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Review

Current Status and Future Research Trends of Construction Labor Productivity Monitoring: A Bibliometric Review

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Abstract: Construction labor productivity (CLP) is a critical measure of efficiency in the construction industry. This bibliometric review comprehensively analyzes global research trends in CLP monitoring over the past 56 years. The review identifies the top journals, authors, and nations contributing to this field and highlights a significant increase in publications since 2000. The co-authorship bibliometric map illustrates how different nations collaborate in research, with Europe and Asia being the most engaged regions in the study of CLP monitoring. The author keyword co-occurrence analysis indicated the need for more consistent and reliable measurements of CLP in the field. Furthermore, the review highlights the importance of factors such as occupational health and safety, change orders, and the adoption of lean construction principles and innovative technologies for monitoring and improving CLP. Finally, we evaluated the characteristics of different modeling approaches utilized in CLP monitoring studies, considering factors such as data availability, the complexity of relationships, and the required expertise. This study highlights the need for real-time and transparent CLP monitoring methods. Overall, this study contributes to the research field by offering insightful information on the current state of CLP monitoring and proposing potential future directions for research.

Keywords: bibliometric analysis; construction projects; labor productivity; VOSviewer; workforce

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1. Introduction

Construction labor productivity (CLP) monitoring is a major area of concern in the construction industry. The construction industry has high labor needs, and labor costs and labor resources frequently make up a significant portion of project costs. Labor costs typically constitute approximately 40–60% of total construction costs [1,2]. A previous study estimated that clients would save GBP 1.5 billion by improving CLP by 10% in the UK, underscoring the need for an effective labor productivity monitoring approach on construction sites [3]. In this context, managing and monitoring CLP are critical for the success of construction projects. However, managing and monitoring CLP can be challenging, especially in large construction projects. Project cost overruns and delays caused by CLP issues may result in significant financial losses for project owners and contractors.

Construction productivity is generally defined as a ratio of output to input [4]. Construction productivity considers input from all resources in the measurement, including but not limited to time, cost, labor, and equipment. On the other hand, CLP focuses solely on the labor resource. Labor is the resource that directly handles material and creates construction products [5]. Concentrating on labor as a single resource measures productivity in a more controllable and accurate manner [6]. CLP monitoring entails tracking, measuring, and evaluating labor productivity to identify areas for improvement and ensure that project objectives are accomplished. Depending on the level of measurement, whether macro or micro, CLP can be assessed using various input and output variables [7].

Macro-level measurement is typically conducted at the project, industrial, and national levels to evaluate and benchmark the overall productivity, with less specificity of site working conditions needed [7]. Conversely, micro-level measurement involves assessing productivity at individual and crew (trade) levels, requiring in-depth data insights that necessitate more time and effort on site. Previous studies have defined CLP in different ways, such as output per labor cost [8], output per labor work hour [9], and productive time used to complete a task [10].

Numerous studies have delved into different facets of CLP monitoring, including the relationship between CLP and construction project success [11], CLP influencing factors [8,12,13], developing models for predicting and monitoring CLP [14–17], and proposing strategies for improving CLP [18–21]. CLP is influenced by a range of factors, both technological and non-technological. Technological advancements, such as the adoption of Building Information Modeling (BIM) [9,22], sensor technologies [23,24], computer vision technologies [25,26], and data analytics tools [27,28], have revolutionized CLP monitoring. Non-technological factors, such as workforce characteristics (such as skill levels, experience, well-being, and motivation), project-related elements (such as task complexity, material shortage, project type, and finances) [8,29,30], as well as external factors (including weather conditions and regulatory requirements) [13,31,32], significantly contribute alongside technological factors. Furthermore, non-technological and technological factors can interact in certain aspects. For example, sensor technologies can track labor's physical demand [33] and monitor heat stress [34], demonstrating the use of technology in supporting and enhancing the monitoring of non-technological aspects.

Despite the growing interest in this field, thorough assessments and analyses of international research trends are scarce. While few studies have reviewed the CLP monitoring literature, they have certain limitations and gaps that must be addressed. For instance, [35] critically reviewed CLP research in construction journals, focusing on industry, project, and activity levels. However, this review was conducted almost 10 years ago, and therefore, it does not capture recent trends, such as the impact of BIM and technological advancements on CLP. Additionally, few reviews have limited their scope to examining the factors influencing labor productivity on construction sites [3,36]. Ref. [7] specifically examined measurement methods for assessing CLP in challenging weather conditions. Ref. [37] conducted a scientometric analysis of construction labor productivity research, identifying trends and research gaps within a specific timeframe. While these existing review studies have provided valuable insights into CLP, they have not conducted a comprehensive bibliometric analysis like the present study. This current review addresses this gap by conducting a large-scale bibliometric analysis of CLP monitoring research.

Bibliometric analysis is a widely adopted research method to evaluate the breadth and depth of research evidence, which provides critical insights into both national and international contributions and identifies research gaps in particular fields of study [38–41]. For instance, bibliometric analyses have been applied across diverse disciplines, including education [42], material science [43], chemistry [44], economics [45], medicine [46], and engineering [47]. Scopus, produced by Elsevier, is a good option for conducting bibliometric analysis due to its unique features encompassing document types, journal names, citation numbers, and h-index. Moreover, Scopus is the largest abstract and citation database of peer-reviewed literature, indexing over 22,800 active titles from more than 5000 international publishers [48]. Its comprehensive coverage of millions of peer-reviewed academic journal papers positions it as the preferred resource for scholars engaging in rigorous bibliometric analysis [38]. Scopus is also updated daily and maintains a high citation linking precision of 99.9% [49].

It would be beneficial and worthwhile to use Scopus as a data source for bibliometric analysis of CLP monitoring to uncover global research trends and focal points in this specific field of study. As a result, the three main objectives of this study were to (1) analyze annual publication trends; (2) identify the most productive journals, authors, and nations contributing to the field of CLP monitoring; and (3) discuss common research topics in CLP monitoring based on author keywords. Overall, the review's findings provide significant knowledge for academics, practitioners, and policy makers in the construction sector to understand the latest developments in CLP monitoring and to identify potential areas for further research and improvement.

2. Bibliometric Procedure

To conduct a comprehensive bibliometric review, data were mined from Scopus on 18 March 2023, specifically targeting journals and articles published until 2022 in the CLP monitoring domain. Scopus was selected as the preferred database for our study due to its comprehensive coverage of peer-reviewed papers from reputable publishers and the accessibility of bibliometric data for conducting in-depth analyses [38]. This makes it an ideal choice for conducting bibliometric analysis. The initial query string was designed to ensure comprehensive coverage of the subject matter by incorporating keywords related to the domain. Initially, the query string used in this study was TITLE-ABS-KEY ((“labor” OR “labour” OR “worker” OR “workforce” OR “personnel”) AND (“track *” OR “monitor *” OR “sampl *” OR “measur *”) AND (“construction”) AND (“productivity”)) AND (LIMIT-TO (DOCTYPE, “ar”)) AND (LIMIT-TO SRCTYPE, “j”)) AND (EXCLUDE (PUBYEAR, 2023)), which yielded 735 documents. This review also further refined the dataset by excluding documents with keywords such as “agriculture”, “plant”, “machinery”, “equipment”, and “material” that were not relevant to the research question, resulting in 477 documents. Additionally, search strings containing words such as “recent”, “progress”, “review”, “critical”, “revisit”, “advance”, “development”, “highlight”, “perspective”, “prospect”, “trends”, “bibliometric”, and “scientometric” were used to spot potential review papers and omit them from the search result [40]. In total, 33 records were identified as potential review articles. After a thorough screening process by reading the title, abstract, and full text, we removed 6 review articles from the final query using their EID, leaving a collection of 471 articles for analysis. A flowchart of the data mining process for this bibliometric review is presented in Figure 1. Table 1 lists the query strings that were used. It is important to note that this review focuses solely on labor resources in the construction industry; other construction resources are not included.

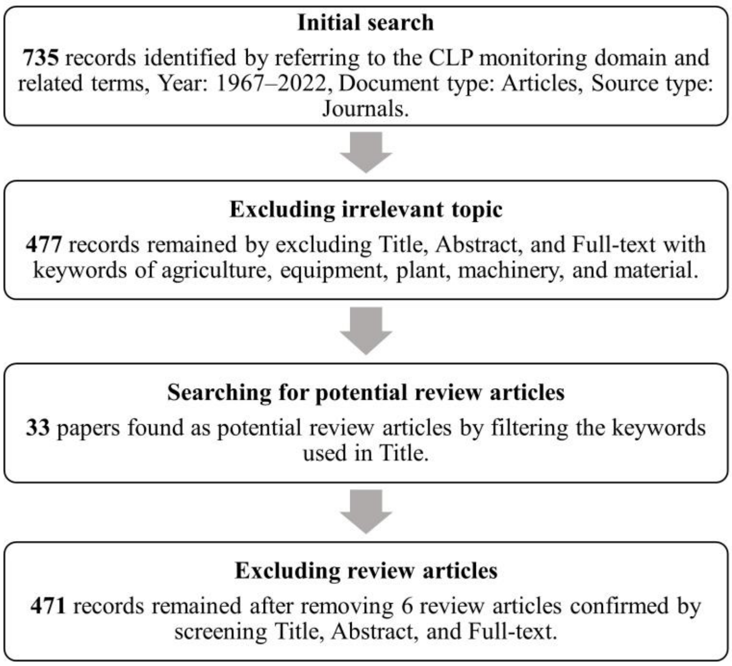

Figure 1. Data mining process for bibliometric review.

Table 1. Search string used in each stage of the data mining process.

Remarks	Search String
Initial search	TITLE-ABS-KEY ((“labor” OR “labour” OR “worker” OR “workforce” OR “personnel”) AND (“track *” OR “monitor *” OR “sampl *” OR “measur *”) AND (“construction”) AND (“productivity”)) AND (LIMIT-TO (DOCTYPE, “ar”)) AND (LIMIT-TO (SRCTYPE, “j”)) AND (EXCLUDE (PUBYEAR, 2023))
Excluding irrelevant topic	TITLE-ABS-KEY ((“labor” OR “labour” OR “worker” OR “workforce” OR “personnel”) AND (“track *” OR “monitor *” OR “sampl *” OR “measur *”) AND (“construction”) AND (“productivity”) AND NOT (“agricultur *” OR “machinery” OR “plant” OR “equipment” OR “material”)) AND (LIMIT-TO (SRCTYPE, “j”)) AND (LIMIT-TO (DOCTYPE, “ar”)) AND (EXCLUDE (PUBYEAR, 2023))
Searching for potential review articles	TITLE-ABS-KEY ((“labor” OR “labour” OR “worker” OR “workforce” OR “personnel”) AND (“track *” OR “monitor *” OR “sampl *” OR “measur *”) AND (“construction”) AND (“productivity”) AND NOT (“agricultur *” OR “machinery” OR “plant” OR “equipment” OR “material”)) AND TITLE (“recent” OR “progress” OR “review” OR “critical” OR “revisit” OR “advance” OR “development” OR “highlight” OR “perspective” OR “prospect” OR “trends” OR “bibliometric” OR “scientometric”) AND (LIMIT-TO (SRCTYPE, “j”)) AND (LIMIT-TO (DOCTYPE, “ar”)) AND (EXCLUDE (PUBYEAR, 2023))
Excluding review articles	TITLE-ABS-KEY ((“labor” OR “labour” OR “worker” OR “workforce” OR “personnel”) AND (“track *” OR “monitor *” OR “sampl *” OR “measur *”) AND (“construction”) AND (“productivity”) AND NOT (“agricultur *” OR “machinery” OR “plant” OR “equipment” OR “material”)) AND NOT EID ((2-s2.0-85128281106) OR (2-s2.0-85116466013) OR (2-s2.0-85010792408) OR (2-s2.0-85028324010) OR (2-s2.0-84910049421) OR (2-s2.0-84906081175)) AND (LIMIT-TO (SRCTYPE, “j”)) AND (LIMIT-TO (DOCTYPE, “ar”)) AND (EXCLUDE (PUBYEAR, 2023))

From the final dataset of 471 records, bibliometric indicators such as the year of publication, source title, author information, total publications, Cite Score 2021, subject area and category, quartile, most cited article title, times cited, publisher, Scopus author ID, h-index, total citations, and affiliation were used to analyze the annual publication trends, productive journals, and prolific authors. Additionally, the study identified and discussed the leading countries, institutions, and international collaborations based on the total number of publications by country (TPC). The study also calculated the single-country publications (SCP) percentage to determine the proportion of papers with affiliations from a single country only, which is a measure of the strength of collaboration between countries. The SCP values were obtained by excluding papers with multiple country affiliations from the Scopus database. The study also listed the top institutions of each country based on the total publications of the academic institution (TPi) in the field.

We used VOSviewer (version 1.6.16) to investigate the complex network of global research collaboration and shed light on recent trends in scholarly work. VOSviewer was chosen for its ability to handle large datasets and produce high-quality visualizations that aid in the interpretation and communication of the findings. We imported the bibliographic information of the final dataset into VOSviewer to create bibliometric maps of the countries' co-authorship and author keyword co-occurrences.

For countries' co-authorship mapping, we set the minimum number of documents by country to 1 and the minimum number of citations to 0. To standardize the country names, we incorporated a thesaurus file into the VOSviewer. This resulted in the renaming of “univ van stellenbosch” to “South Africa”. Consequently, we generated a comprehensive list of 65 countries for bibliometric mapping. The countries' co-authorship map was also edited to capitalize the first letter of each country's name.

To identify the current areas of interest, we used VOSviewer to produce an author keyword co-occurrence map. We scrutinized 1375 keywords, with 99 meeting the minimum threshold of at least three co-occurrences. We created a thesaurus file to rename certain keywords with synonyms, such as relabeling “worker”, “workers”, “workforce”, and "labor" to "labour". We then analyzed the resulting map using 75 keywords to extract information about links, occurrences, and link strengths. The collected data were utilized to facilitate a discussion on the current research trends and topics of interest for CLP monitoring in the industry.

3. Results and Discussions

3.1. Annual Publication Trends

The data collection on topics related to CLP monitoring encompassed all papers published up to 2022, enabling the analysis of publication trends and annual growth. Notably, the investigation revealed that the earliest reference in the dataset dates to 1967. Figure 2 displays the annual publication frequency and cumulative frequency over 56 years.

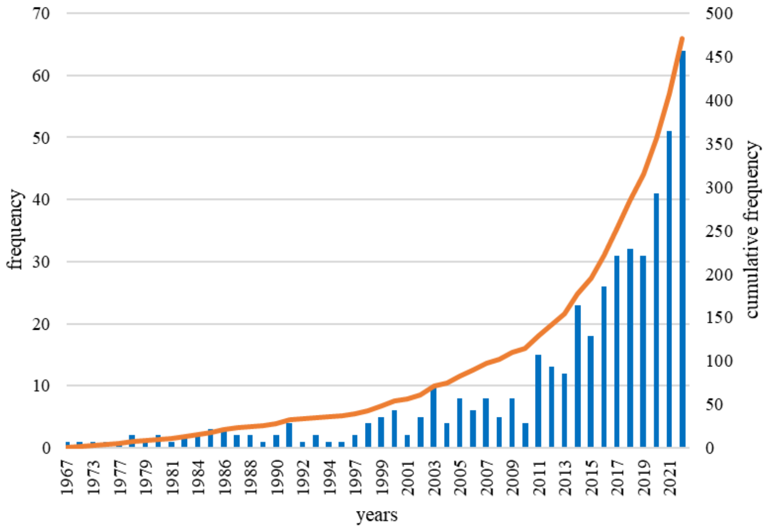

Figure 2. Annual CLP monitoring research publication trends.

Bibliometric analysis of CLP monitoring research reveals significant growth in publications over the years, with the oldest publication dating back to 1967. In the first 32 years (1967–1999), the research trend did not receive much attention as the annual publications were relatively low, with each year having fewer than five publications. Only 48 articles were reported during this period, which is equivalent to just 10% of all publications between 1967 and 2022. However, the total number of publications has increased significantly since 2000, with a surge of approximately 967% over the preceding 22 years (2000–2022).

From 2000 onwards, the number of annual publications on this topic started to increase, with an annual publication count of 6 in 2000, which peaked at 64 in 2022. The years 2011 to 2022 saw the most significant increase in publications, with 357 publications during this period. This accounts for approximately 84% of the total publications between 2000 and 2022. The remarkable rise in publications in recent years can be attributed to the adoption of new technologies and techniques, such as BIM, wearable devices, computer vision, and machine learning algorithms, enabling more accurate and efficient tracking and monitoring of CLP [9,24,26]. Furthermore, the steady and nonlinear increase in the cumulative number of publications indicates that the annual publication trends of this research field will persist in the future.

3.2. Most Productive Journals

Based on the extracted data, the top 10 most productive journals were ranked based on the number of publications they have contributed to the field of CLP monitoring. Table 2 presents a summary of these journals, including their rank, name, total number of publications, Cite Score 2021, subject area and category, quartile, most cited article title, and publisher.

Table 2. The top 10 most productive journals in CLP monitoring research publications.

Rank	Journal	Total Number of Publications	Cite Score 2021	Subject Area and Category	Quartile	Most Cited Article Title	Times Cited	Publisher
1	*Journal of Construction Engineering and Management*	50	6.3	Engineering-Building and Construction	Q1	Factors affecting construction labor productivity in Kuwait [12]	240	ASCE
2	*Engineering, Construction and Architectural Management*	19	5.2	Engineering-Building and Construction	Q1	Profiling causative factors leading to construction project delays in the United Arab Emirates [50]	80	Emerald
3	*Automation in Construction*	18	15	Engineering-Building and Construction	Q1	Location tracking and data visualization technology to advance construction ironworkers' education and training in safety and productivity [51]	174	Elsevier
4	*Construction Management and Economics*	18	6	Engineering-Building and Construction	Q1	Total factor productivity growth accounting in the construction industry of Singapore [52]	59	Taylor and Francis
5	*Canadian Journal of Civil Engineering*	14	2.3	Engineering-Civil and Structural Engineering	Q3	Impact of change orders on construction productivity [53]	49	Canadian Science Publishing
6	*International Journal of Construction Management*	12	6	Engineering-Building and Construction	Q2	Factors influencing labour productivity in Bahrain's construction industry [29]	65	Taylor and Francis
7	*Buildings*	11	3.8	Engineering-Building and Construction	Q2	Worker 4.0: The future of sensored construction sites [24]	29	MDPI
8	*Journal of Management in Engineering*	11	9.1	Engineering-Building and Construction	Q1	Work flow variation and labor productivity: Case study [19]	93	ASCE
9	*Journal of Computing in Civil Engineering*	7	10.2	Computer Science-Computer Science Applications	Q1	Towards a Mixed Reality System for Construction Trade Training [54]	62	ASCE
10	*Sustainability (Switzerland)*	7	5	Engineering-Building and Construction	Q1	Analysis of musculoskeletal disorders and muscle stresses on construction workers' awkward postures using simulation [55]	11	MDPI

Notably, several publishers are among the top 10 most productive journals in the field of CLP monitoring. These include the American Society of Civil Engineers (ASCE), Elsevier, Taylor and Francis, Emerald, Canadian Science Publishing, and Multidisciplinary Digital Publishing Institute (MDPI). Among these, ASCE and Taylor and Francis are the most frequently appearing on the relevant topic, with ASCE publishing three of the top ten journals and Taylor and Francis publishing two. Notably, *Journal of Construction Engineering and Management*, published by ASCE, has the highest number of publications among the top 10 productive journals, with a total of 50 publications. This is significantly higher than the second most productive journal, *Engineering, Construction and Architectural Management*, which has 19 publications. However, when examining the Cite Score in 2021, *Automation in*

Construction, which ranked third, had the highest Cite Score (15) among all journals. This indicates that although *Automation in Construction* may publish fewer articles on the relevant topic than the top two productive journals, the published articles are more influential or highly cited. Furthermore, it is noteworthy that 8 out of 10 journals have a Cite Score of 5 or higher, indicating that the articles published in these journals are of high quality and have a significant impact on their fields. Moreover, 9 out of 10 journals were placed in the top 2 quartiles (Q1 and Q2) of their respective subject areas and categories, further emphasizing the high quality and significant impact of published articles in these journals.

The top-cited articles shed light on the factors influencing CLP and emerging technologies. The article "Factors affecting construction labor productivity in Kuwait" stands out with the highest number of citations (240), followed by "Location tracking and data visualization technology to advance construction ironworkers' education and training in safety and productivity" (174) and "Work flow variation and labor productivity: Case study" (93). These articles suggest that the construction industry is increasingly adopting technology, such as location tracking and mixed reality systems, to improve productivity and safety. Additionally, research has focused on identifying factors that affect productivity, such as workflow variation and causative factors. They highlighted the need to address issues that negatively influence CLP and cause project delays, as well as a trend towards using technology to increase CLP and safety. By addressing these concerns, the construction industry can continue to make major advancements towards higher productivity and efficiency.

3.3. Most Prolific Authors

Table 3 presents information on the 10 authors who have made significant contributions to the CLP monitoring research area. The authors' names, Scopus author IDs, h-index, total number of publications, total citations, and average citations per publication are listed, along with their current affiliations. The ranking is based on the total number of publications that have been made on our topic, not necessarily on the importance or impact of those articles. When assessing an author's research output and influence, it is vital to consider other variables, such as citation count and h-index.

The authors in the table have h-indices ranging from 16 to 75, with an average of 37.6, indicating that they have made significant contributions to the field. Among the authors, Heng Li had the highest h-index of 75, followed by Martin Skitmore with an h-index of 63. Paul M. Goodrum, Awad S. Hanna, Abdulaziz M. Jarkas, and H. Randolph Thomas were ranked as the top four most prolific authors in terms of the number of publications. Paul M. Goodrum published twelve papers, as opposed to the next three authors, each of whom published six papers. However, it should be noted that the number of publications alone is not a reliable indicator of an author's impact or productivity because some authors may have published fewer papers but with higher citation rates. For example, Jochen Teizer achieved an average citation per publication of 76.60, although only five related articles were published. The findings also show the authors' current affiliations, with most of them being affiliated with universities in the United States. However, there are authors from Canada, Hong Kong, Denmark, Kuwait, and Australia, indicating the international nature of the field of construction management.

Upon further examination of the authors' affiliations and publication records, some collaborations were observed. For example, Paul M. Goodrum and William F. Maloney worked together to produce articles related to spatial engineering for CLP improvement [56,57]. Paul M. Goodrum and Carl T.M. Haas have also collaborated on multiple publications, including "U.S. construction labor productivity trends, 1970–1998" [58], "Construction small-projects rework reduction for capital facilities" [59] and "The divergence in aggregate and activity estimates of US construction productivity" [60]. These collaborations suggest a shared interest in improving construction productivity through innovative technologies and management practices. Collaboration between authors can help generate new research ideas and perspectives, enhance the quality and impact of research, and facilitate knowledge exchange between different fields of study.

Table 3. The top 10 most prolific authors in CLP monitoring research publications.

Rank	Author	Scopus Author ID	H-Index	Total Number of Publications	Total Citations	Average Citations per Publication	Current Affiliations
1	Paul M. Goodrum	57192406460	28	12	395	32.92	Colorado State University, Fort Collins, United States
2	Awad S. Hanna	7103318488	30	6	183	30.50	University of Wisconsin-Madison, Madison, United States
3	Abdulaziz M. Jarkas	36091113900	16	6	393	65.50	Al Mazaya Holding Co., Al Murqab, Kuwait
4	H. Randolph Thomas	7403743141	25	6	303	50.50	Pennsylvania State University, University Park, United States
5	Aminah Robinson Fayek	55662922200	27	5	114	22.80	University of Alberta, Edmonton, Canada
6	Carl T.M. Haas	7202620442	47	5	356	71.20	University of Waterloo, Waterloo, Canada
7	Heng Li	8692514900	75	5	119	23.80	Hong Kong Polytechnic University, Kowloon, Hong Kong
8	William F. Maloney	56277587300	19	5	99	19.80	University of Kentucky, Lexington, United States
9	Martin Skitmore	7003387239	63	5	179	35.80	Bond University, Gold Coast, Australia
10	Jochen Teizer	12753630700	46	5	383	76.60	Technical University of Denmark, Lyngby, Denmark

3.4. Leading Countries, Institutions, and International Collaboration

The productivity of countries in the research field can be measured by the total number of publications. Figure 3 displays the top 10 countries contributing to the development of CLP monitoring research activities according to this criterion.

The United States led the ranking with 135 total publications, followed by Canada with 43 and China with 40. Among the most productive academic institutions, the University of Alberta in Canada produced the highest number of publications (15), followed by Hong Kong Polytechnic University (13). However, it is worth noting that the institutions with the highest number of publications may not necessarily be the most influential or of the highest quality. The quality of an institution's research output can be evaluated by other factors such as citation counts and impact factors. Therefore, it is essential to consider several factors when evaluating the efficacy and productivity of academic institutions' research.

Based on the SCP percentage, India is at the top of the list at 87.5%, followed by the United States at 70.4% and Malaysia at 66.7%. These statistics show that despite the United States having the highest number of publications, the high percentage of SCP shows that a significant portion of these publications is a result of collaboration within the nation, rather than with academics from other countries. Conversely, the lowest SCP percentage (19.4%) was found in Australia, which is rated fourth based on the number of publications and indicates that they engage in greater international collaborations. It is important to emphasize that international collaboration is essential for fostering knowledge transfer and advancing research in various fields. Scholars can use varied viewpoints to handle challenging research problems by collaborating with researchers from other nations, gaining new insights, and sharing resources and skills. The collaborative research relationships between countries were also analyzed based on the co-authorship bibliometric map of countries, as shown in Figure 4.

Rank	Country	TPc	SCP (%)	The most productive academic institution	TPi
1	United States	135	95 (70.4%)	University of Colorado Boulder	9
2	Canada	43	22 (51.2%)	University of Alberta	15
3	China	40	16 (40%)	Chongqing University	4
4	Australia	36	7 (19.4%)	Curtin University	7
5	United Kingdom	36	14 (38.9%)	Nottingham Trent University	4
6	India	24	21 (87.5%)	Indian Institute of Technology Delhi	5
7	South Korea	21	12 (57.1%)	Hanyang University	4
8	Hong Kong	16	5 (31.3%)	Hong Kong Polytechnic University	13
9	Malaysia	15	10 (66.7%)	Universiti Teknologi Malaysia	4
10	Germany	14	5 (35.7%)	Ruhr-Universitat Bochum	3

Figure 3. The top 10 most productive countries and academic institutions in CLP monitoring research publication.

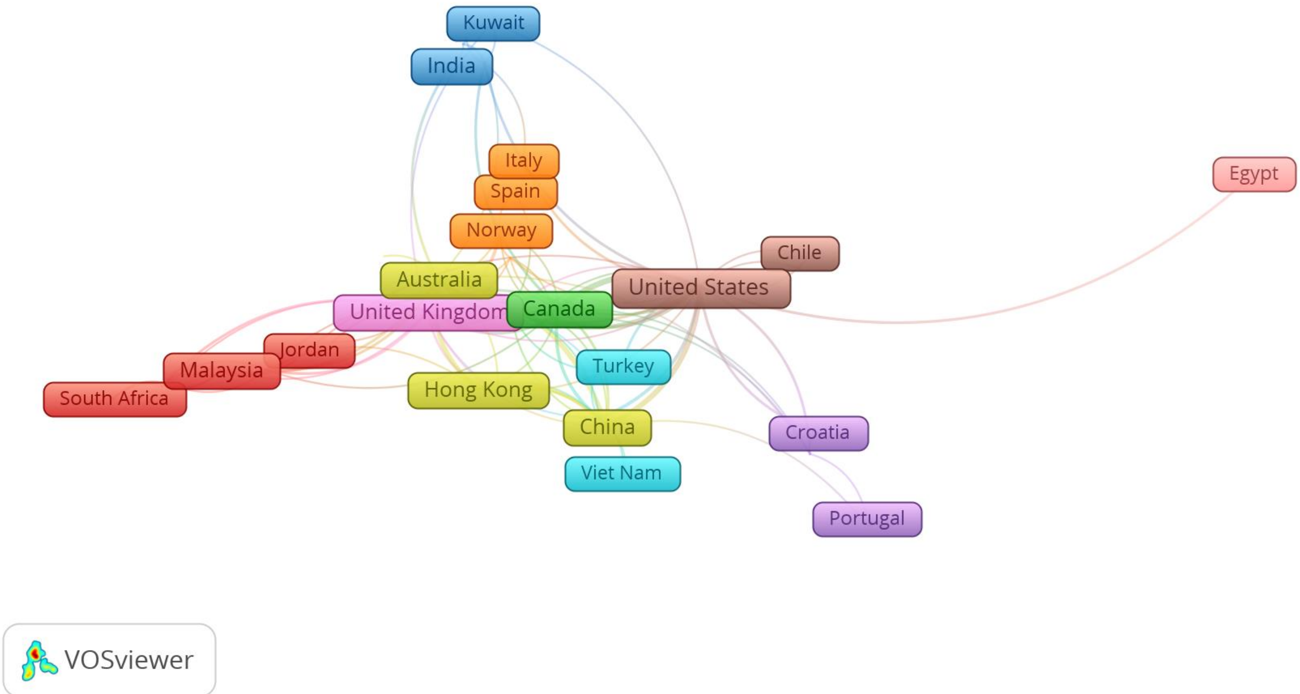

Figure 4. Bibliometric map of countries co-authorship.

Co-authorship bibliometric maps offer valuable insights into global research collaboration patterns in CLP monitoring. In total, 65 countries contributed to the research, with the majority coming from Europe (26) and Asia (25). Although Africa (6) and America (6) had smaller representations, Oceania (2) contributed the least. This suggests that Europe and Asia are the most active in this area of research and have established strong research networks among themselves compared to other regions. However, it is essential to highlight that some countries were eliminated from the bibliometric map because of their zero-link strength with other countries. These countries include Austria, the Czech Republic, Ethiopia, France, Hungary, Iran, Lithuania, Poland, Slovakia, Sri Lanka, Ukraine, and the United Arab Emirates.

In the map, the size of the nodes represents the density of publications from each country, and the thickness of the lines indicates the co-authorship relationships between countries. The United States (US) emerged as a leading contributor, having the highest number of links (25) and total link strength (54) among the 49 countries on the map, indicating a strong co-authorship relationship with other countries. The US also had the highest strength of co-authorship with Canada and China, with link strengths of 9 and 8, respectively. Australia and China also had a strong link strength of 7. Encouragingly, 75% of the countries collaborated internationally, indicating a growing trend toward global partnerships in research. Overall, the co-authorship bibliometric maps provide a comprehensive overview of the global research landscape, highlighting the strengths and opportunities for collaboration among countries.

3.5. Author Keywords

Bibliometric analysis can provide valuable insights into research trends, hot topics, and research directions in CLP monitoring. By analyzing the co-occurrence data of author keywords in publications, we can determine the research focus and popularity of specific topics. Furthermore, the links between these keywords provide insight into the relationships between topics in the context of CLP monitoring. To illustrate this point, Figure 5 depicts a bibliometric map of the co-occurrence of author keywords. This map visually represents the relationships between topics in the context of CLP monitoring and provides a useful tool for researchers to gain a deeper understanding of this field.

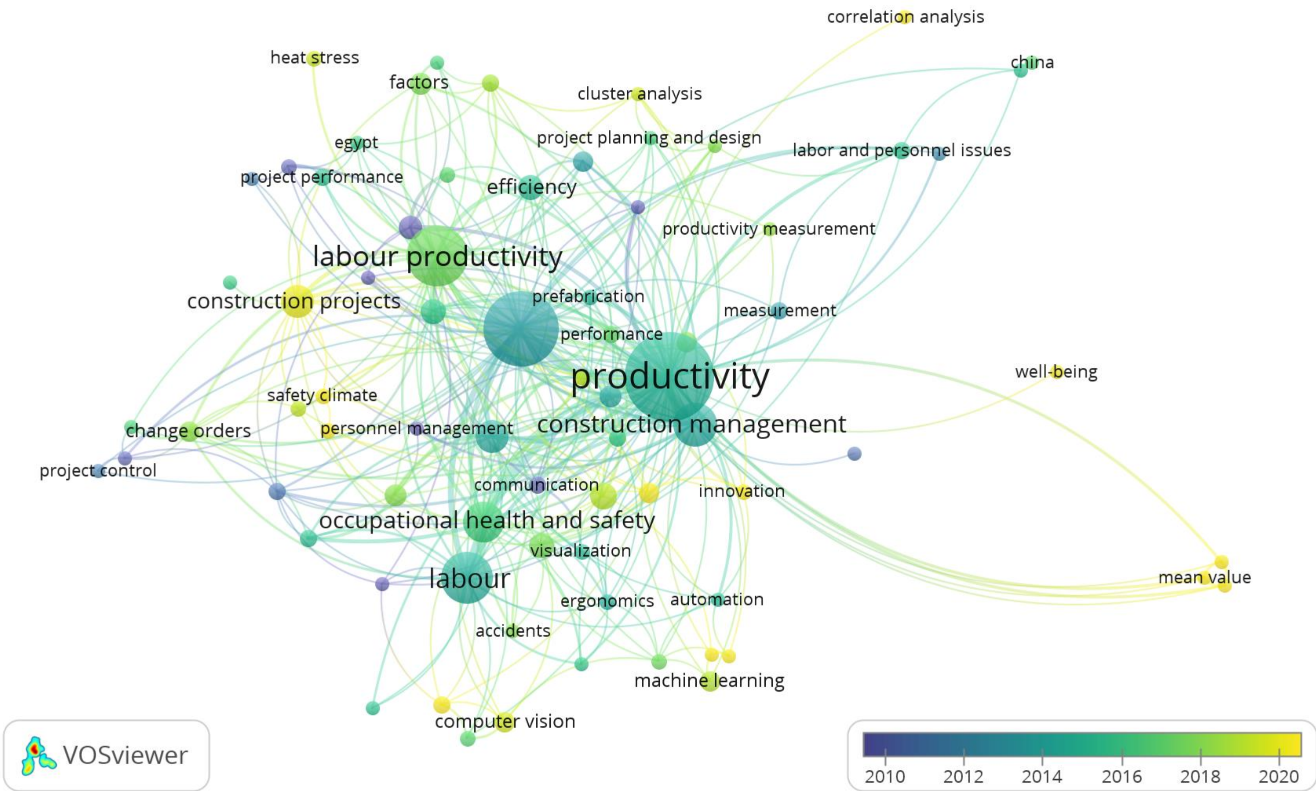

Figure 5. Bibliometric map of author keyword co-occurrence.

Overall, 1351 author keywords were found in our research using VOSviewer, and 79 of those met the threshold of having at least three occurrences. After relabeling, we finalized the 75 keywords to generate a bibliometric map. Based on the bibliometric findings, some insights into the concepts of productivity and labor productivity and topics of interest are identified and discussed in the following sections.

3.5.1. Key Concepts of Productivity and Labor Productivity in the Construction Industry

The bibliometric analysis revealed that the most used keyword was "productivity", appearing 114 times with 60 links to other author keywords, and a total link strength of 200, indicating a strong association with other related concepts. Productivity can be defined as the quantity of output produced per unit of input and is a measure of how effectively resources are utilized to produce goods and services in the construction sector [35,37,61]. Labor productivity, another important concept in the construction industry, measures the amount of output produced per unit of labor input [6,36]. The analysis revealed that "labour productivity" was one of the top three keywords, with 55 occurrences, 37 links, and a total link strength of 77. Labor productivity is often used as an indicator of the overall productivity of the construction industry because labor is one of the primary inputs in construction projects. However, our analysis also revealed an unexpected result. Despite the high occurrence of both "productivity" and "labour productivity", we did not find any significant association between these two terms as no links were found between them. However, the bibliometric map revealed that these two keywords co-occur with numerous other keywords that are similar, including "occupational health and safety", "work sampling", "productivity measurement", "lean construction", "efficiency", "building information modelling", and others. Despite the absence of any direct linkages between the two keywords, these data imply that there is some degree of association between them. This finding may be caused by inconsistencies in productivity measurement and reporting in the literature when researchers employ different definitions or metrics of productivity in their studies. For instance, some studies define labor productivity as the productive time used to produce the output [6,10], while others refer to it as the output per total working hours [9]. Furthermore, CLP can be measured at various levels, from macro to micro, with different measurement units at each level [7,62]. The authors recommend that future studies carefully define and operationalize the terms used to ensure consistent and reliable measurements of productivity in the field and facilitate better comparisons between studies.

3.5.2. CLP Influencing Factors and Improvement Approaches

CLP monitoring is essential for improving project performance and profitability in the construction industry. By identifying and addressing areas of inefficiency, firms can increase their productivity, reduce costs, and gain a competitive advantage. Based on the existing literature and bibliometric findings, this review critically analyzes CLP's influencing factors and improvement approaches. The keywords "occupational health and safety", "factors", "work sampling", "lean construction", "efficiency", "change orders", and "simulation" were among the most frequently occurring keywords in the top 25% of the keyword list.

CLP research has focused on identifying the various factors that affect it, minimizing their impact, and improving work processes. Workforce-related factors, such as skill level, training, motivation, and health and safety, as well as project-related factors such as management, planning, design, and technology, are the most common factors affecting CLP [12,29,30,63–65]. However, some studies have only focused on specific geographic regions or types of construction projects, which limits their generalizability to other contexts. The literature has also paid less attention to other factors, such as political and economic issues, as well as cultural and social norms. Future research should consider a broader range of factors and contexts to develop more robust and context-specific strategies to improve CLP. Moreover, most existing studies used cross-sectional designs [12,29,30,63–65], which have limitations in determining causality and providing insight into changes over time. To better understand the causal relationships between variables and track changes in CLP over time, future research in the construction industry should incorporate longitudinal designs using real-time technology. This approach could provide valuable information for evaluating the effectiveness of interventions aimed at improving CLP and identifying the factors that contribute to long-term improvements.

High occurrences of the keyword "Occupational health and safety" (25 occurrences) indicate that it is a key factor in improving CLP. This is further evidenced by the occurrence of keywords related to occupational health and safety, including "heat stress", "safety climate", "safety performance", "accidents", "well-being", "risk management", "labour and personnel issues", and "ergonomics". The integration of safety practices and productivity improvement strategies has been emphasized as a comprehensive approach that considers both safety and productivity [66–68]. According to [34,69], labor well-being significantly affects CLP, with heat stress having a significant detrimental effect. The use of wearable biosensors to measure worker stress levels has also been investigated, and the results indicate their potential for enhancing productivity and safety [70]. It is essential to highlight that by emphasizing safety and health alongside productivity, researchers and industry professionals in the construction sector may create a safer and more productive workplace. Productivity is crucial; however, worker safety must never be sacrificed.

In multistory construction projects, a hybrid approach that assesses the impact of safety management practices on CLP brings attention to the relationship between productivity and safety [68]. However, the study by [67] also warns about the unanticipated effects of productivity development measures on safety behavior. Therefore, it is essential to explore new ways to comprehensively integrate safety and productivity in addition to current approaches. The construction industry can also consider incorporating Building Information Modeling (BIM), labor tracking technologies, and lean practices to improve safety and productivity. BIM has been demonstrated to assist in safety performance [71] and CLP monitoring [18]. Lean practices aim to maximize value and minimize waste, which can lead to improved safety and productivity [66]. Real-time tracking technologies can also be used to constantly monitor the well-being and activity status of labor, leading to increased CLP and performance [72,73]. Thus, a comprehensive approach utilizing BIM, labor tracking technologies, and lean practices can further enhance safety and productivity in the construction industry.

Change orders are a common occurrence in the construction industry, where modifications to original project plans are requested by clients or stakeholders. The impact of change orders on CLP has been extensively studied in previous studies. Refs. [74–76] used different approaches, such as system dynamics modeling and evolutionary fuzzy support vector machine inference modeling, to predict the productivity loss caused by change orders. Understanding the impact of change orders on CLP is important because they can result in delays, increased costs, and decreased productivity, which can ultimately affect the success of a project [74–76]. Construction managers can more accurately analyze the potential impact of change orders and take necessary action to reduce their detrimental effects on productivity by establishing models to quantify this impact. However, the significance of project management techniques, including lean approaches, risk management, and communication strategies, in reducing the negative impact of change orders on CLP has received less attention in the present research field. More thorough research is required to better understand how change orders affect CLP and to develop effective strategies to minimize their impact.

The comparison of the bibliometric findings with existing studies on factors influencing CLP reveals a notable absence of labor skill and experience in the keyword co-occurrence list, despite their commonly identified significance [8,29,30]. This discrepancy indicates a research gap in the emphasis on these factors within the literature captured by the analysis. This is attributed to the predominant use of questionnaire surveys as the common research method [8,29,30], which led to a lack of focused investigation on the identified top factors. Consequently, there is a need for further investigation and exploration of the role of labor skill and experience in CLP monitoring and improvement to bridge this research gap.

Lean construction has emerged as a widely adopted strategy in the construction industry to reduce waste and optimize efficiency [77]. By leveraging strategies such as just-in-time delivery, continuous improvement, and standardized work, workflows can be streamlined, material waste can be reduced, and labor resources can be optimized. One common method used to achieve this is work sampling, which is also known as activity analysis. Work sampling has been used for decades to examine workflow efficiency, identify workflow variability, and eliminate non-value-adding work time [78–81]. However, there is still a lack of consensus on how to define and measure these metrics accurately.

Further research is required to standardize the definitions and methodologies for measuring workflow variability. Additionally, the advancement of technology has transformed traditional work sampling into automated work sampling, with computer vision [28,82] and wearable sensors [83,84] showing potential for monitoring the physical and physiological conditions of labor. However, further investigation is required to ascertain the reliability and effectiveness of these technologies for real-world construction projects. Further investigation and study are needed to fully understand the direct impact of automated work sampling on CLP. The potential of technology such as the KanBIM workflow management system has also been demonstrated to improve craft time utilization.

The integration of lean principles and BIM technology has produced encouraging improvements in workflow efficiency and error reduction [18]. Stimulation tools have also been investigated to detect construction workflow bottlenecks and assess the effectiveness of lean initiatives [20]. A study [85] that adopted lean principles during the COVID-19 pandemic further highlighted the value of using these principles to manage labor in the construction industry. Lean construction practices prioritize process improvement and waste minimization, which are helpful in ensuring labor safety and the ongoing development of construction projects during the pandemic [85].

In summary, the construction industry faces various challenges in managing and improving CLP, ranging from workforce-related to project-related factors. It is crucial to consider a thorough and integrated strategy that incorporates lean principles, modern technologies such as BIM, and the labor tracking approach, as well as safety measures and productivity improvement strategies. Moreover, future research should consider a broader range of factors and contexts to develop more reliable, robust, and context-specific strategies to enhance CLP. Adopting a proper strategy for boosting CLP benefits construction firms by reducing costs and gaining a competitive edge in the construction sector. The opportunities for enhancing CLP are limitless due to the rapid advancements in technology and continuous changes in the industry, highlighting the need to remain updated with the latest developments in the field.

3.5.3. Innovations and Technologies for CLP Data Collection

The construction business is a vibrant, constantly changing sector that seeks new ways to boost productivity and efficiency. The implementation of BIM, which has drawn significant attention in CLP monitoring, is one of the notable advances in this field. Specifically, the keyword “Building Information Modelling (BIM)” was used 11 times, and it appears together with “visualization”, “prefabrication”, “occupational safety and health”, “construction planning”, and “labor productivity” keywords. This indicates that BIM is increasingly being used for monitoring safety and health hazards and labor productivity in the construction industry, moving beyond its primary design and planning functions [9,13,86]. Previous research has demonstrated that the visualization capabilities of BIM can identify potential safety hazards and promote worker safety at construction sites [87]. Furthermore, prefabrication is another innovation that has emerged to enhance CLP, enabling the manufacture of building modules in a factory and their subsequent on-site assembly. This process results in improved productivity and quality and reduced construction time and waste. Moreover, studies on adopting BIM and Mixed Reality (MR) for prefabrication projects have been conducted, demonstrating the potential of MR technology for CLP improvement in the industry [88]. The highly cited paper “Towards a Mixed Reality System for Construction Trade Training” [54] exemplifies this potential. While the keyword “mixed reality” did not meet the threshold for bibliometric analysis, research findings revealed that the integration of BIM and MR positively influences CLP. However, further research is required to establish the optimal use of MR technology in the construction industry.

Construction labor tracking technologies, as indicated by the keywords "computer vision", "action recognition", "activity recognition", "location tracking", "tracking", and "wearable sensor", have the potential to revolutionize the way labor productivity is monitored and managed in the construction industry, enabling real-time monitoring of labor productivity, and providing insights into every movement and activity. Currently, computer vision and wearable sensors are used for labor tracking. With computer vision, camera devices are employed to capture site conditions, including worker movements and activities. By leveraging machine learning and deep learning algorithms, the labor activity status can be recognized [25,89–91], with some studies even using computer vision for ergonomic posture monitoring [92,93]. On the other hand, different types of wearable sensors such as Radio Frequency Identification (RFID), Global Positioning System (GPS), Bluetooth Low Energy (BLE), accelerometers, heart rate sensors, and temperature sensors can be worn by laborers to track their presence in specific zones [94,95], recognize the activity status [83,96], and assess their well-being in terms of workload, heart rate, and working intensity [97], ultimately linking these factors to CLP [95,98]. However, despite the potential of wearable sensors, they were the least frequently occurring keyword in the bibliometric map, with only three occurrences. This suggests that there is still much to explore in terms of how wearable sensors can be used to monitor and optimize labor productivity in the construction industry. With further investigation, wearable sensors could be a game-changer for labor tracking, providing valuable data on worker movements and activities, and helping project managers identify areas for improvement and optimize resource allocation.

However, the adoption and implementation of these technologies may be limited by cost, specialized expertise, privacy and security concerns, and potential social and ethical implications. Therefore, it is essential to refine and optimize the use of these technologies in the construction industry, considering broader social and ethical considerations. Although the discussion provides a comprehensive overview of innovations and technologies for CLP data collection in the construction industry, further investigation is necessary to ensure their optimal use and alignment with social and ethical considerations.

3.5.4. CLP Prediction Models

Various models have been developed and applied in construction projects to monitor and improve CLP. Eight keywords related to the modeling methods were found: "machine learning", "regression analysis", "deep learning", "system dynamics", "fuzzy logic", "fuzzy set theory", "artificial neural network (ANN)", and "data envelopment analysis". The occurrence frequencies of these keywords are summarized in Figure 6.

Based on Figure 6, "machine learning" was the most frequently used keyword, with six occurrences, followed by "regression analysis" and "deep learning", with five occurrences each, indicating their popularity in CLP monitoring research. "System dynamics", "fuzzy logic", "fuzzy set theory", "artificial neural network (ANN)", "cluster analysis", and "data envelopment analysis" had three occurrences each. Notably, the range of occurrence counts for each keyword is small (3–6 occurrences), indicating that these methods are being studied with similar levels of interest and attention.

The findings suggest that machine learning and its subfields, such as deep learning and ANN, are popular keywords in the construction industry because of the growing availability of construction-related data and their potential to improve productivity at construction sites. The neural network model has been increasingly used for CLP monitoring, owing to its ability to learn the complex nonlinear relationships between variables. An ANN is commonly adopted to analyze the complex relationship between variables for CLP prediction, as shown in previous studies [15,16,99]. Meanwhile, deep learning methods such as recurrent neural networks and convolutional neural networks have been adopted for labor activity recognition, which involves work sampling to monitor CLP [100–102]. These neural network models have shown promise for improving the accuracy of productivity predictions. However, vast datasets are required to train the model. They are also often criticized for their lack of transparency, which makes it difficult for laypeople to understand how they came to their predictions.

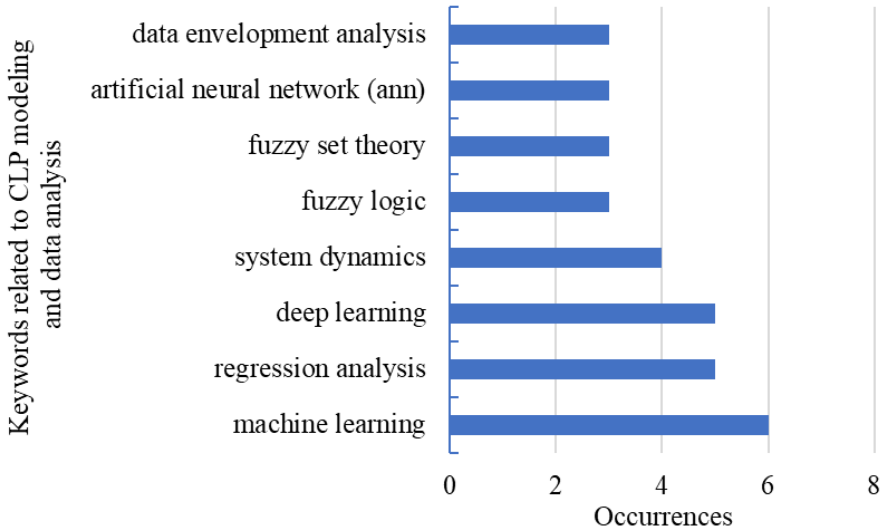

Figure 6. The occurrences of keywords related to CLP modeling and data analysis.

Regression analysis is one of the earliest modeling methods applied to analyze construction productivity. Its application to CLP analysis was initially published in 1899 [103] and is still widely used today. According to various studies [17,68,104], regression models are frequently used to measure and model CLP using historical data. However, regression models have limitations when addressing complicated and nonlinear connections between variables, which may impair their ability to accurately forecast future productivity.

Fuzzy models that can account for uncertainty and imprecision in construction data, as well as the subjective nature of productivity factors, were developed using fuzzy logic and fuzzy set theory. For example, these models have been applied to evaluate the motivation for labor [105] and to predict context-specific labor productivity, where the data can have a high level of subjectivity [14,105]. However, fuzzy models can be difficult to interpret, and their correctness may be based on the caliber of the expert knowledge utilized to create them. Therefore, it is essential to evaluate models by using real-world information to determine their accuracy.

System dynamics models consist of a complex, interrelated structure that uses feedback loops to model the dynamic relationships between the CLP-influencing factors. This model is useful for understanding the complex relationships between different CLP influencing factors [74,76]. System dynamics models employ a feedback loop to replicate the dynamic interactions between CLP-influencing factors. This approach helps comprehend the intricate relationships between the various factors that impact production [74,76]. However, system dynamics models may not be appropriate for real-time monitoring because they are complex and require significant expertise to develop, calibrate, and apply effectively.

Data envelopment analysis is a useful method for measuring the efficiency and productivity of construction. However, its adoption in research and study is constrained by its complexity and specialized knowledge requirements. It is commonly used for benchmarking and comparing the performance of construction projects, companies, and the industry [11], making it more suitable for larger-scale analyses rather than predicting CLP at individual and trade levels.

In summary, different modeling methods have been developed to monitor and improve CLP, based on data availability, relationship complexity, and required expertise. Future research should aim to develop transparent, real-time models that combine methods such as fuzzy, system dynamics, neural networks, and regression. Hybrid models should be developed to leverage the strengths of these methods and provide comprehensive insights into CLP.

3.6. Implications in Theory and Practice

This review has important implications for both theory and practice in the field of CLP monitoring:

1. Knowledge Transfer and Collaboration: The study identifies publication trends, productive journals, authors, nations, and collaboration patterns, fostering future research collaboration and knowledge exchange in CLP monitoring. Practitioners and researchers can also actively seek opportunities for collaboration to leverage diverse perspectives and foster innovation in CLP monitoring.
2. Advancing Knowledge: The study contributes to CLP monitoring by providing a comprehensive overview of key concepts and research topics. The analysis of author keywords reveals interrelationships between different CLP monitoring topics, guiding further exploration.
3. Improved Productivity Measurement: The study emphasizes the need for consistent definitions and reliable measurement approaches for construction productivity. Standardized metrics enable benchmarking, performance evaluation, and identification of improvement opportunities.
4. Identification of Significant Influencing Factors: The analysis highlights significant technological and non-technological factors impacting CLP, including occupational health and safety, change orders, lean construction, BIM, prefabrication, and labor tracking technologies. However, the study also reveals limitations in the scope of factors and contexts examined. Future research should address the existing research gaps and provide a more comprehensive understanding of CLP improvement strategies.
5. Integrated Approaches: The study underscores the significance of integrating safety practices, lean construction principles, and innovative technologies in CLP monitoring. This integrated approach ensures a safer and more productive work environment, optimizing workflow efficiency and reducing waste.
6. Leveraging Innovations and Technologies for CLP Monitoring: The study recognizes the significance of innovations such as BIM and labor tracking technologies in revolutionizing labor productivity monitoring and management. Practical guidance is provided to industry professionals, considering implementation challenges and ethical considerations.
7. Decision Support Systems: The study highlights the potential of advanced modeling techniques, such as machine learning and artificial neural networks, for CLP prediction and monitoring. These tools support data-driven decision making on labor allocation, resource optimization, and productivity improvement initiatives.
8. Considering these implications, researchers, practitioners, and policy makers can drive advancements in CLP monitoring practices and contribute to overall productivity improvement in the construction industry.

3.7. Limitations of Study

Despite providing a thorough overview of the major developments in CLP monitoring research, this bibliometric review has certain limitations. First, although the search terms used were carefully chosen to capture the essence of the topic, some relevant articles may have been missed. This could be because some researchers used different keywords or terminologies that were not included in our search strategy. However, we believe that the search string we used provides a solid foundation for future researchers to build upon. Second, the search was limited to journal articles and excluded other types of publications such as conference proceedings, which may contain valuable information. Nonetheless, this decision was made to ensure the quality and reliability of the sources used in this review. Journals provide comprehensive and in-depth coverage of specific research topics and undergo rigorous peer-review processes, ensuring the quality and credibility of published articles. Third, we excluded review articles from the analysis because the focus is on original research articles and conducting objective quantitative analyses of the primary literature. We also excluded certain terms, such as agriculture, machinery, plants, equipment, and materials, when collecting relevant records for review. While adopting this strategy may increase the accuracy of our review, it is crucial to acknowledge that it may also cause the omission of pertinent publications that could provide insightful information. Additionally, articles published in 2023 were excluded to guarantee that only well-established research was included, decreasing the possibility of analyzing incomplete or preliminary research.

Therefore, while acknowledging the limitations of this bibliometric review, we believe that the presented analysis provides a comprehensive overview of the annual publication trends; identifies the most productive journals, authors, and nations contributing to the field of CLP monitoring; and discusses common research topics based on author keywords. We believe that this review will inspire future researchers to build upon our work and explore additional search terms and publication types, thus uncovering even more valuable insights into this important topic.

4. Conclusions

This study presents the global research trends of CLP monitoring based on 471 Scopus database records from 1967 to 2022. The review showed that throughout the past 56 years, particularly since 2000, there has been a nonlinear increase in publications, which suggests that this inclination will continue. Based on the number of publications, the top journal, author, and country are *Journal of Construction Engineering and Management*, Paul M. Goodrum, and the United States, respectively. However, it is important to understand that the impact or productivity of authors, countries, and journals cannot be judged solely based on the number of publications; additional metrics, such as an author′s h-index and a journal's impact factors, should also be considered.

VOSviewer was used to conduct countries' co-authorship and keyword co-occurrence analyses. The co-authorship bibliometric map illustrates how different nations collaborate in research, with Europe and Asia being the most active regions in the study of CLP monitoring. This finding emphasizes the importance of international collaboration in fostering knowledge transfer and advancing research in various fields. The co-occurrence analysis of the authors' keywords in the literature shows that labor productivity and productivity are among the most frequently studied concepts in the construction industry. Despite the frequent occurrence of both "productivity" and "labor productivity", the lack of a linkage between these two terms on the bibliometric map suggests that there is a need for a more consistent and reliable approach to measuring productivity in the field. In addition, this review highlights the significance of non-technological and technological factors concerning CLP. Non-technological factors, such as occupational health and safety, change orders, and implementation of lean construction concepts, play a significant role in enhancing CLP. Furthermore, technological factors, including BIM, MR, prefabrication, computer vision, and wearable sensors, are recognized as innovative technologies for tracking, monitoring, and enhancing labor productivity in the construction industry.

The findings of this review reveal that deep learning and artificial neural networks, which are both subfields of machine learning, are widely utilized methods for CLP prediction and monitoring. Regression modeling is still a popular modeling technique; however, its inability to handle complex and nonlinear relationships between variables may restrict its CLP prediction accuracy. System dynamics, data envelopment analysis, fuzzy logic, fuzzy set theory, and fuzzy logic are helpful methods for accounting for the subjectivity, ambiguity, and uncertainty of CLP factors. Combining these methods can provide comprehensive insights into CLP.

However, there are a few limitations to this bibliometric review, including the potential for relevant papers to be overlooked owing to various keywords and the exclusion of other types of publications. Nevertheless, this study offers a solid basis for future scholars to build upon and explore more insightful data on this topic.

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References

1. Smith, R.C. *Estimating and Tendering for Building Work*; Routledge: London, UK, 2013.
2. Neve, H.; Wandahl, S.; Lindhard, S.; Teizer, J.; Lerche, J. Learning to see value-adding and non-value-adding work time in renovation production systems. *Prod. Plan. Control* **2022**, *33*, 790–802. [CrossRef]
3. Naoum, S.G. Factors Influencing Labor Productivity on Construction Sites: A State-of-the-Art Literature Review and a Survey. *Int. J. Product. Perform. Manag.* **2016**, *65*, 401–421. [CrossRef]
4. Hwang, B.-G.; Soh, C.K. Trade-Level Productivity Measurement: Critical Challenges and Solutions. *J. Constr. Eng. Manag.* **2013**, *139*, 04013013. [CrossRef]
5. Khanh, H.D.; Kim, S.-Y.; Van Khoa, N.; Tu, N.T. The relationship between workers' experience and productivity: A case study of brick masonry construction. *Int. J. Constr. Manag.* **2021**, *23*, 596–605. [CrossRef]
6. Jarkas, A.M.; Horner, R.M.W. Creating a baseline for labour productivity of reinforced concrete building construction in Kuwait. *Constr. Manag. Econ.* **2015**, *33*, 625–639. [CrossRef]
7. Moohialdin, A.S.M.; Lamari, F.; Miska, M.; Trigunarsyah, B. Construction worker productivity in hot and humid weather conditions: A Review of Measurement Methods at Task, Crew and Project Levels. *Eng. Constr. Arch. Manag.* **2020**, *27*, 83–108. [CrossRef]
8. Hiyassat, M.A.; Hiyari, M.A.; Sweis, G.J. Factors affecting construction labour productivity: A case study of Jordan. *Int. J. Constr. Manag.* **2016**, *16*, 138–149. [CrossRef]
9. Lee, J.; Park, Y.-J.; Choi, C.-H.; Han, C.-H. BIM-assisted labor productivity measurement method for structural formwork. *Autom. Constr.* **2017**, *84*, 121–132. [CrossRef]
10. Kumar, Y.; Kumar, G.H.; Myneni, S.B.; Charan, C.S. Productivity Analysis of Small Construction Projects in India. *Asian J. Appl. Sci.* **2014**, *7*, 262–267. [CrossRef]
11. Nazarko, J.; Chodakowska, E. Labour efficiency in construction industry in Europe based on frontier methods: Data envelopment analysis and stochastic frontier analysis. *J. Civ. Eng. Manag.* **2017**, *23*, 787–795. [CrossRef]
12. Jarkas, A.M.; Bitar, C.G. Factors Affecting Construction Labor Productivity in Kuwait. *J. Constr. Eng. Manag.* **2012**, *138*, 811–820. [CrossRef]
13. Wu, Q.; Chen, L.; Shi, P.; Wang, W.; Xu, S. Identifying Impact Factors of MEP Installation Productivity: An Empirical Study. *Buildings* **2022**, *12*, 565. [CrossRef]
14. Tsehayae, A.A.; Fayek, A.R. Developing and Optimizing Context-Specific Fuzzy Inference System-Based Construction Labor Productivity Models. *J. Constr. Eng. Manag.* **2016**, *142*, 04016017. [CrossRef]
15. Nasirzadeh, F.; Kabir, H.D.; Akbari, M.; Khosravi, A.; Nahavandi, S.; Carmichael, D.G. ANN-based prediction intervals to forecast labour productivity. *Eng. Constr. Arch. Manag.* **2020**, *27*, 2335–2351. [CrossRef]
16. Badawy, M.; Hussein, A.; Elseufy, S.M.; Alnaas, K. How to predict the rebar labours' production rate by using ANN model? *Int. J. Constr. Manag.* **2021**, *21*, 427–438. [CrossRef]
17. Ma, L.; Liu, C. Decomposition of temporal changes in construction labour productivity. *Int. J. Constr. Manag.* **2018**, *18*, 65–77. [CrossRef]
18. Rafael, S.; Ronen, B.; Biniamin, B.; Ury, G.; Ergo, P. KanBIM Workflow Management System: Prototype Implementation and Field Testing. *Lean Constr. J.* **2013**, 19–35.
19. Liu, M.; Ballard, G.; Ibbs, W. Work Flow Variation and Labor Productivity: Case Study. *J. Manag. Eng.* **2011**, *27*, 236–242. [CrossRef]
20. Bajjou, M.S.; Chafi, A. Lean construction and simulation for performance improvement: A case study of reinforcement process. *Int. J. Prod. Perform. Manag.* **2020**, *70*, 459–487. [CrossRef]
21. Khaleghian, H.; Shan, Y.; Lewis, P. A Case Study of Productivity Improvement by Electrical Prefabrication. In Proceedings of the Construction Research Congress 2016, San Juan, PR, USA, 31 May–2 June 2016; pp. 1753–1761.
22. Arif, F.; Khan, W.A. A Real-Time Productivity Tracking Framework Using Survey-Cloud-BIM Integration. *Arab. J. Sci. Eng.* **2020**, *45*, 8699–8710. [CrossRef]

23. Rao, A.S.; Radanovic, M.; Liu, Y.; Hu, S.; Fang, Y.; Khoshelham, K.; Palaniswami, M.; Ngo, T. Real-time monitoring of construction sites: Sensors, methods, and applications. *Autom. Constr.* **2022**, *136*, 104099. [CrossRef]
24. Calvetti, D.; Mêda, P.; Gonçalves, M.C.; Sousa, H. Worker 4.0: The Future of Sensored Construction Sites. *Buildings* **2020**, *10*, 169. [CrossRef]
25. Luo, H.; Xiong, C.; Fang, W.; Love, P.E.; Zhang, B.; Ouyang, X. Convolutional neural networks: Computer vision-based workforce activity assessment in construction. *Autom. Constr.* **2018**, *94*, 282–289. [CrossRef]
26. Xu, S.; Wang, J.; Shou, W.; Ngo, T.; Sadick, A.-M.; Wang, X. Computer Vision Techniques in Construction: A Critical Review. *Arch. Comput. Methods Eng.* **2021**, *28*, 3383–3397. [CrossRef]
27. Nath, N.D.; Behzadan, A.H. Construction Productivity and Ergonomic Assessment Using Mobile Sensors and Machine Learning. *Comput. Civ. Eng.* **2017**, 434–441. [CrossRef]
28. Ying, W.; Shou, W.; Wang, J.; Shi, W.; Sun, Y.; Ji, D.; Gai, H.; Wang, X.; Chen, M. Automatic Scaffolding Workface Assessment for Activity Analysis through Machine Learning. *Appl. Sci.* **2021**, *11*, 4143. [CrossRef]
29. Jarkas, A.M. Factors influencing labour productivity in Bahrain's construction industry. *Int. J. Constr. Manag.* **2015**, *15*, 94–108. [CrossRef]
30. Tuan Hai, D.; Van Tam, N. Analysis of Affected Factors on Construction Productivity in Vietnam. *Int. J. Civ. Eng. Technol.* **2019**, *10*, 854–864.
31. Agrawal, A.; Halder, S. Identifying factors affecting construction labour productivity in India and measures to improve productivity. *Asian J. Civ. Eng.* **2020**, *21*, 569–579. [CrossRef]
32. Gurcanli, G.E.; Mahcicek, S.B.; Serpel, E.; Attia, S. Factors Affecting Productivity of Technical Personnel in Turkish Construction Industry: A Field Study. *Arab. J. Sci. Eng.* **2021**, *46*, 11339–11353. [CrossRef]
33. Hwang, S.; Lee, S.H. Wristband-type wearable health devices to measure construction workers' physical demands. *Automat. Constr.* **2017**, *83*, 330–340. [CrossRef]
34. Chinnadurai, J.; Venugopal, V.; Kumaravel, P.; Paramesh, R. Influence of occupational heat stress on labour productivity–a case study from Chennai, India. *Int. J. Prod. Perform. Manag.* **2016**, *65*, 245–255. [CrossRef]
35. Yi, W.; Chan, A.P.C. Critical Review of Labor Productivity Research in Construction Journals. *J. Manag. Eng.* **2013**, *30*, 214–225. [CrossRef]
36. Hamza, M.; Shahid, S.; Bin Hainin, M.R.; Nashwan, M.S. Construction labour productivity: Review of factors identified. *Int. J. Constr. Manag.* **2019**, *22*, 413–425. [CrossRef]
37. Adebowale, O.J.; Agumba, J.N. A scientometric analysis and review of construction labour productivity research. *Int. J. Prod. Perform. Manag.* **2022**. [CrossRef]
38. Fahimnia, B.; Sarkis, J.; Davarzani, H. Green supply chain management: A review and bibliometric analysis. *Int. J. Prod. Econ.* **2015**, *162*, 101–114. [CrossRef]
39. Van Eck, N.J.; Waltman, L. Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics* **2010**, *84*, 523–538. [CrossRef] [PubMed]
40. Khudzari, J.M.; Kurian, J.; Tartakovsky, B.; Raghavan, G. Bibliometric analysis of global research trends on microbial fuel cells using Scopus database. *Biochem. Eng. J.* **2018**, *136*, 51–60. [CrossRef]
41. Maryniak, A.; Bulhakova, Y. Benefits of the Technology 4.0 Used in the Supply Chain-Bibliometric Analysis and Aspects Deferring Digitization. In *Lecture Notes in Business Information Processing: Proceedings of the BIS 2020 International Workshops, Colorado Springs, CO, USA, 8–10 June 2020*; Springer International Publishing: Cham, Switzerland, 2020; Volume 394, pp. 173–183. [CrossRef]
42. Hallinger, P.; Wang, R.; Chatpinyakoop, C.; Nguyen, V.-T.; Nguyen, U.-P. A bibliometric review of research on simulations and serious games used in educating for sustainability, 1997–2019. *J. Clean. Prod.* **2020**, *256*, 120358. [CrossRef]
43. Chanchetti, L.F.; Leiva, D.R.; de Faria, L.I.L.; Ishikawa, T.T. A scientometric review of research in hydrogen storage materials. *Int. J. Hydrogen Energy* **2020**, *45*, 5356–5366. [CrossRef]
44. Abejón, R.; Pérez-Acebo, H.; Clavijo, L. Alternatives for Chemical and Biochemical Lignin Valorization: Hot Topics from a Bibliometric Analysis of the Research Published during the 2000–2016 Period. *Processes* **2018**, *6*, 98. [CrossRef]
45. Ramona, O.; Cristina, M.S.; Raluca, S. Bitcoin in the Scientific Literature—A Bibliometric Study. *Stud. Bus. Econ.* **2019**, *14*, 160–174. [CrossRef]
46. Yang, C.; Wang, X.; Tang, X.; Wang, R.; Bao, X. Stem-Cell Research of Parkinson Disease: Bibliometric Analysis of Research Productivity from 1999 to 2018. *World Neurosurg.* **2020**, *134*, e405–e411. [CrossRef] [PubMed]
47. Chen, S.; Desai, D.A.; Heyns, S.P.; Pietra, F. A bibliometric analysis of the research on shot peening. *Afr. J. Sci. Technol. Innov. Dev.* **2019**, *12*, 69–77. [CrossRef]
48. Scopus. *Scopus Content Coverage Guide*; Scopus: Amsterdam, The Netherlands, 2016.
49. Baas, J.; Schotten, M.; Plume, A.; Côté, G.; Karimi, R. Scopus as a curated, high-quality bibliometric data source for academic research in quantitative science studies. *Quant. Sci. Stud.* **2020**, *1*, 377–386. [CrossRef]
50. Mpofu, B.; Ochieng, E.G.; Moobela, C.; Pretorius, A. Profiling causative factors leading to construction project delays in the United Arab Emirates. *Eng. Constr. Arch. Manag.* **2017**, *24*, 346–376. [CrossRef]
51. Teizer, J.; Cheng, T.; Fang, Y. Location tracking and data visualization technology to advance construction ironworkers' education and training in safety and productivity. *Autom. Constr.* **2013**, *35*, 53–68. [CrossRef]

52. Zhi, M.; Hua, G.B.; Wang, S.Q.; Ofori, G. Total factor productivity growth accounting in the construction industry of Singapore. *Constr. Manag. Econ.* **2003**, *21*, 707–718. [CrossRef]
53. Moselhi, O.; Leonard, C.; Fazio, P. Impact of Change Orders on Construction Productivity. *Can. J. Civ. Eng.* **1991**, *18*, 484–492. [CrossRef]
54. Bosché, F.; Abdel-Wahab, M.; Carozza, L. Towards a Mixed Reality System for Construction Trade Training. *J. Comput. Civ. Eng.* **2016**, *30*, 04015016. [CrossRef]
55. Palikhe, S.; Yirong, M.; Choi, B.Y.; Lee, D.-E. Analysis of Musculoskeletal Disorders and Muscle Stresses on Construction Workers' Awkward Postures Using Simulation. *Sustainability* **2020**, *12*, 5693. [CrossRef]
56. Dadi, G.B.; Goodrum, P.M.; Taylor, T.R.; Maloney, W.F. Effectiveness of communication of spatial engineering information through 3D CAD and 3D printed models. *Vis. Eng.* **2014**, *2*, 9. [CrossRef]
57. Dadi, G.B.; Taylor, T.R.; Goodrum, P.M.; Maloney, W.F. Performance of 3D computers and 3D printed models as a fundamental means for spatial engineering information visualization. *Can. J. Civ. Eng.* **2014**, *41*, 869–877. [CrossRef]
58. Allmon, E.; Haas, C.T.; Borcherding, J.D.; Goodrum, P.M. U.S. Construction Labor Productivity Trends, 1970–1998. *J. Constr. Eng. Manag.* **2000**, *126*, 97–104. [CrossRef]
59. Zhang, D.; Haas, C.T.; Goodrum, P.M.; Caldas, C.H.; Granger, R. Construction Small-Projects Rework Reduction for Capital Facilities. *J. Constr. Eng. Manag.* **2012**, *138*, 1377–1385. [CrossRef]
60. Goodrum, P.M.; Haas, C.T.; Glover, R.W. The divergence in aggregate and activity estimates of US construction productivity. *Constr. Manag. Econ.* **2002**, *20*, 415–423. [CrossRef]
61. Alaloul, W.S.; Alzubi, K.M.; Malkawi, A.B.; Al Salaheen, M.; Musarat, M.A. Productivity monitoring in building construction projects: A systematic review. *Eng. Constr. Arch. Manag.* **2021**, *29*, 2760–2785. [CrossRef]
62. Chia, F.C.; Skitmore, M.; Runeson, G.; Bridge, A.; Skitmore, R. Economic development and construction productivity in Malaysia. *Constr. Manag. Econ.* **2014**, *32*, 874–887. [CrossRef]
63. Van Tam, N.; Toan, N.Q.; Hai, D.T.; Quy, N.L.D. Critical factors affecting construction labor productivity: A comparison between perceptions of project managers and contractors. *Cogent Bus. Manag.* **2021**, *8*, 1863303. [CrossRef]
64. Gupta, M.; Hasan, A.; Jain, A.K.; Jha, K.N. Site Amenities and Workers' Welfare Factors Affecting Workforce Productivity in Indian Construction Projects. *J. Constr. Eng. Manag.* **2018**, *144*, 04018101. [CrossRef]
65. Odesola, I.A.; Idoro, G.I. Influence of Labour-Related Factors on Construction Labour Productivity in the South-South Geo-Political Zone of Nigeria. *J. Constr. Dev. Ctries.* **2014**, *19*, 93.
66. Soltaninejad, M.; Fardhosseini, M.S.; Kim, Y.W. Safety climate and productivity improvement of construction workplaces through the 6S system: Mixed-method analysis of 5S and safety integration. *Int. J. Occup. Saf. Ergon.* **2022**, *28*, 1811–1821. [CrossRef] [PubMed]
67. Ghodrati, N.; Yiu, T.W.; Wilkinson, S.; Poshdar, M.; Talebi, S.; Elghaish, F.; Sepasgozar, S.M.E. Unintended Consequences of Productivity Improvement Strategies on Safety Behaviour of Construction Labourers; A Step toward the Integration of Safety and Productivity. *Buildings* **2022**, *12*, 317. [CrossRef]
68. Gurmu, A.T. Hybrid Model for Assessing the Influence of Safety Management Practices on Labor Productivity in Multistory Building Projects. *J. Constr. Eng. Manag.* **2021**, *147*, 04021139. [CrossRef]
69. Yi, W.; Chan, A.P.C. Effects of Heat Stress on Construction Labor Productivity in Hong Kong: A Case Study of Rebar Workers. *Int. J. Environ. Res. Public Health* **2017**, *14*, 1055. [CrossRef]
70. Jebelli, H.; Choi, B.; Lee, S. Application of Wearable Biosensors to Construction Sites. I: Assessing Workers' Stress. *J. Constr. Eng. Manag.* **2019**, *145*, 04019079. [CrossRef]
71. Kim, K.; Cho, Y.; Zhang, S. Integrating work sequences and temporary structures into safety planning: Automated scaffolding-related safety hazard identification and prevention in BIM. *Autom. Constr.* **2016**, *70*, 128–142. [CrossRef]
72. Hashiguchi, N.; Yeongjoo, L.; Sya, C.; Kuroishi, S.; Miyazaki, Y.; Kitahara, S.; Kobayashi, T.; Tateyama, K.; Kodama, K. Real-time Judgment of Workload using Heart Rate and Physical Activity. In Proceedings of the 37th International Symposium on Automation and Robotics in Construction (ISARC 2020), Kitakyushu, Japan, 27–28 October 2020; pp. 849–856. [CrossRef]
73. Gatti, U.C.; Migliaccio, G.C.; Bogus, S.M.; Schneider, S. An exploratory study of the relationship between construction workforce physical strain and task level productivity. *Constr. Manag. Econ.* **2014**, *32*, 548–564. [CrossRef]
74. Al-Kofahi, Z.G.; Mahdavian, A.; Oloufa, A. System dynamics modeling approach to quantify change orders impact on labor productivity 1: Principles and model development comparative study. *Int. J. Constr. Manag.* **2022**, *22*, 1355–1366. [CrossRef]
75. Cheng, M.-Y.; Wibowo, D.K.; Prayogo, D.; Roy, A.F.V. Predicting Productivity Loss Caused by Change Orders Using the Evolutionary Fuzzy Support Vector Machine Inference Model. *J. Civ. Eng. Manag.* **2015**, *21*, 881–892. [CrossRef]
76. Al-Kofahi, Z.G.; Mahdavian, A.; Oloufa, A. A dynamic modelling of labor productivity impacts arising from change orders in road projects. *Can. J. Civ. Eng.* **2022**, *49*, 159–170. [CrossRef]
77. Salem, O.; Solomon, J.; Genaidy, A.; Minkarah, I. Lean Construction: From Theory to Implementation. *J. Manag. Eng.* **2006**, *22*, 168–175. [CrossRef]
78. Thomas, H.R. Labor Productivity and Work Sampling: The Bottom Line. *J. Constr. Eng. Manag.* **1991**, *117*, 423–444. [CrossRef]
79. Josephson, P.-E.; Björkman, L. Why do work sampling studies in construction? The case of plumbing work in Scandinavia. *Eng. Constr. Arch. Manag.* **2013**, *20*, 589–603. [CrossRef]

80. Joshua, L.; Varghese, K. Classification of Bricklaying Activities in Work Sampling Categories Using Accelerometers. In *Construction Research Congress 2012: Construction Challenges in a Flat World*; American Society of Civil Engineers: New York, NY, USA, 2012. [CrossRef]
81. Hajikazemi, S.; Andersen, B.; Langlo, J.A. Analyzing electrical installation labor productivity through work sampling. *Int. J. Prod. Perform. Manag.* **2017**, *66*, 539–553. [CrossRef]
82. Liu, K.; Golparvar-Fard, M. Crowdsourcing Construction Activity Analysis from Jobsite Video Streams. *J. Constr. Eng. Manag.* **2015**, *141*, 04015035. [CrossRef]
83. Gong, Y.; Yang, K.; Seo, J.; Lee, J.G. Wearable acceleration-based action recognition for long-term and continuous activity analysis in construction site. *J. Build. Eng.* **2022**, *52*, 104448. [CrossRef]
84. Cheng, T.; Teizer, J.; Migliaccio, G.C.; Gatti, U.C. Automated task-level activity analysis through fusion of real time location sensors and worker's thoracic posture data. *Autom. Constr.* **2013**, *29*, 24–39. [CrossRef]
85. Jiang, L.; Zhong, H.; Chen, J.; Cheng, J.; Chen, S.; Gong, Z.; Lun, Z.; Zhang, J.; Su, Z. Study on the construction workforce management based on lean construction in the context of COVID-19. *Eng. Constr. Arch. Manag.* **2022**. [CrossRef]
86. Rui, Y.; Yaik-Wah, L.; Siang, T.C. Construction Project Management Based on Building Information Modeling (BIM). *Civ. Eng. Arch.* **2021**, *9*, 2055–2061. [CrossRef]
87. Park, J.W.; Kim, K.; Cho, Y.K. Framework of Automated Construction-Safety Monitoring Using Cloud-Enabled BIM and BLE Mobile Tracking Sensors. *J. Constr. Eng. Manag.* **2017**, *143*, 05016019. [CrossRef]
88. Chalhoub, J.; Ayer, S.K. Using Mixed Reality for electrical construction design communication. *Autom. Constr.* **2018**, *86*, 1–10. [CrossRef]
89. Yang, J.; Shi, Z.; Wu, Z. Vision-based action recognition of construction workers using dense trajectories. *Adv. Eng. Inform.* **2016**, *30*, 327–336. [CrossRef]
90. Han, S.; Achar, M.; Lee, S.; Peña-Mora, F. Empirical assessment of a RGB-D sensor on motion capture and action recognition for construction worker monitoring. *Vis. Eng.* **2013**, *1*, 1–13. [CrossRef]
91. Konstantinou, E.; Lasenby, J.; Brilakis, I. Adaptive computer vision-based 2D tracking of workers in complex environments. *Autom. Constr.* **2019**, *103*, 168–184. [CrossRef]
92. Chu, W.; Han, S.; Luo, X.; Zhu, Z. Monocular Vision–Based Framework for Biomechanical Analysis or Ergonomic Posture Assessment in Modular Construction. *J. Comput. Civ. Eng.* **2020**, *34*, 04020018. [CrossRef]
93. Chu, W.; Han, S.; Luo, X.; Zhu, Z. 3D Human Body Reconstruction for Worker Ergonomic Posture Analysis with Monocular Video Camera. In Proceedings of the 36th International Symposium on Automation and Robotics in Construction (ISARC 2019), Banff, AB, Canada, 21–24 May 2019; pp. 722–729. [CrossRef]
94. Zhao, J.; Pikas, E.; Seppänen, O.; Peltokorpi, A. Using Real-Time Indoor Resource Positioning to Track the Progress of Tasks in Construction Sites. *Front. Built Environ.* **2021**, *7*, 661166. [CrossRef]
95. Zhao, J.; Seppänen, O.; Peltokorpi, A.; Badihi, B.; Olivieri, H. Real-time resource tracking for analyzing value-adding time in construction. *Autom. Constr.* **2019**, *104*, 52–65. [CrossRef]
96. Joshua, L.; Varghese, K. Accelerometer-Based Activity Recognition in Construction. *J. Comput. Civ. Eng.* **2011**, *25*, 370–379. [CrossRef]
97. Hashiguchi, N.; Kodama, K.; Lim, Y.; Che, C.; Kuroishi, S.; Miyazaki, Y.; Kobayashi, T.; Kitahara, S.; Tateyama, K. Practical Judgment of Workload Based on Physical Activity, Work Conditions, and Worker's Age in Construction Site. *Sensors* **2020**, *20*, 3786. [CrossRef]
98. Alzubi, K.M.; Alaloul, W.S.; Malkawi, A.B.; Al Salaheen, M.; Qureshi, A.H.; Musarat, M.A. Automated monitoring technologies and construction productivity enhancement: Building projects case. *Ain Shams Eng. J.* **2022**, *14*, 102042. [CrossRef]
99. El-Gohary, K.M.; Aziz, R.F.; Abdel-Khalek, H.A. Engineering Approach Using ANN to Improve and Predict Construction Labor Productivity under Different Influences. *J. Constr. Eng. Manag.* **2017**, *143*, 04017045. [CrossRef]
100. Torabi, G.; Hammad, A.; Bouguila, N. Two-Dimensional and Three-Dimensional CNN-Based Simultaneous Detection and Activity Classification of Construction Workers. *J. Comput. Civ. Eng.* **2022**, *36*, 04022009. [CrossRef]
101. Bangaru, S.S.; Wang, C.; Aghazadeh, F. Automated and Continuous Fatigue Monitoring in Construction Workers Using Forearm EMG and IMU Wearable Sensors and Recurrent Neural Network. *Sensors* **2022**, *22*, 9729. [CrossRef] [PubMed]
102. Ogunseiju, O.R.; Olayiwola, J.; Akanmu, A.A.; Nnaji, C. Recognition of workers' actions from time-series signal images using deep convolutional neural network. *Smart Sustain. Built Environ.* **2021**, *11*, 812–831. [CrossRef]
103. Handa, V.K.; Abdalla, O. Forecasting productivity by work sampling. *Constr. Manag. Econ.* **1989**, *7*, 19–28. [CrossRef]
104. Bonham, D.R.; Goodrum, P.M.; Littlejohn, R.; Albattah, M.A. Application of Data Mining Techniques to Quantify the Relative Influence of Design and Installation Characteristics on Labor Productivity. *J. Constr. Eng. Manag.* **2017**, *143*, 04017052. [CrossRef]
105. Yeheyis, M.; Reza, B.; Hewage, K.; Ruwanpura, J.Y.; Sadiq, R. Evaluating Motivation of Construction Workers: A Comparison of Fuzzy Rule-Based Model with the Traditional Expectancy Theory. *J. Civ. Eng. Manag.* **2016**, *22*, 862–873. [CrossRef]