https://doi.org/10.3311/PPci.38067 | 1

Periodica Polytechnica Civil Engineering

An Investigation into the Digital Construction Progress Monitoring Models

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Received: 10 August 2024, Accepted: 22 November 2024, Published online: 05 December 2024

Abstract

Construction exhibits relatively low efficiency and a modest annual productivity growth rate despite being one of the largest industries. As digitalizing the construction progress monitoring process and ensuring the objectivity of the obtained data is considered as a critical area for enhancing efficiency of the AEC (Architecture, Engineering, and Construction) industry, AEC companies invest in resources to extract and report construction data obtained from the site. This paper examines digitalization efforts in construction progress monitoring, focusing particularly on studies proposing new monitoring models. Articles focusing on studies proposing a specific model for digitalization of progress monitoring was searched in databases. A framed literature review study is conducted, bibliometric analysis is performed via keywords and the Vosviewer tool and finally semantic and methodological variations of models studied. An in-depth analysis of these studies reveals that the proposed models fundamentally consist of four different elements defined as: data collection methods, data processing methodologies, the specific construction areas they focus on, and the primary input objects they address. All studies were examined and categorized under these four distinct headings and mapped accordingly. The relationships between the emerging methods and their frequency of preference were also analyzed. Both more frequently and less commonly employed approaches have been identified in the literature. Additionally, this paper highlights potential research areas on possible data collection and processing ways, specific construction areas and input sources to focus in the literature by emphasizing the existing relationships and correlations between the mentioned categories.

Keywords

data processing, digitalization, literature review, model generation, progress monitoring

1 Introduction

The global construction industry (CI)'s market size reached $15.46 trillion in 2023, with a compound annual growth rate (CAGR) of 6.6% over the preceding years [1]. The future CAGR projections for the sector are expected to vary between 6% and 6.5%, with estimates indicating that it will reach $19.52 trillion by 2027 [1] and $23.92 trillion by 2032 [2]. CI has experienced an annual productivity growth rate of 1% over the past two decades and that this slow growth is mainly attributed to insufficient digitalization, suboptimal planning, and ineffective project management, resulting in frequent budget overruns and project delays [3]. Insufficient adaptation of CI to technological developments along with dependency on solutions generated at site may be seen as main reasons for lack of processable data generated and used in activities [4]. Adaptation of automation and digital technologies in CI, however, can resolve many of chronic problems, and ultimately boost the industry's profitability [5]. The CI's reliance on outdated monitoring and control systems considerably impedes the speed of and effectiveness in decision-making processes [6]. To effectively address the issue of overruns in construction projects, it is imperative to implement rigorous and reliable monitoring systems that can promptly identify delays and their underlying causes, thereby enabling timely corrective actions to mitigate their impact [7].

Effective monitoring of construction project progress is critical to identifying deviations from planned outcomes

Cite this article as: Mazlum, S. K., Sertyesilisik, B. "An Investigation into the Digital Construction Progress Monitoring Models", Periodica Polytechnica Civil Engineering, 2024. https://doi.org/10.3311/PPci.38067

and promptly implementing necessary corrective actions [8]. Ineffective and inaccurate progress tracking is widely regarded as a key factor contributing to delays and cost overruns in construction projects. [9]. As digital transformation emerges, the effectiveness of monitoring methods is anticipated to markedly improve through data-driven management and control approaches [10]. Progress tracking in construction has relied on manual field measurements and paper-based Daily Progress Reports, which are time-consuming and labour-intensive, and which cannot instantaneously verify three-dimensional progress status through these conventional methods [5]. Primary projections' incompatibility with as-completed situation is a common problem faced in construction practice [11].

For project management practices focused on productivity, having timely and accurate advancement data is crucial [12]. Availability of constant and filtered information flow can make progressive continuation of construction activities possible [13]. Late detection of application mistakes at site can lead to nearly a 10% increase in overall construction costs [14]. Furthermore, destruction and reconstruction actions mainly cover 6–12% of total budget in a typical project [15]. To address the aforementioned challenges, researchers are conducting various studies to digitalize construction progress monitoring methods [5]. To illustrate, the use of unmanned aerial vehicles, photogrammetry-based measurements, point cloud solutions, and airborne laser scanning applications in various tasks at construction sites is almost inevitable with the implementation of machine learning algorithms [16]. Similarly, in recent years, autonomous vehicles have proven to be successful and productive in understanding their surroundings, thanks to the sensors they are equipped with, including cameras, LİDAR, and radar [17].

Specifically on progress monitoring field of construction, model suggesting studies introduced as a category for researches that propose a methodology for digitalization of progress monitoring by emphasizing the diversity of their relationships with data [18]. In this context, this study investigates the scopes of studies proposing models for the digitalization of construction progress monitoring and to examine their data collection and processing methods, their focused specific construction areas, and their data sources in depth, while identifying gaps in the literature.

2 Methodology

The study aims to identify state-of-the-art of the model suggesting literature on digital construction progress monitoring. With this aim, the objectives were to: examine employed data gathering and processing methods for construction progress monitoring technologies; investigate specific construction areas and data input subjects that construction progress monitoring models particularly focus on; and identify and compare the relationships of data gathering and processing methodologies of model suggesting studies.

Comprehensive systematic searches were conducted separately within the ScienceDirect [19], ASCE [20], and Taylor & Francis [21] online databases. Keywords of the searches are determined as "data" or "image" or "sound" or "sensor" or "AI" and "construction" and "progress" and "management" or "track" or "monitor". The words "construction" and "progress" were kept constant and searched with different keyword alternatives that could evoke digitalization and management in this field. The search was constrained to studies published between 2017 and 2024. For each search, the first 100 articles appearing in the results were meticulously reviewed and included in the analysis without exception, ensuring a robust and exhaustive examination of the relevant literature. In all searches, works in the categories of "engineering" or "engineering and technology" were filtered within the options offered by the database. A total of 4,500 article titles were accessed as a result of 15 different keyword search combinations in three databases.

Following the elimination of duplicate entries, the initial total of 4,500 articles was reduced to 583 articles. In the next stage of filtering, both the abstracts and titles of all these articles were thoroughly reviewed and studies that did not specifically address the construction progress monitoring were excluded from the research scope. Remaining 316 articles covered as pertinent literature, thereby maintaining a focused examination of relevant digitalization efforts in construction progress tracking. In the subsequent filtering phase, the complete texts of the selected articles were examined. Articles that tackled the topic from alternative perspectives such as occupational safety or progress payments were excluded. 198 articles remained for these evaluation level. The focus was then narrowed to articles that proposed either conceptual or practical progress monitoring models, allowing for a more in-depth examination of these specific contributions in the final stage: 140 articles remained.

Fig. 1 shows after database search, network visualizations of the most frequently used keywords, using co-occurrence density and network analysis, were generated with the VOSviewer software [22]. RIS files corresponding to 140 manually filtered articles from databases were imported into VOSviewer, and the application was executed.

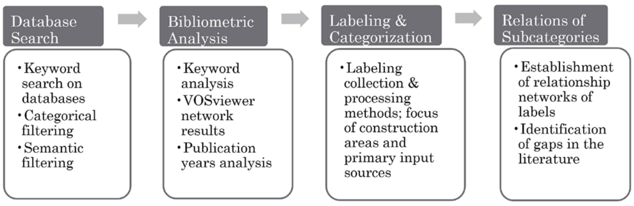

Fig. 1 Methodology flowchart

The primary subject of this research is the articles that propose conceptual or practical models aimed at enhancing decision-making mechanisms and efficiency in construction project management through the digitalization of process monitoring. Various approaches within this field were comprehensively evaluated, using key terms likely to yield the most insightful results across recognized databases. The perspectives and methodologies employed by these studies were critically examined.

After identifying model suggesting studies in the literature, these studies have been observed to establish relationships with construction data by exhibiting different approaches. To facilitate a mapping study related to these differences, the search was conducted using keywords likely to yield results relevant to different types of data. This approach aimed to systematically capture and analyze the diverse methodologies employed in relation to data within the scope of model-proposing research.

All articles retrieved during the survey were evaluated within the scope of the study's objectives, focusing on the methodologies adopted and the specific areas of focus in model development. When examining the concepts grouped around specific structure clusters, it was found that these concepts mainly pertain to the:

1. data collection methods,
2. data processing methods,
3. specific construction areas of focus, and,
4. primary data sources addressed by the model-proposing studies.

After identifying the differentiation of studies in these four categories, all articles were analyzed and labeled by researchers based on their adopted data collection methods, data processing methodologies, specific construction areas of focus (if any), and input sources.

Establishment of relationships among studies with different labels were investigated (e.g., how studies utilizing specific data collection methods, process the data and which sources are used by studies focusing on particular areas). Sankey charts representing the relationships between different categories were created using the software Tableau [23], based on the labels assigned by researchers. These figures illustrate more used combinations of data approaches in the literature, while highlighting less popular methodologies, thereby indicating gaps in the literature.

3 Results

The findings of the studies included in the analysis after passing through all filters during the literature review are given. Initially, the density, network relationships, and usage frequency analyses related to the keywords are discussed. Following the examination of the publication years of the studies, the model development approaches of the studies are methodologically categorized under four different headings (i.e., data gathering model / tool, data processing method, specific construction area and specific input subject), and the frequency of preference for these categories as well as the relationships between them were analyzed.

3.1 Keywords and conceptual relationships

Evaluation of the density and co-occurrence analysis of the keywords shown in Fig. 2, revealed that artificial intelligence-based data processing methods (e.g., computer vision, deep learning, machine learning, image processing, activity recognition) stand out in terms of number and density. Additionally, 3D technologies (e.g., BIM, point cloud(s), scan to BIM) emerged prominently too. Furthermore, keywords that can be considered as data collection methods (e.g., unmanned aerial vehicles, photogrammetry, internet of things) are also represented in the analysis visual. Another topic highlighted in Fig. 2 is the presence of keywords that describe specific specialized areas in the CI, such as "indoor construction," "offsite construction," and "modular construction." This indicates

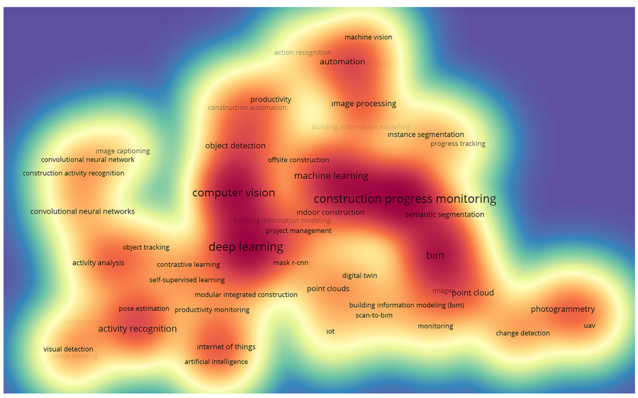

Fig. 2 Keyword co-occurrence density analysis

the presence of progress monitoring studies specialized in specific areas. Furthermore, the existence of keywords indicating the preference for technologies that focus on different data sources in construction progress monitoring technologies is also noteworthy. For example, the keyword "object tracking" involves using objects at site as data sources, while "pose estimation" pertains to tracking people at site, "point clouds" to the 3D reality of the field, and "IoT" to the sensors as data sources.

All keywords of these articles were analyzed, and the keywords repeated at least 6 or more times are given in Table 1.

Table 1 shows AI related concepts such as "deep learning" (e.g., [24, 25]), "computer vision" (e.g., [26, 27]) and "machine learning" (e.g., [28, 29]) are used as keywords 36 times in total by the authors. Apart from these items, another word that was exclusively emphasized by the authors was BIM (e.g., [30]). Among the concepts such as "progress monitoring" (e.g., [31, 32]), "construction progress monitoring" (e.g., [5, 33]), and "automation" (e.g., [34, 35]) which describe the main topic of the studies subject to the research, the selection of the keywords "point cloud(s)" (e.g., [36]) and "photogrammetry" (e.g., [9]) also shows model methodologies mostly employed by the authors. The use of the keywords „activity recognition" (e.g., [29, 37]) and „object detection" (e.g., [38, 39]) a total of 13 times indicates that there are studies in the literature aimed at automating process monitoring by focusing on worker and machine / equipment movements, as well as materials, tools, and supplies.

The relationships between the keywords can be seen along with the network diagram in Fig. 3. It can be observed that the data processing methods (e.g., deep learning, computer vision, BIM, machine learning, activity recognition)

Table 1 Author keywords

Ranking	Keyword	Count
1	Deep learning	16
2	BIM	15
3	Construction progress monitoring	13
4	Computer vision	11
5	Point cloud(s)	10
6	Machine learning	9
7	Progress monitoring	9
8	Photogrammetry	7
9	Activity recognition	7
10	Object detection	5
11	Automation	5

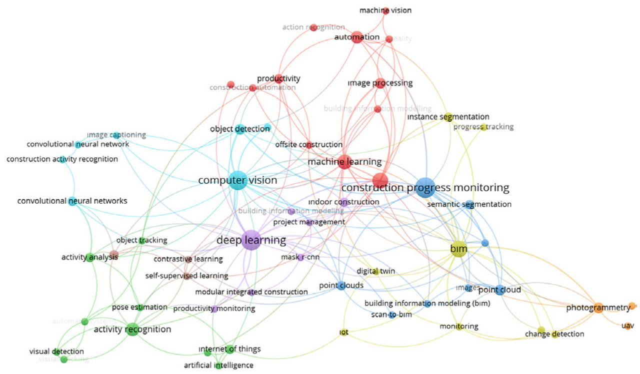

Fig. 3 Keyword co-occurrence network visualization

are situated at the centers of gravity in different regions of the mapping. Additionally, it is evident from the Fig. 3 that these data processing methods are related to different data collection methods / tools (e.g., photogrammetry, UAV, IoT sensors), specific construction areas they focus on (e.g., indoor construction, offsite construction), and data sources (e.g., objects, activities, 3D data).

3.2 Publication years of studies

The annual distribution of all model-proposing articles examined in this study is in the Fig. 4. The year with the highest number of publications included in this study during the three-year period from 2017 to 2019 is 2018, with a total of 18 articles. Furthermore, there has been a consistent annual publication of at least 18 articles (2020 and 2022) over the five years from 2020 until the present. In the other three years, the number of published articles exceeded this amount. This trend indicates an increasing interest in the literature regarding model-proposing studies in the field of construction progress monitoring over the past five years compared to the previous three years.

3.3 Model suggesting studies

Researchers, recognizing the significant advantages that automated and human-subjectivity-free digital construction progress monitoring can offer to CI, have engaged extensively in this area. They have conducted a multitude of studies and proposed a variety of models utilizing different methodologies. This body of work reflects a concerted

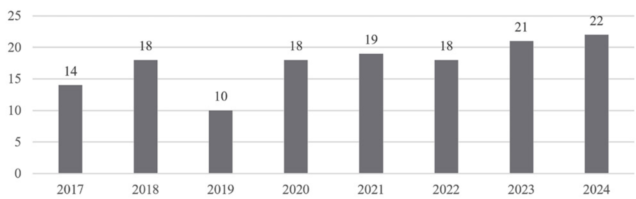

Fig. 4 Distribution of publications by year

effort to increase the precision, effectiveness, and objectivity of construction progress monitoring through the integration of advanced digital technologies and automation. By doing so, literature aims to mitigate the limitations associated with human subjectivity and improve the overall effectiveness in progress tracking within CI.

The large number of articles with different approaches necessitates a mapping study to offer a comprehensive overview of the literature. While certain studies (e.g., [40, 41]) concentrate on distinct and specialized areas within CI, others (e.g., [42]) may adopt a more comprehensive perspective, addressing the issue on a broader scale. Additionally, there are researches (e.g., [38, 39]) dedicated to developing methodologies targeting specific input-related problems. Consequently, model-proposing articles adopt distinct approaches in four different areas: data gathering model / tool, data processing methodology, specific construction area, and specific input subject. Model suggesting studies shown in Fig. 5 are analyzed separately in the following sections.

3.3.1 Data gathering models / tools

With the increase in digitalization of daily life, the amount of data created in construction, as in many sectors, has recently increased enormously [43]. The data in question can be created by many different sources and can also be obtained by various methods. As there can be different approaches to the methodology of using big data, obtaining data in construction projects can also be achieved through various methods.

All studies proposing models were analyzed in depth according to their data gathering way and grouped under the relevant headings. As seen in Fig. 6, the most employed data collection method was "camera & smartphone photography" (e.g., [44, 45]) with 34 of 140 studies in total, followed by "fixed sensors / scanners" (e.g., [46, 47]) with 30 studies, "video recordings" (e.g., [37, 39]) with 23 studies and "UGV / UAV hardware" (e.g., [48, 49]) with 22 studies. "Event logs / BIM documents" (e.g., [50, 51]), "wearable sensors" (e.g., [41, 52]) and "audio recordings" (e.g., [53, 54]) are the next most utilized data collection ways by the authors. In total, 8 studies collected data using more than one of the mentioned methods in different combinations (e.g., [5, 55]). There is one study using "satellite" data (e.g., [56]) and another employing "thermal cameras" (e.g., [57]) as data collection methods.

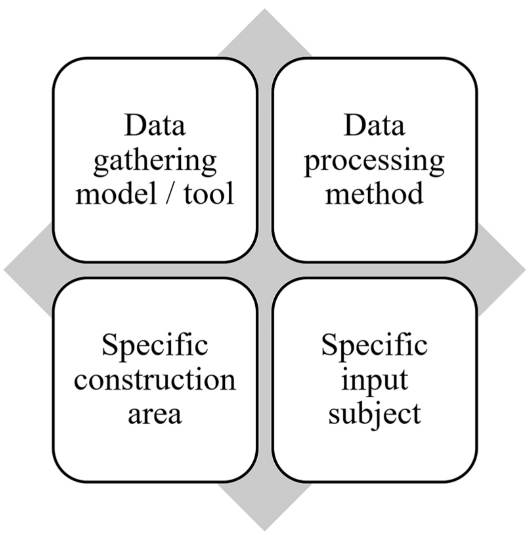

Fig. 5 Labeling categories of model suggesting studies

3.3.2 Data processing methodologies

The application of digital technologies in areas concerning efficiency and productivity necessitates not only the acquisition but also the comprehensive processing of substantial volumes of temporal data to achieve meaningful insights and improvements (e.g., [58]). When the articles subject to the literature review are analyzed, it can be observed that different data processing methodologies are applied based on the data collection method used. This situation has re-emerged as a distinct element that enriches digitalization studies in the field of construction progress monitoring. In this study, the research has been categorized by emphasizing the data processing methodologies.

Fig. 7 shows the most operated data processing method among the studies proposing models is "computer vision" (e.g., [44, 59]) with 46 studies. It is followed by "point cloud / BIM comparison" (e.g., [5, 36]) with 27 studies, and "AI & BIM" which corresponds together use of both technologies with 14 (e.g., [57, 60]) articles. 13 studies using "non imagery machine learning" technologies (e.g., [41, 52]). Following these methods, 9 studies

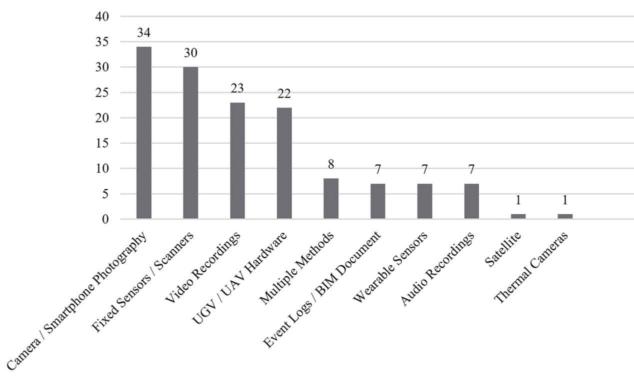

Fig. 6 Data gathering models / tools of model suggesting studies

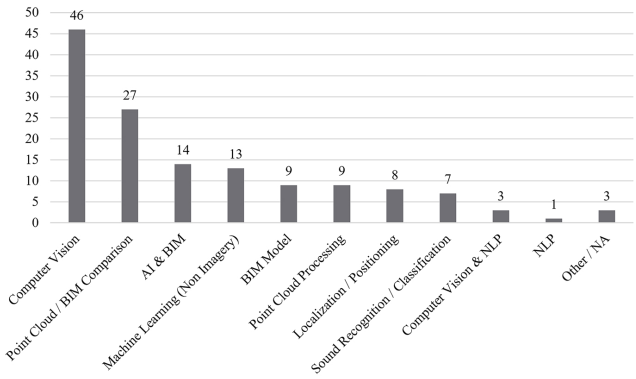

Fig. 7 Data processing methodologies of model suggesting studies

processed data with "BIM model" only (e.g., [50, 61]) and 9 other studies processed via "point cloud processing" (e.g., [49, 62]) without use of BIM comparison. It is seen that there are 8 studies that process data with "localization / positioning" technologies (e.g., [47, 63]). Studies that process information about the construction site by determining the location of a worker, vehicle, equipment, or material have been categorized in this area. 7 studies work by "sound recognition or classification" (e.g., [53, 54]). Of the 4 studies using "NLP" (e.g., [64]), 3 of them also utilized "computer vision" technology together (e.g., [55]).

Attention was drawn to the intricate relationship between data collection and processing methods, the specific construction area of interest, and the concepts considered as data sources in previous keyword analyzes. The Sankey chart in Fig. 8 spots the relationship between the data collection methods and data processing methods of the model-suggesting studies. Accordingly, it can be observed that models using computer vision as a data processing method primarily collect data through camera and smartphone photos (e.g., [36]) and video recordings (e.g., [65]) (Fig. 8). These types of studies were later predominantly supported by UGV/UAV hardware (e.g., [48]), followed – albeit in limited numbers – by fixed sensors/scanners (e.g., [66]) and multiple methods.

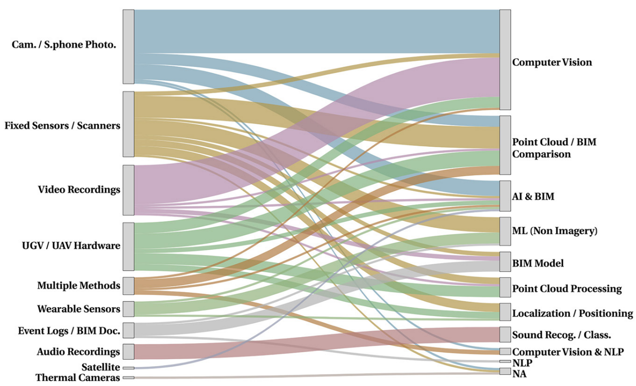

Fig. 8 The relationships between data gathering models / tools and processing methodologies of model suggesting studies

An important conclusion to be drawn from Fig. 8 is that the articles collecting data using fixed sensors/scanners and UGV/UAV hardware have processed the data using a variety of methods, exhibiting a more homogeneous distribution. On the other hand, articles collecting data via camera / smartphone photography and video recordings have predominantly employed computer vision for data processing (e.g., [67, 68]). Similarly, articles using wearable sensors have typically processed data using non-imagery machine learning (e.g., [52]), those utilizing event logs/BIM documents have processed data using BIM models (e.g., [50]), and those collecting data through audio recordings have relied on sound recognition and classification methods for processing (e.g., [54]).

3.3.3 Specific construction focus areas

In CI, data can be used to monitor different business lines in different areas. In-depth review of model suggesting studies demonstrated that the articles focus on various work items within the CI, with studies targeting different areas labeled and categorized into specific groups.

Considering the specific construction areas that the model proposing studies focus on, Fig. 9 shows that the highest number of focused works with 32 studies can be gathered under the category of "exterior / facade works" (e.g., [69, 70]), all studies related to open areas and exterior works in superstructure construction have been included in this category. On the other hand, there are 25 studies focusing on "indoor space works" (e.g., [71, 72]), followed by "infrastructure works" with 14 studies (e.g., [56, 73]). Studies focusing on works such as tunnels, bridges, and highways, aside from superstructure construction, have been grouped under this heading. There are

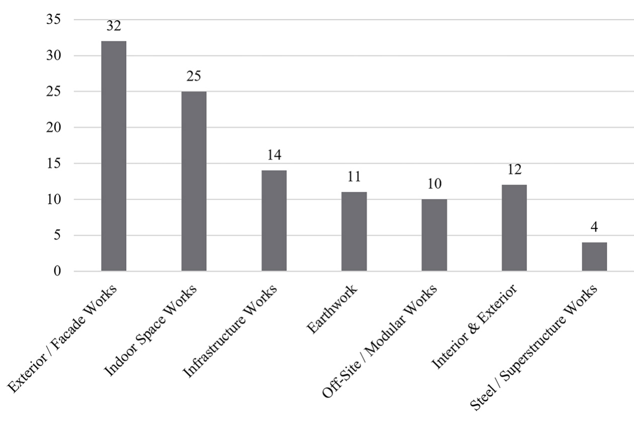

Fig. 9 Specific area of construction model suggesting studies focused on

12 studies focused on "interior & exterior" work items together (e.g., [5, 74]), 11 studies focused on "earthwork" (e.g., [40, 75]), 10 studies focused on "off-site / modular works" (e.g., [35, 65]) and finally 4 studies focused on "steel & superstructure works" (e.g., [63, 76]). There are also numerous studies that are more inclusive in terms of the construction areas they cover and do not focus on a specific area. Such works (e.g., [55, 57]) are not specifically included in a category.

Fig. 10 shows the relationship between the data collection methods of model-suggesting studies and the specific construction areas they focus on. A relatively homogeneous distribution can be seen. However, it can be inferred that studies focusing on earthwork and off-site/modular construction using wearable sensors for data collection would contribute to the literature. Additionally, although exterior/facade works is the most extensively studied area (e.g., [70, 77]), the limited number of approaches using wearable sensors (e.g., [52]) and event logs/BIM documents in these studies is noteworthy. The majority of studies focusing on off-site/modular works have collected data primarily through video recordings (e.g., [35, 65]). In the future, studies collecting data via camera/smartphone photography, fixed sensors/scanners, and UGV/UAV hardware may focus more on off-site/modular works. The relationships between all other data collection methods and the specific construction areas they focus on can be examined in Fig. 10.

3.3.4 Specific input subjects

During the literature review, it has been seen that the data obtained from different sources can be processed and converted into information (e.g., [37, 61]), thus contributing to digitalization in the field of construction progress monitoring. The source of data obtained in CI is determined as an important element of the studies in the field of progress monitoring together with the other 3 topics (i.e., data collection way, data processing method and specific focus area). Studies derived from different data sources have been grouped and mapped.

In the field of construction progress monitoring, the most common data source used by the studies proposing models was "3D form of built area" with 49 different studies (e.g., [50, 57]) according to Fig. 11. 22 studies processed data generated by "construction materials" (e.g., [26, 73]) and 21 studies processed data generated by "machine / equipment" (e.g., [40, 67]). Data collected from the movement and operation of any type of vehicle, machine, or equipment used at the construction site is included in this category. Following them, 12 studies proposed a model using data generated by "number/movements of workers" (e.g., [78, 79]), 9 studies by "activity sounds/vibrations" (e.g., [53, 80]) and 6 studies by "structural elements" (e.g., [66, 81]). In addition to these, 16 studies used at least two of the mentioned sources together (e.g., [82, 83]). A total of 5 studies (e.g., [64]) were not eligible for inclusion in any of these categories.

Fig. 12 shows studies that develop progress monitoring models in construction management by focusing on the form of the built area predominantly collect data using camera / smartphone photography (e.g., [44]), fixed sensors / scanners (e.g., [32]) and UGV / UAV hardware

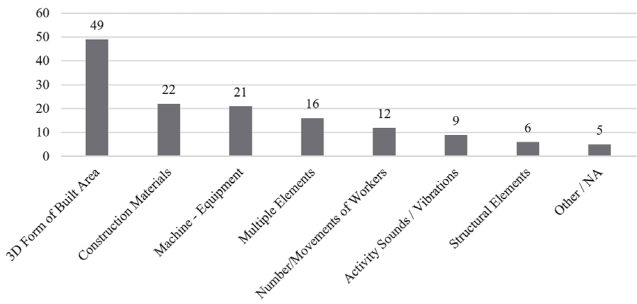

Fig. 11 Specific input subject of model suggesting studies focused on

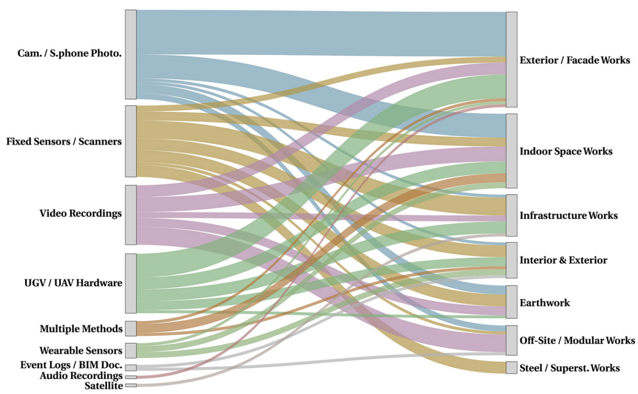

Fig. 10 The relationships between data gathering models / tools and specific focused construction areas of model suggesting studies

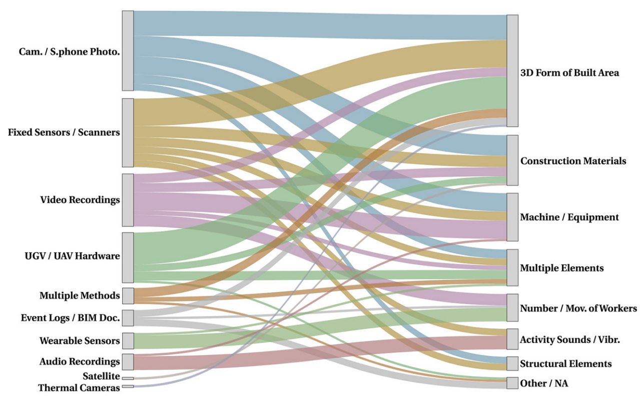

Fig. 12 The relationships between data gathering models / tools and specific input subjects of model suggesting studies

(e.g., [70]). However, it is observed that among the most applied data collection methods, video recordings, as well as wearable sensors and audio recordings are much less frequently used in articles within this area.

Although camera/smartphone photography is the most frequently used data collection method, none of the articles included in the study have used it to obtain data on the number or movements of workers.

The majority of models that collect data using UGV/UAV hardware have focused on obtaining the 3D form of built areas (e.g., [84]). This suggests that articles collecting data through the same method but focusing on construction materials, machine / equipment, the number/movement of workers, and structural elements could differentiate themselves in the literature and contribute valuable insights.

Fig. 13 illustrates the relationship between the data processing methods proposed by the studies and the inputs they focus on. Although computer vision is the most commonly preferred method, the number of articles that utilize it to process the most frequently used data type, the 3D form of built area (e.g., [48]), is relatively low. It is highly likely that the number of studies processing 3D form of built area data with computer vision will increase in the future.

It has been observed that nearly all studies processing data through point cloud/BIM comparison utilize 3D form of built area data (e.g., [48]), and similarly, nearly all studies processing data through sound recognition/classification rely on activity sounds/vibrations data (e.g., [54]). While these relationships may not be surprising, they are considered important as they highlight the rationality of the study's approach. None of the articles included in the study that process data using localization / positioning, have focused on machine / equipment data. This area holds potential for new studies should researchers choose to explore it further.

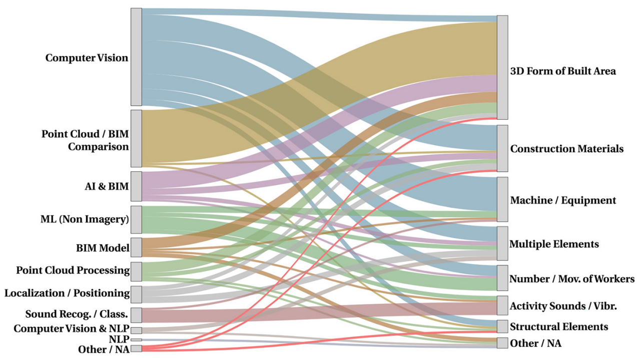

Fig. 13 The relationships between data processing methodologies and specific input subjects of model suggesting studies

Studies that process data using non-imagery machine learning applications have not been found to focus on the 3D form of built areas or construction materials. However, these two data types are the most frequently used by process monitoring studies proposing models. It has been evaluated that the combination of these data types and data processing methods presents an area open for further research in future studies. The relationships between all relevant categories, the most utilized combinations in the literature, and thus the gaps, can be analyzed by examining Fig. 13.

Fig. 14 highlights another notable relationship between the specific construction areas that model suggesting studies focus on and the data sources they use as inputs. When these relationships are examined, a more homogeneous distribution can be observed compared to previous binary diagrams. There are, however, significant divergences. To illustrate, indoor space works represent the second most focused work type category (e.g., [27]), but none of the studies included in the research have addressed machine / equipment data or activity sounds/vibrations data.

A very small percentage of the articles focusing on both interior and exterior work items have concentrated on obtaining construction materials data (e.g., [26]). Furthermore, the majority of studies focusing on earthwork have addressed machine / equipment data (e.g., [29]). Approaches with a higher intensity of research are important as they reflect the information provided by the literature and the areas of greater focus. Conversely, less-explored approaches may address gaps in the literature for future studies.

4 Conclusion

This study identified the state-of-the-art in the model-suggesting literature on the digitalization of construction progress monitoring models. Even if the importance

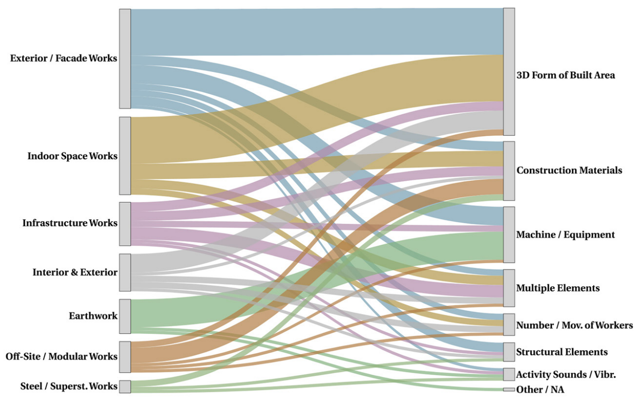

Fig. 14 The relationships between specific focused construction areas and input subjects of model suggesting studies

of progress monitoring in construction management and its potential value to CI is emphasized in the literature (e.g., [8, 9]), a literature review specifically targeting model-suggesting studies in this area could not be found. As part of the study, bibliometric analysis, data relationship labeling & categorization, and the relationship network of subcategories were presented.

4.1 Bibliometric analysis

The bibliometric analysis revealed conceptual structure clusters of keywords with relationships among them, highlighting the prominence of the following areas:

- AI-based data processing methods such as *computer vision, deep learning* and *image processing*,
- 3D technologies to be used as data source and data processing method such as *BIM*, *photogrammetry* and *point clouds*,
- Data collection tools and methods such as *unmanned aerial vehicles, internet of things*, and *photogrammetry*,
- Specific construction focus areas such as *indoor construction, off-site construction* and *modular construction* and,
- Those addressing specific data sources such as *object tracking* and *pose estimation*.

The relationships among keywords observed in different areas were revealed by VOSviewer outputs. Keyword analyses have revealed that the articles differentiate in previously addressed four distinct areas i.e.:

1. data collection way,
2. data processing method,
3. specific focus area and,
4. specific input source.

This complex network of relationships necessitated the examination of all included studies under these four main headings. In a sense, it has been identified that authors make preferences within these four areas. Consequently, a holistic framework regarding the information preferences across different categories was established.

4.2 Data relationship labeling & categorization

This study categorized the relationships that articles establish with data in the first step. Subsequently, authors analyzed the connections between the approaches of studies that focus on different construction work items and data sources, utilizing various data collection and processing methods.

The most exercised data collection methods and tools were camera / smartphone photography, followed by fixed sensors / scanners, video recordings and UGV / UAV hardware. Considering the increase in the use of cameras and smartphones [85], the increase in the accessibility and use of sensor devices [86] construction areas monitored by jobsite video systems [82], the ease of access to unmanned aerial vehicles such as drones and the widespread use of such devices [87], this ranking of data collection methods and tools appears to be justified. In addition to these, event logs / BIM documents, wearable sensors, audio recordings, satellite data and thermal imagery methods were also employed. An increase in the number of academic studies in these areas can be expected.

An analysis over data processing methods of the studies shows computer vision (e.g., [86]), point cloud / BIM comparison (e.g., [84]), AI & BIM usage together (e.g., [27]), non-imagery machine learning (e.g., [76]), BIM model (e.g., [61]) and point cloud processing (e.g., [62]) concepts come to the fore. These results align with the widespread use of 3D scanners [88] and BIM [34] at a time when the application of artificial intelligence in the CI, as well as in other industries, is particularly prominent [89]. Studies that utilize localization / positioning technologies (e.g., [47]) and sound recognition / classification (e.g., [24]) and NLP (e.g., [64]) were also found, even though it is the subject of fewer studies. The limited number of these studies indicates a gap in the literature in this field and highlights these areas as potential subjects for further academic research.

Most of the studies evaluated within the scope of the research focus on a specific area and focus on solving the problems in this field. As a result of the categorization, it was seen that the highest number of studies focused on activities in the field of exterior / façade works (e.g., [70]), and a high number of studies prioritized indoor space works (e.g., [44]). Considering the possibilities such as camera placement, object recognition, it can be regarded as justifiable to focus on any of these areas due to constraints such as camera angle [90]. One reason for the relatively high number of studies conducted in indoor environments is that the conditions are more controllable and the possibilities are narrowed, making them closer to a laboratory setting. The significant presence of articles focusing on infrastructure manufacturing is meaningful due to their composition of repetitive sequential activities and the limited number of activities that need to be monitored. Similarly, the specific characteristics of earthmoving vehicles that make them suitable for the application of object recognition technologies have enabled the development of progress monitoring models in this field. Off-site or modular construction activities may be at the forefront of automatization efforts as they form the interface between modern industries and CI [86]. Furthermore, there is a possibility that more studies will be published in the future in the areas of linear construction works and steel & superstructure works.

When the input sources investigated in model suggesting studies are analyzed, it can be seen that the concepts of 3D form of built area (e.g., [48]), machine / equipment (e.g., [86]), construction materials (e.g., [35]) and number / movements (e.g., [91]) of workforce come to the fore in parallel with concepts such as artificial intelligence, BIM, sensor and image processing. In addition to these, it has been observed that there are also studies that use the data generated by activity sounds (e.g., [24]) and structural elements (e.g., [84]) as input, and some of them are applied together (e.g., [42]). The items listed under this heading are also considered to be consistent when evaluated together with the information obtained in the rest of the study.

4.3 Relationship network of subcategories

Model suggesting studies prefer different combinations of data collection and processing methods. Most of them focus specific areas of construction and use specific data sources as inputs. By labelling all studies from this perspective, it has been possible to see the links that utilized more and less by the literature. A wide range of interpretations can be drawn by examining the areas covered by the included studies and their preferences for establishing relationships with data. To provide some examples of the numerous possible inferences:

- The studies using computer vision as data processing methodology, mostly gather camera & smartphone photography (e.g., [68]) and video recordings (e.g., [35]) data. On the other hand, there are fewer studies using fixed sensors / scanners (e.g., [66]) and no study included using wearable sensors for gathering data to be used in computer vision methodology (Fig. 8).
- A significant portion of studies utilizing wearable sensors for data collection process the data using non-imagery machine learning techniques (e.g., [46]). This suggests that the potential for further research lies in exploring how this sensor data could be processed through other advanced methods, such as point cloud / BIM comparisons, AI & BIM integration, or localization/positioning systems. These areas represent gaps in the current literature, where sensor data have not yet fully leveraged for comparison with 3D models or for real-time localization, which could offer new insights for construction progress monitoring and digital twin development (Fig. 8).
- Although exterior / façade works is the most preferred construction area to study by the researchers (e.g., [92]), a very limited number of studies included in this paper employs fixed sensors / scanners (e.g., [70]), wearable sensors (e.g., [52]) and audio recordings (e.g., [93]) for data collection while no study uses event logs / BIM documents (Fig. 10).
- Among the articles included in this paper, no research focusing on machine or equipment data was found among those that collect data using UGV or UAV hardware (Fig. 12).
- Despite computer vision being the most widely used data processing method, only a few studies focus on processing the 3D form of built area data using computer vision (e.g., [48]). The number of studies in this field is expected to increase in the future (Fig. 13).
- Most of studies focused on earthwork activities employ machine / equipment data (e.g., [40]) for progress monitoring. No earthwork focused study gathering data of 3D form of built area, construction materials, number / movements of workers or structural elements was encountered within the scope of the research (Fig. 14).

With a systematic approach, this study filtered the articles that propose a model on the topic of digitalizing construction progress monitoring. The listed studies were first examined bibliographically, with a focus on their keywords and the relationships between them. From the outputs of this analysis, four fundamental elements determining the model development approaches of the articles were identified: Data gathering model / tools, Data processing methodology, Specific construction area of focus, and Specific input subject.

The preferences across these four categories in all studies were identified, and the approaches adopted in the literature, as well as their frequency of preference, were determined separately for each topic. Since the preferences in different categories for each study were individually labeled, the combinations of these subheading preferences were also revealed.

This study has examined the relationships established with data in model suggesting research studies within the literature, highlighting the more frequently employed methods. As an inevitable outcome of this, areas that have been less explored and can be considered as gaps in the literature have also been identified by the authors. This paper can be useful for future academic studies targeting the development of process monitoring models in construction practices.

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