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Review

Review of the Application of Wearable Devices in Construction Safety: A Bibliometric Analysis from 2005 to 2021

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Abstract: Wearable devices as an emerging technology to collect safety data on construction site is gaining increasing attention from researchers and practitioners. Given the rapid development of wearable devices research and the high application prospects of wearable devices in construction safety, a state-of-the-art review of research and implementations in this field is needed. The aim of this study is to provide an objective and extensive bibliometric analysis of the published articles on wearable applications in construction safety for the period of 2005–2021. *CiteSpace* software was used to conduct co-citation analysis, co-occurrence analysis, and cluster identification on 169 identified articles. The results show that 10 research clusters (e.g., attentional failure, brain-computer interface) were extremely important in the development of wearable devices for construction safety. The results highlight the evolution of wearable devices in construction-safety-related research, revealing the underlying structure of this cross-cutting research area. The analysis also summarizes the status quo of wearable devices in the construction safety field and provides a dynamic platform for integrating future applications.

Keywords: wearable device; bibliometric analysis; construction safety; *CiteSpace*

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1. Introduction

The construction industry has long been regarded as one of the most dangerous industries worldwide [1,2]. It employs approximately 7% of the global workforce but contributes to 30–40% of total fatalities [3]. Among all causes of construction accidents, unsafe behaviors of construction workers are the primary and immediate causes. For instance, a study has reported that 88% of accidents are related to unsafe behaviors [4]. To reduce unsafe behaviors and improve the safety performance of construction workers, various measures have been proposed, such as establishing multiple training programs, applying academic knowledge to work sites, and exploring new technologies [5,6]. Wearable devices that offer a promising solution for construction safety management and risk identification are increasingly adopted on construction sites [7]. Due to the dynamic and transient nature of construction [8], traditional manual collection of construction safety data is time intensive [9], and needs to be automated by an effective tool that provides timely information for safety managers to take positive actions. As an emerging technology, wearable devices can potentially realize real-time and accurate security monitoring [10]. They are products controlled by electronic components and software that can be incorporated into clothing or worn on the body like accessories. Wearable devices collect information through tiny, easily worn sensors [11]. Such non-invasive devices avoid the obvious problems of large and complex physical examination devices [12,13], and provide real-time information interaction with the wearer [7]. Timely monitoring and feedback ensure the effectiveness of the information provision. Automated safety monitoring systems based on wearable devices are another promising avenue of research. The data of construction sites collected through wearable devices have been evaluated by researchers and practitioners, providing early warnings of the safety risks in construction environments [14–16], physiological signals from construction workers [6,17,18] and automatic recognition of workers' actions [11,19]. Wearable devices have also assisted safety training [20] and accident prevention [21]. For example, the biomechanical gait-stability parameters can prevent falling and colliding accidents, which are common occurrences on construction sites [21,22].

To reveal the possible connections among the studies on wearable-device applications in construction safety, some studies have reviewed the past development and proposed new research trends in this area. For example, Wang et al. (2015) reviewed the available techniques for the risk assessment of work-related musculoskeletal disorders, and summarized the advantages and limitations of wearable-device systems in this theme [23]. Awolusi et al. (2018) reviewed the application of wearable technologies in construction-safety monitoring, and analyzed the relevant safety performance metrics [24]. Ahn et al. (2019) recently reviewed and identified general wearable-sensing technology applications in construction safety and health, and indicated the challenges and future research opportunities for advancing this field [6]. However, these reviews are often qualitative or based on manual process and researchers' subjective judgement. Such methods may overlook some articles available for review and thus be vulnerable to biases.

This study aims to conduct a comprehensive and objective bibliometric analysis of the research on the application of wearable devices in construction safety from 2005 to 2021 with the help of *CiteSpace* software. This research clusters the applications of wearable devices in construction safety, reviews the whole development framework, and suggests future research trends. Based on the bibliometrics, the study quantitatively summarizes the status quo and establishes the important issues concerning the new technologies of wearable devices in construction safety. The research hotspots are illustrated on visual maps. This study extends traditional literature review methods to carry out a bibliometric analysis to delineate the intellectual structure and quantitatively summarizes the related knowledge in graphical form.

2. Research Method

2.1. Data Collection

The data collection consisted of two stages. In Stage 1, a comprehensive search was carried out in the online academic database. This study used *Scopus* database for literature search, as it could provide a comprehensive coverage of the sciences, social sciences, arts, and humanities across journals, books, and conference proceedings and was sufficiently large for most bibliometric analysis. Articles containing the specific terms in the title/abstract/keyword' were firstly retrieved. Five experts were interviewed to provide the key search words for the research topic. Based on the analysis of interviews, the following search string was used in the 'title/abstract/keyword' fields: ("Wearable devices" OR "Wearable systems" OR "Wearable technology" OR "Wearable sensor") AND ("construction safety"). The search was further refined by limiting the time span into the recent 16 years—'from 2005 to 2021' and the document type to 'article, review and conference paper'. At the same time, the same search string was used in the Web of Science database to find the articles not included in the *Scopus* database. A total of 239 articles were identified in this stage.

Given that the search results of Stage 1 may include irrelevant papers that contain the search keywords but do not actually focus on wearable devices in construction safety, Stage 2 was conducted to eliminate the irrelevant literature. To ensure the accuracy and relevance of data, the titles and abstracts of all 239 articles retrieved in Stage 1 were carefully scrutinized by authors. During this process, two authors examined these articles independently and their results of screening were compared and consolidated. After removing 70 irrelevant articles, 169 papers were retained as the basis of our bibliometric analysis.

The bibliographic records of the identified 169 literatures were downloaded from the database, including the article title, article type, a list of authors, a set of keywords, the abstract, the journal name, publication year, volume, issue number, number of citations, and a list of the cited references. These bibliographic records were further standardized (e.g., correcting the different spellings of authors, journal, or keywords) through manually checking for bibliometric analysis.

2.2. Bibliometric Analysis

The term of bibliometric was first introduced as "the application of mathematical and statistical methods to books and other means of communication" by Pritchard (p. 349) [25]. Bibliometric analysis is a quantitative statistical analysis of the literature [26], which has been widely used for identifying the relationships among authors, institutions, research directions, and other variables [27–29]. A bibliometric analysis can be realized through visualization tools to identify the emerging trends and knowledge structures in a specific research field. The results are often presented intuitively in visual maps. The present study focuses on author co-citation analysis, keyword co-occurrence network, and cluster identification. These techniques are advantageous over the conventional manual review method.

Co-citation analysis measures the semantic similarity among documents, authors, or journals by computing their co-citation relationships. A co-citation relationship defines the frequency at which two items are cited together [30]. Co-citation analysis assumes that when two items are commonly cited together, their contents are relevant to each other. Co-citation analysis can be performed on documents, authors, or journals, which connects the cited documents, authors, or journals that researchers consider as valuable and interesting. The present study conducts an author co-citation analysis, which identifies the relationships among authors whose publications are cited in the same literature. More specifically, an author co-citation analysis identifies and visualizes the knowledgeable structure of a specialist research area by counting the co-citation frequency of two authors' publications among the reference lists of cited literature [31].

Keywords represent the core content of a research article. A keyword co-occurrence network constructs and maps the knowledge domain of a particular area over a specific time span. This method acknowledges that when keywords frequently co-occur in publications, their underlying ideas are closely associated [32]. A keyword co-occurrence network constructs a similarity measure from the literature contents themselves, rather than linking the literature indirectly through citations. In the present analysis, the bibliometric analysis results of wearable devices in construction safety were demonstrated in a keyword network, which identifies the keywords that co-occur in at least two different articles in a given time span. High-frequency keywords are recognized as indicators of research hotspots or directions over a specified period.

Cluster analysis is commonly applied in knowledge discovery, which identifies the profound themes hidden in the textual data [33]. Cluster analysis categorizes a mass of data into different units with common relevancy of terms, which identifies the research topics and their interrelation within a research domain. In cluster analysis, the homogeneity or consistency of clusters is evaluated from the mean silhouette of the network [34]. When the silhouette value is 1, the clusters in the network are completely separated. Research trends can also be effectively analyzed by cluster analysis [35].

At present, there are many widely used bibliometric tools, such as *CiteSpace*, *VOSViewer*, and *HistCite*. In terms of cluster analysis, *VOSViewer* does not have as many algorithms as *CiteSpace* to extract cluster labels. *HistCite* is relatively simple to operate, but its graphical presentation is not as rich as *CiteSpace*'s. *CiteSpace* software has all the functions mentioned above, as well as time slicing technology, which supports more intuitive performance of time series in network analysis for systematic review[36]. *CiteSpace* is a Java application for structural and temporal analyses of various networks derived from the academic literature and has been optimized several times in recent years to improve its function and practicability [27]. It supports networks with hybrid node types (e.g., institutions and countries), and hybrid link types (e.g., co-citations and co-occurrence) [29,37]. *CiteSpace* can also detect trends and citation bursts of academic papers by calculating publication indicators [34]. Therefore, version 5.8R3 of the *CiteSpace* software was chosen as the bibliometric tool to conduct a comprehensive analysis.

3. Results

3.1. Overview of Research

Tables 1 and 2 illustrate the trends of identified articles regarding the wearable devices in construction safety by country, year, and journal/conference. The data in Table 1 are derived from the article list filtering function in *Scopus* database. In term of the geographic distribution, the contribution of the United States to the literature of wearable devices in construction safety is the most (N = 88, P = 42.1%). In fact, it is much larger than the second one, i.e., Hong Kong (N = 31, P = 14.8%) and the third one, i.e., Mainland of China (N = 23, P = 11.0%) (see Table 1).

Table 1. Main research origin of papers published.

Country	Institute/ University	Researchers Involved	Number of Papers	Percentage Contribution
United States	73	135	88	42.1%
Hong Kong	28	54	31	14.8%
China	36	72	23	11.0%
South Korea	25	48	22	10.5%
United Kingdom	16	28	10	4.8%
Australia	22	36	9	4.3%
Japan	22	40	8	3.8%
Italy	6	26	5	2.4%
Saudi Arabia	3	10	5	2.4%
Germany	7	15	4	1.9%
Canada	10	16	4	1.9%

Countries or regions with four or more papers are counted in the table.

As shown in Table 2, *Automation in Construction* and *Journal of Construction Engineering and Management* have published the most articles at 36 (i.e., 21.3%) and 18 (i.e., 10.7%) out of 169 identified articles. The papers published in *Automation in Construction* are significantly more than those published in other journals. The total number of publications on this topic by year has increased. Until 2016, the number of articles was under 10 per year, but from 2017 to 2021 the number of publications has increased to triple, e.g., 2021 (N = 31). It indicates that the study on applying wearable devices in construction safety has attracted increasing interest of researchers and practitioners.

Table 3 lists the top 10 cited papers of wearable devices in construction safety. Six papers were published in *Automation in Construction* and two were published in *Applied Ergonomics*. The remaining two papers were published in *Journal of Construction Engineering and Management* and *Journal of Computing in Civil Engineering.* In terms of research content, many of them focus on the construction workers' posture and activity, including three concerning about work-related musculoskeletal disorders (WMSDs) [23,38,39], and three concentrating on ergonomic analysis, fall detection, and activity recognition [19,40,41]. In these studies, inertial measurement unit (IMU), accelerometer gyroscope, and linear accelerometer, etc., were the most commonly used wearable sensors. The remaining of them focus on workers' fatigue or stress levels, collecting physiological data from construction workers using heart rate, body surface temperature, and EEG data [18,42].

Table 2. The publishing year of journals/conference proceedings contributing to the area of wearable devices in construction safety.

Source	**Publication Year**											
	2005–2010	**2011**	**2012**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**Total**
Automation in Construction						3	10	7	6	3	7	36
Journal of Construction Engineering and Management					1			2	6	5	4	18
Sensors (Switzerland)									1	5	2	8
Advanced Engineering Informatics							1	2	1	1		5
Congress on Computing in Civil Engineering, Proceedings		1	2				1					4
Engineering, Construction and Architectural Management										2	2	4
Safety Science									1	2	1	4
Construction Research Congress 2020: Safety, Workforce, and Education—Selected Papers from the Construction Research Congress 2020										4		4
Others	6	2	4	3	3	6	6	11	10	20	15	86
Total	6	3	6	3	4	9	18	22	25	42	31	169

Journals and conference proceedings with less than four paper were classified into Others.

Table 3. Top 10 cited articles on wearable devices in construction safety.

Rank	**Authors**	**Title**	**Cited Frequency**	**Journal**	**Refs.**
1	Awolusi et al. (2018)	Wearable technology for personalized construction safety monitoring and trending: Review of applicable devices	143	*Automation in Construction*	[24]
2	Yan et al. (2017)	Wearable IMU-based real-time motion warning system for construction workers' musculoskeletal disorders prevention	135	*Automation in Construction*	[38]
3	Aryal et al. (2017)	Monitoring fatigue in construction workers using physiological measurements	111	*Automation in Construction*	[42]
4	Valero et al. (2016)	Musculoskeletal disorders in construction: A review and a novel system for activity tracking with body area network	111	*Applied Ergonomics*	[39]
5	Wang et al. (2015)	Risk assessment of work-related musculoskeletal disorders in construction: State-of-the-art review	109	*Journal of Construction Engineering and Management*	[23]
6	Jebelli et al. (2018)	EEG-based workers' stress recognition at construction sites	101	*Automation in Construction*	[18]
7	Nath et al. (2017)	Ergonomic analysis of construction worker's body postures using wearable mobile sensors	94	*Applied Ergonomics*	[19]
8	Yang et al. (2016)	Semi-supervised near-miss fall detection for ironworkers with a wearable inertial measurement unit	92	*Automation in Construction*	[40]
9	Joshua et al. (2011)	Accelerometer-based activity recognition in construction	86	*Journal of Computing in Civil Engineering*	[41]

10	Choi et al. (2017)	What drives construction workers' acceptance of wearable technologies in the workplace?: Indoor localization and wearable health devices for occupational safety and health	85	*Automation in Construction*	[43]

3.2. Co-Authorship Analysis

Co-authorship analysis can identify main researchers and research communities in this field. Figure 1 depicts the co-authorship network generated from the literature data, and visualized by *CiteSpace*. The 212 nodes represent the authors in the cited literature, and the 340 links represent their co-authorship relationships. The color of the links represents different ranges of years, e.g., gray, blue, green, yellow, orange, and red, and those colors range from light to dark, corresponding to different years from 2005 to 2021, as shown in Figure 1. A high 'count' parameter indicates a great influence of authors in the field. As shown in Figure 1, the larger the 'count' parameter, the larger the author's name label size, e.g., *Heng Li* (Hong Kong, count = 19), *Houtan Jebelli* (USA, count = 15), *SangHyun Lee* (USA, count = 13), *Antwi-Afari Maxwell Fordjour* (United Kingdom, count = 10), *Changbum Ryan Ahn* (USA, count = 9), *Jiayu Chen* (Hong Kong, count = 8), *Chukwuma Nnaji* (USA, count = 8), *Kanghyeok Yang* (South Korea, count = 7), *Byungjoo Choi* (South Korea, count = 7), *Ibukun Gabriel Awolusi* (USA, count = 7).

When the links form a closed-loop circuit, the linked authors share a strong interaction relationship. such as the circuit of *SangHyun Lee*, *Houtan Jebelli*, *Yizhi Liu* and *Mahmoud Habibnezhad*. In addition, multiple research communities can be identified through these closed loops and productive authors can be found within them. For example, *Heng Li* and *Antwi-Afari Maxwell Fordjour* are the two crucial authors of a research community, including *Waleed Umer*, *Shahnawaz Anwer*, *Arnold Wong*, etc., and *Jiayu Chen* is the crucial author of a research community, consisting of *Di Wang*, *Dong Zhao*, *Dai*, *Fei*, etc.

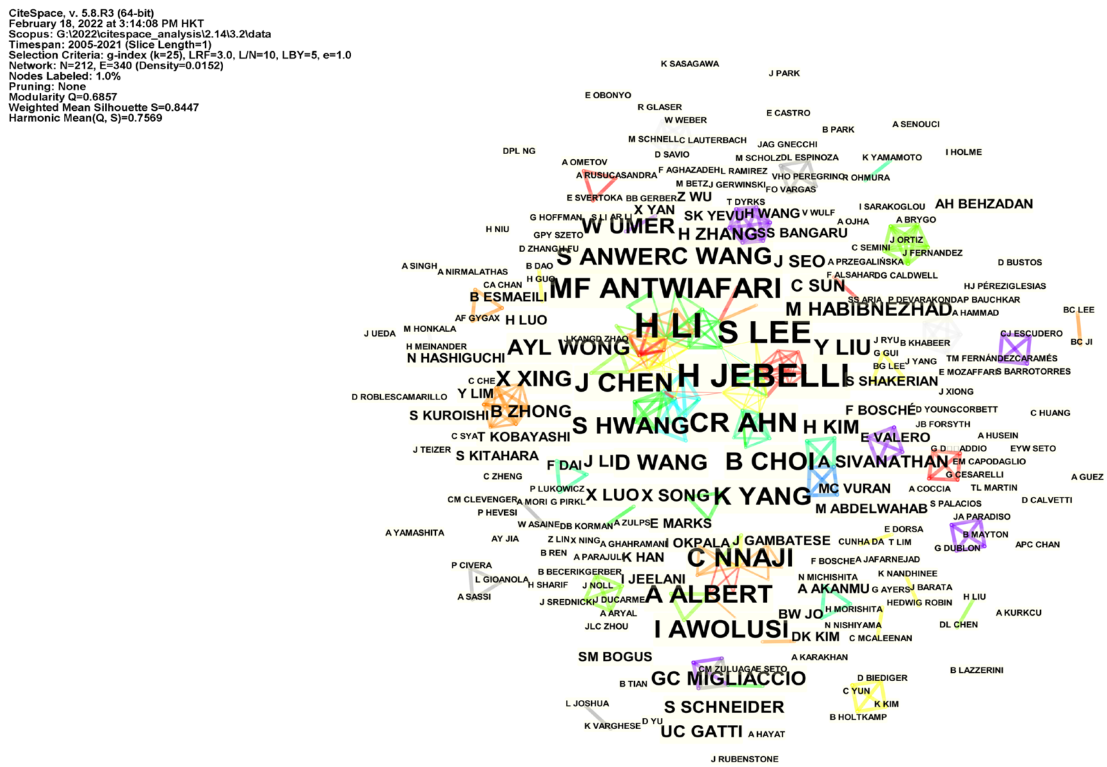

Figure 1. Co-authorship network of wearable devices in construction safety.

In graph theory, a node with high betweenness centrality usually means that the node is located in a more crucial position in the network. The top five authors with this property were *Heng Li* (centrality = 0.05), *JoonOh Seo* (centrality = 0.03) *Jiayu Chen* (centrality = 0.02), *Cenfei Sun* (centrality = 0.02), and *SangHyun Lee* (centrality = 0.01). An author with many counts and a high betweenness centrality in Figure 1 will most likely lead the research field of wearable devices in construction safety. Combined with the above metrics of main researchers and the links of research communities in Figure 1, we can continue to explore the research direction of specific communities and find the most influential articles based on node information.

3.3. Keyword Co-Occurrence Network

Figure 2 shows an overview of the keywords co-occurrence network with 379 nodes generated from the dataset. Each node represents one keyword term specified in the articles. Table 4 lists the top 28 terms (frequency > 10) with a total of 752 co-occurrence frequencies, which account for 47.9% of all keyword frequencies.

Figure 2. Keyword co-occurrence network of wearable devices in construction safety.

According to Figure 2 and Table 4, occupational risk is the most frequent keyword, appearing 77 times, revealing that most studies are inspired by the occupational injuries suffered by workers in the construction industry. The second most frequently mentioned keyword is wearable technology (73 times), showing that wearable technology is the main research focus in this field. Following these two keywords, construction workers, construction industry, wearable sensor and construction safety are also mentioned frequently, with 66, 54, 47 and 40 times, respectively. These terms constitute the background and objectives of the construction safety research domain. Most of the remaining keywords appear less than 40 times. Some of these low-frequency keywords refer to specific wearable technologies, such as electroencephalography (16 times), inertial measurement unit (13 times), and heart (generally refers to heart rate, 12 times). Some keywords explain the method of analyzing data collected by wearable devices, e.g., ergonomics (19 times), machine learning (15 times), and physiological model (11 times). In addition, some keywords have high betweenness centrality, such as construction worker (centrality = 0.17), risk assessment (centrality = 0.17), accident prevention (centrality = 0.15), construction worker (centrality = 0.14), health (centrality = 0.13). These keywords constitute different research topics and are interrelated. The co-occurrences of these keywords report the major research interests of wearable devices in construction safety.

Table 4. Occurrence frequencies of specified keywords in the literature of wearable devices in construction safety.

Keywords	Frequency	Keywords	Frequency
Occupational risk	77	Health risk	18
Wearable technology	73	Accident	17
Construction worker	66	Physiology	17
Construction industry	54	Electroencephalography	16
Wearable sensor	47	Machine learning	15
Construction safety	40	Safety engineering	13
Accident prevention	36	Inertial measurement unit	13
Risk assessment	30	Monitoring	12
Human resource management	29	Heart	12
Construction site	27	Survey	12
Hazard	26	Wearable device	12
Health	19	Safety	11
Human	19	Physiological model	11
Ergonomics	19	Productivity	11

3.4. Cluster Identification

Knowledge domains can be identified and presented as clusters by the bibliometric review method based on information with the relevant articles. *CiteSpace* extracts the term from the titles, keywords, or abstracts of the literature as text resource, and then the calculation can be carried out after setting parameters such as node type and selection criteria. *CiteSpace* provides three assessment measures: *Latent Semantic Indexing* (LSI), *Likelihood Ratio Test* (LLR), and *Mutual Information* (MI) index. One of the methods is selected to extract clustering labels from the titles or abstracts of cited references [44]. In this paper, LLR, recommended by the software author, was chosen as the algorithm, which calculates the p-value based on the likelihood ratio or compares it with a critical value to decide whether to reject the null model, thus obtaining the clustering label of the optimal confidence. Figure 3 illustrates a cluster view of the knowledge domains of wearable devices in construction safety, by the *loglikelihood ratio* (LLR) algorithm. The modularity score of the network is 0.6857. As this score lies between 0.4 and 0.8, the clustering is deemed to be acceptable. The weighted mean silhouette metric measures the average homogeneity of a cluster [45]. When the clustering size is similar, a higher weighted mean silhouette indicates better consistency of the cluster [46]. Therefore, the weighted mean silhouette score of 0.8447 indicates that the consistency of cluster members is enough. The cluster ID ranges from 0 (largest) to 9 (smallest). The size and quality of each cluster are decided by the number of papers assigned to the cluster and the silhouette value of the cluster, respectively. In Table 5, the mean silhouette of each cluster exceeds 0.6, confirming an acceptable level of clustering validity. The hybrid node network is composed of 379 nodes and 1430 links. The 10 major knowledge clusters are attentional failure (#0), brain-computer interface (#1), activity tracking (#2), industrial work safety (#3), corporate clothing (#4), construction site (#5), accelerometer-based activity recognition (#6), intelligent monitoring (#7), building site (#8), and wearable wireless identification (#9). The next section will discuss these clusters in detail.

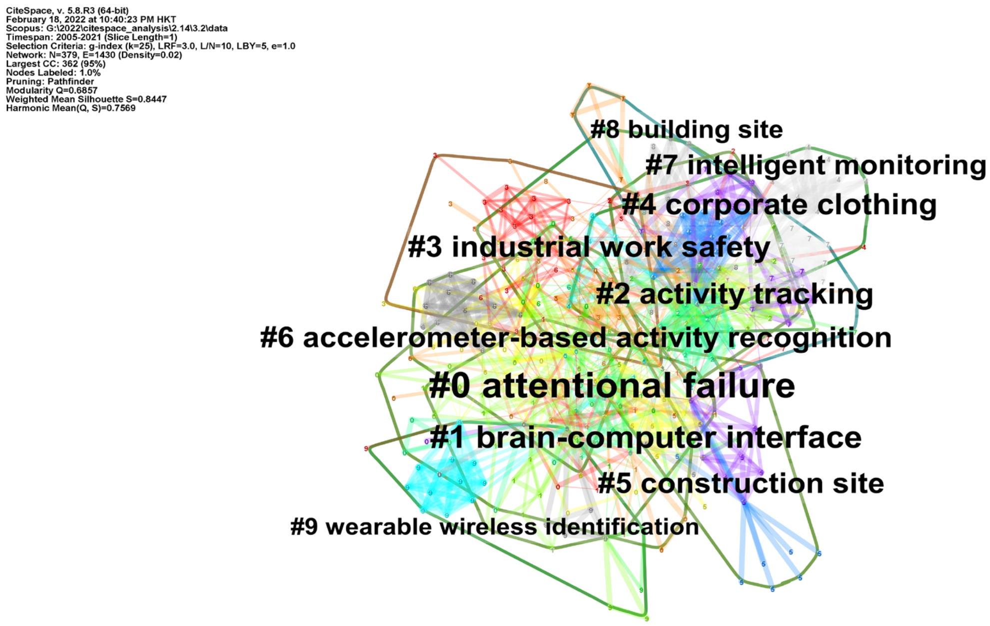

Figure 3. Cluster view of knowledge domains for wearable devices in construction safety.

Table 5. Top-ranked clusters and their main terms.

Cluster ID	Size	Silhouette	Mean Year	Cluster Label (LLR)	Alternative Label	Representative articles
0	47	0.731	2017	Attentional failure	Fall-hazard condition; hazard identification	[47–51]
1	38	0.672	2017	Brain-computer interface	Quantitative framework; construction safety management	[18,52–56]
2	34	0.857	2017	Activity tracking	Body area network; novel system	[19,21,39,57,58]
3	33	0.770	2019	Industrial work safety	Health risk mitigation; ann-based automated scaffold builder activity recognition	[57,59–62]
4	33	0.963	2011	Corporate clothing	Engineering industry; cyber-physical gaming system;	[58,63–66]
5	32	0.891	2014	Construction site	Wearable biosensor; physical demand	[17,18,67–69]
6	31	0.779	2015	Accelerometer-based activity recognition	Using body-mounted sensor; automated ergonomic risk monitoring	[11,16,41,70,71]
7	30	0.929	2012	Intelligent monitoring	Carbon monoxide poisoning; gait pattern	[48,58,72–74]
8	24	0.855	2012	Building site	Risk mitigation system; scaffolds monitoring	[57,71,75–77]
9	21	0.979	2014	Wearable wireless identification	Sensing platform; self-monitoring alert	[22,61,78–80]

Figure 4 shows the timeline view of the network. Each horizontal line represents one cluster and the size of each ring represents the centrality of the nodes. The curved lines represent the relationships between the clusters and the authors. Unlike the cluster view in Figure 3, the timeline view in Figure 4 shows the temporal evolution patterns of the 10 clusters. Specifically, Figure 4 reveals that keywords in cluster #1 (brain-computer interface) and cluster #7 (intelligent monitoring) have the longest time range covered, with relevant keywords appearing from 2005 to 2021. In addition, cluster #0 (attentional failure), cluster #3 (industrial work safety), cluster #5 (construction site), cluster #6 (accelerometer-based activity recognition), and cluster #9 (wearable wireless identification) all emerged after 2010. Cluster #4 (corporate clothing) and cluster #5 (construction site) contain some central keywords, making the tree-ring circles in the figure larger. Moreover, it can be found that red links are mostly distributed in the first five clusters (#0–#3), indicating that the research hotspots in the recent five years are concentrated in these clusters.

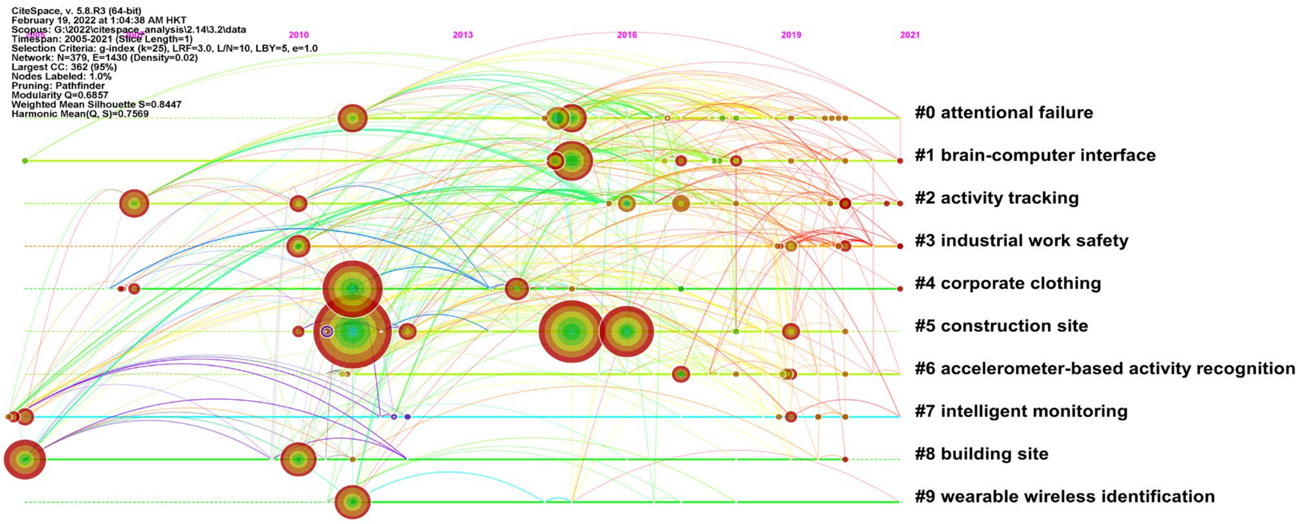

Figure 4. Timeline view of the co-occurrence network cluster of keywords.

4. Discussion

Wearable devices in construction safety have focused on technologies and applications. Four clusters—brain–computer interface (#1), accelerometer-based activity recognition (#6), and wearable wireless identification (#9)—are placed into the technology category, which encompasses the basic functions of wearable devices and sensors. Most of the tags in this category possess obvious technical attributes. Accelerometer-based activity recognition, for example, are commonly employed as collectors of worker activity data (e.g., identifying body posture and acceleration, and walking steps) in construction safety. The remaining clusters—attentional failure (#0), activity tracking (#2), corporate clothing (#4), and intelligent monitoring (#7)—are categorized as applications. Most of the works in these clusters employ existing wearable technologies in novel assessment systems of construction risk (e.g., worker pressure, worker falls and collision damage, and other relevant occupational disease risk). In addition, cluster #3 (industrial work safety), cluster #5 (construction site), and cluster #8 (building site) also illustrate the application scenarios of wearable technology. The clustering results effectively identify the emerging research hotspots in this domain.

4.1. Cluster #0 (Attentional Failure)

The most significant cluster is cluster #0 (attentional failure). The construction industry is labor-intensive and necessarily involves repetitive manual labor [81]. Highly physically demanding activities increase the risk of physical fatigue [43], which increases the likelihood of attentional failure and tends to have adverse consequences for construction workers [82].The most common construction accidents are usually related to equipment operation, and attention failure is the leading cause of equipment operator error [83,84]. Using eye-tracking technology, workers' attention allocation, mental fatigue, and hazard detection abilities can be well evaluated [84,85]. Eye-tracking devices can also be used to measure some metrics of visual search patterns (e.g., fixation count, fixation rate, fixation spatial density, and fixation time [86]) to determine workers' perception of hazard in empirical investigation [87]. Meanwhile, based on computer vision technology, the data of eye-tracking devices can be uploaded to 3D point cloud to build a training environment, which can further analyze the attention distribution of workers [20]. Besides, Jebelli et al. (2019) reported that the physical state of workers is measurable [17]. As fatigue is mainly related to work intensity, it can also be measured in terms of physical demands [88]. In recent years, obtaining the physical demand levels of workers through physiological signals has followed a common research path. Jebelli et al. (2019) revealed that the physical demand levels and stress states of workers are important considerations in a construction environment, and that physical demand on the construction site can be detected by wearable devices [17]. Aryal et al. (2017) monitored physical fatigue by wearable devices, and subjectively collected the fatigue level by the Borg's Rate of Perceived Exertion scale [42]. Li and Gerber (2012) non-intrusively evaluated the physiological load of construction workers using wearable sensors, and found that heartrate was sensitive to rest breaks during the construction test [89]. Gatti et al. (2012) related the physical strain measured by wearable devices to the productivity of construction, and identified heartrate as a significant predictor with a strong parabolic relationship to productivity [90].

4.2. Cluster #1 (Brain-Computer Interface)

The second most significant cluster is cluster #1 (brain-computer interface). This cluster label refers to the exchange of information between the brain and the device, and the main way to achieve this in construction safety research community is through wearable electroencephalography (EEG) devices. In the application stage, it has proved feasible to identify workers' stress status by brain waves. For example, wearable EEG devices can assess the mental workload, attention, and vigilance of workers [78]. EEG captures the electrical activity of firing neurons in the brain [91], and hence the mental statuses (e.g., emotional states) of construction workers [18]. This widely used technique assesses individuals' stress by analyzing their brain waves [18]. The attention levels of construction workers can also be effectively monitored by wearable EEG systems [92]. EEG rapidly indicates any changes in workers' mental statuses. However, acquiring high-quality EEG signals is more challenging than collecting other physiological indicators, because the signals are interfered by automatic actions such as eye blinking. Previous studies have also shown that displaying images of construction hazard in a laboratory environment can lead to information distortion, and these images do not have as much impact on the pupil or brain as they do in real life [93]. Therefore, hazard recognition process can be simulated as far as possible by simulating construction hazards site with virtual reality (VR) technology and collecting data through wearable electroencephalogram in VR environment [94]. Jebelli et al. (2019) found that stress is less accurately recognized by EEG than by physiological signals collected by a wristband-type sensor[67]. Additionally, wristband devices can measure their physical demands. Wearable devices equipped with photo plethysmography sensors can monitor a worker's heart rate [95]. Besides, human-robot collaboration can be achieved through brain-computer interface (BCI) [96]. Liu et al. proposed a BCI based system that can control collaborative construction robots with 90% accuracy using EEG signals [56]. This technology has the potential to improve productivity and help workers to avoid hazardous working conditions.

4.3. Cluster #2 (Activity Tracking) and Cluster #6 (Accelerometer-Based Activity Recognition)

Cluster #2 (activity tracking) and cluster #6 (accelerometer-based activity recognition) represent a similar research topic. For construction workers, lifting, squatting, walking, and even turning screws and swinging tools can be repeated many times. Therefore, the recognition of workers' movements or behavior patterns is the first step to find the abnormal situation of construction workers. Koskimaki et al. (2009) identified these movements with accelerometer and gyroscope (angular speed) with 88.2% accuracy. The study of Work-related Musculoskeletal Disorders (WMSDs) has been developed by many researchers in recent years on the basis of the identification of worker postures and activities [19,23,38,39]. According to relevant study, falling from heights is among the most common accidents in the construction industry [97], which is strongly associated with loss of balance [21]. Some previous empirical research on falling-risk assessment have shown that wearable inertial measurement units (WIMUs) effectively gather the data of workers' body responses (such as balance and gait) [12,21,98]. For example, Umer et al. (2018) detected task-induced changes in the static balances of construction workers equipped with WIMUs[99]. In addition, some systems (such as multi-parameter monitoring wearable sensor (MPMWS)) composed of multiple sensors are widely used in analysis of worker's trunk posture[100]. However, these devices need to be placed in multiple places on the worker's body, which can cause mobility inconvenience. It is worth noting that some researchers have devoted to developing less invasive wearable measurement devices in recent years. For example, utilizing a wearable insole system with higher accuracy than previous wearable inertial devices to identify falling risk [48,101]. The wearable insole pressure system provides more substantial safety gait metrics than the WIMU system, and extends the current wearable technologies for construction safety [21,48]. In laboratory conditions, built-in sensors of smartphones have been proven to recognize worker's postures effectively [16,19,102]. According to previous studies, accelerometers are usually placed at the waist or back [38,103,104]. By contrast, wristband-type activity tracker has higher flexibility and lower hardware costs [11]. Therefore, future research is promising to focus on the portability and accuracy of wearable devices.

4.4. Cluster #5 (Construction Site)

It is worth noting that cluster #5 (construction site) has two alternative labels ("wearable biosensor" and "physical demand"). It appears that most of these studies are based on wearable sensors that measure the workers' physiological states. The measurement and collection of safety data is essential for safety monitoring in the construction industry. As shown in Figure 4, there are three large tree-ring circles in the timeline of cluster #5 (construction site), indicating that keywords in this cluster were widely cited by articles of the construction safety research community. The wearable technologies applied in other sectors can monitor and measure a wide variety of safety performance metrics within this industry [24]. In addition to the EEG devices mentioned in cluster #1, Guo et al. (2017) found that workers' physical data (heart rate, skin temperature, calorie consumption, etc.) could indirectly measure their psychological status [76]. Pillsbury et al. also effectively assessed the physical and health status of workers by measuring heart rate, respiration rate, and core temperature through physiological status monitors [61]. In addition, upper body posture angle, traveling speed, and acceleration have also been shown to be added to the system of physiological metrics [105]. These case studies have shown the practical effectiveness of safety monitoring based on various physiological indicators collected by wearable biosensor.

4.5. Relationships between Clusters

The remaining clusters represent specific techniques and knowledge domain in construction safety research. For example, cluster #4 (corporate clothing) illustrates the application potential of textile technology in wearable devices, cluster #7 (intelligent monitoring) summarizes the prospect of intelligence and automatic monitoring for the construction safety, and cluster #3 (industrial work safety), cluster #5 (construction site), and cluster #8 (building site) echo the application scenarios of wearable technology in this review. From the above discussion, it can be found that these cluster labels well represent the respective knowledge domain. In addition, different research directions may use the same wearable devices, which means that the database of construction safety field has the potential to be established. At the same time, further development of wearable technology in the future will constantly open up new application scenarios for this field.

5. Conclusions

This paper provides an objective and accurate bibliometric analysis of wearable applications in the field of construction safety. The analysis was based on selected papers published between 2005 and 2021. Many key areas were identified by keyword co-occurrence analysis, such as ergonomics, electroencephalography, and inertial measurement unit. Ten knowledge clusters were identified: attentional failure, brain-computer interface, activity tracking, industrial work safety, corporate clothing, construction site, accelerometer-based activity recognition, intelligent monitoring, building site, and wearable wireless identification.

Through this systematic and quantitative bibliometric analysis, we could clearly visualize and explain the knowledge clusters and the frontier of wearable devices in construction safety. The present work highlights the developments and trends in this research domain and provides a clear perspective based on comprehensive data and statistical analysis. The developments have been clearly summarized by information maps and statistical descriptions. In future work, the performance of wearable devices should be further improved to reduce monitoring bias and to create low-cost systems with potential for commercial promotion. Future construction safety might also employ integrated wearable sensors for multi-parameter monitoring. In fact, to design an integrated multi-functional wearable system is another developmental trend. It is worth noting that some wearable technologies have been available for other industries for years, but have only recently been applied to construction safety. Further research could focus on whether mature equipment from other industries can be adapted to scenarios in the field of construction safety.

Although the relevant literature has been carefully collected and analyzed, this research has several limitations. Although this paper screened literatures from the *Scopus* database and the Web of Science database, a manual review would inevitably be subjective. At the same time, due to the limitation of the software algorithm, the discussion part is based on the 10 clusters identified, which may result in the omission of some relevant knowledge fields. Significant contributions could be ignored as a result of this deficient coverage. In addition, some literature might be ignored when using keywords to search for literature. Therefore, the research results could not completely cover the entire literature related to wearable devices in construction safety. Future studies should address the limitations by utilizing various databases and broadening data sources to collect and review literature.

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