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Systematic Review

A Bibliometrics-Based Systematic Review of Safety Risk Assessment for IBS Hoisting Construction

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Abstract: Construction faces many safety accidents with urbanization, particularly in hoisting. However, there is a lack of systematic review studies in this area. This paper explored the factors and methods of risk assessment in hoisting for industrial building system (IBS) construction. Firstly, bibliometric analysis revealed that future research will focus on "ergonomics", "machine learning", "computer simulation", and "wearable sensors". Secondly, the previous 80 factors contributing to hoisting risks were summarized from a "human–equipment–management–material–environment" perspective, which can serve as a reference point for managers. Finally, we discussed, in-depth, the application of artificial neural networks (ANNs) and digital twins (DT). ANNs have improved the efficiency and accuracy of risk assessment. Still, they require high-quality and significant data, which traditional methods do not provide, resulting in the low accuracy of risk simulation results. DT data are emerging as an alternative, enabling stakeholders to visualize and analyze the construction process. However, DT's interactivity, high cost, and information security need further improvement. Based on the discussion and analysis, the risk control model created in this paper guides the direction for future research.

Keywords: hoisting; risk assessment; systematic review; digital twins; artificial neural network; bibliometric analysis

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1. Introduction

Construction is still considered one of the most hazardous industries, with safety accidents being a primary concern for many years [1,2]. These accidents have severe implications that cannot be ignored [3,4]. In Malaysia alone, there were 148 construction accidents in 2022, resulting in 59 fatalities [5]. Even in economically developed European countries, construction still causes many casualties. For instance, in Germany, 115,739 people were injured due to construction accidents in 2020, according to the ILO [6].

In the construction industry, hoisting accidents are an unfortunately common occurrence. Studies conducted by Shao (2019) and Simutenda (2022) have shown that a significant proportion of safety incidents can be attributed to hoisting [7,8]. This is particularly true for equipment such as tower and truck cranes, which are critical in transporting loads in high-rise construction projects. Hoisting machinery is a fundamental part of modern construction sites [9–11]. However, using such enormous equipment also has inherent risks, as Xu et al. and Grant and Hinze highlighted [12,13]. Project teams must conduct practical risk assessments during the hoisting process to mitigate these risks. Unfortunately, as noted by Esmaeili (2015) and Kargar (2022), many teams only become aware of the dangers once an accident has occurred [14,15]. Therefore, identifying and evaluating the risks associated with hoisting is essential. By doing so, management can take the necessary steps to ensure a safe and secure work environment. Recent research by Wan (2022) and Pan (2021) has emphasized the importance of conducting thorough risk assessments during hoisting [16,17].

Research in this field currently faces an issue with incomplete indicator systems. Most articles only include small-scale indicators, and there is significant variation in the elements used [18–21]. This highlights the urgent need to generalize risk factors. While various studies use different assessment methods, there is a lack of comparison between them [22–25]. In fact, the niche area of hoisting in IBS construction has only attracted the interest of researchers in recent years. As a result, there are only a handful of review articles in this area. The uniqueness of this paper lies in the fact that, firstly, we have combined a systematic review approach with bibliometrics, which offers new ideas in terms of methodology compared to traditional reviews. Secondly, this paper uses Bibliomatrix® software to visualize content such as keywords and co-authors to uncover research trends and topical themes. This new software, based on the R language, is powerful but complex to use and, therefore, currently underused, making this paper somewhat pioneering in its technical approach. Finally, our findings interest construction industry professionals, policymakers, and researchers involved in IBS construction projects. The identified framework for future research can guide the development of effective safety protocols and strategies that can contribute to the overall improvement of safety standards for the hoisting of IBS construction.

The following sections are structured as shown in Figure 1. Section 2 covers the research material and methodology, including an introduction to the systematic review and bibliometric approaches. Section 3 provides an overview of the results of the bibliometric and inductive analyses, mainly covering risk factors and assessment methods. Section 4 provides a framework discussion on the application and future research directions of ANN and DT, and Section 5 concludes with a summary and limitations.

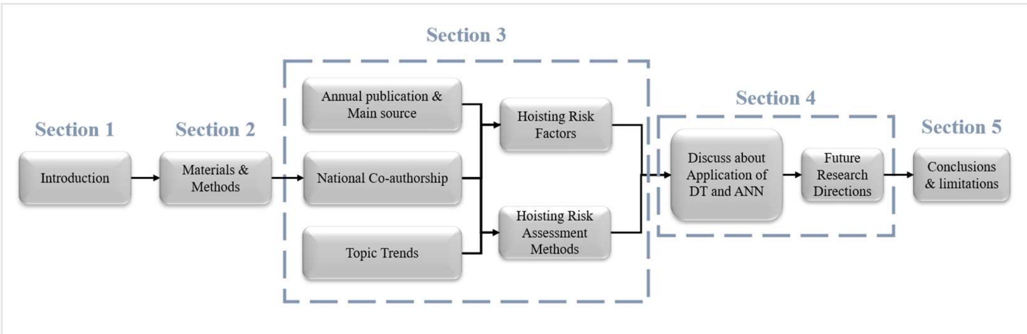

Figure 1. Research framework.

2. Materials and Methods

2.1. Materials

The PRISMA protocol (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) was used in this literature review. The PRISMA guidelines outline the necessary components of a systematic review or meta-analysis report, including the research question, search strategy, study selection criteria, data extraction methods, data analysis, and conclusions [26]. Following these guidelines ensures that the research process is transparent and comprehensive, essential in assessing the validity and replicability of studies [27–29].

Figure 2 illustrates the PRISMA method, which utilizes the comprehensive civil engineering literature available on the Web of Science (WoS) and Scopus databases. While both databases offer vast literature, WoS provides more refined articles, and Scopus provides a broader range of topics [30,31]. To demonstrate, we used WoS's search process and entered keywords such as "hoisting", "safety", "risk assessment", "risk evaluation", and "crane" to perform a combined topic search, which yielded 597 records. We filtered the search results by specifying the fields of specialization as "public environmental occupational health", "engineering civil", "engineering multidisciplinary", and "construction building technology", resulting in 231 records. After narrowing down the search results to only records in English, we were left with 226 records. Peer-reviewed articles undergo rigorous evaluation processes by field experts, ensuring the reliability and quality of the research. They provide the most up-to-date research findings and are more likely to reflect the current state of knowledge in the field. Furthermore, journal articles offer more detailed and in-depth analyses of specific research questions or topics, presenting empirical evidence, methods, results, and discussion more comprehensively, which makes them suitable for rigorous literature reviews. Therefore, we identified only 136 peer-reviewed articles as the dataset. Similarly, we obtained 342 articles from Scopus, and after a manual review of the full text by three experts, we identified 197 records that met the criteria.

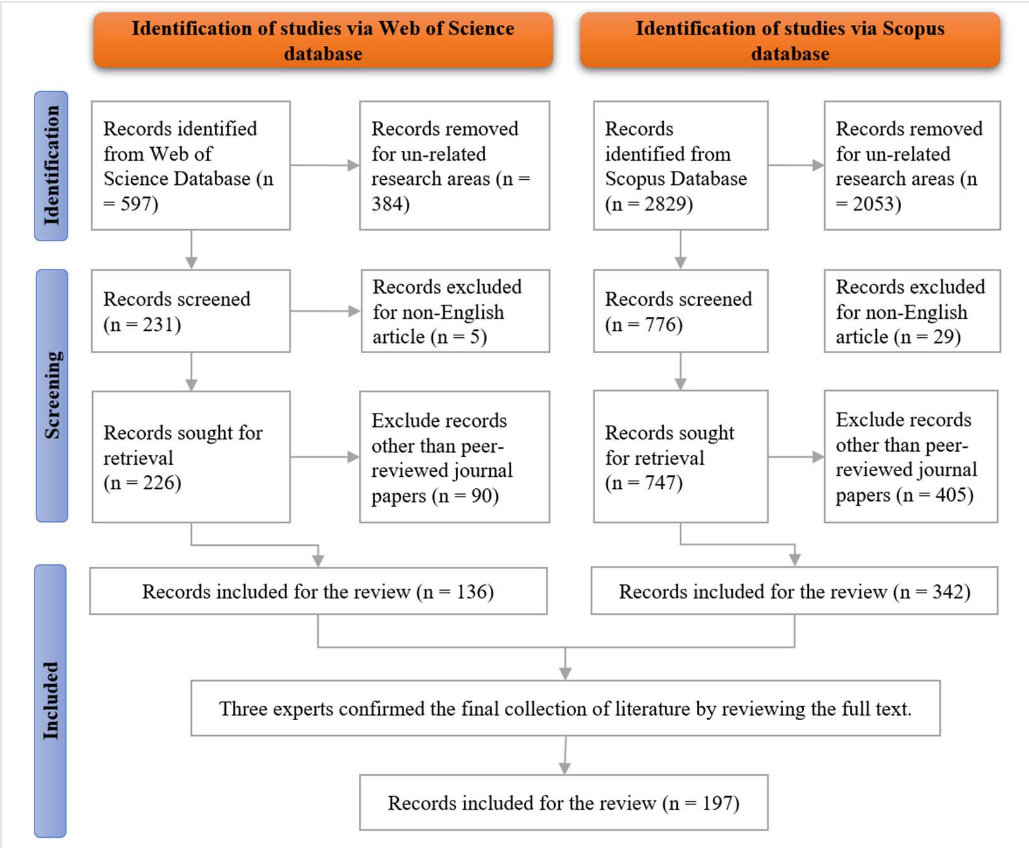

Figure 2. PRISMA literature collection procedure.

2.2. Methods

Bibliometric analysis is a technique that originated from Nalimov and Mulchenko's (1971) book on the progression of science as an information process. This approach employs statistical methods to investigate the influence of scientific publications, encompassing author distribution, citations, keywords, and publications [32,33]. To monitor the development of the field more impartially, the researcher usually entails utilizing bibliometric databases such as Web of Science, Scopus, or Google Scholar, as they contain extensive metadata on scientific publications [34,35].

Numerous tools are available for conducting bibliometric analysis, including VOSviewer®, Gephi®, CiteSpace®, SciMAT®, Bibliomatrix®, and HistCite®. Each tool has its own strengths and weaknesses, as highlighted in recent studies [36–38]. For this study's bibliographic data analysis, Bibliomatrix® was selected due to its rich features and reliable data visualization capabilities [39–41]. In the construction field, recent literature reviews have focused on topics such as BIM collaboration and risk [42], construction waste [43], wood waste from construction [44], and stakeholder relationships in off-site construction [45]. By using Bibliomatrix®, researchers can conduct co-word analysis and co-citation network analysis to visualize the field's research evolution [46–48].

Our team also has conducted an inductive analysis of recent high-quality papers by creating concise summaries of key findings. The analysis focused on two main aspects—risk factors and assessment methods. Qualitative content analysis can be inductive or deductive; we used the former. We extracted specific factors from previous studies to establish a formal IBS hoisting risk control model, which aims to clarify and create more cohesion in the field of knowledge.

3. Results

3.1. Annual Publication and Main Sources

Annual publication volume is often used to gauge the level of productivity within a specific field, indicating its research intensity [49]. Figure 3 displays the yearly publication count in this area from 1994 to 2023. Between 1992 and 2012, the number of publications remained low, with a high of only 9, indicating that the topic needed to receive more attention during that period. However, after 2012, there was a significant surge in published articles, reaching 21 in 2022, indicating that the topic is now a thriving academic area.

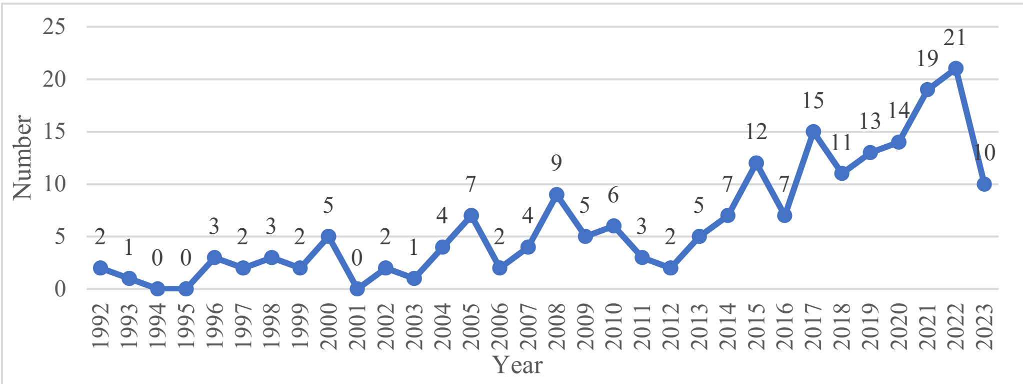

Figure 3. The number of annual publications.

MeanTCperYear is a metric measuring the total publications and average total citations per year. It provides valuable insights into the impact of publication [50]. To calculate MeanTCperYear, we divide the total citations by the years between the current and publication years. Total citations refer to the number of citations a research paper or publication receives, while the current year represents the current year, and the publication year denotes the year the paper was published. For example, if a paper has received 100 citations since its publication five years ago, the average total citations per year would be 100/5 = 20 citations per year. Figure 4 displays the MeanTCperYear values in this field from 1992 to 2023. From 1992 to 2011, it remained below 2.5, fluctuating consistently. After 2013, there were two significant swings, with a peak of 4.74 in 2017. However, in the last five years, it has steadily declined from 4.74 to 1.41, indicating a need for more influential and high-quality articles in the field as it is inversely proportional to the number of published articles.

For the convenience of readers, Table 1 displays the top 10 primary sources related to this field. Notably, "Applied Ergonomics" dominates the category of occupational health journals with 35 sources. "Safety Science" and "Sensors" are closely behind, with 22 and 9 sources, respectively. This information can aid readers in quickly identifying relevant sources.

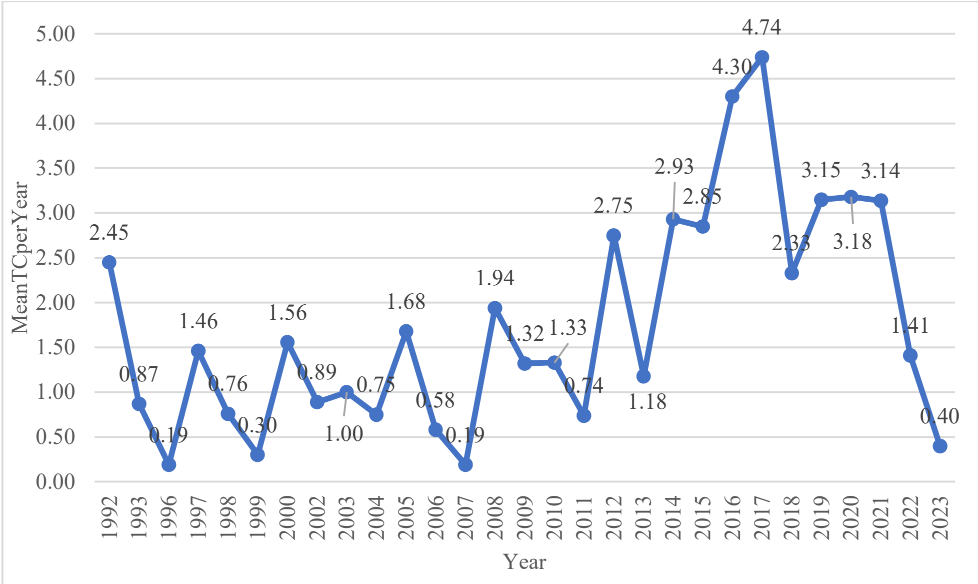

Figure 4. The value of MeanTCperYear.

Table 1. Top 10 main sources.

Sources	Articles
Applied Ergonomics	35
Safety Science	22
Sensors	9
International Journal of Occupational Safety and Ergonomics	7
Journal of Biomechanics	5
Journal of Construction Engineering and Management	5
Mathematical Problems in Engineering	4
Safety and Health at Work	4
Automation in Construction	3
IEEE Transactions on Human-Machine Systems	3

Table 2 indicates the top three institutions as follows: Vanderbilt University (United States), Hong Kong Polytechnic University (China), and Southwest Petroleum University (China). In terms of authors, the top three are N. Arjmand, Z. Liu, and ON. Aneziris.

Table 2. Top 10 institutions and authors of publications.

Institution	Number	Author	Number
Vanderbilt University	11	Arjmand, N.	5
Hong Kong Polytechnic University	6	Liu, Z.	5
Southwest Petroleum University	6	Aneziris, ON.	4
Shanghai Jiao Tong University	5	Li, L.	4
Sharif University of Technology	5	Lu, ML.	4
University of Belgrade	5	Papazoglou, IA.	4
Beijing University of Technology	4	Shirazi-Adl, A.	4
Purdue University	4	Bloswick, DS.	3
University of Alberta	4	Drinkaus, P.	3
Universiti Sains Malaysia	4	Gallagher, S.	3

3.2. National Co-Authorship

In Figure 5 from Bibliomatrix®, the frequency of collaboration between countries is visualized; the connection line's thickness reflects the cooperation's strength. The darker the color of the country, the higher the number of publications (Grey means there are no articles that meet the screening criteria). The collaboration frequency of Iran and Canada is the highest at 4, while the United Kingdom and Italy have the second-highest rating at 3. Partnerships between other countries such as Iran and Germany or Canada and the United States also hold significant importance.

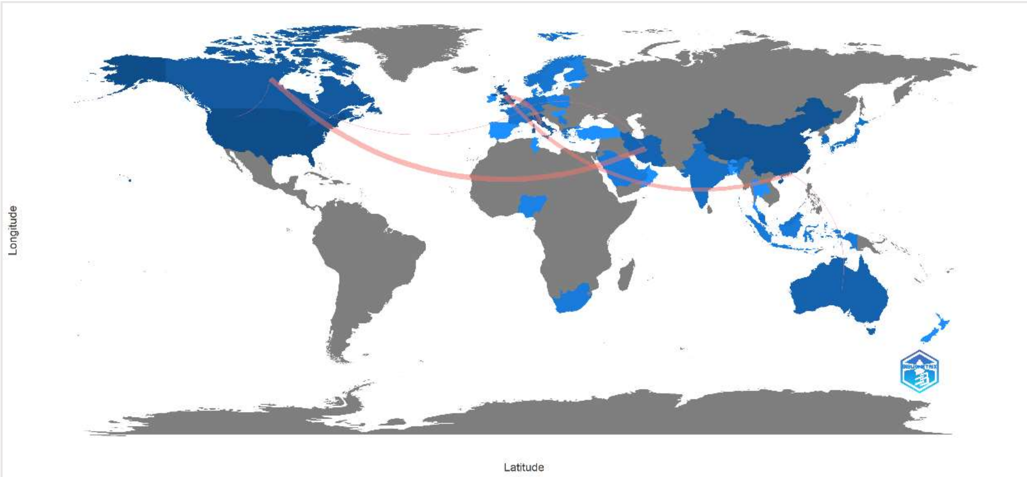

Figure 5. Country cooperation map.

Bibliomatrix®'s Figure 6 displays the primary co-author's team, with colors representing different groups and node sizes indicating author productivity [51]. For example, the blue team includes Liu Z, Sun Z, Meng X, Chu X, and Ma H. It is worth noting that all teams depicted in the figure have made remarkable contributions to field development.

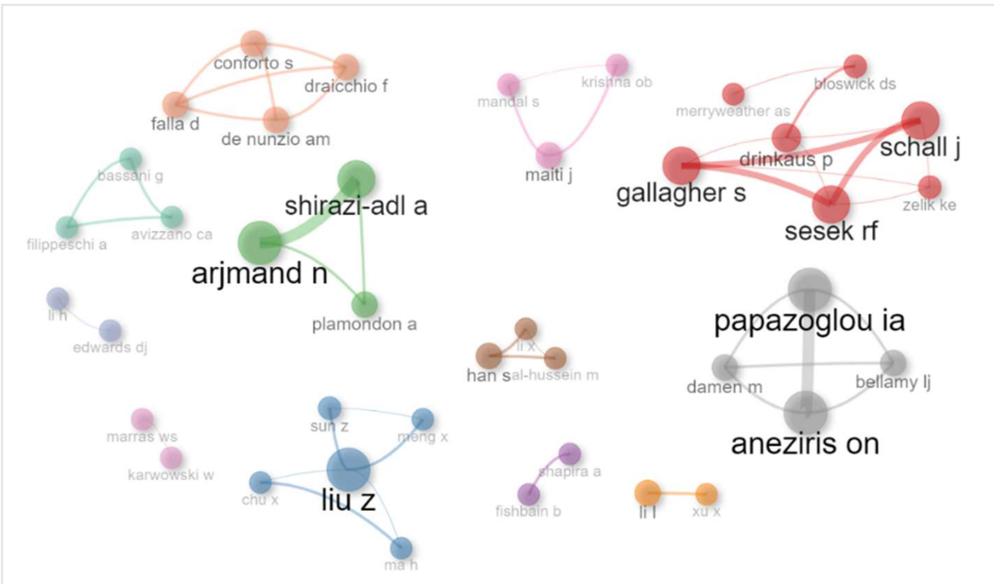

Figure 6. Network of co-authors.

Figure 7 from Bibliomatrix® shows the changes in lead authors in a particular field over time. The nodes in the graph represent authors, and the lines connecting them indicate citation relationships. The graph shows the radial network, suggesting the field is expanding gradually. Notably, articles by Nurse Ca, Zhou G, Hu S, and Sadeghi H in 2023 are worth referencing for interested readers.

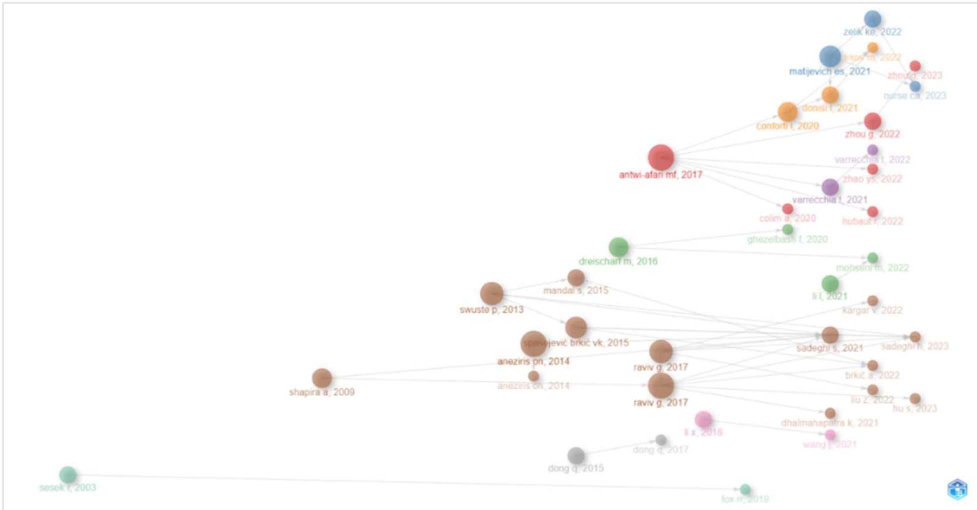

Figure 7. Historiography of authors.

3.3. Topic Trends

Figure 8 displays the development of critical keywords. The present focus of evaluation centers around "crane operations" [52–55]. Analyzing "accidents" remains the dominant method [56]. "Machine learning" is gradually replacing traditional approaches [57–59]. "Wearable sensors" is increasingly apparent in addressing human risks [60–62], which can monitor the factors that may impact operation [63,64]. "Manual material handling" poses various risks, and it is vital to include it in a hoisting risk assessment. "Musculoskeletal disorder" is an injury or illness that affects the musculoskeletal system, and occurs due to repetitive or awkward movements, constant poor posture, or physical exertion, leading to pain, discomfort, and functional limitations [65,66]. "Backache" is one of the most prevalent types of work-related musculoskeletal disorders (WMSDs) and a risk factor [67,68]. Therefore, it is essential to provide "ergonomics" equipment and "personnel training" to promote correct lifting techniques [69,70].

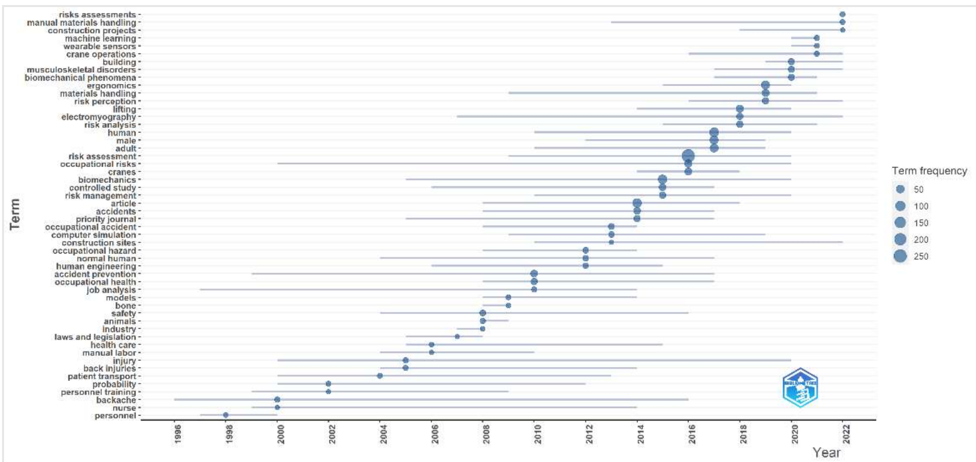

Figure 8. Topic trends.

3.4. Hoisting Risk Factors

The risks associated with hoisting in construction are multifaceted and interconnected [52,71,72]. Zavadskas (2010) examined the interests, objectives, and factors influencing construction efficiency [73]. Song (2022) identified the external environment, organizational factors, preconditions that trigger accidents, and unsafe leadership behaviors as the main factors impacting safety in assembly building construction [25]. Wang (2022) stressed the importance of scaffolding, footings, and formwork support systems [74]. Wang (2022) classified risk factors based on the Wuli–Shili–Renli (WSR) system and found that risk probabilities show seasonal and dynamic trends, requiring targeted measures to prevent and neutralize different risk sources at other points in time [16]. Ajith (2019) used hazard identification and risk assessment (HIRA) techniques to prioritize risks on construction sites and found that crane operations, working at height, and drilling were the top three high-risk tasks [75]. Shapira (2009) identified the main factors affecting safety in the tower crane environment, including crowded conditions, overlapping work areas, and time, budget, and labor constraints [76]. Umar (2020) found that management commitment, training, employee engagement, behavior, communication, accountability, fairness, and leadership were the most prevalent safety climate factors [77]. Jamalluddin (2022) found that design, management, financial, safety, and logistical factors were significant risk factors that must be considered when implementing IBS construction [78]. Amin (2019) identified UV exposure and mobile equipment risks as the primary risks for IBS construction sites [79]. Ismail (2012) found that personal awareness and communication significantly impacted the implementation of safety management systems on construction sites [80]. Wuni (2019) identified critical risk factors (CRFs) in modular integrated build (MiC) applications, including stakeholder fragmentation, high initial capital costs, poor supply chain integration, delayed delivery of modular components, and inadequate government support and regulation [81]. Finally, Construction site layout plans (CSLP) are crucial to prefabricated building project management, especially with the prevalence of hoisting operations, emphasizing the importance of tower cranes and precast supply point locations [82].

Through a thorough review of the literature, we have identified 80 key risk factors (Table 3). On a human level, the crane operator's proper training and adherence to safety procedures are crucial to prevent accidents. Detecting errors related to human factors, such as distraction, fatigue, or misjudgment, may not always be easy. Regular training, certification, and monitoring of crane operators and appropriate rest periods can help reduce this risk. Effective communication between crane operators, fitters, signalers, and others involved in lifting operations is also essential for safe crane operations. Poor communication can lead to the mishandling of loads or other accidents. Clear communication protocols, standardized hand signals, and practical communication training can help reduce this risk. Cranes are complex machines with many mechanical and electrical components that can fail, leading to equipment failure, structural collapse, or other accidents. Regular maintenance, inspection, and compliance with the manufacturer's recommendations for using and maintaining the equipment can help identify and reduce this risk. Overloading is another common risk factor in crane operations. It can lead to instability, tipping, or structural failure. This risk factor is usually detectable and can be mitigated by following the load capacity limits specified by the crane manufacturer and performing appropriate load calculations. Rigging, which involves attaching a load to a crane hook using slings, chains, or other lifting equipment, is critical to prevent loads from becoming unstable or falling off during lifting operations. Improper rigging can usually be detected by visual inspection. Proper training and certification of the rigging, inspecting the rigging for damage, and using adequate rigging techniques following industry standards can help reduce this risk. Environmental factors such as wind, rain, snow, and uneven ground can also pose risks during crane operations. Wind gusts can cause loads to swing or sway, leading to accidents. Although weather conditions are usually detectable, sudden changes in the weather or wind gusts may be difficult to anticipate, making it challenging to reduce the risk. Monitoring weather conditions and developing appropriate protocols for adverse weather conditions can help minimize this risk.

Table 3. The summary of hoisting risk factors.

Classification	No.	Risk Factors	Reference
Human	H1	Crane drivers and signalers need to be qualified to perform specific trades.	[16,21,83–89]
	H2	The safety awareness of crane erection and dismantling workers, drivers, and ground workers were not strong.	
	H3	Inadequate safety supervision of crane operations by the contractor.	
	H4	Safety checks on cranes by maintenance staff and drivers needed to be more thorough.	
	H5	Workers continued to work when the crane's position did not match the scope of work.	
	H6	The physical condition of the crane driver and ground workers.	
	H7	The psychological stress of crane drivers and ground workers is brought on by the construction schedule.	
	H8	Lack of skills practice for crane drivers and ground workers.	
	H9	Poor communication between crane drivers and ground workers.	
	H10	Workers are moving or staying within the hoisting area.	
	H11	Simultaneous multi-tasking of crane drivers and ground workers.	
	H12	Low level of site coordination management.	
	H13	Workers operating against work regulations.	
	H14	Workers ignore the impact of their surroundings on the work.	
	H15	Lack of coordination between work types on site.	
	H16	Inadequate emergency response capability of operators.	
Management	MA1	Inadequate technical safety standards for hoisting construction.	[25,83,90–95]
	MA2	Inadequate management methods for special operators.	
	MA3	Lack of registration management and inspection of cranes.	
	MA4	Inadequate safety program for the assembly, operation, and separation of cranes.	
	MA5	Unreasonable construction schedule.	
	MA6	Lack of safety education and training.	
	MA7	Authorization of tower cranes for additional services.	
	MA8	Inadequate site supervision staffing.	
	MA9	The proportion of personnel participating in safety exits.	
	MA10	Unreasonable or no specific lifting plan for hoisting operations.	
	MA11	No safety inspection on entry of materials and machinery.	
	MA12	No regular safety checks and maintenance.	
	MA13	Inadequate disclosure of safety techniques.	
	MA14	Insufficient financial investment in safety measures.	
	MA15	Unreasonable location of lifting points.	
	MA16	Inadequate safety monitoring techniques for time-varying structures.	
	MA17	Inadequate safety accident prevention and emergency response measures.	
	MA18	Inadequate protective measures around work at height.	
	MA19	Inadequate safety storage measures for flammable and explosive materials.	
	MA20	Security measures fee as a percentage of investment.	
Equipment	EQ1	Safety defects in imported tower cranes, spreaders, slings, baskets, and hoists.	[55,76,83,85,96–101]
	EQ2	No safety protection measures, e.g., scaffolding, slings, and locks.	
	EQ3	The tower crane hook visualization system is not in use.	
	EQ4	Safety load indicators and graphic displays of crane operation were not used.	
	EQ5	Safety monitoring system for collision avoidance on tower cranes not used.	
	EQ6	Height of the tower crane.	
	EQ7	Lifting of prefabricated elements without the use of special spreaders and slings.	
	EQ8	The strength of lifting connections needed to be revised.	
	EQ9	Actual load factor.	
	EQ10	Sling angle/°.	
	EQ11	The wear rate of lifting equipment.	
	EQ12	Lifting speed.	
	EQ13	Lifting acceleration.	
	EQ14	Overloading of cranes.	
	EQ15	Long-term operation of equipment leading to the deterioration of parts.	
	EQ16	The failure rate of lifting machinery.	
	EQ17	Inadequate stability of temporary support systems.	
	EQ18	Type of crane machinery.	
	EQ19	The life cycle of cranes.	
	EQ20	Cranes' movement devices.	

Table 3. *Cont.*

Classification	No.	Risk Factors	Reference
Materials	MA1	Quality changes in precast components due to groundwater on construction sites.	[83,84,102–106]
	MA2	Design and production quality of precast elements.	
	MA3	Strength of precast elements.	
	MA4	Component weight.	
	MA5	Types of components.	
	MA6	Component materials.	
	MA7	Dimensions of prefabricated elements.	
	MA8	Substandard materials and fittings are used for the installation of the elements.	
	MA9	Unreasonable attachments.	
Environment	EN1	Lack of warning signs for isolated areas for tower crane installation, dismantling, and lifting.	[17,22,25,83,96,107–110]
	EN2	Poor ground conditions at the construction site.	
	EN3	Poor visibility of the construction site.	
	EN4	Cross-operation of multiple tower cranes.	
	EN5	Wind speed.	
	EN6	Adverse weather conditions.	
	EN7	Inadequate attention to the treatment of surface water.	
	EN8	Inadequate stacking and protection of prefabricated elements.	
	EN9	Unreasonable transport routes on site.	
	EN10	Limited space for cranes.	
	EN11	Inadequate protection of openings and edges.	
	EN12	Work platforms for operators are not operable.	
	EN13	The safe atmosphere on site.	
	EN14	Dangerous sources, such as live high-voltage power lines and underground gas pipes around the construction site.	
	EN15	Relative rate of corrosion.	

3.5. Risk Assessment Methods

We summarized the methods used to assess hoisting risk in recent years, as shown in Table 4. There are many shortcomings in current risk assessment methods for hoisting construction, mainly including the following reasons: (1) Complexity and uniqueness of hoisting construction: Hoisting construction involves complex operations, different site conditions, different equipment, and dynamic interactions between different elements. Many risk assessment methodologies fail to adequately capture the complexity and uniqueness of hoisting, resulting in a limited understanding of the associated risks [55,111,112]. (2) Lack of specific guidance and standards: The lack of comprehensive and standardized guidance specific to lifting construction poses a challenge to risk assessors [22,84]. Generic risk assessment methods may not address the specific hazards and complexities of lifting operations, resulting in the inadequate identification and assessment of risks. (3) Inadequate consideration of the human element: Hoisting construction relies heavily on human operators, riggers, and other personnel, who play a key role in ensuring safety. However, many risk assessment methods tend to focus more on technical aspects and equipment-related risks, often neglecting the critical human factor [15,23,113]. (4) Lack of real-time and dynamic analysis: Traditional risk assessment methods often involve static analysis based on historical data or what-if scenarios. However, hoisting is a dynamic and evolving process where risks can change rapidly due to factors such as changing site conditions, project progress and human behavior. Failure to incorporate real-time and dynamic analysis into risk assessment can lead to outdated and ineffective risk mitigation strategies [4,16,24]. (5) Limited stakeholder involvement: Effective risk assessment requires the active involvement and collaboration of various stakeholders, including project managers, workers, equipment suppliers and safety professionals. However, some methodologies may not adequately engage these stakeholders, resulting in a lack of diverse perspectives and relevant input [100,114,115].

Table 4. The summary of assessment methods for 23 critical articles.

Source	Methodology	Framework	Contribution	Limitations
[55]	Analysis of hierarchy process (AHP); time-varying function	Safety, applicability, and durability	This evaluation method was the overall safety evaluation of hydraulic structures providing a reference basis.	Subjectivity and bias; the relationship between factors not considered.
[84]	Similarity aggregation method (SAM); Bayesian networks (BN)	Human factors analysis and classification system (HFACS)	The project's overall safety risk probability level is obtained through the forward reasoning of BN. The key risk factors of the project are identified through reverse logic.	Subjectivity and bias; incomplete risk factors.
[16]	Two additive Choquet integral (TACI); decision-making trial and evaluation laboratory (DEMATEL)	Wuli–Shili–Renli (WSR) system	A two-stage model for evaluating risk probabilities considering multiple correlations and dynamic stochasticity is constructed from the perspective of the evolutionary mechanism of multiple correlations.	Subjectivity and bias.
[24]	Fault tree analysis (FTA); BP neural network improved by genetic algorithm; Elman neural network	Human–environment	Informing the application of neural networks in security assessment.	Need more systematic, self-correcting indicators; need more statistical data.
[22]	Decision experimentation and evaluation laboratory (DEMATEL) and interpretative structural modelling (ISM); Bayesian Networks (BN)	Human–equipment–components–management–environment	Real-time information interaction and risk correlation.	Limited training sample sets; lack of intelligent decision-making systems to support lifting safety risk control. Not available for risk prediction.
[4]	Radial kernel function (RBF); support vector machine (SVM)	Work breakdown structure; resource breakdown structure	Real-time prediction of lifting risks and examination of the spatial and temporal evolution of risks.	The data can only validate the framework's viability, and the spatiotemporal evolution patterns only apply to the validation project. Automatic controls are inadequate; risks still rely on manual processing.
[100]	Apriori algorithm	Human–equipment–components–management–environment; time; space	Coupling mechanisms between risk factors.	Inadequate collection of validation data samples; lack of an intelligent evaluation system for the rules mined.
[110]	Fault tree analysis (FTA); failure mode and effects analysis (FMEA).	Installation process	Measures of risk factor importance.	Subjectivity and bias.
[113]	Fault tree analysis (FTA); Bayesian networks (BN)	Domino theory	Proactive warning.	Subjectivity and bias; incomplete risk factors
[21]	Fault tree analysis (FTA)	Systems thinking	Measures of risk factor importance.	subjectivity and bias; incomplete risk factors.
[115]	Mixed central point triangle whitening weight function; analysis of network processes (ANP)	Human–technology–components–management–environment	Measures of risk factor importance.	Subjectivity and bias; high calculation volume.
[116]	Structure entropy weight method	Man–material–machine–method–environment (4M1E)	Strong operability and wide application; effectively resolve conflicting problems of uncertainty; synthesizing evidence information to reduce information uncertainty.	Strong dependence on data; incomprehensible principles; of computation; ambiguity in processing; information; difficulty dealing with high; conflicting evidence.
[25]	Structural equation modelling (SEM)	Human factors analysis and classification system (HFACS)	Refinement of the traditional human factors analysis and classification system (HFACS) into the HFACS-assembled building hoisting (PH) risk model.	Subjectivity and bias; incomplete risk factors.
[17]	Bayesian networks (BN)	Systems-theoretic accident model and process (STAMP)	Models are straightforward and can be understood visually.	Determining the topology of its dependencies is complex and ambiguous.
[109]	Finite element method (FEM)	Human-machine	A data flow for real-time dynamic analysis of tower cranes based on the Internet of Things is proposed, which summarized the time-series effects of load excitation, including vertical lifting, inclined lifting, sudden braking, and sudden unloading.	Stability analysis only.
[117]	Cloud model (Expectation–maximization algorithm, EM); Bayesian networks (BN)	Human–object–management–environment	Change the reliance of traditional BN models on large amounts of training sample data or subjective assignment of values, eliminating the influence of real-time observation data during the construction process and randomness of the target safety risk values.	Due to the limited sample data, the CPT between nodes obtained using the cloud model-based EM parameter learning algorithm differs somewhat from the actual situation.
[112]	Analytic hierarchy process (AHP); entropy weight method; grey-fuzzy integrated evaluation method	Management–design–procurement–construction–economics–policy–nature	Building an improved weighting algorithm (AHP-EWM).	Subjectivity and bias; lack of data support.
[20]	A comparative evaluation of case studies and experimental economics	hazard and operability (HAZOP)	Reveals significant unsafe practices in six phases of lifting operations.	Only qualitative analysis.

Table 4. *Cont.*

Source	Methodology	Framework	Contribution	Limitations
[101]	Factor analysis	AcciMap	The hierarchy of tower crane safety systems, the influencing factors, interactions, critical factors at each level, and the main dimensions are revealed.	The findings apply to tower cranes only.
[118]	Frequency analysis	Hazard type	Most of the accidents occurred during the evening.	The findings apply to tower cranes only.
[83]	Structural equation modelling (SEM)	Components–operators–management–environmental–technology	An analysis using Pareto's Law and the diamond model, which states that 20% of the key factors affecting safety risk led to 80% of accidents.	The indicator system is inadequate and general.
[102]	Meta-network analysis	Risk events	The method allows for the visual identification of key risk factors and is simple to use.	Risk events are incomplete; future work should use MNA in other scenarios and add more entities and relationships to the meta-network.
[15]	Fault tree analysis (FTA)	Fault type	Filling the gap in safety assessment for asymmetric tandem lifting (ATL).	The findings apply to mobile cranes only.

One of the most widely used methods for risk analysis is fault tree analysis (FTA). This deductive approach involves identifying and examining all potential events or circumstances that could lead to an undesired outcome, such as a crane accident. A tree structure is employed to demonstrate the events or conditions resulting in the adverse effect, assigning each event or situation a probability [56,110]. FTA enables a quantitative risk assessment by identifying all possible factors and their likelihood [15,24]. However, FTA necessitates specialized knowledge to estimate probabilities accurately and can be complicated and time-consuming [119].

A Bayesian network (BN) is a graphical model that displays the probabilistic relationships between variables, providing a structured method for expressing and modelling the uncertainty and dependencies between variables related to construction risk [113,120]. Nodes within the network represent variables such as weather conditions, equipment failure rates, operator capabilities, and load characteristics, with edges capturing probabilistic relationships; this allows for a quantitative representation of the likelihood of different risk events occurring and their interdependencies [17,84]. Experts can contribute subjective probabilities, data, and domain-specific knowledge, which can be integrated into the Bayesian network to update risk assessments. This helps capture the tacit knowledge of domain experts, which may not be easily quantifiable but can play a crucial role in assessing the risks of hoisting construction [84,86,121,122]. The Bayesian network can be updated as new data becomes available during construction, allowing for real-time risk monitoring and decision-making based on the changing risk landscape. It also enables different risk scenarios to be modelled and analyzed, empowering construction stakeholders to assess the likelihood of risk events occurring under different conditions [122–124].

An artificial neural network (ANN) is a computational model inspired by the structure and function of biological neural networks in the human brain [125,126]. As shown in Figure 9, a classical artificial neural consists of an input layer, hidden layers, and an output layer [127,128]. The hidden layer is many processing elements between the output layer and the input layer, which are interrelated and layered [129,130]. The network learns from example data by adjusting the strength or weight of the connections between neurons, enabling it to make predictions or classify based on new inputs [131]. In dealing with risk assessment, the sources of information are neither complete nor illusory. Decision rules sometimes contradict each other and sometimes do not exist. This poses a great difficulty for traditional information processing methods, but neural networks can handle these problems well and give reasonable recognition and judgments [132,133]. Currently, those such as BP neural networks are used for risk assessment of many projects such as railroads, highways, tunnel openings, etc. [134,135].

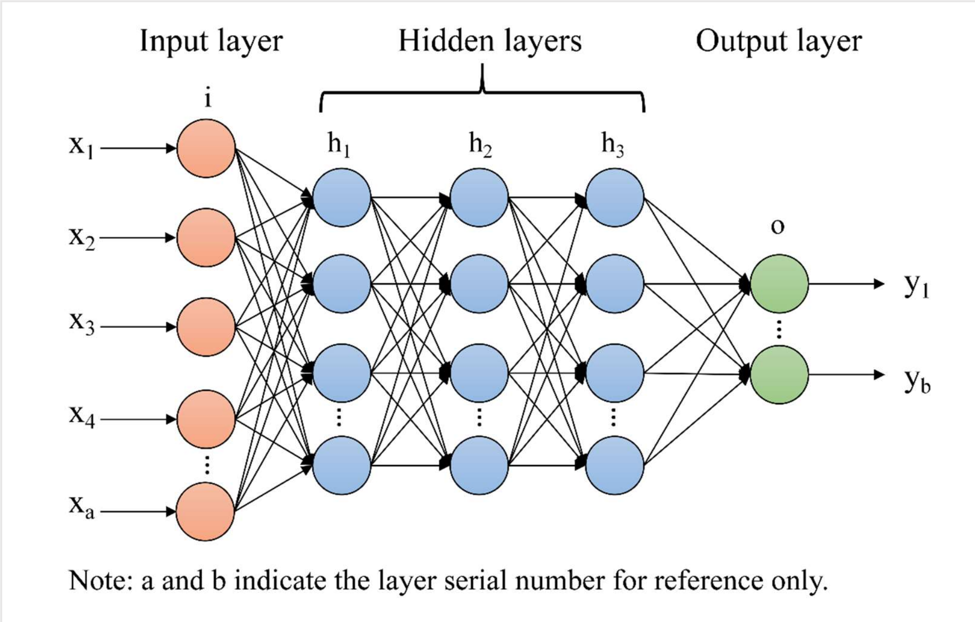

Figure 9. Structure of feed-forward artificial neural network.

Digital twins is a virtual representation or digital copy of a physical object, system, or process, which combines real-time data, sensor information, and advanced modelling techniques to create a virtual copy that mimics the behavior and characteristics of its physical counterpart [136–138]. Digital twins are used in risk assessment because they provide a powerful tool to simulate and analyze potential risks in a secure and controlled environment [139–141]. In DT, inspection data are collected in the real world and then transferred to the simulation environment for further evaluation; the virtual model runs simulations to obtain the best predictions, enabling it to provide rapid solutions for adapting natural processes to changing conditions [142,143].

4. Discussion

4.1. Application of ANN and DT

It is important to discuss the prospects and potential challenges for the application of artificial neural networks and digital twins in hoisting construction risks. The application of these technologies is improving operational efficiency and safety. For example, artificial neural networks can help optimize hoisting parameters, such as load capacity and speed, to minimize risk. Digital twins can identify potential hazards and virtually test different scenarios before they are executed in an actual construction environment. However, the application process involves addressing issues such as data availability, model accuracy, implementation costs and technician requirements. By acknowledging these factors, a balanced view of the opportunities and limitations of these technologies is provided to assist project managers with best practices.

The construction site is not random, it is constructed according to the laws of physics, biology, and sociology, and the mind reflects this structure [144–146]. Artificial neural networks, as approximators for identifying objective laws, are often criticized for "fitting" and "black boxes" in the application of risk assessment [147–149]. The three common cases of model fitting are "ideal fit", "underfitting", and "overfitting" [150]. An underfit model has too few parameters to capture the underlying structure of the observed data and therefore provides poor predictions or fails to generalize; an overfit model is flexible enough to adapt and/or remember the structure of the training sample [151]. An ideal-fit model learns the data's underlying generative or global structure by exposing some underlying factors or rules [152]. In contrast to underfitting and overfitting models, ideal fit models can generalize, which means accurately predicting new observations that were never seen during training. Traditionally, experimenters have used highly controlled data to construct rule-based ideal-fit models in the hope that these models will generalize beyond the training set into real life [153]. However, the "ideal fit" models thus generated are often heavily noisy. Over-parameterized models will tend to learn traits specific to the training data and will not extrapolate beyond that range [154,155]. In the presence of complex non-linearities and interactions between variables in different parts of the parameter space, extrapolation from such limited data is bound to fail [156]. In such cases, "direct fit" based on big data may be a good option. A "direct fit" is not an "intuitive fit", and allows full regularization only in the interpolation region, provided that the variability in the data is not caused by random noise, to obtain as good or better predictions than an ideal fit model's performance [157]. Direct-fit models regularize the process to avoid excessive overfitting and optimize alignment with the training data structure [158]. This regularization can crucially be achieved using generic local computations and does not require any explicit model of the underlying characteristics of the data [159–161]. Critics often derogate over-parameterized direct-fit models as "black-box" models: models that give the correct inputs produce the correct outputs without explaining their inner workings [130]. Instead, we argue that extensive direct-fit neural network models provide a concise framework for understanding neural code, emphasizing the close connection between the world's structure and the brain's structure [162]. After all, compared to the billions of years that brain nerves have evolved in a complex world, ANNs are still in their infancy. However, "direct fitting" relies on the dense and extensive sampling of the parameter space to obtain reliable interpolations [54]. Thus, the emergence of the "digital twin" is a powerful aid to this idea. In addition, ANN can be mixed with several meta-heuristics, such as the lion optimization algorithm (LOA), the social engineering optimizer (SEO), the red deer algorithm (RDA), and the Levenberg–Marquardt algorithm (LMA) to improve accuracy and speed further [163,164].

Digital twins (DT), on the other hand, use integrated technologies from the Internet of Things (IoT), building information modelling (BIM) and many sensors so that the system can collect data throughout the lifting process [165]. Previous research has shown that DT has many advantages, making it suitable for risk modelling, especially for industrial building systems (IBS) with complex issues and high prefabrication rates [141,166]. Depending on the spatial scale, data from DT provides a virtual copy of the physical construction project compared to other sources and allows stakeholders to visualize and analyze the construction process [167,168]. In addition, DT is beneficial for data sharing and communication to minimize risks and facilitate collaboration between project stakeholders, including architects, contractors, engineers, and owners [169]. However, there are some limitations to using DT in the context of sub-application IBS. Currently, camera positions and poses need to be calibrated individually, bidirectional interaction capabilities between virtual and real models must be implemented, and video data structure algorithms are not integrated. Future work should include the data-driven online updating of 3D scenes, predictive projection, perception, and analysis of application scenes based on the fusion of virtual and accurate models [170,171]. The capabilities and applications of the digital twin are also limited by infrastructure and computing power [172]. DT has limited intelligence and relies on inherent knowledge rules and independent AI-powered simulations and predictions to make decisions and forecasts [142,173]. Not all algorithms produce accurate results, and advanced algorithms should be selected based on their accuracy in producing the desired results. Table 5 shows various machine learning algorithms that can be used in DT, including support vector machines (SVM), random forest (RF), k nearest neighbor (KNN), and convolutional neural networks (CNNs). Implementing DT in construction risk assessment requires significant investment in technical infrastructure, including sensors, data collection, and analytical tools, which can be challenging for smaller construction projects or companies with limited resources, especially for developing countries. Not all countries can afford DT due to economic constraints, so the high cost and difficulty of handling massive DT datasets may be why DT is not used in these countries [168]. Another challenge in using DT is the ample data storage required due to the high density of real-time data; processing multidimensional data requires a long computation time [174]. As data are collected from multiple stakeholders with different data quality standards, DT needs to improve its information processing regarding complex logical relationships between objects, threats, and security rules [175,176]. DT relies on data communication and storage and is vulnerable to cyber threats. Protecting sensitive data from cyber-attacks and ensuring data privacy may be a challenge for the construction industry, where cybersecurity measures may need to be better developed [177,178].

Table 5. Application of machine learning algorithms.

Algorithm	Strengths	Limitations	Reference
Linear regression	Simple and interpretable. It can be used for both regression and classification tasks.	Assumes linear relationship between features and target. Sensitive to outliers. Limited capacity for capturing complex patterns.	[179–181]
Logistic regression	Simple and interpretable. Suitable for binary classification tasks.	Assumes a linear relationship between features and log-odds. Limited capacity for capturing complex patterns. Not suitable for multi-class classification tasks without modification.	[151,182,183]
Decision trees	Can capture non-linear relationships. Interpretable and can be visualized. Can handle both categorical and numerical data.	Prone to overfitting. Can be sensitive to small changes in data. Lack of robustness to outliers.	[184–186]
Random forests	Can handle large datasets. Can capture non-linear relationships. Robust to outliers and noise.	Can be computationally expensive. Prone to overfitting if not tuned properly. Lack of interpretability compared to individual decision trees.	[187,188]
Support vector machines	Effective for high-dimensional data. Robust to outliers. Can handle both linear and non-linear relationships.	Can be computationally expensive. Requires careful tuning of hyperparameters. Limited interpretability.	[189–191]
K nearest neighbors	Simple and easy to implement. Can be used for both classification and regression tasks. Robust to outliers.	Sensitive to data scaling and dimensionality. Can be slow with large datasets. Prone to overfitting with small datasets.	[192–194]
K means clustering	Simple and easy to implement. Can handle large datasets. Can identify patterns in unlabeled data.	Requires pre-specification of the number of clusters. Sensitive to initialization. May converge to local optima.	[195–197]
Principal component analysis (PCA)	Effective for dimensionality reduction. It can be used for feature extraction. Can handle large datasets.	Assumes linear relationships between features. It may lose the interpretability of original features. Requires computation of eigenvalues and eigenvectors.	[198,199]
Gradient boosting methods (e.g., XGBoost, LightGBM)	High accuracy and predictive power. Can handle complex patterns and interactions. Robust to outliers.	It can be computationally expensive. Prone to overfitting if not tuned properly. Lack of interpretability compared to individual decision trees.	[200–202]
Convolutional neural networks (CNNs)	Excellent for image and video data. Can automatically learn hierarchical representations. State-of-the-art performance in many computer vision tasks.	Require large amounts of data and computing power. Prone to overfitting with small datasets. Interpretability can be challenging.	[203–205]

4.2. Future Research Directions

Future research can concentrate on critical areas to enhance hoisting construction risk assessment. Firstly, developing advanced risk assessment models that integrate artificial intelligence, machine learning, and data analytics to leverage real-time data from different sources can improve the accuracy and timeliness of identifying and mitigating risks. Secondly, exploring the potential of BIM in risk assessment can provide a comprehensive digital representation of the construction project to identify and analyze potential risks during the design phase. Additionally, considering the impact of human behavior, communication, and organizational culture on hoisting construction safety, research efforts can integrate human factors and organizational aspects into risk assessment methodologies. Lastly, researching the effectiveness of novel risk mitigation strategies, such as autonomous systems, robotics, and sensor technologies, can enhance safety during lifting operations. These research directions can significantly improve risk assessment in hoisting construction, leading to safer and more efficient construction practices. As a result, we propose the hoisting risk control model shown in Figure 10.

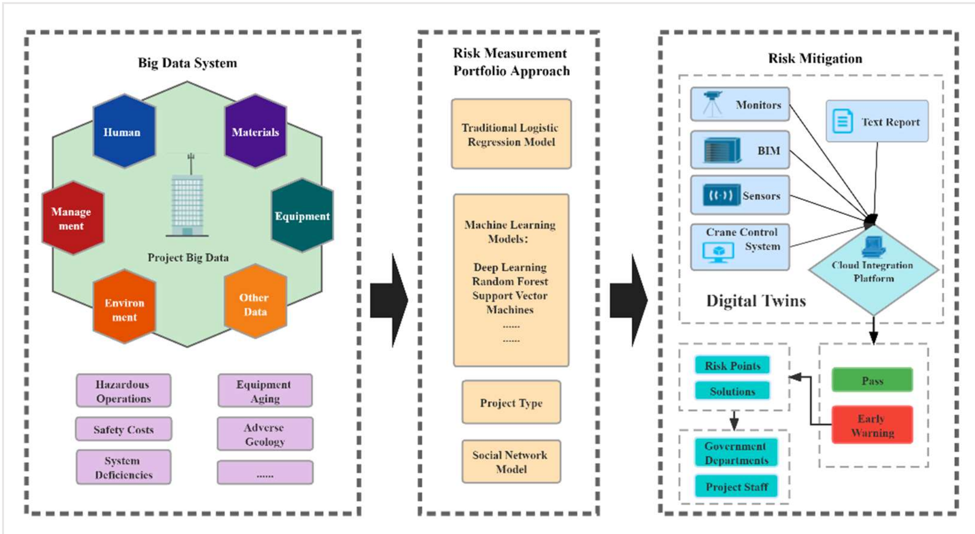

Figure 10. Hoisting risk assessment model based on DT and ANN.

5. Conclusions

Hoisting risk assessment has garnered significant attention due to the high occurrence of construction accidents, particularly in Australia, China, the USA, and Europe. Accurate and valid risk factors are important input parameters for risk modelling and assessment. The performance of risk models is highly dependent on the comprehensiveness of the risk factors, especially in small-scale risk modelling studies. Simulation results from risk models show differences in assessing the impact and likelihood of risk when using detailed risk factors, demonstrating that risk factors significantly impact the risk assessment outcome. The 80 risk factors in this study inform future models. Furthermore, the constant updating of risk models explains the interest in exploring new techniques to produce accurate assessment results. In this review, the modeling results of numerous hoisting risk studies show that DT can provide real-time and precise sensing data to improve the inputs to risk models, enabling risk model results to be more specific. However, data and interaction integration issues, high costs, and information security continue to limit the development of the DT. The human factors involved in hoisting are only captured by sensor data, resulting in too quantitative model parameters. Furthermore, integrating ANNs and other assessment methods or theoretical frameworks is a promising approach to addressing the problems associated with the inadequate representation of multidimensional non-linear data. Thus, research on extending risk data collection systems and more accurate deep learning algorithms can be foreseen in the upcoming applications of hoisting risk.

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