technique	Machine Learning	Technologies
2	automatic vulnerability mining model	Machine Learning	Technologies
3	project performance measurement	Building Physics	Information
4	learning cloud	Machine Learning	Technologies
5	applications barrier	Machine Learning	Technologies
6	vector machine	Machine Learning	Technologies
7	case study	Building Physics	Information
8	smart insole	Machine Learning	Technologies
9	CRT decision tree algorithm	Decision Making	Technologies
10	fuzzy background information	BIM-based Model	Technologies
11	decision support system	Decision Making	Technologies
12	photo-based automatic 3d reconstruction	BIM-based Model	Technologies
13	control system	Building Digital Twin	Technologies
14	emergency evacuation	Machine Learning	Information

"construction site", which have been recent developments in the field of intelligent risk management in the construction industry.

V. RESEARCH GAPS

Several research gaps that this research aimed to fulfil were found and analyzed by Systematic Literature Review. Moreover, the 15 clusters could be grouped into each process of intelligent risk management conceptual model, as demonstrated in Table 6. Through combining conceptual model and literature cluster, there were 5 main research gaps could be found, as is shown in figure 13. Thus, much literature would still be needed to fill the gaps and to overcome the barriers.

The first gap field is intelligent risk management on Digital Twin Building, with only #13 cluster related to it, but not to the construction of specific Building Digital Twin. The next gaps field are No2 "decision making system" and No3. "BIM-based model", and has two related clusters respectively. Thus, the links between them is still in infancy. No. 4 is "Building Physics", has the largest volume of literature, but there is still room for research on the diversity of risk types. Last one No.5, Most scholars currently focus on the analytical level of the technical. The gaps between technology use in intelligent risk management are lacking of detailed risk categorization, and developing the risk knowledge map to better understanding the relationship between risks.

In order to better understanding detailed research gaps, this research retrieved typical papers from each literature clusters and summarized information. Table 7 categorized research barriers and challenges from typical papers into context-related, technology-related, data-related and application-related barriers. As a result, this research would find a model to fulfil these gaps and verify its possibility.

VI. DISCUSSION

According to this study, CiteSpace was used to analyze and elaborate 436 articles on intelligent risk management in the construction industry in the WOS and Scopus databases from 2010 to 2021, which included published countries, authors, authors' institutions, co-citation journals and papers, keywords, and clusters of keywords. Accordingly, this study may identify gaps in intelligent risk management in the construction industry and provide suggestions for future research as follows.

Based on bibliometric analyses of the publications of the literature reviewed in this study, it was evident that China was the country with the highest number of publications in this field, followed by the United States, Italy, the United Kingdom and South Korea. Papers from the United States had the highest centrality and were most closely tied to other countries. They were closely followed by those from China and Spain. Apart from China, the only developing countries that rank in the top ten in terms of number of publications were Iran and India, with very little research from other Asian countries and in Africa and South America, which might be related to the digitalization and intelligence promotion processes. Since the construction industry represents one of the key pillars of the national economy, it is imperative that research be conducted on risk intelligence management in these developing regions in order to improve the efficiency of lean engineering management and gain higher profits to facilitate the development of the construction industry. Furthermore, research into the development of artificial intelligence technology in the construction industry is still in its infancy, and a significant number of actual projects have not yet been fully realized [15]. A large number of these projects will be undertaken in developing countries in the future, and these countries and regions will offer greater opportunities for risk intelligence management.

The E B LEE is the most productive author in the field of intelligent risk management in the construction industry, according to the contributions and influence of the lead authors and institutions identified in the analysis network, and he is from the Pohang University of Science and Technology. Y Yu, Heng Li, and Xiangzhou Zhang are three of the top 10 published authors from Hong Kong Polytechnic University. A research collaboration group has also been established with Huanzhong University of Science and Technology, Sun

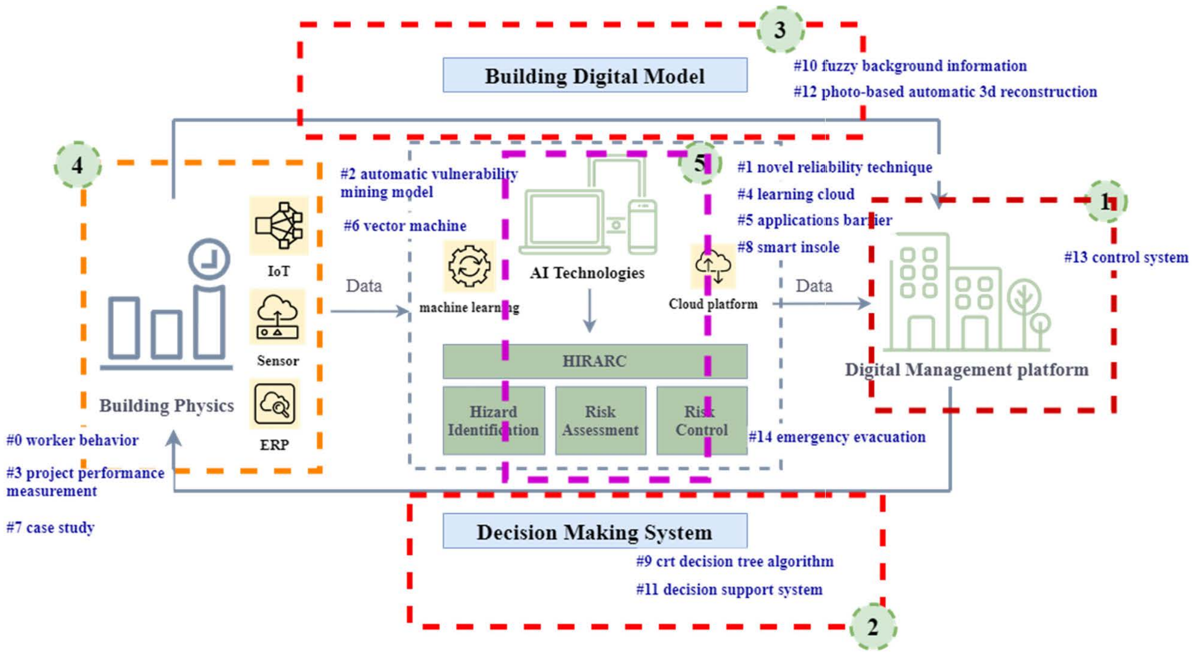


FIGURE 13. Research gap fields.

Yat Sen University, and New Jersey Institute of Technology. There is however, still much room for improvement and development in the overall collaborative network and publication volume.

In this study, the top 10% of co-cited references in each time slice were analyzed, resulting in 405 nodes and 1190 linked lines. Most frequently cited references concern traditional risk analysis methods, as well as specific technical tools. The clustering of all the references revealed two broad categories and seven clusters of co-cited references. The first category is methods, which includes clustering causality constraints, emergency evacuation, rule extraction, and classification methods, including Bayesian networks, software systems, and data models. The second category consists of applications, such as wearable biosensors, blast fragility, and construction workers. These include construction sites, physical tasks, computer vision, and concrete columns, for example. In spite of the fact that risk intelligence has focused primarily on specific construction participants and physical projects, it has not fully addressed, for example, risk management in the pre-construction and operational phases, intelligent risk management for construction participants such as subcontractors and material suppliers. The discussion of intelligent systems such as BIM, cloud platforms, and the Internet of Things, and how they may be integrated with new technologies, needs to be addressed by future scholars.

Analysis of co-cited journals could provide insight into the impact of journals in the field, as well as providing a resource for scholars seeking papers or publications in the same field. In this study, we not only examined the number of journal co-citations through the software, but we also examined the number of articles that had been published in each journal from 2010 to 2021 and calculated the impact factor for a specific field using the method of calculating the WOS journal impact factor. *journal of construction engineering and management, international journal of project management, journal of computing in civil engineering and automation in construction*, these 4 journals contribute more to high-quality studies on the topic of intelligent risk management in construction and focus more on this field. It should be noted, however, that there is no universally recognized standard for calculating a precise journal-specific impact factor. Scholars should focus on these four journals while also searching for high-quality papers in other journals.

The clusters ''workers behaviors'', ''novel reliability technique'', ''automatic vulnerability mining model'', ''project performance measurement'', ''applications barriers'', ''vector machine'', ''CRT decision tree algorithm'' ''fuzzy background information'', and ''3D reconstruction'' will continue to be reviewed. Recent keywords include ''text mining'', ''safety management'', ''building owner'', ''early stage'', and ''BIM platform'', and the next step is for scholars to continue their analysis of these technologies and management objects. As a result of burst word detection, the terms ''deep learning'' and ''machine learning'' in the field of artificial intelligence, as well as ''construction site'' and ''construction worker'' in the field of risk management were identified. Recent hotspot studies have focused on ''worker'' and ''construction site'', and these new directions and hotspots would also form a future research direction for scholars.

Additionally, efficient construction risk management also has significant impacts on society, the environment, and the

TABLE 7. Benchmark of research barriers and challenges.

NO.		Gap Fields		DESCRIPTION	REFERENCES
Context-related barriers	1	4	Research Issues	lack of research considered the relationship between risk management and project outcomes	(Pan & Zhang, 2021)[15] (Yan et al., 2020)[16]
	2	4		Lack of project-specific risk management standards	(W. Zhou et al., 2012)[40]
	3	4		Lack of considering the dynamic nature of risks and causal interactions between risks	(Ying et al., 2021)[35] (Cristian, 2010)[28]
	4	5	Research Methodology	Lack of diagramming and analysis-based risk identification tools and techniques	(Y. Lu et al., 2021)[77] (M. Zhou et al., 2021)[14]
	5	5		Lack of full process risk intelligent management	(M. Li et al., 2018)[67]
	6	1		Lack of research on platforms (EMAP) or Digital Twin for risk intelligence management	(Linn et al., 2000)[7] (Zhong et al., 2017)[1]
	7	1		Lack of research on the combination of intelligent risk management technology and modern information management software (BIM) in the construction industry	(Wu et al., 2021a)[78] (Zhiming et al., 2020)[27] (Hossain et al., 2018)[79]
Technology-related barriers	8	2	AI technology	Lack of research on intelligent risk management techniques for risk control	(Choi et al., 2021a)[49] (J. H. Lee & Yi, 2017)[51]
	9	2		Lack of comparative studies on the applicability of AI technology to risk management	(L. Zhang et al., 2017a)[73] (Cheng & Hoang, 2014)[52] (C. Chen et al., 2020)[47]
	10	2		Lack of research on intelligent optimization and process mining in risk intelligence management	(Chou et al., 2017)[53] (Nie et al., 2020)[65]
	11	2		Lack of application of knowledge graphs in risk intelligent management	(Salling & Leleur, 2017a)[46] (L. Zhang et al., 2017b)[73]
	12	1	Information Technology	Lack of API development for risk intelligent management	(Iranmanesh & Hojati, 2015a)[6] (M. Zhou et al., 2021)[14] (Marefat et al., 2019)[69] (Gunduz & Al-Ajji, 2021)[57]
Data resource-related barriers	13	1, 4	Data collection	Data ownership and data privacy concerns	(L. Zhu et al., 2019)[80] (Yan et al., 2020)[16]
	14	1, 4		Lack of a common data environment (CDE)	(Tixier et al., 2017)[58] (L. Lu & Zhou, 2021)[81] (Z. B. Liu et al., 2021)[82]
	15	1, 4		Data is scattered and lacks categorization and organization	
	16	1	Data processing	Lack of criteria for risk classification	
Application-related barriers	17	1	Range of applications	Lack of research on intelligent risk management from the perspective of all parties involved in the project	(Bayir et al., 2011) [83] (P. C. Lee et al., 2020)[76]
	18	1		Lack of all life-cycle intelligent risk management	(Wu et al., 2021b)[78]
	19	1		Lack of a common risk intelligence management system that can be applied to a variety of project types	
	20	1	Application personalization	Lack of individual applications for each project based on common intelligent risk management	
	21	1		Lack of development and application for intelligent risk management software	
	22	2		lack of providing smart risk response and consequence solutions	

economy [84], [85], however, the common word analysis of the literature shows that there is a lack of keywords related to society, the environment, and the economy, so there is a lack of research on risk intelligence management and these topics. With the development of big data today, the quality and quantity of data are directly related to the efficiency of risk management, but the databases of current studies do not quite meet the requirements of big data [16], [76], [86] and the sample size is small. Moreover, the validation of new technologies, such as artificial intelligence, is limited to a single project [53], [66], [87]. These are all matters worthy of continued research by scholars.

In the future, one of the major research directions will be the further application of artificial intelligence in intelligent risk management, exploring more advanced technology and accumulating more data sources and models. Simultaneously, smart technologies are linked to real-time information management models and platforms for intensive management. In addition, researchers can work on whole-process intelligent risk management and extend intelligent risk management technology throughout the entire industry.

Moreover, the future research trends could be found, including:

1) To develop digital management platform for intelligent construction management and risk management;

2)To build a decision-making system for risk management to find an optimum solution;

3) To refine building digital models which would be the basis of digital management platform;

4) To identify and category the characteristic construction risk factors by using machine learning techniques, just like text mining or knowledge graph;

5) To build an API to embed decision making system into digital management platform.

6) To use intelligent risk management system in real-time projects to verify its possibility.

VII. CONCLUSION

In the context of industry revolution 4.0, and profit revenue declining, AI technology could be used in construction industry. As is shown in figure 2, some of construction management fields have already used different kinds of AI technologies. For instance, the knowledge representation and reasoning by computer has been an efficiency way to manage building design, facility and cost. Meanwhile, machine learning has been used in risk management and building maintenance. There has been a large amount of literature and modelling of AI technology demonstrating the benefits which would impact construction industry; however, the application of practical project and the development of specific software and technology is still lagging behind.

As the main fields of construction management, the intelligent risk management is urgent and necessary to be developed to help construction participants gaining lean projects. This study used Systematic literature Review to analyze intelligent risk management in the building industry from a variety of perspectives. It examined the evolution of research on the application of intelligent risk management in the construction market, thereby providing a reference for future research directions on intelligent risk management.

Currently, scholars have put more emphasis on intelligent management techniques and implement strategies in HIRARC method. However, less literature was conducted to refine data source and categories, consider the link between digital management platform and risk management, develop an intelligent decision support system.

Furthermore, text mining technique, Bayesian network could be used to conduct risk data identification and analysis. Risk factors knowledge graph would be generated to help construction participants find hazard directly. By using Plug-in, the intelligent risk management system could combine with BIM, which would be the basis of Digital Twin Building.

The overall findings in this research demonstrated that the intelligent risk management is the future research trend to meet the construction digitalization. This decision-making system for risk control would be one of important management part in future Digital Twin Building.

This study also has some limitations. In the first instance, only WOS and SCOPUS were used as database sources. For the time period, only the last 12 years were considered. In addition, the total number of articles was only 436. Accordingly, there may be a few omissions. The paper included a comprehensive discussion of the background of the field's development as well. It discussed the evolution of research directions and hot trends, but does not provide an analysis of the interdisciplinary content in depth. This is because risk management is a complex system involving a wide range of disciplines. This aspect will contribute to future research and will be a developing direction.

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