

Contents lists available at ScienceDirect

# Journal of Cleaner Production



journal homepage: www.elsevier.com/locate/jclepro

# Review

# Cross-industry review of autonomous alignment technologies: Adaptation potential for modular construction

Sulemana Fatoama Abdulai<sup>a,\*\*</sup><sup>(0)</sup>, Tarek Zayed<sup>a</sup>, Ibrahim Yahaya Wuni<sup>b</sup>, Maxwell Fordjour Antwi-Afari<sup>c,\*</sup>, Abdul-Mugis Yussif<sup>a</sup>

<sup>a</sup> Department of Building and Real Estate, The Hong Kong Polytechnic University, Hung Hom, Hong Kong

b Department of Architectural Engineering and Construction Management, King Fahd University of Petroleum and Minerals, Dhahran, 31261, East Province, Saudi Arabia

<sup>c</sup> Department of Civil Engineering, College of Engineering and Physical Sciences, Aston University, Birmingham, B4 7ET, United Kingdom

#### ARTICLE INFO

Handling Editor: Giovanni Baiocchi

Keywords: Automation Modular construction Computer vision Module alignment Artificial intelligence Lidar Object detection Industry 4.0

# ABSTRACT

Module alignment in modular construction faces significant challenges due to reliance on manual labor and dimensional complexities, leading to project delays. While other industries have successfully implemented automated alignment technologies, the construction industry has lagged behind, particularly in modular construction. Despite extensive research on construction technologies, there is a notable lack of comprehensive reviews examining alignment technologies from various sectors that could be adapted for modular construction. This study aims to fill this knowledge gap by employing a mixed review approach to explore technologies capable of achieving autonomous module alignment. Analyzing 200 publications from 2006 to 2023, key findings reveal that computer vision systems used in port operations can achieve millimeter-level accuracy in positioning large components, even under challenging environmental conditions-capabilities that can be directly transferred to modular construction. Additionally, LiDAR (Light Detection and Ranging) technology shows promise for exceptional precision in spatial measurement and positioning, particularly valuable for complex module arrangements, while other sensor-based technologies like the Inertial Measurement Unit (IMU), ultrasonic sensor offer orientation tracking and reliable distance measurements, respectively, even in conditions where primary systems might struggle. The study recommends (1) adapting proven container positioning technologies for modular construction, (2) developing construction-specific alignment algorithms that combine computer vision and LiDAR capabilities, (3) implementing sensor-based guidance systems for crane operators, and (4) establishing industry standards for automated module alignment systems. These findings offer a roadmap for researchers and practitioners to advance autonomous alignment solutions in modular construction.

| Nomenclature  |   | (continued) |   |  |
|---------------|---|-------------|---|--|
|               |   | SIFT        | Scale-Invariant Feature Transform                         |  |
| Abbreviations | Term meaning                                | SURF        | Speeded-Up Robust Features                                |  |
| LiDAR         | Light Detection and Ranging                 | ORB         | Oriented Fast and Rotated                                 |  |
| IMU           | Inertia Measurement Unit                    | HOG         | Histogram Oriented Gradient                               |  |
| AIR           | Artificial Intelligence and Robotics        | YOLO        | You Only Look Once  |  |
| IoT           | Internet of Things                          | CNN         | Convolutional Neural Networks                             |  |
| BIM           | Building Information Modelling              | HOG + SVM   | Histogram of Oriented Gradient and Support Vector Machine |  |
| AEC           | Architecture, Engineering, and Construction | KLT         | Kanade-Lucas-Tomasi                                       |  |
| AR            | Augmented Reality                           | KNN         | K-nearest neighbors                                       |  |
| AI            | Artificial Intelligence                     | SVM         | Support vector machines                                   |  |
| MSRCR         | Multi-Scale Retinex with Color Restoration  | UUV         | Unmanned underwater vehicle                               |  |
| HSV           | Hue, Saturation, Value                      | DTW         | Dynamic time warping                                      |  |
|               | (continued on next column)                  |             | (continued on next page)                                  |  |

\* Corresponding author.

\*\* Co-corresponding author.

E-mail addresses: sulemana.abdulai@connect.polyu.hk (S.F. Abdulai), m.antwiafari@aston.ac.uk (M.F. Antwi-Afari).

#### https://doi.org/10.1016/j.jclepro.2025.145101

Received 6 May 2024; Received in revised form 13 January 2025; Accepted 20 February 2025 Available online 21 February 2025

0959-6526/© 2025 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

S.F. Abdulai et al.

(continued)

| FAST   | Fast Feature for Segmented Test  |
|--------|----------------------------------|
| SSD    | Single-shot detectors            |
| AUV    | Autonomous underwater vehicle    |
| MLE    | Maximum likelihood estimation    |
| EM     | Expectation maximization         |
| HTR    | Horizontal transfer robot        |
| CCD    | Charge-coupled device            |
| TS-TOA | Type symmetrical time of arrival |
| FPGAs  | Field-programmable gate arrays   |
| LSTM   | Long short-term memory           |
| RNN    | Recurrent neural networks        |
| EKF    | Extended Kalman Filter           |
| UKF    | Unscented Kalman Filter          |
| FPGAs  | Field-programmable gate arrays   |
| LSTM   | Long short-term memory           |
|        |                                  |

#### 1. Introduction

Modular construction is a method of building that uses prefabricated components or modules that are made off-site in a controlled environment and then transported and assembled on-site (Marzouk and Abubakr, 2016). It combines the aspects of manufacturing (such as process and environment) and construction (such as regulations and delivery methods). Therefore, a modular construction schedule covers the factory production of modules, their transportation to the site, and on-site installation (Alvanchi et al., 2012; Olawumi et al., 2022). Within the scholarly discourse, modular construction has garnered substantial attention, heralded as a transformative paradigm by eminent researchers in the field (Panahi et al., 2023; Zheng et al., 2023). This recognition is substantiated by the manifold advantages that modular construction offers over conventional on-site construction, including expeditious project completion, heightened structural and aesthetic quality, cost-effectiveness, and a diminished environmental footprint (Hussein et al., 2022; Taiwo et al., 2022).

Nonetheless, modular construction encounters notable challenges, with module alignment as a prominent issue (Arshad and Zayed, 2022). Alignment of modules involves guaranteeing that modules are properly positioned and connected not only to the foundation or supporting structures but also to adjacent modules. This precise alignment is crucial for both vertical stacking and horizontal joining of modules, ensuring proper connection at critical interfaces (Srisangeerthanan et al., 2020). The accuracy of these module-to-module connections, along with foundation connections, plays a vital role in the overall structural integrity, functional performance, and aesthetic quality of the completed modular building (Dai et al., 2020).

The precision of module alignment significantly impacts the structural behavior of multi-story modular buildings. Out-of-verticality from misalignment can create unintended load paths and stress concentrations at module connections, potentially compromising the building's structural integrity (Peng and Hou, 2023; Rajanayagam et al., 2021). These misalignments, which may stem from manufacturing inaccuracies, transportation effects, or thermal deformation in steel modules, can accumulate throughout the height of the building, leading to more severe consequences in taller structures (Shahtaheri et al., 2017). The compounded effect of misalignment can result in structural eccentricities, affecting load distribution and potentially causing differential settlement or excessive deformation (Dai et al., 2020). Furthermore, these alignment issues can impact the building's serviceability, including the proper functioning of Mechanical, Electrical, and Plumbing (MEP) systems and the aesthetic quality of the finished structure (Wang et al., 2021). Therefore, achieving precise alignment is crucial for structural safety and the overall performance and longevity of modular buildings.

Achieving such optimal alignment, however, proves to be a complex endeavor influenced by several factors. These factors include the dimensional tolerances inherent in modules, which may vary due to manufacturing inaccuracies, effects of transportation, or thermal expansion and contraction, particularly notable in steel modules (Shahtaheri et al., 2017). Furthermore, the accuracy and precision of installation methods and equipment present inherent limitations, further impeding the alignment process (Enshassi et al., 2019). Presently, the prevalent mode of module alignment in modular construction involves manual intervention, wherein on-site labor is tasked with aligning modules as they are hoisted into position by cranes. Regrettably, this approach has accrued considerable setbacks over time, manifesting as escalated project costs, imprecision issues, and project delays attributable to the time-consuming task of aligning modules with their neighboring counterparts (Dai et al., 2020).

In various domains, such as the port industry, manufacturing industry, and marine industry, akin alignment-related challenges arise. However, these industries have effectively addressed the predicament of manual alignment and positioning of containers in the case of the port industry, as well as the installation of charging stakes on ships, as in the case of the marine industry, by implementing remedial measures (Yu et al., 2023). Predominantly, these industries leverage pivotal technologies that facilitate the alignment process, autonomously aligning units such as containers hoisted by gantry cranes and utilizing spreaders to lift containers from ships to trucks. Notably, within the port industry, a significant portion of the time in the lifting process is dedicated to aligning the spreader with the keyholes of the container for lifting purposes (Park et al., 2006). Integrating technologies such as computer vision has substantially reduced this alignment time, leading to expedited delivery and lifting processes within the port industry (Zhang et al., 2023). Additionally, the adoption of alignment and positioning technologies within the port industry has yielded notable successes, enhancing the overall quality and reliability of port services through optimal placement and connection of containers and cargo units, resulting in a substantial reduction in accident rates at port terminals, for example, over the past decades, there has been a remarkable 70% reduction in accidents (Li et al., 2020).

Currently, in modular construction, module alignment is done manually by workers who direct the modules as cranes lift them. This process is prone to errors and inefficiencies, resulting in structural, functional, and aesthetic issues that compromise modular projects' quality, cost, and schedule (Zhang et al., 2021). For instance, it is recorded that the manual alignment of modules makes up about 30% of the time of the entire duration of the modular construction process when done manually; however, it is estimated that when technology is employed, 27.8% of the time will be saved (Pan and Hon, 2020). Therefore, it is imperative to minimize manual alignment by employing methods and technologies to improve the dimensional quality and compatibility of the modules and ensure the fast delivery of modular construction (Han et al., 2015).

Despite readily embracing technological advancements in sectors like port, manufacturing, and automotive (Bao and Zhang, 2018; Li et al., 2020; Shen et al., 2017), the construction industry has historically lagged behind in adopting such innovations. Consequently, it faces scarcity and underdevelopment of advanced methods and technologies (Alsakka et al., 2023b). These technologies could be adapted and applied to the modular construction process, especially the alignment of modules, since the containers and the modules have similar geometric shapes, such as cellular, steel, or mixed modules. This could enhance the accuracy and efficiency of module alignment and improve the performance and outcomes of modular construction projects. For instance, the recent adoption of transformative technologies such as digital twins has brought significant benefits to construction (Opoku et al., 2021). Therefore, stakeholders and researchers in modular construction need to explore potential technologies that can enable autonomous module alignment, thereby reducing industry dependence on manual labor. Furthermore, technology is increasingly emerging as a transformative force and a competitive edge for those capable of effective investment and adoption (Martínez-Aires et al., 2018). Thus, integrating such innovative solutions holds the potential to revolutionize the modular construction process.

Numerous studies have been conducted in the domain of modular construction by applying diverse technologies (Zhang et al., 2023; Zheng et al., 2020). A thorough review of existing literature reveals minimal efforts in evaluating alignment technologies across diverse disciplines, underscoring the need to integrate alignment technologies in the construction industry, particularly in automating the alignment process during module installations. Table 1 shows the existing review studies relating to various technologies in modular construction, including their research focus and limitations. From Tables 1 and it can be observed that most of the existing literature review centers around the general application of technologies in modular construction. Additionally, some studies delve into specific technology applications within modular construction, albeit not specifically focusing on the alignment of modules. Additionally, a review in this domain could be motivated by the novelty of the research endeavor. This review explores new research avenues by conducting detailed analyses of technologies, including their opportunities and challenges in application. Identifying these gaps and opportunities enables researchers to contribute to advancing the state-of-the-art in modular construction, addressing critical issues such as alignment challenges more comprehensively.

To fill this knowledge gap, this study aims to comprehensively review prominent technologies applicable to aligning modules in modular construction, drawing valuable insights from various disciplines. Furthermore, to the best of the researcher's knowledge, this review represents a pioneering effort encompassing a diverse range of disciplines concerning alignment technologies. Specifically, the study objectives are: 1) to present a comprehensive bibliometric analysis, showing the publication trend, keywords co-occurrence, and journal contributions; 2) to assess the current state of scientific research on module alignment, including advancements, challenges, and future

#### Table 1

| Summaries of | review | studies of | n techno | logies i | n modu | lar construction. |
|--------------|--------|------------|----------|----------|--------|-------------------|
|              |        |            |          |          |        |                   |

| Reference   | Research focus  | Limitations   |
|---|---|---|
| Yin et al.<br>(2019)                                  | This research focused on<br>presenting the state-of-the-art<br>application of Building<br>Information modeling<br>technology in offsite<br>construction.                        | No review of the module<br>alignment technology was<br>presented.   |
| Wang et al.<br>(2020)                                 | The study focused on evaluating<br>the current literature associated<br>with digital technologies.  | No mention of technologies<br>specific to the alignment of<br>modules in modular<br>construction.   |
| Hussein and<br>Zayed<br>(2021)<br>Qi et al.<br>(2021) | The study focused on crane<br>operation and planning in<br>modular integrated construction.<br>The study focused on emerging<br>technologies in industrialized<br>construction. | No mention of technologies for<br>module alignment was<br>presented.<br>There was no mention of the<br>technologies for alignment in<br>modular construction. |
| Pan et al.<br>(2022)                                  | construction.<br>The study explored future<br>research and directions on<br>artificial intelligence and<br>robotics (AIR) for prefabricated<br>and modular construction.        | No detailed review of the<br>techniques in the alignment of<br>modules in modular<br>construction was presented.  |
| Olawumi<br>et al.<br>(2022)                           | Their study reviews the<br>implementation of digital tools<br>and technologies for<br>implementation in modular<br>integrated construction.                                     | No review on the issues of<br>alignment of modules in<br>modular construction.  |
| Zhu et al.<br>(2023)                                  | This research presented an<br>overview of the key technologies<br>of crane lift automation in<br>modular construction.  | No review of technologies for<br>alignment in modular<br>construction.  |
| Alsakka et al.<br>(2023a)                             | They focused on reviewing<br>computer vision technology in<br>offsite construction.   | The study was not directed to<br>applying such technology in<br>module alignment.   |

directions; and 3) to propose innovative and practical technologies tailored for the alignment of modules in modular construction, considering factors such as cost-effectiveness, scalability, and ease of use implementation. Accomplishing these objectives would significantly contribute to the growing body of knowledge in modular construction literature and help outline a research agenda for future researchers. Moreover, using technology in modular construction for alignment aims to enhance accuracy and precision during module installations, streamline assembly processes for greater efficiency, and notably decrease accidents on construction sites by reducing dependence on manual labor.

Following this introduction, the remainder of the paper is organized as follows. Section 2 employs a mixed-method approach to detail the research methodology. Section 3 outlines the mapping of bibliometric data, including annual publication trends of alignment technologies, primary research areas, and top research outlets. Section 4 discusses a comprehensive systematic review of the included studies. Section 5 presents the challenges of the identified technologies. Section 6 discusses a systematic framework for implementing computer vision-based, LiDAR (Light Detection and Ranging) capture-based, and other sensing technologies for module alignment in modular construction. Section 7 delves into the performance comparisons of the various alignment technologies. Finally, Section 8 summarizes the conclusions drawn from this review study.

# 2. Research methodology

This study adopts a mixed-method systematic review comprising bibliometric (i.e., quantitative method) and systematic (i.e., qualitative method) analysis to overcome the biases inherent in mono-method reviews (Heyvaert et al., 2016). Fig. 1 shows the review framework of this study. The review begins by defining research objectives and conducting a bibliometric search using the Web of Science (WoS) and Scopus databases. This is complemented by a scientometric analysis that examines publication trends, keyword co-occurrence, and journal outlets. The review then presents a systematic analysis detailing technologies (such as computer vision-based, LIDAR capture-based, and other sensing technologies) techniques, various applications, and their limitations and potential opportunities for aligning modules in modular construction, a systematic framework discussion. Finally, the review identifies research gaps and suggests future directions.

## 2.1. Search for publications

As shown in Fig. 1, the initial phase of this systematic review comprised a comprehensive literature search strategy to build a foundational database of relevant publications. The literature search utilized Scopus and WoS databases, employing strategically combined keywords with Boolean operators 'OR' and 'AND' to ensure comprehensive coverage of relevant publications (Ohene et al., 2022; Sun et al., 2023). Multiple search strings were employed and refined until a final effective one was determined. Additionally, integrating well-established keywords is crucial to enhance the validity and reliability of the data (Muddassir et al., 2025; Sharma et al., 2022; Taiwo et al., 2023). However, given the vastness of potential keywords, it is impractical to include all in a single study; since this study aims to explore alignment technologies across diverse disciplines, a two-step preliminary search was conducted to identify pertinent alignment technologies.

The keyword string utilized in the first step was: "Technologies" OR "Techniques" AND "alignment" OR "adjustment" OR "positioning" OR "stacking." This initial search yielded a total of 3801 articles. The focus was on journals and conference proceedings without a specific year range limit, aiming to encompass a broad spectrum of alignment technologies. This search query successfully unveiled numerous technologies utilized to address alignment issues. Employing VOSviewer software, all keywords were exported into a tab-delimited file, and

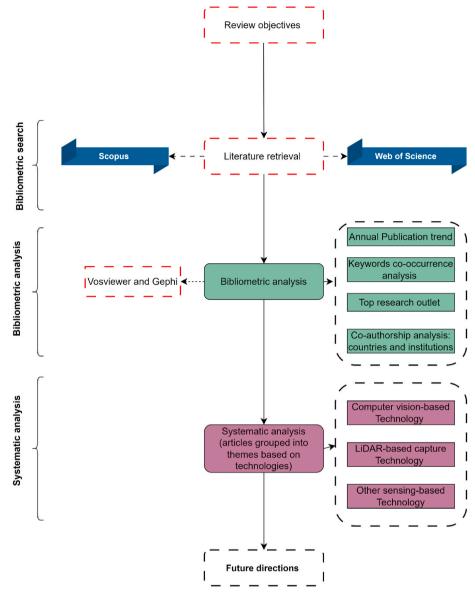


Fig. 1. Research methodological framework.

subsequent analysis of keywords' co-occurrence was conducted to identify technology-related keywords using the tab-delimited file (text file). This iterative process was repeated three times, refining and merging similar technology keywords, ultimately resulting in prominent keywords representing various technologies. At the end of the initial stage of keyword retrieval in the publication search, the following technologies were identified: Artificial Intelligence (AI), Augmented Reality, Building Information Modelling (BIM), Computer Vision, Deep Learning, Digital Twin, Internet of Things (IoT), Lasers, Machine Learning, Point Cloud, Sensors, Virtual Reality, Vision System, Visual Servoing, Infrared, Robot Vision, and Machine Vision.

In the second step, the objective was to identify relevant publications focused on alignment technologies. Initially, all papers were retrieved from Scopus and WoS. Search algorithms or syntax were constructed using keywords such as "artificial intelligence", "augmented reality," "building information modeling (BIM)," "computer vision," "deep learning," "digital twin," "internet of things (IoT)," "lasers," "machine learning," "point cloud," "sensors," "virtual reality," "vision system," "visual servoing," "infrared," "robot vision," and "machine vision." These keywords were then combined with "alignment", "adjustment", "align\*", or "orientation" using the Boolean operator "AND". The Scopus searches

were conducted on publications' titles, abstracts, and keyword sections, yielding a comprehensive dataset of 1022 articles. Simultaneously, a similar search on WoS used the same keyword strings, resulting in 102 articles (as of September 10, 2023). In total, 1124 articles were retrieved from the initial search of the database employed for the study.

#### 2.2. Exclusion and inclusion criteria

The authors refined search parameters to include only "articles" and "conference papers" within the "engineering" subject area to focus on alignment technologies in modular construction. This comprehensive search aimed to integrate these technologies into the construction industry. The systematic review followed a comprehensive search and screening process involving all authors to ensure thorough coverage of relevant literature. Initially, 99 non-English papers were excluded, and 91 duplicates were removed using CiteSpace software. The subsequent screening phase, focusing on titles and abstracts, excluded 198 publications deemed irrelevant to the research objectives. From the remaining 736 publications identified for detailed examination, 109 were inaccessible through available databases. The full-text review of 627 articles excluded 451 publications that presented purely theoretical frameworks without empirical validation or practical implementation. The remaining 176 articles underwent a systematic snowballing process. Through backward snowballing, we analyzed reference lists to identify seminal works, yielding 15 foundational papers. Forward snowballing tracked citations of our core papers, adding 6 recent publications that extended key concepts. Cross-reference validation across all papers revealed 3 additional relevant articles missed in initial searches. This three-phase snowballing process contributed 24 articles (15 backward + 6 forward + 3 cross-reference), bringing the final sample to 200 articles for detailed analysis, as illustrated in Fig. 2.

#### 2.3. Bibliometric analysis

Various bibliometric software tools were used to analyze the data, aiming for a thorough understanding of the knowledge domains. Specifically, VOSviewer 1.6.17 and Gephi 0.9.2 software were utilized to analyze and visually present knowledge maps. Conducting a comprehensive bibliometric analysis necessitates the synergistic use of different software for various analyses. Hence, we utilized multiple bibliometric software tools in this study to map and visualize the bibliometric network. Several software tools are available for bibliometric analysis, each with its strengths and weaknesses (Debrah et al., 2022; Faris et al., 2023; Wuni and Shen, 2020). Gephi, an open-source software, visualizes diverse network structures (Bastian et al., 2009). VOSviewer, known for its user-friendly interface, offers visualizations of bibliometric networks based on distances, illustrating the interconnectedness of various elements (van Eck and Waltman, 2010). The combined use of these software tools ensured a high-quality analysis process. In this stage, VOSviewer and Gephi played a crucial role in performing bibliometric analysis, laying the foundation for the systematic analysis. Further technical information about the applications of VOSviewer and Gephi can be found in the respective references (Chen, 2014; van Eck and

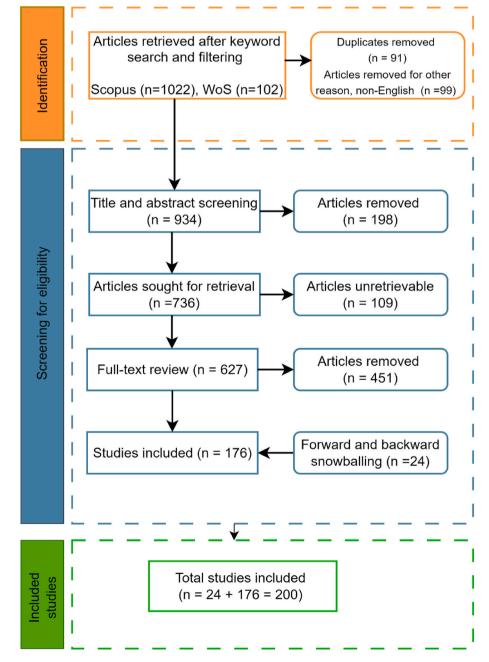


Fig. 2. Procedure for literature retrieval and selection.

#### Waltman, 2010).

# 2.4. Systematic analysis

In this section, we conducted a qualitative analysis of selected papers using Harden and Thomas' mixed-method analysis framework (Harden and Thomas, 2010). This analysis was part of a process that began with a literature search and bibliometric analysis. Finally, we reviewed all 200 papers to identify those most relevant to technology alignment. These articles were then categorized by themes related to their focus on technology applications. We discussed key thematic concepts from these papers and outlined potential future research directions for technologies in modular construction (see section 4 for a detailed systematic analysis).

#### 3. Bibliometric analysis

This section provides a concise overview of the bibliometric analysis results, covering annual publication trends, primary research areas (keywords co-occurrence), and top research outlets.

# 3.1. Annual publication trend

The bibliometric analysis identified 200 articles addressing technological solutions for alignment challenges in Port 4.0, manufacturing, and marine operations from 2006 to 2023 (Fig. 3). Notably, the official publication year was used in cases of discrepancies between online and official publication dates. The first documented use of technology for alignment in this dataset appeared 17 years ago, when researchers introduced a vision-based chassis alignment method for container operations in port terminals, aiming to automate the port industry (Park et al., 2006).

Subsequently, there was a publication gap until 2010, when papers related to alignment technologies re-emerged. From 2010 to 2021, an average of less than eleven papers per year was published addressing alignment challenges, indicating a relatively modest growth rate. In 2022, the number of publications increased to 42, the highest annual count in the dataset. This increase coincided with several technological advancements in the field. Zhang et al. (2023) documented break-through applications of LiDAR-based positioning and navigation for container loading robots in port operations, while Huang et al. (2022) reported progress in artificial intelligence integration for manufacturing

alignment processes. The publication count for 2023 has reached 35 papers as of November 2023, indicating sustained research interest in alignment technologies. Despite the incomplete year, this number indicates ongoing research activity in alignment technologies for Port 4.0, manufacturing, and maritime industry (Debrah et al., 2022).

# 3.2. Main research areas for alignment purpose: keywords co-occurrence analysis

Keyword analysis is crucial for mapping research domains and identifying core research trajectories. Through VOSviewer software, we generated a keyword co-occurrence network where nodes represent keywords and edges indicate their relationships. The node size corresponds to keyword frequency in titles, abstracts, and keywords, while edge weights reflect the strength of relationships between keywords. This visualization technique effectively maps alignment technologies' intellectual structure and interconnections in the Port 4.0, manufacturing, and marine industry (Jan van Eck and Waltman, 2014).

We analyzed index keywords from 200 research papers, identifying 2495 keywords, but only 215 appeared at least twice and were included in the analysis. We standardized terms (e.g., merging 'machine learning' with 'machine-learning') to ensure accurate node representation and omitted irrelevant terms. Further analysis with Gephi 0.9.2 assessed node centrality to identify critical research areas, utilizing betweenness centrality for keywords with the same degree of centrality. Significant findings from this analysis, including the top 10 keywords and their

## Table 2

| Top 1 | 0 keywords i | n technologies | for alignment | research domain areas. |
|-------|--------------|----------------|---------------|------------------------|
|       |              |                |               |                        |

| Keywords                         | Degree<br>Centrality | Betweenness<br>Centrality | Relative<br>importance |
|----------------------------------|----------------------|---------------------------|------------------------|
| Computer vision                  | 61                   | 472.645                   | 1                      |
| Alignment                        | 46                   | 286.031                   | 2                      |
| Image segmentation               | 37                   | 91.437                    | 3                      |
| LiDAR                            | 35                   | 98.904                    | 4                      |
| Reinforcement learning           | 32                   | 64.584                    | 5                      |
| Sensors                          | 30                   | 57.556                    | 6                      |
| Convolutional neural<br>networks | 27                   | 46.336                    | 7                      |
| Machine learning                 | 27                   | 40.496                    | 8                      |
| Cameras                          | 25                   | 55.020                    | 9                      |
| Feature extractions              | 25                   | 30.076                    | 10                     |

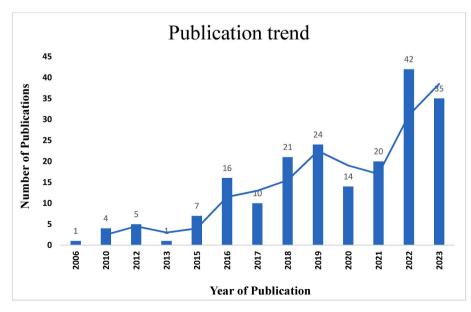


Fig. 3. Annual Publication trend (2006-2023).

centrality rankings, are presented in Table 2 and Fig. 4, highlighting key research domains in alignment technologies.

Analysis of Fig. 4 and Table 2 reveals 'computer vision' as a central node in alignment applications across multiple domains. Its successful implementation in object detection, recognition, and container stacking tasks in the port industry demonstrates significant potential for modular construction applications. As highlighted by Ekanayake et al. (2021), computer vision technology could revolutionize module alignment during hoisting operations, addressing the current inefficiencies of manual methods in the architecture, engineering, and construction (AEC) industry. Given the prevalent manual alignment practices in modular construction (Alsakka et al., 2023b), future research should prioritize integrating advanced computer vision techniques, including pose estimation and object detection, to achieve precise autonomous module alignment.

The findings reveal a skewed research focus towards certain alignment technologies, with a predominant emphasis on computer vision and less attention to "LiDAR technology" and "Augmented Reality (AR) technology". The preference for computer vision is likely due to its benefits, like real-time monitoring, precise pose estimation, object recognition, and enhanced safety by reducing manual labor. Nonetheless, technologies like LiDAR, AR, sensors, and the Internet of Things (IoT) also offer significant potential for alignment, each bringing unique capabilities that can enhance construction efficiency. For instance, LiDAR is invaluable in creating detailed 3D site models crucial for module positioning in modular construction. At the same time, AR and IoT can provide real-time guidance and automatic adjustments, potentially reducing construction time and costs. Given these benefits, research must explore these technologies more, particularly in the context of precise module alignment in modular construction. A focused exploration of these technologies can lead to safer, more efficient, and cost-effective construction practices by leveraging their distinct advantages and promoting their integration.

Moreover, the network's conspicuous lack of focus on the domain of 'construction' highlights a stark deficiency in research concerning the application of technology in addressing alignment challenges within construction, particularly in the context of modular construction. This gap becomes apparent when juxtaposed with the strides made in automation within the manufacturing, marine, and port sectors (Darko et al., 2020). This reinforces this observation, highlighting the construction industry's considerable delay in embracing and leveraging technological progress. Such findings underscore the necessity of this study to investigate these technologies and advocate for their integration into modular construction practices.

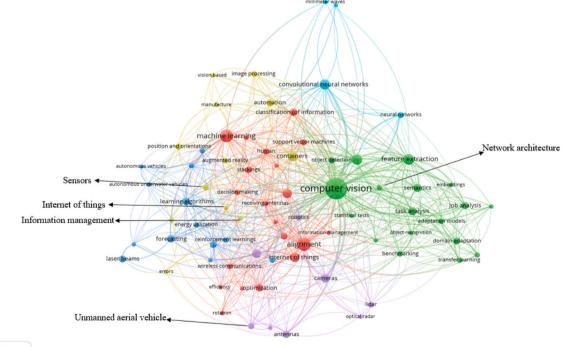
#### 3.3. Top outlets for research in technologies for alignment

Analysis of 102 sources through VOSviewer software, using a minimum criterion of two documents and citations per source, revealed five leading research outlets, IEEE Transactions on Circuits and Systems for Video Technology distinctly emerged as the leading journal, demonstrating exceptional research impact with 27 published documents and 152 citations. The subsequent tier of influential outlets exhibited comparable citation metrics despite varying publication volumes. The journals Aerospace and Reliability Engineering and System Safety each contributed 2 documents and received 40 citations, securing the second and third positions, respectively. Similarly, Automation in Construction, with 7 published articles, and Buildings, with 2 articles, each garnered 38 citations, placing them in the fourth and fifth positions.

These findings highlight these journals' crucial role in advancing research in the field. While IEEE Transactions leads in publication volume and impact, the other four journals exhibit significant influence despite fewer publications. This analysis suggests opportunities for strategic research partnerships with these leading outlets to improve both research productivity and scholarly impact.

#### 4. Systematic analysis

This section discusses the findings of the systematic review of the included studies. A comprehensive systematic review was conducted to gain a deeper understanding of the technologies for alignment and make a case for modular construction module alignment. As depicted in Fig. 5,



Å VOSviewer

Fig. 4. Co-occurrence of keywords network map.

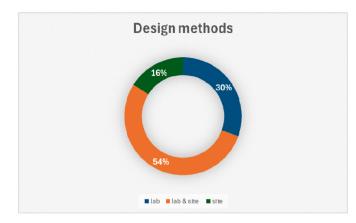


Fig. 5. Design methodologies for the included studies.

the reviewed articles were found to have originated from three main sources: laboratory, site, and a combination of both laboratory and site. This indicates that studies either solely conducted experiments in a laboratory setting, solely conducted experiments onsite, or utilized a combination of both laboratory and onsite experiments for validation purposes. However, all reviews should follow a rigorous scientific methodological approach (Taiwo et al., 2025). Fig. 2 is a flow chart of the PRISMA diagram, which this review follows. Thus, in the subsequent section, various technologies such as computer vision-based technology, LiDAR-based capture technology, and other sensing technologies have been critically explored, and the opportunities they present and the limitations in their usage for alignment purposes have been discussed.

#### 4.1. Computer vision-based technology

Computer vision is a fast-developing technique and has attracted much attention from various domains (Wiley and Lucas, 2018; Xu et al., 2021). The increasing adoption of computer vision can be primarily attributed to its versatility in accomplishing tasks like image classification, semantic segmentation, 3D reconstruction, and human and object pose estimation, among other functions (Szeliski, 2010). Computer vision-based technology aids in alignment purposes in different disciplines (Park et al., 2006; Radkowski, 2015; Yu et al., 2023).

## 4.1.1. Techniques of computer vision

Computer vision encompasses fundamental concepts and techniques enabling machines to interpret and understand visual data. These foundational elements are the building blocks for developing advanced applications within the field. Among the key concepts and techniques explored are image processing, which improves image quality through enhancement and noise reduction (Yu et al., 2023); feature extraction, which identifies unique characteristics essential for accurate alignment (Yang et al., 2008; Yussif et al., 2024); and object detection, utilizing algorithms like YOLO and Faster R-CNN to locate modular components in images. Additionally, segmentation techniques divide images into distinct areas, aiding in identifying relevant parts, while tracking methods monitor component movement across frames to ensure proper positioning (Putz et al., 2019; Shao et al., 2022; Shen et al., 2017). Finally, recognition algorithms categorize and verify the alignment of components, ensuring they meet design specifications (Van De Sande et al., 2010). These integrated techniques significantly contribute to achieving precise modular alignment in construction projects and other disciplines.

# 4.1.2. Computer vision-based applications

The utilization of computer vision technology extends across diverse industries, revolutionizing conventional practices and introducing novel solutions (Leo et al., 2017; Szeliski, 2010). This section briefly outlines

the many sectors that have integrated computer vision technology to automate alignment processes within their respective domains. It is evident from this study that the most common disciplines that employ computer vision for alignment are the port 4.0, the marine industry, and the manufacturing industry. Port 4.0 has the highest number of studies that use computer vision technology for aligning containers, as this technology can perform the task of aligning stacked containers with ease through object detection and recognition, edge detection, etc. (Shao et al., 2022; Shen et al., 2017; Zhang et al., 2023). This is part of the aim to automate container terminals' port and yard management systems. Also, this will improve work efficiency and reduce labor costs, which is significant for container port automation (Li et al., 2020). As indicated in Table 2, computer vision is the technology mainly used for automatic alignment in various disciplines identified in the study. However, the construction industry has not explored the utilization of computer vision in alignment, especially in modular construction, With the emergence of pose estimation computer vision techniques, aligning or stacking modules alongside adjoining modules has become achievable. As modules are hoisted and positioned by cranes, these techniques detect the modules in 3D space, enabling the determination of their pose (position and orientation) relative to world coordinates. This data can then be relaved to crane operators, aiding them in navigating the modules to proper alignment and installation. This concept introduces the possibility of autonomously installing and stacking modules with minimal labor involvement, thereby reducing costs associated with labor. Thus, this presents research directions for researchers in the construction management discipline to investigate in detail how computer vision techniques can enable autonomous module alignment in modular construction and eliminate the human factor in the alignment process when modules are hoisted in position.

# 4.1.3. Algorithmic characteristics of computer vision reviewed studies

The reviewed papers explored the computer vision tasks of object recognition and detection specifically for alignment purposes using various algorithms. These studies demonstrate the application of diverse algorithms to tackle different challenges, including automated inspection of alignment and the automatic recognition and detection of container lockholes. This focus is particularly relevant to the port industry and the goals of autonomous alignment (see Table 3). The port industry has employed several algorithms to automate the port terminals and yard management systems through the quest for real-time and accurate positioning of container keyholes.

Some other disciplines also employed algorithms for object detection and recognition. For example, (Yu et al., 2023), in their quest for automatic alignment of the charging stake in marine, the charging platform of unmanned underwater vehicle (UUV) directs, using target recognition, to direct the charging stake into the charging platform. The investigation uncovered that the utilized approach requires reduced computational resources, lower hardware prerequisites, shorter processing durations, and meets real-time control demands. Furthermore, the accuracy of the method's detection aligns with the criteria for smooth alignment (Prats et al., 2012). developed a technique that autonomously aligns the vehicle relative to it and keeps the pose during the task using the Dynamic time warping (DTW) algorithm.

Lin and Fang (2013) employed a corner detection image known as the Fast Feature for Segmented Test (FAST) for the automatic inspection system for tiles after installation in the construction job. Some of the included studies use a hybrid (two or more algorithms) to improve the accuracy and efficiency of the alignment process. For example, CNN and modified SSD are used to measure the parameters of the container lifting operations and to solve the existing problems of container positioning methods (Zhang et al., 2023). Table 3 summarizes the included algorithms in the computer vision-related studies.

The application of these algorithms has shown lots of success in their respective domains, such as the automatic positioning and alignment of containers in port terminals and the real-time and accurate positioning

#### Table 3

Studies that employ computer vision technologies for alignment.

| Research focus  | Algorithms  | Data splitting   | Data<br>type      | Evaluation matrix   | Reference  |
|---|---|--|-------------------|---|--|
| Automatic inspection<br>of alignment                  | <ul> <li>Feature from Accelerated<br/>Segment Test (FAST)</li> </ul>  | No splitting<br>type   | Digital<br>image  | Simple Pearson's correlation test   | Lin and Fang (2013)  |
| Automatic alignment                                   | <ul> <li>Dynamic time warping (DTW)</li> <li>Generalized Hough transform</li> <li>Niblack algorithms</li> <li>Convolutional Neural Network</li> <li>(CNN) and Modified Single shot<br/>detector (SSD)</li> </ul>    | Train and test   | Digital<br>image  | <ul> <li>Simulation and real autonomous<br/>underwater vehicle (AUV)</li> <li>Speed, Robustness and Accuracy</li> <li>Loss variation</li> <li>Comparison of modified SSD with origin<br/>SSD model</li> </ul>   | (Park et al., 2006; Prats et al., 2012; Putz<br>et al., 2019; Yu et al., 2023; Zhang et al.<br>2023)                                 |
| Automatic<br>recognition of<br>container<br>lockholes | <ul> <li>Generalized Hough transforms</li> <li>Canny edge detector</li> <li>K-means clustering algorithms</li> <li>YOLO</li> <li>General Hough algorithms</li> <li>RGB and blob detection<br/>algorithms</li> </ul> | <ul> <li>Close-set<br/>classifier</li> <li>Training and<br/>splitting</li> </ul> | Digital<br>images | <ul> <li>Recognition rate (daytime) = 95%,<br/>Recognition rate (night time) = 93%,<br/>Average recognition time = 300ms</li> <li>Recognition rate (daytime) = 100%<br/>Location accuracy(daytime) = 98.13%</li> <li>Location accuracy (rainy days) =<br/>95.25% and night = 90.50%, and<br/>recognition accuracy for all is 100%</li> <li>Accuracy rate = 96%; Recall rate = 83%<br/>Average precision (mAP) = 87.7%</li> <li>Accuracy = 99.2% for x -axis, 99.4% for<br/>y-axis and 99.3% for the z-axis</li> <li>Precision x-axis, 0.99 mm; y-axis, 0.98<br/>mm; z-axis, 0.97 mm</li> <li>Recall: 100% for all axis</li> <li>Multiple indices</li> </ul> | (Ahn et al., 2019; Diao et al., 2019; Li<br>et al., 2020; Shao et al., 2022; Shen<br>et al., 2017; Wang, 2021; Yoon et al.,<br>2010) |

and locating of container keyholes by the spreader in loading and unloading of containers in port yards, the automatic insertion of the charging stake of the UUV platform among others. Despite the vast potential of these algorithms, the construction industry has yet to fully embrace them for alignment purposes in modular construction. Currently, the positioning and aligning of modules in construction heavily depend on manual labor. This process encounters similar challenges, as modular construction involves comparable volumetric units and the use of cranes. The efficiency and accuracy of modular construction assembly could be significantly improved by implementing algorithms to automate positioning and module stacking.

# 4.2. LiDAR-based capture technology

In recent years, remote sensing, surveying, and monitoring have seen remarkable advancements due to LiDAR technology. LiDAR, short for Light Detection and Ranging, is a remote sensing technology that has become increasingly popular in recent years due to its ability to generate precise and highly accurate 3D images of the Earth's surface (Zhang and Lin, 2017). This technology has become increasingly prevalent across various industries, including forestry, disaster management, weather prediction, construction, archaeology, autonomous vehicles, and more (Zhang and Zhu, 2023). LiDAR technology is a promising technique for achieving positioning accuracy in various applications. LiDAR technology is the most commonly utilized method for mapping as-built 3D construction models. Also referred to as 3D laser scanning, LiDAR is a leading technology for acquiring spatial data and generating as-built 3D models. It enables swift data acquisition with high sampling frequency and measurement accuracy (Roriz et al., 2022). The next section details how point cloud data acquired are processed for their respective application, such as 3D modeling and visualization, measurement, inspections, etc., as reviewed in the literature.

#### 4.2.1. LiDAR data processing techniques

In LiDAR technology, data collection is a crucial initial phase that lays the foundation for subsequent processing and significantly impacts the accuracy of 3D representations (Zhang and Lin, 2017). LiDAR systems capture detailed information about terrain, objects, and structures by ensuring meticulous data acquisition. The platforms for this data collection fall into three categories: ground-based systems, airborne

systems (manned aircraft or drones), and satellite-based systems, each offering unique advantages based on scope, accessibility, and desired detail (see Fig. 6, an example of the three categories of LiDAR technology) (Soilán et al., 2021). Point cloud preprocessing is essential for refining raw sensor data after data collection. This involves filtering out noise and distortion, georeferencing to align the data with known coordinate systems, and tiling the point cloud into manageable sections for efficient analysis (Chen et al., 2019; Roriz et al., 2022). Once preprocessed, point cloud segmentation utilizes machine learning algorithms or rule-based methods to classify points into categories such as ground, edges, and buildings, enabling object recognition and contextual understanding of complex 3D environments (Chen et al., 2019). Finally, feature extraction further enhances the utility of 3D data by identifying distinct characteristics within the segmented objects. This step focuses on key points, edges, and surfaces, allowing for advanced analyses and applications, including object recognition, classification, and modeling (Gumhold et al., 2001; Wang et al., 2020). These techniques create a comprehensive workflow that maximizes the potential of LiDAR data for various applications.

#### 4.2.2. Opportunities of LiDAR

LiDAR, an advanced detection method that merges laser and modern photoelectric detection technologies, can acquire 3D point clouds of ground objects (Raj et al., 2020). It's noteworthy that LiDAR can be deployed across various platforms, such as manual carrying, onboard, airborne, and on-board configurations. his versatility opens up numerous opportunities for leveraging LiDAR technology, which we explored further. LiDAR technology significantly enhances data collection efficiency by operating effectively under various light conditions, allowing data acquisition day and night. Leveraging optimal weather conditions during nighttime operations can improve this efficiency (Gatziolis and Andersen, 2008). One of the standout features of LiDAR is its ability to create highly detailed 3D maps. By emitting laser pulses and measuring their reflections off surfaces, LiDAR produces intricate and accurate representations of objects, terrain, and environments (Lu et al., 2024). This capability facilitates better decision-making, enhances spatial analysis, and improves environmental visualization. Moreover, LiDAR excels in low-light or nighttime conditions, as it emits its light sources in laser beams. This ensures reliable data collection, overcoming the limitations that traditional optical methods often face in similar

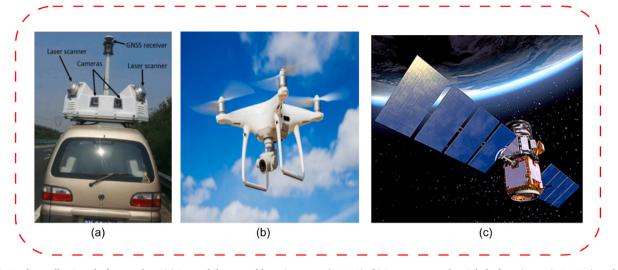


Fig. 6. LiDAR data collection platforms, where (a) is a mobile/ground base (Wang et al., 2018), (b) is an unmanned aerial platform (He and Li, 2020), and (c) is the satellite-based systems (Romsenter, 2012).

#### lighting scenarios (Guo et al., 2023).

Despite the many advantages of LiDAR, analyzing and interpreting the collected data can be challenging and time-consuming. However, LiDAR technology is highly compatible with other technologies, which can streamline this process (Roriz et al., 2022). For instance, some practitioners combine LiDAR with photogrammetry, a technique that creates models from two-dimensional images. This combination allows for gathering surface elevation data even in dense forests or thick vegetation, showcasing the versatility and effectiveness of LiDAR in various applications.

# 4.2.3. LiDAR-based applications

LiDAR, a remote sensing technology, has transformed numerous industries by enabling the creation of exceptionally precise 3D environmental representations. To this end, in the included studies, several researchers have proposed and implemented LiDAR-based methods for different purposes (Karsli et al., 2024; Radkowski, 2015). For instance, in railway construction, a fully automated method was developed by Soilán et al. (2021) to extract the rail alignment and position from 3D point cloud data obtained by LiDAR. The method could generate IFC-compliant files describing the railway geometry and location. It was tested on a large-scale dataset of a 90-km-long railway and showed small errors (order of cm) and high efficiency compared to manual delineation. Similarly, Radkowski (2015) introduces the method of verifying two parts in alignment. The method utilizes point cloud-based tracking to identify and track physical components. It incorporates a maximum likelihood estimation (MLE) approach to assess the probability of achieving accurate alignment between two parts. MLE is based on finding the parameter values that maximize the probability of the data, given a certain probability model (Myung, 2003). Also, MLE is based on a Gaussian error model and an expectation maximization (EM) algorithm. Therefore, their investigation demonstrates that the method can operate effectively with constrained observations, offering a numerical metric for model fitting accuracy. The results were evaluated through an offline simulation utilizing point cloud data, yielding encouraging outcomes.

In the port sector, Zhang et al. (2022) devised a LiDAR-based positioning and navigation system for a container-loading robot. This autonomous robot handles material loading and unloading within containers. The system aimed to identify the container's position and offer a navigation route for the robot during container handling in port terminals. LiDAR scanned the environment, detecting reflectors and the container outline. Subsequently, the global position and attitude of the robot were calculated using trilateral positioning principles and least square methods. The system achieved accurate positioning and orientation for the robot, which is essential for the container handling task.

These studies demonstrate the various applications of LiDAR technology and its advantages in positioning accuracy in different domains. LiDAR technology can provide high-resolution, real-time, and reliable data for positioning and alignment tasks. This suggests that these benefits can also be applied to modular construction, a construction method that involves assembling prefabricated modules on-site. For example, point cloud data can be gathered during the lifting and positioning of modules. This can then be processed to generate real-time scenarios for crane operators, aiding in the precise alignment of the modules during stacking. This innovative approach seamlessly addresses labor scarcity issues in modular construction.

#### 4.3. Other sensing-based technology

Sensors can detect and measure physical phenomena, such as light, sound, temperature, pressure, motion, etc. Sensors have various applications in different fields, such as transportation, communication, security, health care, etc. (Zhang and Zhu, 2023). One of the important applications of sensors is to facilitate the alignment of objects or systems that need to be connected or coordinated (Arshad and Zaved, 2024). This study reviewed existing studies on sensors and their application for alignment purposes. The included studies use different sensors and technologies to achieve alignment in different scenarios (Yue et al., 2003). For example, Jin Lee et al. (2010) proposed an automated electronic alignment system for the automatic alignment of a freight wagon and a trailer for the horizontal movement of containers. They employed electronic sensors such as ultrasonic, photo, and charge-coupled device (CCD) cameras to measure the distance and distortion ratio between the trailer and the wagon. The system displays the information to the driver on an LCD screen to help drivers stop the car in the permitted conditions. A horizontal transfer robot (HTR) moved the container from the wagon to the trailer without employing a crane. The technology employed for alignment purposes has proved significant as it efficiently helps align the two units.

Further, Xu and Wang (2020) designed and implemented an underwater acoustic sensor network-based detection system for detecting submerged containers in seas during transportation. The system employs a collaborative approach with multi-beacon nodes to enhance robustness and accuracy in positioning. Performance evaluation through simulation analysis demonstrates its effectiveness in addressing link breaks, particularly in challenging underwater environments. Additionally, it extends the detection area while improving positioning accuracy. Similarly, Bao and Zhang (2018) designed and implemented a container positioning system based on wireless sensor networks for efficient container yard management. The containers were located using two two-type symmetrical time of arrival (TS-TOA) positioning approaches.

These studies demonstrate some potential applications of sensors for alignment purposes in different domains. These sensors can provide various benefits, such as automation, accuracy, reliability, safety, efficiency, etc., for alignment tasks. However, some challenges and limitations need to be addressed, such as environmental factors, interference, noise, calibration, cost, maintenance, etc., that may affect the performance and quality of the sensors and their systems. Therefore, researchers in the AEC sector could explore the potential usage of sensors to achieve alignment purposes autonomously, especially in modular construction.

#### 5. Challenges of the technologies

This section highlights the challenges of employing the identified technologies to achieve alignment within their specific domains (see Fig. 7). As discussed in this section, exploring the limitations lays the groundwork for future directions in applying these technologies for module alignment in modular construction.

Image processing algorithms face significant performance challenges when dealing with low-contrast images, where the limited visual distinction between objects and their backgrounds reduces detection accuracy and processing speed (Kitayama et al., 2015; Lee and Park, 2019). Similarly, while effective for lock hole detection, AdaBoost recognition algorithms exhibit two key limitations: they require extensive training datasets to achieve optimal efficiency, and their performance degrades significantly when processing poor-quality video feeds or degraded images. These quality-related constraints can substantially reduce the algorithm's recognition accuracy in real-world applications (Huang et al., 2022).

Moreover, utilizing stereo vision techniques to extract positional information of containers in 3D space introduces the challenge of balancing computation time and accuracy in position estimation (Kitayama et al., 2015). In addition, LiDAR technology generates large volumes of point cloud data, necessitating advanced algorithms to extract relevant information for alignment tasks (Guo et al., 2023; Lu et al., 2024). However, one limitation of LiDAR is its restricted field of view (FoV); when generating a point cloud for pose calculation, objects outside this FoV can pose challenges, thereby impacting the technology's accuracy (Zhang et al., 2022). Finally, in underwater scenarios, the roll and pitch degrees of freedom are not actively controlled, which complicates accurate alignment since Kalman filters and template tracking rely on these parameters (Inniyaka et al., 2022).

# 6. Systematic framework for implementing automated module alignment in modular construction

The alignment of modules in modular construction can be significantly enhanced through the implementation of the aforementioned technologies. These technologies offer different approaches to addressing the challenges of precise module alignment and positioning. Based on the subsequently highlighted limitations of the technologies, the

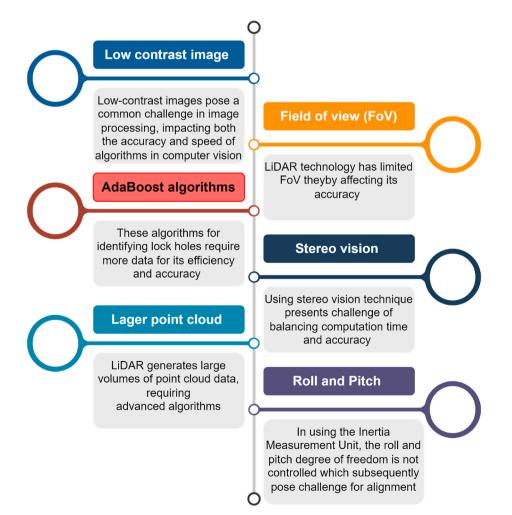


Fig. 7. Limitations of the technologies identified.

following explores the pertinent systematic directions for researchers for future discourse in adapting these technologies for module alignment in modular construction. Fig. 8 summarizes some of the research directions for future research in modular construction.

# 6.1. Computer Vision Technology in modular construction module alignment

Computer vision technology offers significant potential for automating module alignment in modular construction through various mechanisms. The technology employs sophisticated algorithms for realtime detection, recognition, and tracking, which has the potential to detect and track modules during the installation process. As evidenced in the port industry applications (Li et al., 2020; Zhang et al., 2023), computer vision systems can achieve high precision in alignment tasks, with reported accuracy rates exceeding 90% in container positioning. Computer vision can assist in several critical aspects of module alignment when applied to modular construction.

The implementation begins with a comprehensive image acquisition system with multiple cameras strategically positioned around the construction site and mounted on crane systems. These cameras continuously capture high-quality image streams of modules during the critical lifting and positioning phases. However, image contrast is vital in determining the efficacy and accuracy of algorithm processing tasks. To address this, image enhancement techniques must be applied to adjust contrast before processing, facilitating better edge and corner segmentation for precise module detection and informed decision-making during stacking operations. The core processing system would utilize advanced AI and deep learning algorithms, specifically adapting proven architectures like CNN and YOLO for module recognition and tracking. Based on Wang (2021) successful implementation of container lock hole detection, the system would employ a multi-stage processing pipeline. For steel modules where accurate recognition of lock holes is crucial for proper stacking, recognition algorithms like AdaBoost require extensive data collection and augmentation. Additionally, high-resolution cameras for video streams can improve algorithm efficiency. The initial image processing stage would incorporate advanced noise reduction algorithms specifically designed to handle construction site conditions and dynamic exposure adjustment for varying lighting conditions. Real-time image stabilization would compensate for camera movement, while color space optimization would enhance feature detection capabilities.

In the feature detection and recognition stage, traditional vision methods often lack robustness in detecting lock holes, especially in steel modules. Therefore, a hybrid vision method combining CNN, RNN, and LSTM is implemented, exploring synergies between different recognition and detection algorithms to detect corners, edges, and module orientation. The system implements specialized edge detection algorithms optimized for module geometries alongside sophisticated corner point detection using advanced Harris or FAST algorithms. Modulespecific feature descriptors developed using SIFT or SURF techniques integrate with deep learning models explicitly trained on modular construction elements.

Balancing computation time and accuracy presents a significant challenge when extracting positional information in 3D space using stereo-vision cameras. Hardware acceleration techniques like GPU computing or field-programmable gate arrays (FPGAs) help offload computationally intensive tasks and enhance stereo vision algorithm processing speed. The spatial tracking and position estimation phase incorporates multi-view geometry algorithms for precise 3D positioning. To address occlusion limitations, UAV integration enables continuous module monitoring, addressing shadow occlusion in 3D reconstruction while integrating detectors and trackers to enhance tracking performance and pre-emptively identify occlusion through entity matching.

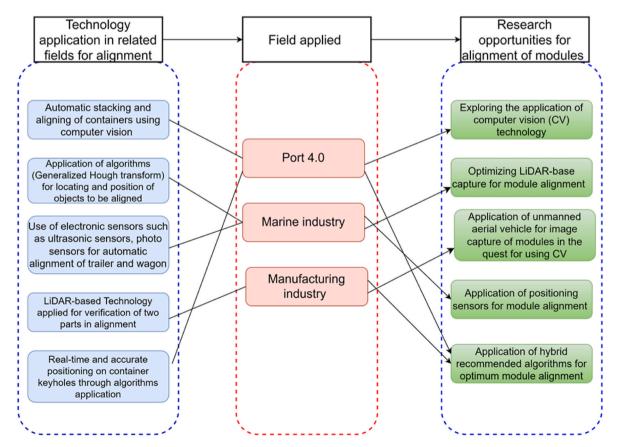


Fig. 8. Directions to future research for module alignment in modular construction.

Kalman filtering ensures smooth motion tracking while compensating for environmental interferences.

Implementing computer vision technology in modular construction necessitates extensive customization to tackle the unique challenges posed by this method. This customization involves recognizing various module types (steel, concrete, and composite modules) and detecting different interfaces like mechanical, welded, and bolted connections. The real-time processing capacity of computer vision technology allows for instant feedback by providing continuous position updates at a minimum refresh rate of 30 Hz and the capability to handle multiple data streams concurrently. Moreover, the technology can achieve submillimeter accuracy in alignment calculations, offering predictive movement suggestions for crane operators and delivering immediate feedback on alignment status and necessary corrections.

# 6.2. LiDAR technology in modular construction module alignment

LiDAR technology introduces unprecedented precision to module alignment through its advanced laser scanning and its ability to create precise 3D point cloud representations of construction sites and modules. These scanners, capable of operating at frequencies of up to 1 million points per second, establish precise baseline measurements crucial for accurate module positioning (Zhang and Lin, 2017; Zhang and Zhu, 2023). This initial documentation creates a detailed digital record of manufacturing tolerances that would directly inform alignment strategies during installation.

During the critical module installation phase, LiDAR technology performs continuous real-time scanning of module movement and positioning, generating dynamic point clouds that provide instant, highly accurate spatial data. To manage the substantial data generated, advanced compression and encoding techniques such as octree-based compression and progressive encoding reduce point cloud size while preserving essential information. This optimization ensures efficient processing without compromising alignment accuracy. The system requires two or more LiDAR sensors to achieve comprehensive site coverage and wider field of view. Integration with complementary sensors, such as cameras or radar, provides a more comprehensive view of the surroundings, enhancing overall perception capabilities for alignment tasks. This multi-sensor approach enables immediate comparison with Building Information Modeling (BIM) models, with comparative analysis occurring in real-time to provide immediate feedback about positioning accuracy relative to designed module locations.

The practical implementation requires interfacing with crane control systems through sophisticated data processing algorithms (see section 4.2). These algorithms would translate point cloud data into actionable positioning guidance through automated crane control inputs or visual feedback systems for operator guidance. The system would generate real-time positioning maps displaying the current module location relative to the target position, with color-coded visualization of alignment accuracy across all connection points. The system can detect discrepancies as small as 1-2 mm, enabling extremely precise alignment adjustments during the positioning process through automated crane control inputs or visual feedback systems for operator guidance. Beyond alignment applications, LiDAR technology offers the potential for automated quality inspection and verification of modules in modular construction. As demonstrated by Zhou et al. (2023) in tunnel lining segments, implementing LiDAR-based inspection can significantly reduce the time and costs associated with manual inspection while enhancing the accuracy and reliability of outcomes. This alignment and integration of quality verification capabilities create a comprehensive system for ensuring precise module installation and construction quality.

#### 6.3. Other sensor-based technologies in modular construction alignment

Other sensing technologies, including ultrasonic sensors, IMUs, and acoustic sensors, offer complementary approaches to module alignment in modular construction. When strategically implemented, these technologies could form an integrated sensing network that addresses the complex challenges of precise module positioning and alignment while reducing human errors and labor costs. The ultrasonic sensing system has a high frequency operating at 40–400 kHz (Xu and Wang, 2020), achieving distance measurements with accuracies of  $\pm 0.5$  mm at ranges up to 10 m (Bao and Zhang, 2018). The system would enable continuous distance monitoring between adjacent modules and real-time gap measurement at connection interfaces by deploying multiple sensor arrays to create overlapping measurements. This approach would be particularly valuable in low-visibility conditions where current visual systems face limitations.

We propose incorporating advanced MEMS-based IMUs on modules and crane hooks for enhanced motion tracking. These units, featuring three-axis accelerometers, gyroscopes, and magnetometers, could provide real-time orientation tracking with 0.1-degree accuracy. Operating at 200–1000 Hz sampling rates, these IMUs would capture rapid changes in module orientation and movement, essential for precise alignment during positioning operations. This capability would be particularly valuable for detecting vibrations and compensating for wind-induced movement.

The integrated sensor-based system combines real-time position and orientation data through a sophisticated processing pipeline. Advanced fusion algorithms, specifically the Extended Kalman Filter (EKF) for nonlinear motion estimation and the Unscented Kalman Filter (UKF) for state estimation merge data streams from various sensors to generate comprehensive positioning information. Environmental interference and sensor noise are managed through adaptive filtering techniques, while dynamic calibration mechanisms continuously adjust system parameters in response to changing site conditions. This integrated approach would ensure reliable and accurate positioning data throughout the module alignment process.

Implementing sensor-based technologies in modular construction requires careful consideration of sensor selection based on specific application scenarios. Different sensors have demonstrated various levels of accuracy and effectiveness in related domains such as transportation, marine applications, and port operations. Future research should focus on comparative analysis of different sensor types through simulations and experiments to evaluate their advantages and disadvantages in modular construction contexts. This evaluation would provide crucial insights for selecting optimal sensor combinations for specific alignment tasks.

Performance evaluation of these sensing technologies must consider multiple factors, including accuracy, reliability, cost-effectiveness, and environmental resilience. Integrating multiple sensor types requires sophisticated data fusion algorithms to leverage the strengths of each technology while compensating for individual limitations. This comprehensive approach ensures robust performance across varying construction conditions while maintaining the high precision required for successful module alignment.

Developing sensor-based alignment systems represents a significant advancement in modular construction technology, offering enhanced precision, reduced human error, and improved safety. The combination of ultrasonic sensing, IMU tracking, and other sensor technologies, integrated through sophisticated processing algorithms, provides a robust solution for the complex challenges of module alignment. Continued research and development in this area will further refine these systems, leading to more efficient and reliable modular construction processes.

#### 7. Performance comparison of alignment technologies

#### 7.1. Accuracy and precision

Computer vision technology demonstrates high accuracy in module positioning, the review reveals that computer vision has accuracy rates exceeding 90% (Li et al., 2020). The technology's precision is particularly evident in edge and corner detection, which is crucial for module alignment. However, as noted in section 4.1.2, its performance can be affected by environmental conditions such as lighting variations and occlusions. The system's ability to reduce alignment time by 27.8% while maintaining high precision makes it particularly effective for typical modular construction scenarios. On the other hand, LiDAR technology, according to Zhang and Lin (2017) and Zhang and Zhu (2023), achieves superior measurement accuracy at the millimeter level. LiDAR provides exceptional spatial measurement and positioning precision, which is particularly valuable for complex module arrangements. The technology's ability to create detailed point cloud data enables precise comparison between planned and actual module positions, though this comes with increased computational demands and higher implementation costs (Roriz et al., 2022). While other sensing technologies generally offer lower absolute accuracy than computer vision or LiDAR, they provide complementary precision in specific aspects. For instance, ultrasonic sensors and IMUs, as discussed by Jin Lee et al. (2010), offer reliable distance measurements and orientation tracking, respectively, even in conditions where primary systems might struggle.

#### 7.2. Environmental adaptability

Computer vision technology exhibits moderate to high adaptability in diverse environmental conditions, requiring additional processing and algorithm adjustments to sustain optimal performance. As discussed in section 4.1.1, various image processing techniques can be utilized to address environmental obstacles like low contrast and fluctuating lighting conditions. In contrast, LiDAR technology, as highlighted by Gatziolis and Andersen (2008), showcases superior environmental adaptability, effectively functioning in different lighting and weather conditions. Nevertheless, LiDAR technology may encounter challenges in handling large data volumes and processing demands in real-time applications. Complementary sensing technologies often display notable environmental adaptability within their specific functions, with ultrasonic sensors and IMUs maintaining reliable performance across diverse conditions, as outlined in the study by Xu and Wang (2020).

# 7.3. Processing speed and real-time performance

Computer vision technology exhibits robust real-time performance capabilities, allowing for immediate feedback, as evidenced in studies by (Zhang et al., 2023; Li et al., 2020). These studies highlight that modern algorithms facilitate the swift processing of visual data for real-time guidance. On the contrary, LiDAR technology, renowned for its high accuracy, may encounter challenges in real-time processing due to the handling of substantial data volumes. Section 4.2.2 notes that point cloud preprocessing and analysis could introduce minor delays in feedback provision with LiDAR technology. Furthermore, other sensing technologies, such as IMUs and acoustic sensors, typically deliver excellent real-time performance within their designated functions. Tang et al. (2022) emphasize that their effectiveness is optimized when integrated with primary alignment systems.

# 7.4. Cost-effectiveness and implementation

Computer vision is the most cost-effective solution for most modular construction module alignment applications. The study suggests that while requiring initial investment in cameras and processing systems, the technology offers a favorable balance between implementation costs and performance benefits, particularly given its significant reduction in alignment time. LiDAR technology, while offering superior accuracy, comes with higher implementation costs. Section 4.2 of the study suggests that these systems are most justified in projects requiring exceptional precision or handling complex module arrangements where the precision requirements can justify the additional expense. Additionally, other sensing technologies, like the IMU, generally present moderate implementation costs but require integration with primary systems for optimal effectiveness. These technologies are most cost-effective when used as complementary systems rather than standalone solutions (Tang et al., 2022).

## 8. Conclusions

This study reviewed autonomous alignment technologies in Port 4.0, manufacturing, and marine industries, highlighting their significant potential to address module alignment challenges in modular construction. Several findings were revealed through systematic literature and bibliometric analysis. Key findings indicate that computer vision technology is a primary solution, comprising six critical components forming a comprehensive alignment application framework. Image processing techniques enable accurate feature identification and measurement, while feature extraction capabilities facilitate precise positioning and orientation determination. Object detection systems support real-time tracking and alignment, working with segmentation processes and allowing detailed component identification. Finally, tracking mechanisms enable continuous monitoring during alignment procedures and recognition systems that accurately identify alignment points and surfaces. Furthermore, LiDAR technology also emerges as a cornerstone solution, excelling in high-precision 3D representations and providing accurate real-time positioning data. Its effectiveness in port operations suggests strong applicability in modular construction, particularly due to its robust performance in varying environmental conditions. Also, further findings reveal that other sensing technologies round out the technological landscape, each offering specific strengths to the alignment process. For instance, IMU sensors provide valuable orientation and motion data, while acoustic sensors offer effective proximity detection capabilities. Ultrasonic sensors enable precise distance measurements. While these technologies face environmental and maintenance challenges, they demonstrate essential supporting roles in comprehensive alignment systems.

The study identifies three critical development suggestions. The first priority is the creation of integrated systems that effectively combine computer vision, LiDAR, and complementary sensing technologies to leverage their respective strengths. Second, the field requires specialized algorithms, particularly focusing on edge detection and efficient point cloud processing to enhance alignment accuracy and speed. Third, robust multi-sensor calibration systems must be developed to ensure precise alignment in modular construction applications. These findings offer actionable insights for researchers and practitioners to advance technology adoption in modular construction, addressing challenges related to manual labor, dimensional complexities, and lengthy positioning procedures.

## CRediT authorship contribution statement

Sulemana Fatoama Abdulai: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. Tarek Zayed: Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization. Ibrahim Yahaya Wuni: Writing – review & editing, Supervision, Methodology. Maxwell Fordjour Antwi-Afari: Writing – review & editing, Visualization, Software, Methodology. Abdul-Mugis Yussif: Writing – original draft, Software, Methodology.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### Acknowledgment

This research was supported by the Department of Building and Real Estate at The Hong Kong Polytechnic University. This study is part of a broader Ph.D. research initiative focused on developing automated alignment systems for modular construction. This paper shares methodological foundations with related papers to be published by the same authors but with different scopes and objectives. The authors express sincere appreciation to the Editor and Reviewers for their thorough feedback, which substantially enhanced the quality of this manuscript.

# Data availability

Data will be made available on request.

#### References

- Ahn, S., Han, S., Al-Hussein, M., 2019. 2D drawing visualization framework for applying projection-based augmented reality in a panelized construction manufacturing facility: proof of concept. J. Comput. Civ. Eng. 33. https://doi.org/10.1061/(asce) cp.1943-5487.0000843.
- Alsakka, F., Assaf, S., El-Chami, I., Al-Hussein, M., 2023a. Computer vision applications in offsite construction. Autom. ConStruct. 154. https://doi.org/10.1016/j. auton.2023.104980.
- Alsakka, F., El-Chami, I., Yu, H., Al-Hussein, M., 2023b. Computer vision-based process time data acquisition for offsite construction. Autom. ConStruct. 149. https://doi. org/10.1016/j.autcon.2023.104803.
- Alvanchi, A., Azimi, R., Lee, S., Simaan, M., AbouRizk, M., Zubick, P., 2012. Off-site construction planning using discrete event simulation. J. Architect. Eng. 18, 114–122. https://doi.org/10.1061/(ASCE)AE.1943-5568.0000055.
- Arshad, H., Zayed, T., 2024. A multi-sensing IoT system for MiC module monitoring during logistics and operation phases. Sensors 24. https://doi.org/10.3390/ s24154900.
- Arshad, H., Zayed, T., 2022. Critical influencing factors of supply chain management for modular integrated construction. Autom. ConStruct. 144. https://doi.org/10.1016/j. autcon.2022.104612.
- Bao, X., Zhang, D., 2018. Design and implementation of container positioning system based on wireless sensor network. International Journal of Online Engineering 14, 129–142. https://doi.org/10.3991/ijoe.v14i05.8645.
- Bastian, M., Heymann, S., Jacomy, M., 2009. Gephi: an open source software for exploring and manipulating networks visualization and exploration of large graphs. In: Proceedings of the Third International ICWSM Conference, pp. 361–362, 2009.
- Chen, C., 2014. The CiteSpace manual [WWW Document]. URL. http://www.dobraca.co m/wp-content/uploads/2019/03/CiteSpacePracticalGuide-Nova-Sample1-50pp.pdf, 11.14.23.
- Chen, M., Feng, A., Mcalinden, R., Soibelman, L., 2019. Photogrammetric point cloud segmentation and object information extraction for creating virtual environments and simulations. J. Manag. Eng. 36. https://doi.org/10.1061/(ASCE.
- Dai, Z., Pang, S.D., Liew, J.R., 2020. Axial load resistance of grouted sleeve connection for modular construction. Thin-Walled Struct. 154. https://doi.org/10.1016/j. tws.2020.106883.
- Darko, A., Chan, A.P.C., Adabre, M.A., Edwards, D.J., Hosseini, M.R., Ameyaw, E.E., 2020. Artificial intelligence in the AEC industry: scientometric analysis and visualization of research activities. Autom. ConStruct. 112. https://doi.org/ 10.1016/j.autcon.2020.103081.
- Debrah, C., Chan, A.P.C., Darko, A., 2022. Artificial intelligence in green building. Autom. ConStruct. 137. https://doi.org/10.1016/j.autcon.2022.104192.
- Diao, Y., Cheng, W., Du, R., Wang, Y., Zhang, J., 2019. Vision-based detection of container lock holes using a modified local sliding window method. EURASIP J Image Video Process. https://doi.org/10.1186/s13640-019-0472-1, 2019.
- Ekanayake, B., Wong, J.K.W., Fini, A.A.F., Smith, P., 2021. Computer vision-based interior construction progress monitoring: a literature review and future research directions. Autom. ConStruct. 127. https://doi.org/10.1016/j.autcon.2021.103705.
- Enshassi, M.S.A., Walbridge, S., West, J.S., Haas, C.T., 2019. Integrated risk management framework for tolerance-based mitigation strategy decision support in modular construction projects. J. Manag. Eng. 35. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000698.
- Faris, N., Zayed, T., Abdelkader, E.M., Fares, A., 2023. Corrosion assessment using ground penetrating radar in reinforced concrete structures: influential factors and analysis methods. Autom. ConStruct. 156. https://doi.org/10.1016/j. autcon.2023.105130.

- Gatziolis, D., Andersen, H.-E., 2008. A Guide to LIDAR Data Acquisition and Processing for the Forests of the Pacific Northwest. United state. <u>https://doi.org/10.2737/PNW-GTR-768</u>.
- Gumhold, S., Scott MacLeod, R., Wang Y, X., MacLeod b, R., 2001. Feature extraction from point clouds. In: IMR, pp. 293–305.
- Guo, W., Pan, Z., Liang, Y., Xi, Z., Zhong, Z.C., Feng, J., Zhou, J., 2023. LiDAR-based person Re-identification. https://doi.org/10.48550/arXiv.2312.03033.
- Han, S.H., Hasan, S., Bouferguène, A., Al-Hussein, M., Kosa, J., 2015. Utilization of 3D visualization of mobile crane operations for modular construction on-site assembly. J. Manag. Eng. 31. https://doi.org/10.1061/(asce)me.1943-5479.0000317.
- Harden, A., Thomas, J., 2010. Mixed Methods and Systematic Reviews: Examples and Emerging Issues. Sage Publications Corporation, pp. 749–774. https://doi.org/ 10.4135/9781506335193.n29.
- He, G.B., Li, L.L., 2020. Research and application of LiDAR technology in cadastral surveying and mapping. In: International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives. International Society for Photogrammetry and Remote Sensing, pp. 33–37. https://doi.org/10.5194/isprsarchives-XLIII-81-2020-33-2020.
- Heyvaert, M., Hannes, K., Onghena, P., 2016. Using Mixed Methods Research Synthesis for Literature Reviews: the Mixed Methods Research Synthesis Approach. Sage Publications.
- Huang, J., Liu, J., Gong, H., Deng, X., 2022a. A comprehensive review of loosening detection methods for threaded fasteners. Mech. Syst. Signal Process. 168. https:// doi.org/10.1016/j.ymssp.2021.108652.
- Huang, Q., Zhang, Y., Huang, Y., Mi, C., Zhang, Z., Mi, W., 2022b. Two-stage container keyhole location algorithm based on optimized SSD and adaptive threshold. J. Comput. Methods Sci. Eng. 22, 1559–1571. https://doi.org/10.3233/JCM-226135.
- Hussein, M., Darko, A., Eltoukhy, A.E.E., Zayed, T., 2022. Sustainable logistics planning in modular integrated construction using multimethod simulation and taguchi approach. J. Construct. Eng. Manag. 148. https://doi.org/10.1061/(asce)co.1943-7862.0002273.
- Hussein, M., Zayed, T., 2021. Crane operations and planning in modular integrated construction: mixed review of literature. Autom. ConStruct. 122. https://doi.org/ 10.1016/j.autcon.2020.103466.
- Inniyaka, I.R., Solpico, D.B., Hamada, D., Sugino, A., Tanaka, R., Nishida, Y., Ishii, K., 2022. Underwater acoustic positioning based on MEMS microphone for a lightweight autonomous underwater vehicle "kyubic,". In: Proceedings of International Conference on Artificial Life and Robotics, pp. 349–353.
- Jan van Eck, N., Waltman, L., 2014. VOSviewer Manual [WWW Document]. URL. https://www.vosviewer.com/documentation/Manual\_VOSviewer\_1.6.8.pdf, 11.14.23.
- Jin Lee, Y., Won Park, S., Cheol Cho, H., Seop Han, D., Jo Han, G., Soon Lee, K., 2010. A development of auto alignment system between trailer and freight wagon using electronic sensors for intermodal transportation. In: IECON 2010-36th Annual Conference on IEEE Industrial Electronics Society. IEEE, pp. 1217–1221.
- Karsli, B., Yilmazturk, F., Bahadir, M., Karsli, F., Ozdemir, E., 2024. Automatic building footprint extraction from photogrammetric and LiDAR point clouds using a novel improved-Octree approach. J. Build. Eng. 82. https://doi.org/10.1016/j. iobc.2023.108281.
- Kitayama, D., Touma, Y., Hagiwara, H., Asami, K., Komori, M., 2015. 3D map construction based on structure from motion using stereo vision. In: 2015 International Conference on Informatics, Electronics and Vision (ICIEV).
- Lee, Y.J., Park, M.W., 2019. 3D tracking of multiple onsite workers based on stereo vision. Autom. ConStruct. 98, 146–159. https://doi.org/10.1016/j. autom 2018.11.017
- Leo, M., Medioni, G., Trivedi, M., Kanade, T., Farinella, G.M., 2017. Computer vision for assistive technologies. Comput. Vis. Image Understand. 154, 1–15. https://doi.org/ 10.1016/j.cviu.2016.09.001.
- Li, Y., Fang, L., Fang, J., 2020. Container keyhole positioning based on deep neural network'. Int. J. Wireless Mobile Comput. 18, 40–50. https://doi.org/10.1504/ IJWMC.2020.10026470.
- Lin, K.L., Fang, J.L., 2013. Applications of computer vision on tile alignment inspection. Autom. ConStruct. 35, 562–567. https://doi.org/10.1016/j.autcon.2013.01.009.
- Lu, Y., Sun, Z., Shao, J., Guo, Q., Huang, Y., Fei, S., Chen, Y., 2024. LiDAR-forest dataset: LiDAR point cloud simulation dataset for forestry application. ArXiv. https://doi. org/10.48550/arXiv.2402.04546 [WWW Document].
- Martínez-Aires, M.D., López-Alonso, M., Martínez-Rojas, M., 2018. Building information modeling and safety management: a systematic review. Saf. Sci. 101, 11–18. https:// doi.org/10.1016/j.ssci.2017.08.015.
- Marzouk, M., Abubakr, A., 2016. Decision support for tower crane selection with building information models and genetic algorithms. Autom. ConStruct. 61, 1–15. https://doi.org/10.1016/j.autcon.2015.09.008.
- Muddassir, M., Zayed, T., Ali, A.H., Elrifaee, M., Abdulai, S.F., Yang, T., Eldemiry, A., 2025. Automation in tower cranes over the past two decades (2003–2024). Autom. ConStruct. 170. https://doi.org/10.1016/j.autcon.2024.105889.
- Myung, I.J., 2003. Tutorial on maximum likelihood estimation. J. Math. Psychol. 47, 90–100. https://doi.org/10.1016/S0022-2496(02)00028-7.
- Ohene, E., Chan, A.P.C., Darko, A., 2022. Review of global research advances towards net-zero emissions buildings. Energy Build. 266. https://doi.org/10.1016/j. enbuild.2022.112142.
- Olawumi, T.O., Chan, D.W.M., Ojo, S., Yam, M.C.H., 2022. Automating the modular construction process: a review of digital technologies and future directions with blockchain technology. J. Build. Eng. 46. https://doi.org/10.1016/j. jobe.2021.103720.

Opoku, D.G.J., Perera, S., Osei-Kyei, R., Rashidi, M., 2021. Digital twin application in the construction industry: a literature review. J. Build. Eng. 40. https://doi.org/ 10.1016/j.jobe.2021.102726.

- Pan, M., Yang, Y., Zheng, Z., Pan, W., 2022. Artificial intelligence and robotics for prefabricated and modular construction: a systematic literature review. J. Construct. Eng. Manag. 148. https://doi.org/10.1061/(asce)co.1943-7862.0002324.
- Pan, W., Hon, C.K., 2020. Briefing: modular integrated construction for high-rise buildings. Proc. Inst. Civ. Eng.: Municip. Eng. 173, 64–68. https://doi.org/10.1680/ jmuen.18.00028.
- Panahi, R., Louis, J., Podder, A., Swanson, C., Pless, S., 2023. Bottleneck detection in modular construction factories using computer vision. Sensors 23. https://doi.org/ 10.3390/s23083982.
- Park, D., Park, S., Byun, S., Jung, S., Kim, M., 2006. Container chassis alignment and measurement based on vision for loading and unloading containers automatically. In: 2006 International Conference on Hybrid Information Technology. IEEE, pp. 582–587. https://doi.org/10.1109/ICHIT.2006.253665.
- Peng, J., Hou, C., 2023. Effects of constructional tolerances on lateral resistance of steel–concrete composite modular buildings with various connection rigidity. Structures 57. https://doi.org/10.1016/j.istruc.2023.105226.
- Prats, M., Palomeras, N., Ridao, P., Sanz, P.J., 2012. Template tracking and visual servoing for alignment tasks with autonomous underwater vehicles. In: IFAC Proceedings Volumes (IFAC-PapersOnline). IFAC Secretariat, pp. 256–261. https:// doi.org/10.3182/20120919-3-IT-2046.00044.
- Putz, V., Stangl, M., Kohlberger, C., Naderer, R., 2019. Computer vision approach for the automated tool alignment of an orbital sanding robot. In: IFAC-PapersOnLine. Elsevier B.V., pp. 19–24. https://doi.org/10.1016/j.ifacol.2019.11.643
- Qi, B., Razkenari, M., Costin, A., Kibert, C., Fu, M., 2021. A systematic review of emerging technologies in industrialized construction. J. Build. Eng. 39. https://doi. org/10.1016/j.jobe.2021.102265.
- Radkowski, R., 2015. A point cloud-based method for object alignment verification for augmented reality applications. In: Proceedings of the ASME 2015 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference, pp. 1–10. https://doi.org/10.1115/DETC2015-47842.
- Raj, T., Hashim, F.H., Huddin, A.B., Ibrahim, M.F., Hussain, A., 2020. A survey on LiDAR scanning mechanisms. Electronics (Switzerland) 9. https://doi.org/10.3390/ electronics9050741.
- Rajanayagam, H., Poologanathan, K., Gatheeshgar, P., Varelis, G.E., Sherlock, P., Nagaratnam, B., Hackney, P., 2021. A-State-Of-The-Art review on modular building connections. Structures 34, 1903–1922. https://doi.org/10.1016/j. istruc.2021.08.114.
- Romsenter, N., 2012. Satellite missions catalogue [WWW Document]. AISSat-1 and 2. URL. https://www.eoportal.org/satellite-missions/aissat-1-2#eop-quick-facts-sect ion, 12.18.24.
- Roriz, R., Cabral, J., Gomes, T., 2022. Automotive LiDAR technology: a survey. IEEE Trans. Intell. Transport. Syst. 23, 6282–6297. https://doi.org/10.1109/ TUTS.2021.3086804.
- Shahtaheri, Y., Rausch, C., West, J., Haas, C., Nahangi, M., 2017. Managing risk in modular construction using dimensional and geometric tolerance strategies. Autom. ConStruct. 83, 303–315. https://doi.org/10.1016/j.autcon.2017.03.011.
- Shao, J., Zhou, Y., Li, W., Wang, G., 2022. Automatic container recognition and positioning method based on hough transform and mask RCNN. In: Proceedings of 2022 8th IEEE International Conference on Cloud Computing and Intelligence Systems, CCIS 2022. Institute of Electrical and Electronics Engineers Inc., pp. 84–89. https://doi.org/10.1109/CCIS57298.2022.10016394
- Sharma, N., Kalbar, P.P., Salman, M., 2022. Global review of circular economy and life cycle thinking in building Demolition Waste Management: a way ahead for India. Build. Environ. 222. https://doi.org/10.1016/j.buildenv.2022.109413.
- Shen, Y., Mi, W., Zhang, Z., 2017. A Positioning Lockholes of Container Corner Castings Method Based on Image Recognition, vol. 24. Polish Maritime Research, pp. 95–101. https://doi.org/10.1515/pomr-2017-0110.
- Soilán, M., Nóvoa, A., Sánchez-Rodríguez, A., Justo, A., Riveiro, B., 2021. Fully automated methodology for the delineation of railway lanes and the generation of IFC alignment models using 3D point cloud data. Autom. ConStruct. 126. https:// doi.org/10.1016/j.autcon.2021.103684.
- Srisangeerthanan, S., Hashemi, M.J., Rajeev, P., Gad, E., Fernando, S., 2020. Review of performance requirements for inter-module connections in multi-story modular buildings. J. Build. Eng. 28. https://doi.org/10.1016/j.jobe.2019.101087.
- Sun, W., Antwi-Afari, M.F., Mehmood, I., Anwer, S., Umer, W., 2023. Critical success factors for implementing blockchain technology in construction. Autom. ConStruct. 156. https://doi.org/10.1016/j.autcon.2023.105135.

Szeliski, R., 2010. Computer Vision: Algorithms and Applications, first ed.

- Taiwo, R., Bello, I.T., Abdulai, S.F., Yussif, A.-M., Salami, B.A., Saka, A., Ben Seghier, M. E.A., Zayed, T., 2025. Generative artificial intelligence in construction: a Delphi approach, framework, and case study. Alex. Eng. J. 116, 672–698. https://doi.org/ 10.1016/j.aej.2024.12.079.
- Taiwo, R., Hussein, M., Zayed, T., 2022. An integrated approach of simulation and regression analysis for assessing productivity in modular integrated construction projects. Buildings 12. https://doi.org/10.3390/buildings12112018.
- Taiwo, R., Shaban, I.A., Zayed, T., 2023. Development of sustainable water infrastructure: a proper understanding of water pipe failure. J. Clean. Prod. 398. https://doi.org/10.1016/j.jclepro.2023.136653.
- Tang, J., Luo, H., Chen, W., Wong, P.K.Y., Cheng, J.C.P., 2022. IMU-based full-body pose estimation for construction machines using kinematics modeling. Autom. ConStruct. 138. https://doi.org/10.1016/j.autcon.2022.104217.

- Van De Sande, K., Gevers, T., Snoek, C., 2010. Evaluating color descriptors for object and scene recognition. IEEE Trans. Pattern Anal. Mach. Intell. 32, 1582–1596. https:// doi.org/10.1109/TPAMI.2009.154.
- van Eck, N.J., Waltman, L., 2010. Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics 84, 523–538. https://doi.org/10.1007/ s11192-009-0146-3.
- Wang, J., Zhao, H., Wang, D., Chen, Y., Zhang, Z., Liu, H., 2018. GPS trajectory-based segmentation and multi-filter-based extraction of expressway curbs and markings from mobile laser scanning data. Eur J Remote Sens 51, 1022–1035. https://doi.org/ 10.1080/22797254.2018.1533388.
- Wang, L., Jiang, W., Xiao, L., Li, H., Chen, Z., Liu, Y., Dou, J., Li, S., Wang, Q., Han, W., Wang, Y., Liu, H., 2020a. Self-reporting and splitting nanopomegranates potentiate deep tissue cancer radiotherapy via elevated diffusion and transcytosis. ACS Nano 14, 8459–8472. https://doi.org/10.1021/acsnano.0c02674.
- Wang, M., Wang, C.C., Sepasgozar, S., Zlatanova, S., 2020b. A systematic review of digital technology adoption in off-site construction: current status and future direction towards industry 4.0. Buildings. https://doi.org/10.3390/ buildings10110204.
- Wang, X., 2021. Recognition and positioning of container lock holes for intelligent handling terminal based on convolutional neural network. Trait. Du. Signal 38, 467–472. https://doi.org/10.18280/ts.380226.
- Wang, Z., Song, P., Pauly, M., 2021. State of the art on computational design of assemblies with rigid parts. Comput. Graph. Forum 40, 633–657. https://doi.org/ 10.1111/cgf.142660.
- Wiley, V., Lucas, T., 2018. Computer vision and image processing: a paper review. International Journal of Artificial Intelligence Research 2, 22. https://doi.org/ 10.29099/ijair.v2i1.42.
- Wuni, I.Y., Shen, G.Q., 2020. Barriers to the adoption of modular integrated construction: systematic review and meta-analysis, integrated conceptual framework, and strategies. J. Clean. Prod. 249. https://doi.org/10.1016/j. jclepro.2019.119347.
- Xu, M., Wang, Y., 2020. An underwater sensor networks based cooperative positioning system for falling water containers. In: Lecture Notes in Electrical Engineering. Springer Verlag, pp. 784–788. https://doi.org/10.1007/978-981-13-6508-9 95.
- Xu, S., Wang, J., Shou, W., Ngo, T., Sadick, A.M., Wang, X., 2021. Computer vision techniques in construction: a critical review. Arch. Comput. Methods Eng. 28, 3383–3397. https://doi.org/10.1007/s11831-020-09504-3.
- Yang, M., Kpalma, K., Ronsin, J., Ronsin, J.A., Mingqiang, Y., Kidiyo, K., Joseph, R., 2008. Survey of shape feature extraction techniques. Peng-Yeng Yin.
- Yin, X., Liu, H., Chen, Y., Al-Hussein, M., 2019. Building information modelling for offsite construction: review and future directions. Autom. ConStruct. 101, 72–91. https://doi.org/10.1016/j.autcon.2019.01.010.
- Yoon, H.-J., Hwang, Y.-C., Cha, E.-Y., 2010. Real-time container position estimation method using stereo vision for container auto-landing system. In: International Conference on Control, Automation and Systems 2010. IEEE, pp. 872–876.
- Yu, A., Wang, Y., Li, H., Qiu, B., 2023. Automatic alignment method of underwater charging platform based on monocular vision recognition. J. Mar. Sci. Eng. 11. https://doi.org/10.3390/jmse11061140.
- Yue, N., Sharif Khodaei, Z., Aliabadi, M.H., Coverley, P.T., Staszewski, W.J., 2003. Impact damage location in composite structures using optimized sensor triangulation procedure. Smart Mater. Struct.
- Yussif, A.M., Zayed, T., Taiwo, R., Fares, A., 2024. Promoting sustainable urban mobility via automated sidewalk defect detection. Sustain. Dev. https://doi.org/10.1002/ sd.2999.
- Zhang, C., Ai, C., Yan, J., Wang, J., Ren, G., Hu, R., 2022. LiDAR-based positioning and navigation technology for container loading robot. In: ACM International Conference Proceeding Series. Association for Computing Machinery, pp. 208–211. https://doi. org/10.1145/3584376.3584414.

Zhang, J., Lin, X., 2017. Advances in fusion of optical imagery and LiDAR point cloud applied to photogrammetry and remote sensing. Int J Image Data Fusion 8, 1–31. https://doi.org/10.1080/19479832.2016.1160960.

- Zhang, S., Rong, X., Bakhtawar, B., Tariq, S., Zayed, T., 2021. Assessment of feasibility, challenges, and critical success factors of MiC projects in Hong Kong. J. Architect. Eng. 27. https://doi.org/10.1061/(asce)ae.1943-5568.0000452.
- Zhang, Y., Huang, Y., Zhang, Z., Postolache, O., Mi, C., 2023a. A vision-based container position measuring system for ARMG. Measurement and Control (United Kingdom) 56, 596–605. https://doi.org/10.1177/00202940221110932.
- Zhang, Z., Wong, M.O., Pan, W., 2023b. Virtual reality enhanced multi-role collaboration in crane-lift training for modular construction. Autom. ConStruct. 150. https://doi. org/10.1016/j.autcon.2023.104848.
- Zhang, Z., Zhu, L., 2023. A review on unmanned aerial vehicle remote sensing: platforms, sensors, data processing methods, and applications. Drones 7. https://doi.org/ 10.3390/drones7060398.
- Zheng, Z., Pan, M., Yang, Y., Pan, W., 2023. Motion planning for efficient and safe module transportation in modular integrated construction. Comput. Aided Civ. Infrastruct. Eng. 38, 580–600. https://doi.org/10.1111/mice.12835.
- Zheng, Z., Zhang, Z., Pan, W., 2020. Virtual prototyping- and transfer learning-enabled module detection for modular integrated construction. Autom. ConStruct. 120. https://doi.org/10.1016/j.autcon.2020.103387.
- Zhou, Z., Zheng, Y., Zhang, J., Yang, H., 2023. Fast detection algorithm for cracks on tunnel linings based on deep semantic segmentation. Front. Struct. Civ. Eng. 17, 732–744. https://doi.org/10.1007/s11709-023-0965-y.
- Zhu, A., Zhang, Z., Pan, W., 2023. Technologies, levels and directions of crane-lift automation in construction. Autom. ConStruct. 153. https://doi.org/10.1016/j. autcon.2023.104960.