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Review

An Evaluation of the Technologies Used for the Real-Time Monitoring of the Risk of Falling from Height in Construction—Systematic Review

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Abstract: The construction industry has the highest number of fatal accidents compared to other industries. However, manual safety compliance monitoring is complex and difficult for safety engineers, and more automated solutions need to be found. The main research objective was to review the state of the art of real-time monitoring technologies used to assess the risk of falling from height in the construction sector. A systematic review is proposed in order to summarise the technologies used for real-time monitoring in the construction sector, following the PRISMA methodology. Only studies that assessed the risk of falling in real time were selected. From an initial set of 1289 articles, 40 were classified as strictly relevant to addressing the research questions. Various technologies that use artificial intelligence have been designed to monitor workers in real time and to send alerts to workers at any time in the event of a risk situation, thus preventing accidents. This study showed that new technologies are being introduced to predict the risk of a fall in real time, changing the approach from reactive to proactive and allowing this monitoring to improve workplace surveillance and safety. Further research is needed to develop effective systems that are easy for people to use without compromising productivity.

Keywords: construction; risk management; risk assessment; real time; fall; safety

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1. Introduction

The International Labour Organisation (ILO) estimates that 2.6 million work-related deaths are due to occupational diseases, with 330,000 deaths due to accidents at work [1]. The construction industry is a high-risk sector, and according to data collected from accident reports around the world, construction sites remain the most dangerous workplaces compared to other industries [2,3]. Despite initiatives by companies, workers, safety experts, and researchers to improve construction safety, construction sites still pose a high risk to workers. In the European Union, the construction sector employed around 6.7% of the total number of workers in 2023, making it the sixth largest sector in terms of the number of workers. In Portugal, the sector employed 7.1% of the total number of workers. Here, it is also the sixth largest sector in terms of the number of workers, in line with the European average [4]. Worker safety in this sector is of concern in several countries due to high accident rates, such as Portugal [2], Spain [2,5], the United States [6], and China [7]. Work-related accidents impact human integrity significantly, but they also entail high costs for a country's social security system. This situation affects the productivity and competitiveness of companies, which in Europe are predominantly small and micro-sized [8].

Although construction is not the sector with the most employees in the European Union, it was responsible for one-fifth (22.5%) of all fatal work accidents in 2021 [2]. A study by the Occupational Safety and Health Administration (OSHA) showed that the construction industry was responsible for 18% of fatal workplace accidents in the United States in 2022 [9] and about half of all fatal accidents in Korea [10].

The most common accidents in South Korea are falls from height, being struck by objects, and being injured by overturning and falling objects [11]. According to the ILO [12] and OSHA [13], falls from heights are the leading cause of death in the construction industry, accounting for about 35% of accidents in South Korea [10] and 50% in China [14]. In addition, fall protection from heights tops the list of safety violations in OSHA reports, with inadequate fall prevention [15].

Between 2018 and 2020, the number of fatal accidents in construction in Portugal increased, while the number of non-fatal accidents decreased [16]. In 2020, it was the second sector in terms of the number of non-fatal accidents at work, representing around 16% of the total, surpassed only by the manufacturing industry [16]. According to the Government Strategy and Planning Office (GEP), construction is also the sector with the most fatal accidents, accounting for 27% of the total number of fatal accidents in 2020 [16].

Falls from height are the main cause of fatal accidents in the construction sector, accounting for around 39% of the total number of fatal accidents in this sector in Portugal in 2020 [16]. The other main causes of fatal work accidents are collapse, which occurs in 25% of cases, and the loss of control of machinery, which occurs in 17% of cases [16]. Even among non-fatal accidents at work, falls from heights are the second most common cause, accounting for 20% of cases [16].

Construction sites change dynamically compared with other industries due to variations in work teams, spaces, and atmospheric conditions. In the absence of an effective way of predicting risk under these circumstances, safety management on construction sites focuses on passive or proactive measures. Passive strategies are based on analysing data from fall accidents to develop future prevention plans, while proactive measures are preventative measures that focus on safety training [17]. Despite these efforts, fatalities continue to rise.

Research has shown that human error is involved in two-thirds of fatal workplace accidents. A proactive pre-assessment of risk, carried out repeatedly before a task is performed, is an effective and essential safety measure [3]. To reduce the number of falls from height on construction sites, employers conduct safety training to inform workers and site managers about safety risks and measures to be taken.

The traditional manual approach to monitoring workers is based on observation by safety engineers. It is time-consuming and ineffective for complex sites [18]. As a result, various researchers have developed studies looking at different technologies and methods for assessing risk in real time. Despite previous research into monitoring technologies, there are still some limitations to their use in construction projects. The main limitation is the feasibility of implementing technologies for widespread use in construction projects of varying size and complexity [19]. A previous systematic review [19] evaluated all technologies that can be used to prevent falls from height, from the design phase to the construction phase, although only part of the work relates to real-time monitoring technologies.

As accidents from heights greatly impact the total number of accidents in the sector, it is urgent to create conditions that help to reduce this occurrence. The real-time monitoring of workers in the construction sector is, therefore, something that must be carried out frequently on construction sites to understand exposure to the risk of falling. These monitoring technologies provide large volumes of data about management and construction tasks, leading to a growing interest in the construction industry in using artificial intelligence technologies [20,21].

The importance of this issue justifies a review of the most recent studies on relevant technologies used to monitor the risk of falling from heights in real time. This study aims to understand real-time worker monitoring technologies in order to assess the benefits and impact they can have on reducing workplace accidents and to identify possible opportunities to make them more effective. The literature was searched, screened, and analysed systematically using a review protocol of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [22,23]. The main contribution of this study is to identify the technologies used to monitor workers in real time in order to assess the benefits and impact they can have in contributing to a reduction in accidents at work, and to identify possible situations that deserve to be developed in future studies.

The remainder of this study is organised as follows. Chapter 2 presents the methodology applied to carry out this systematic review. Chapter 3 presents the results obtained from this review, including the selected articles, followed by a discussion of the results and future developments in Chapter 4. The last chapter presents the conclusions of this systematic review.

2. Materials and Methods

This section describes the systematic review as a methodological approach used to explore useful findings in the existing literature on real-time worker monitoring technologies in the construction sector and to identify knowledge gaps for future research. A systematic review identifies, selects, and appraises all the literature at a certain agreed-upon level of quality that is relevant to a research question [24]. This systematic review followed the PRISMA methodology [22,23].

The information was searched in Scopus, Web of Science, and Inspec, which are relevant international databases in different scientific fields and are often used for literature searches [25]. These sources were last consulted between 10 April and 20 May 2024.

The search strategy combined keywords with the Boolean operators 'AND' and 'OR' to produce the following search string: (construction OR building) AND ("risk assessment" OR "risk management" OR "safety") AND ("real time" OR "BIM" OR "building information model*") AND ("fall*" OR "safety"). The search string was applied to the title, abstract, and keyword fields for Scopus and Inspec, and the topic was selected on Web of Science. The search was continued by checking the reference lists of the first articles retrieved and by snowballing until no further relevant articles were found.

Firstly, filters were applied to the databases, and studies were restricted by document type (research articles), source type (indexed peer-reviewed journals), and language (English). The aim was to collect indexed scientific studies published in the most relevant sources. After this initial automated screening, the studies were checked to see if they met the objectives of the review by reading the title and abstract. Studies were only eligible if they met the following criteria: (1) they were applied in the construction sector, (2) they assessed the risk of falling from height, (3) they presented a risk assessment method and/or technique, and (4) they monitored risk in real time. Each collected study was qualitatively evaluated, and its results were analysed for the review.

If the interest in a reference was unclear after this preliminary screening, it was assessed in the next selection stage. Duplicate records were eliminated using reference management software (Mendeley Reference Manager, version 1.19.8). Each article was then analysed and read fully to remove those not meeting the eligibility criteria.

Information of interest was collected from each study using an adapted table:

- General information: authors, year of publication, and country.
- Study characteristics: parameters assessed, procedures/methods, equipment and software, real-time monitoring, and the type of work or phase of work in which it was applied.
- Results of the studies, main conclusions, and limitations.

It was also necessary to understand the concept of real time, i.e., to know whether continuous monitoring was indeed implemented, by gathering information on the monitoring period and the stage at which the evaluation methodology was applied.

In order to analyse the technologies and/or risk assessment methodologies, information on the physical equipment and software that allowed this assessment to be performed was extracted from each article.

In order to study any scientific field, it is necessary to adopt an appropriate scientific mapping tool. VOSviewer is one of the most recommended mapping and visualisation tools that can present data in an optimal visualised form [26]. Therefore, scientific articles obtained through searches with relevant keywords in the Scopus, Web of Science and Inspec databases were analysed using the VOSviewer software, version 1.6.20. Scientometric analyses, i.e., keyword co-occurrence analysis and citation analysis, were then carried out using the VOSviewer software to identify the most concentrated areas of research and trends in the literature, together with the sources [27].

3. Results

3.1. Selection of Studies

Following the PRISMA guidelines [22,23], 1289 articles were initially found, as shown in Figure 1. After restricting by document type (research articles), source type (journals), and language (English) and excluding duplicate articles, 572 articles remained for title and abstract reading. After this step, 147 articles remained for the assessment of their eligibility to be read in full and 117 were excluded because they did not present a risk assessment and evaluation method and/or prevention technique, did not assess the risk in real time, did not assess the risk of falls from height, did not assess the risk during the construction phase, were related to worker training, were literature reviews, or did not relate to the construction sector. The remaining 30 articles were considered relevant for inclusion in this literature review. The snowballing process was repeated on these, resulting in a further 9 relevant articles, leaving 40 to be analysed in the current review.

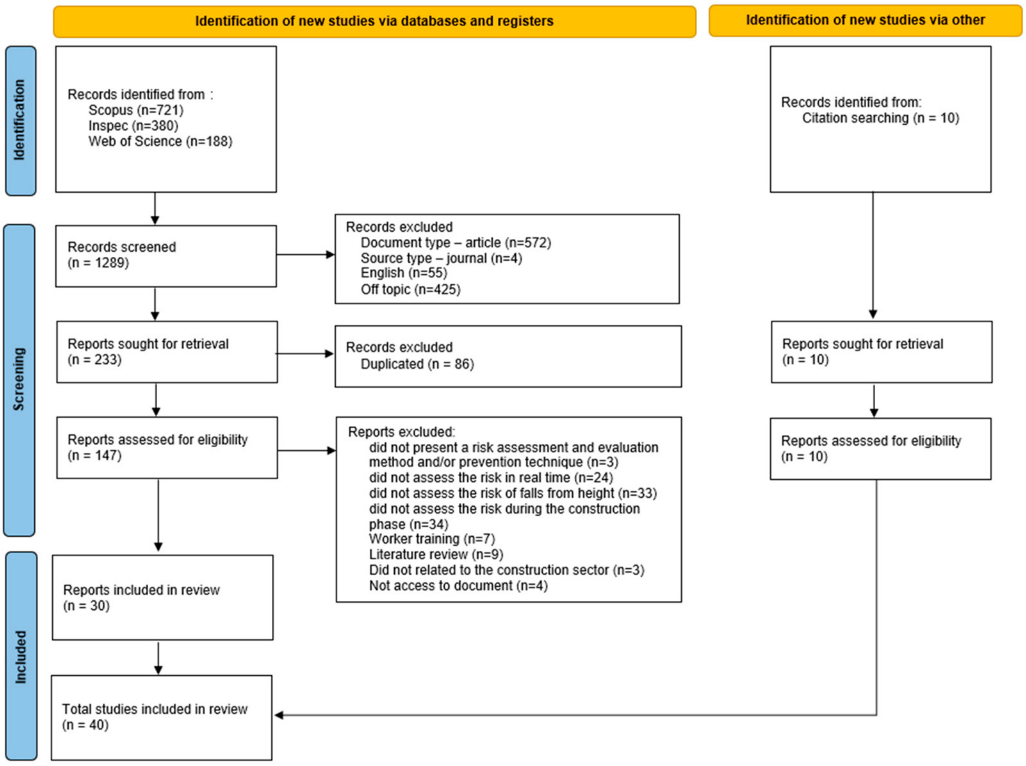

Figure 1. PRISMA diagram [22,23] of the systematic review conducted for this study.

3.2. Characteristics of Included Studies

This review focused on the technologies used to monitor the risk of falling from height in real time in the construction sector. Figure 2 shows an increase in the number of relevant articles in recent years, with a peak in 2022 and 2023, seeing 8 and 6 articles published, respectively. The data for 2024 are incomplete, as the survey was performed on *DATE*.

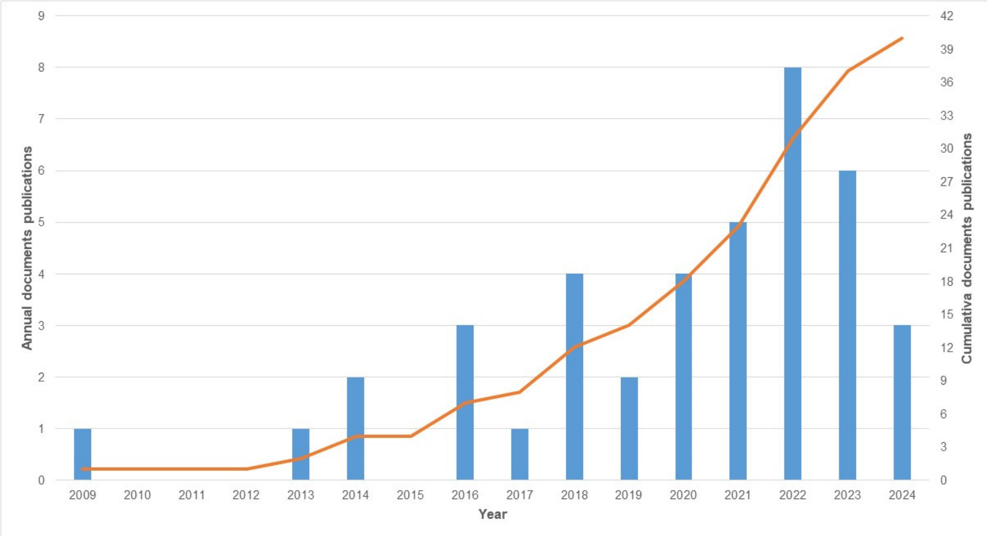

Figure 2. Number of relevant publications per year.

The number of publications is shown as blue bars, while the orange line shows the cumulative number of annual publications. This shows an increasing trend in publications on real-time monitoring technologies, reflecting a growing interest among researchers in finding new ways to manage the risk of falling from height on construction sites.

The selected articles were analysed in terms of their geographical distribution. As shown in Figure 3, the highest number of studies was conducted in China (19), followed by South Korea (9), the United States (2), Spain (2), the United Arab Emirates (2), and other countries with one study (5).

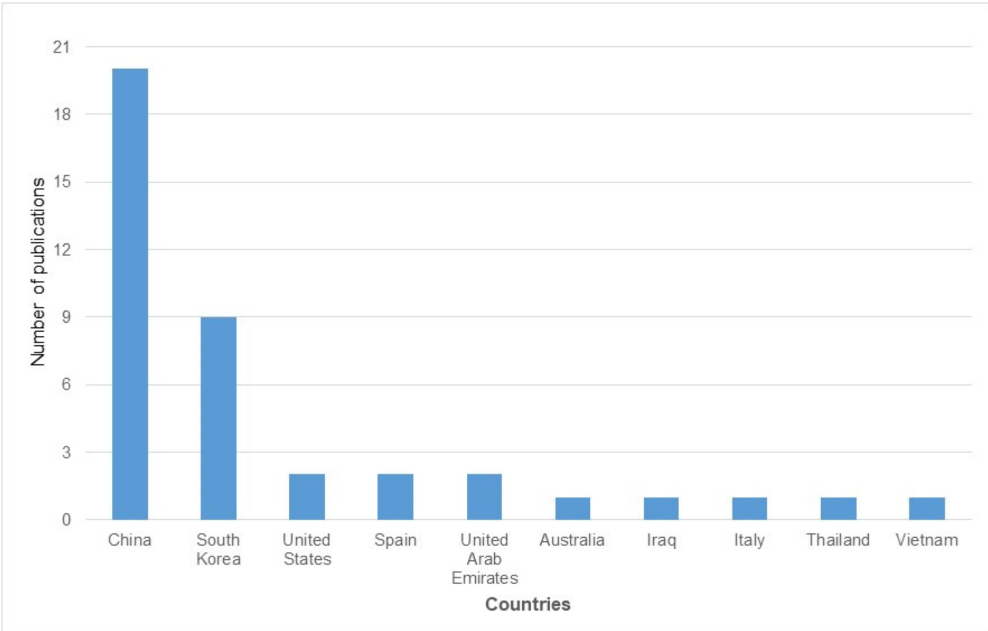

Figure 3. Number of publications per country.

Citation–sources analysis was employed to identify the leading journals in terms of research into technologies used for real-time monitoring of the risk of falling from height. The 40 articles collected in this study were published in 25 journals. Figure 4 displays the citation network of these extracted journals. *Automation in Construction* is the dominant journal for research into the real-time monitoring of the risk of falling from height, as illustrated by the obvious differences in node size and link strength in the network. Furthermore, a comparison of the average citation per journal paper shows that papers published in interdisciplinary journals such as the *Journal of Construction Engineering and Management* and the *Journal of Safety Research* are more likely to be cited by other scholars.

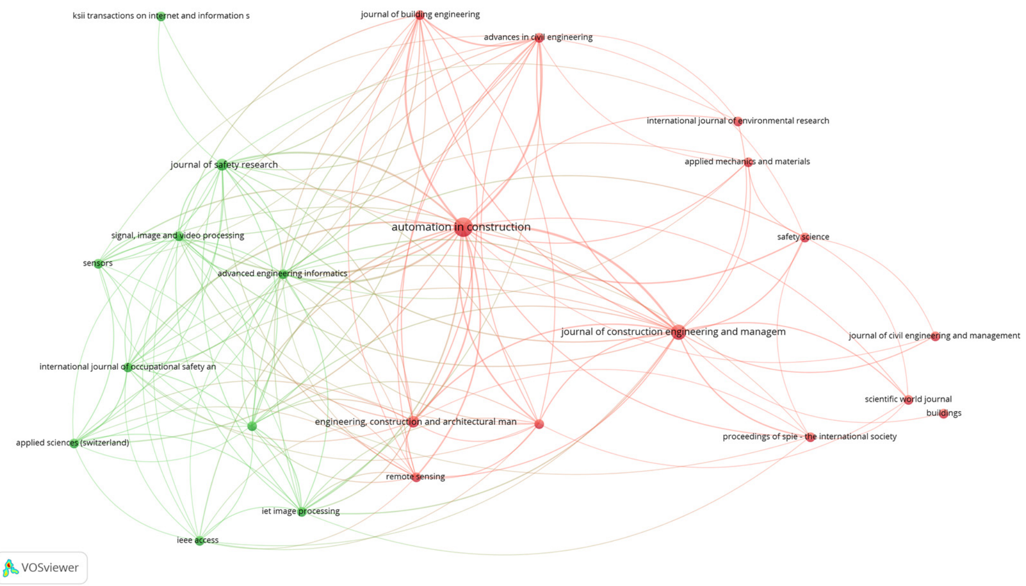

Figure 4. Citation–sources network of the representative journals.

As shown in Figure 5, the keyword "accident prevention" exhibits the highest frequency of co-occurrence with "computer vision", indicating its significance as a technology within the context of researching technologies used for real-time monitoring of the risk of falling from height. Users can apply computer vision to monitor workers in real time to prevent workplace accidents.

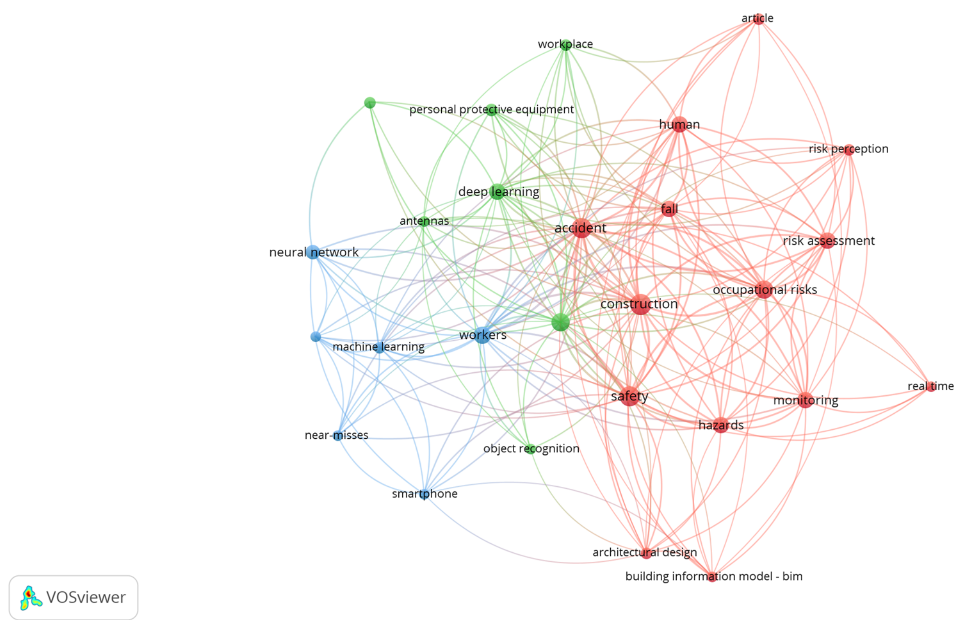

Figure 5. Keyword co-occurrence networks of technologies used for real-time monitoring research.

VOSviewer employs a local moving algorithm to partition the keyword network into three distinct clusters, as illustrated in Figure 5. The details for the 27 keywords present within the network are enumerated across the three clusters. Each cluster is named by analysing the commonalities between its constituent keywords. Specifically, Cluster 1 (red cluster) relates to real-time monitoring in construction. Cluster 2 (green cluster) is related to object and worker detection technology. Cluster 3 (blue cluster) is related to accidents and workplace risks. As shown in Table 1, the research areas can be grouped into five areas, namely, techniques for improving real-time monitoring, techniques for monitoring worker behaviour and PPE use, techniques for the real-time monitoring of sites and/or equipment, techniques for real-time monitoring by creating databases of safe and unsafe behaviour, and techniques for monitoring the correct use of PPE.

Table 1. Mapping the items repeated in papers.

Keyword	Occurrences	Total Link Strength	Research Area
construction	27	171	Real-time monitoring techniques
accident	22	151	
safety	22	129	
occupational risks	15	105	
workers	14	103	
fall	12	90	
hazards	12	75	
human	12	91	
monitoring	12	70	
architectural design	4	26	
article	4	19	
risk perception	4	32	
unsafe behaviours	4	20	
workplace	4	31	
antennas	3	19	
building information model—BIM	3	18	
near-misses	3	26	
real time	3	18	
computer vision	17	88	Techniques for monitoring worker behaviour and PPE use
smartphone	3	24	
risk assessment	11	76	Real-time site and/or equipment monitoring techniques
deep learning	11	70	Real-time monitoring techniques by creating databases of safe and unsafe behaviour
neural network	8	38	
machine learning	4	36	
learning systems	3	27	
personal protective equipment	5	37	Techniques for monitoring the correct use of PPE
object recognition	3	16	

The risk of falling from a height can be monitored by directly monitoring workers to check the risks to which they are exposed at any given time or by monitoring the site in general to analyse the existing risks. Table 2 classifies each eligible study according to the type of monitoring carried out by each author to prevent falls from height, the direct monitoring of the worker, or the monitoring of the site and/or equipment. The proposed approaches are then described, and the technologies used to achieve them, namely hardware and software, are listed. Finally, critical analysis is given in the form of "final remarks".

Table 2. Studies' technologies characteristics.

Type of Monitoring	Study	Proposed Approach	Equipment for Collecting Physical Information	Software for Information Analysis and Processing	Final Remarks
Site and/or equipment monitoring	[28]	Automatically detect the presence of people on concrete/steel supports to assess their safety	Computer vision is used to collect data from the site in real time.	Mask R-CNN is a deep learning model that detects structural supports and people to automatically determine worker safety.	Despite occlusion issues, the accuracy was considered good for the study.
	[29]	Hazard detection system	Computer vision is used to collect data from the site in real time	Artificial intelligence and the Internet of Things for information processing	The study has shown that it is possible to manage risk monitoring in the field.
	[30]	Deep learning-based approach for exchanging information from physical sites with 3D digital models	Computer vision is used to collect data from the site in real time.	Object detection algorithm based on deep learning and existing BIM identifies existing hazards	The accuracy of the results was found to be good when compared with the results of the safety engineer's manual judgement.
	[31]	Combines computer vision and ontology techniques to facilitate security management through semantic reasoning	Computer vision is used to collect data from the site in real time.	Mask R-CNN module used to check SWRL rules on extracted visual site information, automatically signalling situations where there is a risk of falling from a height	The result shows that the developed framework is successful in construction safety management.
	[32]	Combines computer vision and the TOPSIS method to automate the quantification and visualisation of security risks	Computer vision is used to collect data from the site in real time.	(1) Deep learning algorithms (YOLOv3) are used to process video feeds (2) The TOPSIS model assesses hazards and associated risks to help security engineers	Enhances traditional risk identification and forecasting, assessing risk through real-time monitoring
	[33]	It provides a safety early warning mechanism.	Computer vision is used to collect data from the site in real time.	(1) Uses the API platform (based on AI) to detect objects and classify behaviour (2) Data processing to analyse security information from the collected images and assess security risks (3) BIM used to simulate different security scenarios	Can analyse integrated human–machine-environment risks, categorising risks into different levels
	[34]	Automated safety monitoring system to support the construction safety monitoring process	BLE sensors distributed throughout the site and personal mobile devices are tracked to create an automated security monitoring system.	(1) BIM is used as a platform to identify, record and visualise hazards automatically. (2) Cloud servers are used to communicate with mobile devices to collect and share information in real time.	The results showed that it could help monitor construction sites and improve safety.

Table 2. *Cont.*

Type of Monitoring	Study	Proposed Approach	Equipment for Collecting Physical Information	Software for Information Analysis and Processing	Final Remarks
Site and/or equipment monitoring	[35]	A skeleton-based recognition method for detecting human stair-climbing behaviour	Computer vision is used to collect data from the site in real time.	(1) Deep learning extracts multimodal skeletal information from real-time video data (2) Compare this information with the IAGCN to recognise risky behaviour	Although it has not been applied in a real context, the results show that the method has advantages.
	[36]	Presents an approach to modify safety behaviour by integrating location-based technology with BBS	Real-time location system (RTLS) applies tags and reference anchors and transmits information wirelessly.	The virtual construction system (VCS) defines workers' positions and danger zones and tracks their movements in real time. Warnings are sent to alert workers via tags attached to their helmets.	The study shows that unsafe behaviour can be accurately and objectively identified and assessed.
	[37]	Integrates computer vision algorithms with ontology models to automatically and accurately recognise dangers	Computer vision is used to collect data from the site in real time.	The R-CNN Mask algorithm processes the collected images and matches them against the ontology models to identify hazards	Despite the problems of object occlusion, the proposed model can accurately recognise the dangers of images.
	[38]	Addresses safety risk assessment using real-time location data of workers and existing equipment	PCMS is a real-time positioning system consisting of tags (attached to workers' helmets or fixed to construction sites), anchors, and wireless communication devices.	CSS technology has been used to implement location-based proximity alert systems that send a voice message to tags worn by workers.	These assessments provide security managers with a powerful tool to maximise the cost-effectiveness of their decisions.
	[39]	Visual warning system that combines safety management and mixed reality (MR) scenarios to provide and visualise information about hazards in the field.	Computer vision is used to collect data from the site in real time.	(1) Deep learning (YOLOv4-Tiny) used to process the received information (2) 4D BIMs used to create a VCS (virtual construction site) (3) MR goggles to display hazard information to the worker when he is in a hazardous area	Presenting hazard information to workers with a level of accuracy deemed good using portable MRI equipment
	[40]	Deep learning model based on computer vision to automate the process of monitoring worker compliance with safety rules to prevent falls from ladders.	Computer vision is used to collect data from the site in real time.	Deep learning algorithm (YOLOv5) used to process the collected images and compare them with defined knowledge-based models to detect non-compliance with security rules	Although not applied in a real context, the results show that the method can contribute to safety in construction.

Table 2. *Cont.*

Type of Monitoring	Study	Proposed Approach	Equipment for Collecting Physical Information	Software for Information Analysis and Processing	Final Remarks
Site and/or equipment monitoring	[41]	The study provides a real-time safety risk assessment to reduce uncertainty and support rapid response by technicians.	Real-time location system (RTLS), in this specific case GPS from the worker's smartphone	The HMM was used as a risk assessment algorithm in the construction of an RTSRA method for safety management, which can also send alerts to workers and supervisors.	The results of the study show that it reflects the real situation on the ground.
	[42]	The study developed a guardrail detection model based on a convolutional neural network (CNN)	Computer vision is used to collect data from the site in real time.	Machine learning to automatically detect missing guardrails in images collected from the site	The results show that the model is suitable for detecting objects in safety management on construction sites.
	[43]	Hybrid deep learning model that integrates a convolutional neural network (CNN) and long short-term memory (LSTM) to detect unsafe actions climbing a ladder	Computer vision is used to collect data from the site in real time.	The model integrates CNN and LSTM so that unsafe worker behaviour captured on site video is automatically detected.	The results show that the proposed hybrid model can automatically extract and classify unsafe behaviour.
	[44]	Develop a structure for automatically monitoring the safety of work areas	Imaging by UAS (aircraft/drone systems)	CNN-based deep learning algorithm used to detect workers, vehicles and equipment from UAS images, automatically monitoring safety conditions on site.	This study has contributed to the expansion of the application of UAS in construction safety monitoring.
	[45]	Improve the efficiency of risk assessment and reduce the risk of falls from ladders by automatically detecting risk factor information in the field	(1) Computer vision is used to collect data from the site in real time. (2) The warning module can use computer vision to communicate risk information to the worker.	The Data Acquisition Module focuses on building a database of risk factor information. A Dynamic Bayesian Network (DBN) performs dynamic fall risk assessment.	Although not applied in a real context, the results show that the method can contribute to safety in construction.

Table 2. *Cont.*

Type of Monitoring	Study	Proposed Approach	Equipment for Collecting Physical Information	Software for Information Analysis and Processing	Final Remarks
Worker monitoring	[46]	The study proposes a method to detect the use of safety harnesses by workers.	Computer vision is used to collect worker data in real time.	A deep learning algorithm (YOLOv5) is used to detect the harness. Loudspeakers installed on-site emit alarms to remind workers to wear their personal protective equipment.	A security monitoring and alarm system based on the latest computer technology supports the manual monitoring with a high degree of accuracy.
	[47]	New technique for monitoring the use of personal fall arrest systems (PFASs) by workers	Computer vision is used to collect worker data in real time.	A deep learning algorithm (YOLOv3) was used to detect objects in real-time automatically, namely the harness and the lifeline.	The proposed model gave very good results.
	[48]	This article develops a methodology for the real-time monitoring of the position of workers and equipment on outdoor construction sites.	The UWB (worker location) system consists of active tags, UWB receivers and central processing units. Information is transmitted via ultra-wideband (UWB) technology.	Forecasting API software tool for real-time risk management	UWB systems can be successfully applied in the real-time management of construction sites.
	[49]	Location-based safety management system that tracks and visualises workers' locations in real time and sends early warnings	An RTLS, consisting of a tag attached to a worker, a reader installed on the site, and a base station receives information, processes data, and sends them to the location engine.	(1) ArchiCAD 12 to map the location of workers on a computerised building model (2) Alarm technology to send early warnings with detailed information to workers at risk	The system has proven effective in tracking and monitoring workers in real time and preventing accidents.
	[50]	Pressure sensor for textile insole, evaluating its effectiveness in real-time safety management for construction workers	Lightweight, low-cost, and portable textile insole pressure sensor to assess stair climbing and descent, and to check that insoles detect changes in posture	Bluetooth-based worker monitoring system that predicts and alerts workers of falls as they ascend or descend ladders by processing information based on a k-NN algorithm	The results obtained provided reliable data and could be used in the future to predict worker falls.

Table 2. *Cont.*

Type of Monitoring	Study	Proposed Approach	Equipment for Collecting Physical Information	Software for Information Analysis and Processing	Final Remarks
Worker monitoring	[51]	Proposes a technology for tracking the location of workers based on personal identification (ID)	(1) Location technology identifies workers and provides Job Hazard Analysis (JHA) information about the work area via a QR code or RFID (2) When the work zone and JHA are synchronised, workers entering the work zone automatically receive the site's safety information	This study integrated ASRC (Automated Safety Rules Verification System) systems into BIM-based projects to identify work zones with hazards to workers	The results of this study will serve as an effective tool for preventing accidents in high-risk workplaces.
	[18]	Proposes a smart safety hook (SSH) monitoring method to eliminate the risk of falls from scaffolding	Computer vision is used to collect worker data from monitoring the status of the harness connection.	Internet of Things (IoT), inertial measurement unit (IMU) and altimeter used to assess worker behaviour and alert in case of hazard	Despite occlusion issues, accuracy is high for real-time detection and classification.
	[17]	This paper develops an automated method to determine whether workers are wearing a harness when performing tasks at height.	Computer vision is used to collect worker data in real time.	Deep learning (Faster R-CNN) has been used to accurately identify objects with minimal time delay, making it possible to assess whether workers are wearing the harness.	The results showed that by combining the CNNs, a high level of accuracy can be achieved in detecting the incorrect use of safety harness.
	[52]	Detection of personal protective equipment (PPE) on site, namely footwear, suits/vest, harnesses, gloves, goggles and helmets	Computer vision is used to collect worker data in real time.	A deep learning algorithm (YOLOv5) was run to detect objects automatically in real time, namely PPE.	Automated tools overcome the limitations of manual monitoring methods.
	[53]	Monitor the correct use of harnesses in the workplace to prevent falls from height	(1) Harness fitted with BLE receiver (2) Beacon installed on the lifeline karabiner and additional active BLE beacons installed in fall hazard areas	Use BIM to identify areas that should be marked out, i.e., where there is a risk of a fall from height	Solutions can help to improve worker safety by reducing the number of falls from height.

Table 2. *Cont.*

Type of Monitoring	Study	Proposed Approach	Equipment for Collecting Physical Information	Software for Information Analysis and Processing	Final Remarks
Worker monitoring	[54]	Monitor the correct use of harnesses in the workplace to prevent falls from height	Various sensors distributed throughout the site: BLE receiver; harness with integrated BLE; virtual barrier of n BLE beacons to delimit the space; altimeter; anemometer. Communication between the sensors and the rest of the system is based on wireless Internet.	Fuzzy Combination Markup Language (FML) in JFML and Internet of Things (IoT) assess worker behaviour regarding the use of safety harnesses in specific areas	The developed system produced promising results, with the identified risk level matching the manual results defined by the security engineers.
	[55]	Developed a new system to monitor workers in real time when they are working at height	Imaging by UAS (aircraft/drone systems)	The deep learning algorithm (YOLOv4) was used to detect the main components of the PFAS (harness and lifeline) and the helmet.	This study shows that a UAV is a tool that can help technicians monitor the safety of workers working at height
	[56]	A model for assessing the risk of workers falling, taking into account the predominant and high temperature risk factors, as well as the physiological workload of the worker.	(1) Smartphone GPS is used to monitor the location of workers (2) WBGT values collected for indoor and outdoor environments were combined with the Clothing Adjustment Factor (CAF) (3) HR values collected using personal body measurements and HR sensors Data streams were transmitted via BLE.	The risk level is then used to calculate a downside risk score for each worker.	An overall downside risk score is calculated as the product of the two factors, providing a reference point for site managers to review the safety status of site workers and take timely action to improve areas of concern.
	[57]	Proposes an automatic worker location tracking and risk alert system for detection and effective risk management	The smartphone contains several sensors, such as a GPS receiver, accelerometer, magnetometer and gyroscope that measure the user's location	Building Information Model (BIM), Revit 2013 software, and Visual Studio 2010 are used to develop the automated risk alert system.	Although the results have not yet been applied in a real-world context, they will help to improve the identification of fall risks in the workplace.

Table 2. *Cont.*

Type of Monitoring	Study	Proposed Approach	Equipment for Collecting Physical Information	Software for Information Analysis and Processing	Final Remarks
Worker monitoring	[58]	Proposes a smart safety hook (SSH) monitoring method to eliminate the risk associated with falls from height	Computer vision is used to collect worker data from monitoring the status of the harness connection.	Machine learning (ML) is used to predict the status of the safety hook in real time. The SSH system generates an alarm (via buzzer and LED) if the hook is not secured as required.	The system detects and classifies hook status with high accuracy in real time.
	[59]	The purpose of this article is to promote the use of personal fall arrest systems (PFASs) when working at height	Computer vision is used to collect worker data, via cameras installed inside the building, as he passes through a window to carry out work at height on scaffolding outside the building	The ASC classifier detects climbers passing through a window in a work zone, and the SSD object detection method detects the use of harnesses and helmets. An alarm is given via a megaphone placed at the window	Although not applied in a real-world context, the results show that the method is robust to the risk of occlusion that may exist
	[60]	Use IMU sensor data to predict the risk of falling at height for accident prevention	An IMU sensor was attached to the worker to provide data on behaviours that are common or dangerous.	Several deep learning models (1D-CNN, 2D-CNN, LSTM and Conv-LSTM) were applied to the acceleration of three axes, the angular velocity of three axes, and their SVM feature vectors.	Although not used in a real-world context, the algorithm successfully predicted the risk of movement and was able to prevent fatal injuries.
	[61]	Investigate the effectiveness of a simple Environmental Intelligence (AmI) device as a tool to reduce the potential for fall accidents	The AmI is a device consisting of a microcontroller, microwave sensors, a light-emitting diode (LED), and an audible alarm	The analysis of the collected data is carried out by an application using X-bar graphs and one-way analysis of variance (ANOVA)	Data analysis revealed a reduction in the number of workers crossing fall hazard areas
	[62]	A helmet and harness monitoring system based on attribute knowledge modelling	Computer vision is used to collect worker data in real time.	A deep learning algorithm (YOLOv5) was used to detect the use of harnesses and helmets by workers.	Experimental results demonstrated the effectiveness and efficiency of this remote vision-based safety helmet and harness monitoring system.

Table 2. *Cont.*

Type of Monitoring	Study	Proposed Approach	Equipment for Collecting Physical Information	Software for Information Analysis and Processing	Final Remarks
Worker monitoring	[63]	This study focused on the posture of workers to directly detect the signs of a fall.	Computer vision is used to collect worker data in real time.	An improved machine model fusion–KNN learning method was used to detect fall omens and divide the entire fall process into three stages (stable–unstable–fall).	Although it has not been used in a real-world context, it achieves good accuracy and can help to promote proactive risk assessment.
	[64]	The study proposes a method of monitoring safety hooks (SSHs) to eliminate the risk of falls from scaffolding.	Computer vision, using cameras installed in the workplace, is used to collect worker data in real time.	A deep learning algorithm (YOLO) is used to detect the correct use of the harness by monitoring the connection status of the harness's safety hook.	The results showed that this method helped to reduce the number of falls caused by not using a harness.
	[65]	This article explores the potential applications of the smartphone as a data collection tool for near-miss detection and identification.	Smartphone strapped to the worker's back with data collection software, accelerometer and gyroscope installed to collect and record sensor data	A machine learning algorithm using an artificial neural network (ANN) to process data	Although it has not been used in a real-world context, it demonstrates the feasibility of integrating smartphones and ANNs to measure near-miss falls.

All the articles in this review had applications in the construction phase and allowed for real-time monitoring. From the information in Table 2, it can be seen that the most notable result relates to the direct monitoring of the worker in real time [17,18,46–65], with the remainder monitoring the site and/or the equipment present on site. It can also be seen that 11 of the studies assess the correct use of personal protective equipment (PPE) to eliminate the risk of falls from a height, and the remaining 29 monitor the risks to which workers are exposed on site, including the risk of falls from a height, as summarised in Table 3.

Table 3. Research methods of the selected studies.

Method and Approach		Number of Studies
Type of monitoring	Workers	22
	Site and/or equipment	18
Type of evaluation	Evaluates the use of PPE to prevent falls	11
	Evaluates the risk of falling from height	29

Most articles have used computer vision to monitor workers and the risks they face on a construction site [17,18,28–33,35,37,39,40,42,43,45–47,52,58,59,62–64], using installed cameras to capture information directly from the site and processing the information using deep learning algorithms. Less common is the use of worker localisation technologies to process the information and compare it with virtual 3D risk models to assess the risk the worker is exposed to at any given time [34,36,49,57].

3.3. Real-Time Monitoring of Falling from Height

The traditional risk assessment process relies solely on the subjective experience of local supervisors and is unsuitable for the automation of risk assessment. Real-time monitoring has the advantage of alerting people to a hazardous situation and thus preventing an accident, identifying imminent risks before they occur and affect workers.

Computer vision techniques are used in construction-related research for object detection. Studies have focused on detecting construction workers and machinery, and on monitoring construction progress. Several studies integrate computer vision with convolutional neural networks (CNNs) to detect unsafe behaviour by workers on construction sites, allowing safety engineers to be alerted to these situations and take action to prevent accidents [28,29,31–33,35,37,40,43,45,63]. Three of these studies assessed the behaviour of workers on mobile ladders, which could increase the risk of falling from height [35,40,45].

Some studies have integrated deep learning with computer vision to automatically detect the risks faced by workers on construction sites (not just the risk of falling) and display them in a BIM [30,39]. The results were similar to those achieved by the safety engineers, but the image-based technique is still unstable due to occlusion issues.

Collective fall protection systems, such as safety nets, guardrails, and platforms, are designed to protect workers in high-risk areas without requiring specific knowledge from the user [66]. In one study [42], a CNN-based guardrail detection model was developed to detect the presence of this safety equipment.

Monitoring mechanisms can focus on detecting personal protective equipment (PPE) and assessing its correct use by workers. Personal fall arrest systems (PFASs) refer to technology designed to be worn or attached to the worker to stop a fall and prevent injury. A study group proposed integrating computer vision with deep learning to directly monitor the worker's use of PPE, namely, the safety harness that eliminates the risk of falling from height [17,18,46,47,52,58,59,62,64]. It should be noted that the studies [18,58,64] assess whether the worker is using the harness correctly by assessing the status of the hook, whether it is engaged or not, and one of the studies proposes a solution that raises a warning if it is not used correctly [58]. Of these nine studies, only three allow a warning to be issued if the worker is behaving unsafely by not wearing a safety harness [46,58,59].

An inertial measurement unit (IMU) is a device that measures and reports body orientation and force. In one study, an IMU sensor was used to predict the risk of falling from a height, taking into account commonly observed or dangerous behaviours on construction sites, which were processed using deep learning models that had been developed [60], making it possible to predict the risk of movement.

Another technology in use is the application of sensors to assess the behaviour of workers as they move around a construction site. Study [50] uses wearable textile insole pressure sensors, which assess workers' behaviour when walking up and down stairs, using a Bluetooth Low Energy (BLE)-based monitoring system to predict fall risk and alert workers. Study [65], on the other hand, uses sensors built into a smartphone with data collection software, an accelerometer and a gyroscope, and the data are processed using a machine learning algorithm based on an artificial neural network (ANN).

Some researchers have attempted to integrate real-time location and behaviour-based safety (BBS) technologies. Study [36] introduced a BBS with intrusion warning technology and an assessment method, supported by online support systems, to reduce unsafe behaviour by workers and prevent, for example, falling from height.

Another example of technology being used to monitor hazards in real time is seen with unmanned aerial vehicles (UAVs) such as drones, which capture visual data from construction sites and allow better image processing. This information is then used to predict fall risks. This technology is used to monitor the worker and check that they are wearing their harness and lifeline (PFASs) when working at height using a deep learning algorithm [55]. UAVs combined with a deep learning algorithm can detect workers, vehicles, and equipment in the workplace, helping to monitor safety conditions [44].

Worker location technologies are widely used, and several techniques are instrumental in achieving automation in construction safety management. Study [48] uses an ultra-wideband (UWB) system to monitor workers and the site, using tags worn by workers and receivers installed in areas to be monitored that are defined as hazardous, thus enabling the detection of a hazardous situation, together with predictive software for real-time risk management.

Another tracking technology used is Radio Frequency Identification (RFID), which identifies the workers when they enter a work area that is considered hazardous and provides them with information about the hazards in that area based on BIMs [51].

The use of BLE technology to monitor workers, integrated with BIMs, makes it possible to identify the worker's location based on information transmitted by BLE sensors installed in the field and to view hazards in the BIM in an automated way, alerting safety engineers [34]. Another approach to applying this positioning technology is to install sensors in the harness and surrounding areas where there is a risk of falling, with communication via BLE to the receiver, which transmits the information and assesses the actual risk using the Internet of Things (IoT), generating an alert for the worker in situations of non-compliance [53,54].

Several studies have used Global Positioning System (GPS) technologies and real-time location systems (RTLSs) to monitor the location of workers on a construction site. Study [56] used the GPS on the workers' smartphone to locate them and assess the risk of falling from height based on information about pre-classified hazard areas, thus assisting safety managers on site. Other studies have used 3D software to map the location of workers and process the data to issue an alert if the worker is at risk [49,57]. A different approach to the use of GPS can be taken by mapping the location of workers and equipment on site, where it is possible to determine the proximity of workers to hazards, thus creating a method of assessing safety risks in real time, implementing a dynamic assessment of the safety status of workers on site [41], and assisting safety engineers in their decision-making.

Chirp Spread Spectrum (CSS) technology is used to monitor worker behaviour by placing tags in the worker's helmet or in areas of the site with a wide field of view that communicate with each other, making it possible to warn in real time of the proximity of hazards, including falls from height, by issuing an alert in a hazardous situation [38].

To make workers aware of the risk of falling, the study [61] developed a safety prevention mechanism by installing sensors in areas where there was a risk of falling, and whenever a worker entered this area, an audible alarm sounded to warn them of the risks.

Table 4 summarises the assessment of technologies used to eliminate the risk of falling from a height.

Table 4. Fall-from-height technologies in construction.

Types of Technologies for Predicting the Risk of Falling from Height	No. of Studies	References
Image processing for fall hazard monitoring	14	[28–33,35,37,39,40,42,43,45,63]
Image processing to monitor the correct use of PPE to prevent falling from height	9	[17,18,46,47,52,58,59,62,64]
Predicting fall risk using IMU	1	[60]
Insole pressure sensor-based tracking system for BLE-based safety footwear	1	[50]
Sensors integrated into a smartphone with data collection software, an accelerometer and a gyroscope to detect near misses	1	[65]
Use of location-based and behaviour-based security (BBS) technology	1	[36]
Use of UAVs to monitor the risk of falling from height	2	[44,55]
Use of location technology based on UWB to monitor the risk of falling from height	1	[48]
Use of location technology based on RFID to monitor the risk of falling from height	1	[51]
Use of location technology based on BLE to monitor the risk of falling from height	3	[34,53,54]
Use of location technology based on GPS and RTLS to monitor the risk of falling from height	4	[41,49,56,57]
Use of location technology based on CSS to monitor the risk of falling from height	1	[38]
Sensor-based tracking system to alert workers to the risk of falling	1	[61]

4. Discussion

This review focused on the methods and/or techniques used to monitor falling from height in real time in the construction sector. The studies focus on predicting the risk of falls in the tasks performed by workers in order to prevent accidents at work. The real-time monitoring of safety risks helps alert workers and safety engineers that they are in a risky situation that could lead to an accident. In this review, it was possible to identify studies that directly monitored workers and studies that monitored the site and/or existing equipment.

4.1. Technologies to Prevent the Risk of Falling from Height

Hands-on worker monitoring models have the advantage of assessing risk levels in real time. This is an important advance over traditional risk assessment, where the risk is assessed before construction begins. However, the risk of falling can change in dynamic environments, such as construction sites [67].

These practical models for monitoring the risks of falling from height in the workplace do not replace primary prevention measures, i.e., identifying the risks associated with each task performed, implementing these preventive measures, training workers in occupational safety and health, etc. They are only reinforcements of the safety prevention that must be carried out by safety technicians, and they can help detect non-compliance and irregular situations, thus preventing the occurrence of accidents.

The traditional risk assessment process is based solely on the experience of security engineers, and the use of new technologies is required to automate risk assessment [10]. Prevention comes from predicting risk. The development of preventive technologies requires rigorous forecasting and in-depth risk analysis using automated techniques. The technologies used facilitate risk assessment in a more visual and interactive way [19].

Prediction can take place during the construction phase by collecting data and alerting workers to hazardous situations, as demonstrated by the studies included in this review [17,18,28–65].

Real-time monitoring allows data to be collected from sites, using equipment, sensors, and data analysis for preventative action. The inertial measurement unit (IMU) is a device that measures and communicates body orientation and force. In the study developed by Lee et al. [60], this technology was used to obtain information about the worker's posture in order to avoid the risk of falling. This technology has been used extensively, particularly in the development of airbags placed inside the overcoat worn by workers, which are activated when the parameters detected by the inertial measurement unit exceed defined limits [68].

Radio Frequency Identification (RFID) systems are among the technologies used to detect the presence of obstacles and send alerts to those involved, and have great potential to reduce the number of accidents caused by equipment collisions in construction sites and other hazardous areas [69]. Study [51] combined RFID technology with BIMs to alert workers to hazards in a particular work area, including the risk of falling.

Another approach to real-time risk monitoring is exemplified by real-time location systems (RTLSs or GPS), which can locate workers and alert them if they are in a hazardous situation so that appropriate preventative action can be taken, as shown by studies [41,49,56,57]. The real-time location-based workplace safety management system developed by Lee et al. [49], which records and visualises the location of workers in real time and sends early warnings to at-risk workers, demonstrates that this technology can be used to monitor the different types of occupational hazards to which workers are exposed in the workplace.

Mobile monitoring devices, integrated into personal protective equipment (PPE), enable the real-time monitoring of risks and real-time advice in order to influence worker behaviour [70]. Personal fall arrest systems (PFASs) are the last line of defence against hazards, as they cannot proactively prevent fall hazards, but they do protect workers from injury. Studies [17,18,46,47,52,58,59,62,64] use computer vision with 2D image capture to check whether workers are using PPE correctly and to warn if they are not and if there is a risk of a fall. Studies [53,54], on the other hand, use localisation systems using BLE, whose sensors, installed in areas where there is a risk of falling and in the PPE itself, warn of this situation in order to prevent an accident.

Computer vision-based object detection techniques are designed to automatically extract a large number of image features and then use these features for image classification, such as in CNNs. The advantage of these algorithms is that they can learn from a given data set. With advances in hardware and software, deep neural networks are considered the most powerful technology for image processing and solving problems related to computer vision [71]. Studies [28–33,35,37,39,40,42,43,45,63] used computer vision combined with artificial intelligence and deep learning algorithms to detect unsafe behaviour and alert workers when they were at risk of falling.

Another system used to monitor risks in real time is exemplified by unmanned aerial vehicles (UAVs), such as drones, which can collect visual data from construction sites, access inaccessible areas, and cover large areas quickly [72]. Studies [44,55] developed a system based on deep learning and aircraft systems to help identify potentially unsafe situations and the use of safety harnesses based on defined rules and object detection results from aerial imagery, allowing safety technicians to monitor risk areas and provide additional warnings to workers to avoid the risk of falling.

BIM is the process of creating a virtual model of the building's technical information, enabling different professionals to work together at all stages of the building's design, construction, and operation [73]. This software is one of the technologies used to assess risk through safety rules in design models [10]. Studies [30,33,34,39,51,53,57] confirm that BIM is a robust predictive tool that integrates data collected on site during construction, predicts risks, and eliminates or mitigates them through changes introduced by engineers. This system can also be used to alert workers near risk areas.

Studies using computer vision technology have identified the main difficulties in detecting workers and personal protective equipment, namely, the presence of occlusions that prevent all risk behaviours from being detected [17,18,28–33,35,37,39,40,42,43,45–47,52,58,59,62–64].

4.2. Challenges of Implementing Technology in Prevention

The construction industry needs to focus on leadership commitment and continuous improvement, and there needs to be a commitment to safety from everyone involved and the creation of a culture where safety is valued. Various industries, such as agriculture and livestock, transport, manufacturing, energy, and healthcare, have a strong safety culture that is an integral part of health and safety management [74]. Following the example of these industries, the construction sector needs to embrace safety and create a culture where safety is valued. To achieve this, the construction industry can learn from the success of other industries by implementing regulations and standards that target specific risks, establish strict safety protocols, and emphasise risk management and emergency response. By taking these steps, the construction industry can create a safer working environment for everyone. Exploring new technologies and their potential applications to improve safety measures in the construction industry is a critical endeavour that can have transformative results in terms of reducing workplace accidents [74].

The implementation of advanced technologies to effectively manage fall risks on construction sites is fraught with challenges, such as the high cost of providing hardware and software within a limited project budget, the allocation of time and budget to train construction personnel in the use of fall protection technology [75], and the reduction in worker mobility when using wearable devices [59]. Despite the costs and limitations associated with implementing new technologies, they can introduce a proactive approach to automatically predicting and controlling fall risks [76].

Real-time detection and monitoring [77] are among the technologies whose use can be justified in complex, large-scale projects due to the significant cost, time, and resources involved. Although real-time monitoring benefits projects in terms of collecting real-time data in the field, assessing risk situations, and monitoring dangerous activities, location-based detection technologies have been criticised for their poor penetration performance when covering large areas, indicating that there are some limitations to their use in various locations [78]. The application of these technologies for the real-time monitoring of workers is somewhat complex, as it involves the use of interrelated hardware and software, i.e., sensory equipment, information technology systems, an integrated platform, and training for all involved [19].

Some of the studies included in this review [17,18,46,47,52,58,59,62,64] aim to verify the use of personal protective equipment (PPE), such as harnesses and fall arrest devices, to protect workers at risk of falling from a height. The correct use of this equipment is linked to initial and ongoing training to increase workers' awareness of hazardous situations [19].

Worker movement has a significant impact on construction safety. Some of the studies included in this review [28–33,35,37,39,40,42,43,45,63] use vision technology to monitor worker movements in real time; this technology is pre-parameterised to detect unsafe behaviour automatically. Image processing technology has traditionally been time-consuming due to the excessive amount of redundant information present in the images. Monitoring worker movement requires the parameterisation of all possible behaviours to create the most comprehensive database and make the technology efficient [78].

BIM is one of the main technologies used to assess the risk of a fall from height. It works by automatically checking the safety rules of building models and plans [10]. Real-time detection and monitoring allow data to be collected from workers using sensor devices and analysed for appropriate preventative action [19]. This software can be integrated with other technologies that can identify the location of workers in real time, such as RFID [51], BLE [34,53], GPS [57], RTLS [49], and computer vision [30]. The choice of localisation technology must be appropriate, as it can affect the reliability of the result depending on the type of construction (external or internal), and there is no single perfect system for achieving the accurate internal positioning of the worker [79].

The use of these technologies to monitor workers in real time does not require in-depth knowledge on their part to use them correctly, as most involve sensors being attached to the personal protective equipment they wear [38,48,49,51,53,54], or location information received from a smartphone [34,41,56,57].

Technologies using RFID [51], BLE [34,53,54], or RTLS [48,49] require the installation of tags on site in areas where there is a risk of a fall and, therefore, are more complex and limited systems in terms of monitoring this risk in these specific areas.

4.3. Emerging Trends in Construction Safety Technology

The rapid pace of the development of construction technology provides new opportunities to ensure adequate security measures and to cope with the uncertainties of the modern building environment. Many primary studies have sought to introduce appropriate technologies to improve safety risk management processes, decisions, and outcomes. Prediction, prevention, and mitigation are three important pillars of occupational health and safety risk management [19]. However, whether the impact of these advanced technological aids in addressing safety risks, particularly those related to falls from height, is yet to be established convincingly.

The prediction of fall hazards is currently based on manual hazard identification and risk assessment, safety talks, and job safety analyses [67]. The appropriate use of new technologies can facilitate the implementation of such methods and increase the chances of successfully predicting fall hazards. New technologies can help to assess work situations and predict hazards, allowing professionals to consider critical risks early in the design phase before they occur [19].

Foresight platforms and software have been developed to identify and assess the associated risks and monitor controls effectively. Recent advances in BIM and related tools allow the automated assessment of fall risks and help to develop appropriate preventative measures [10].

BIM can also be used in Prevention through Design (PtD), making it possible to identify safety risks early in the planning and design phase, propose preventive measures, and monitor the implementation of control measures [80].

The real-time monitoring of safety risks helps to alert workers who are at risk of falling, and it is necessary to identify imminent risks before they occur and affect workers [19]. Several technologies have been reviewed in the literature to assess the positive impact they can have on preventing falls from heights [17,18,28–65].

Of the studies included in this review, few use BIM to assess workers' exposure to the risk of falls from height. BIM technology facilitates effective collaboration on projects and data integration from the design phase to project completion. In addition, BIM provides a solid visual understanding of a site and working conditions before construction begins and facilitates the visual representation of site conditions. As noted above, this technology, integrated with other innovative technologies, allows the workplace to be visualised in real time due to the different capabilities of these technologies [81].

BIM, combined with technologies used for site monitoring systems, allows the safety engineer to receive real-time alerts when workers leave a fall protection zone. This type of solution allows a single safety engineer to monitor all workers on site using a virtual model. In contrast, this is a complex task in the traditional method due to the characteristics of large construction sites, and the model allows almost immediate action to be taken to prevent accidents [82].

4.4. Future Studies

One of the most important research areas is the use of computer vision to detect unsafe worker behaviour concerning fall risk or harness use.

Although there has been some research into fall risk prediction systems, there are still gaps in the use of BIM integrated with worker tracking systems to monitor and prevent fall risks in real time.

These technologies, used to predict and mitigate the risk of falls from height, have been studied in the construction industry for decades. However, their use has been limited, meaning that future research should address and develop effective systems that are easy for construction workers to use in order to proactively eliminate the risk of falls from height without compromising productivity.

Future studies need to take into account the processing of sensitive personal data that may be generated by the real-time monitoring of workers. This situation was not addressed in the studies analysed, and therefore, effective framing strategies and systems need to be developed, as do ways of making ethical decisions [83,84].

4.5. Limitations

Despite the results obtained, limitations of the review include language bias, as studies in languages other than English were not included, and publication bias, as unpublished studies were not included. Given the high variability between studies, it was not possible to directly compare the results obtained due to the different monitoring parameters, and only a descriptive synthesis of the methods and/or techniques used by each study was considered.

5. Conclusions

This article presents the results of a systematic review conducted using the PRISMA methodology [22,23] to understand real-time worker monitoring technologies in the construction sector.

The complexity of construction sites and their dynamic and ever-changing environments means that traditional methods of managing occupational safety, based on manual processes and dependent on the supervision and experience of safety engineers, are too subject to human limitations and failures. In recent years, there has been a growing trend of exploring the latest technologies, particularly those related to artificial intelligence, to monitor workers and/or the workplace in real time and in a real context, contributing to greater safety on construction sites.

It can be concluded that there is significant potential for implementing real-time monitoring technology in the construction context, as studies have generally demonstrated its feasibility and effectiveness in terms of safety and the prevention of workplace accidents. However, it was not possible to directly compare the results obtained due to the different monitoring parameters and working contexts used by the different researchers.

It was found that there was no single method and/or technique for assessing risk; rather, a combination of risk assessment, prevention, and mitigation techniques must be applied to contribute to the safety of these sites. This new risk prevention technique changes the approach from reactive to proactive, enabling real-time monitoring to improve site surveillance and safety.

The balance between productivity and safety remains an important consideration when carrying out such technology studies. Construction companies need technologies that can improve their fall protection performance while maintaining high levels of productivity and operational agility.

This review has shown that different researchers are studying this topic. The growing trend in research into fall prevention technologies has demonstrated the potential to develop viable technologies that can be effectively implemented on construction sites, improving the performance of companies in terms of workplace safety without compromising productivity.

This study concludes that the emerging concepts of virtual reality, unmanned aerial vehicles, and BIM are beginning to take hold in the construction context, emphasising the use of high-tech equipment, analytical modules, and information technology systems to improve the effectiveness of the fall-from-height risk management process in the construction industry.

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