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Review

Sensor adoption in the construction industry: Barriers, opportunities, and strategies

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ABSTRACT

This paper examines the underutilization of sensors in the construction industry despite their significant potential for improving performance. A systematic review was conducted on research published between 2004 and 2024, identifying 11 key barriers such as the need for advanced skill sets and user-centric design, lack of standardized practices, and challenges in data networks and management. The study applied both quantitative descriptive analysis and qualitative content analysis to explore these barriers across five stages of sensor adoption. A total of 63 articles were thoroughly reviewed to identify thematic patterns and chronological trends. The findings highlight critical areas that require attention, including the development of standardized protocols, enhancing data-driven decision-making with advanced analytics, and fostering industry-wide training programs. Additionally, leveraging Lean Construction 4.0 principles is proposed to address these challenges. The insights from this research aim to support the construction industry in integrating sensor technologies more effectively, leading to greater efficiency and improved performance.

1. Introduction

The construction industry is a significant component of the global economy, with annual expenditures on construction-related goods and services surpassing $10 trillion and contributing over 13 % to the global GDP in 2022 [1]. Despite its substantial size, the sector accounted for only a $12.3 billion market share in 2022, representing less than 6 % of its total market potential [2]. In contrast, the manufacturing industry, which has a similar contribution to the global GDP, had more than double the market share of sensors in 2022 [3,4]. The reasons behind the successful adoption of sensors in the manufacturing industry include the controlled environments that allow for easier integration of automated systems, as well as early investments in Industry 4.0 initiatives supported by clear policies and standards [5]. Additionally, the industry's focus on lean principles aligns well with sensor technologies and facilitates real-time process optimization [6]. The limited use of sensors in the construction industry may stem from skepticism about the cost-benefit ratio of these technologies, along with a reliance on traditional operational methods and a potential underestimation of the benefits sensors offer [7]. However, key transferable practices from other industries, such as developing standardization protocols, investing in workforce training, and establishing industry-wide policies to promote digital innovation, can be applied to the construction industry. Sensors are pivotal for measuring a variety of metrics and enhancing the integration and utility of data across various platforms. Significantly, implementing sensors has led to a positive return on investment for 94 % of businesses included in a global report, highlighting their positive impact [8]. In addition, the construction sector is a significant contributor to environmental challenges, such as carbon emissions, which underscores the potential for digitalization and sensor technology to not only improve operational efficiencies but also enhance sustainability performance. Sensor technologies offer significant environmental benefits by enabling real-time monitoring and precise control over resource use in construction projects. For instance, sensors can help optimize energy consumption by adjusting lighting and HVAC systems based on occupancy or environmental conditions, leading to energy savings of up to 47 % from lighting [9] and 30 % from HVAC [10]. Furthermore, the ability to track material usage and reduce waste contributes to more sustainable practices, with studies indicating that sensors can offer opportunities to improve the efficiency of waste collection and reducing carbon footprint [11,12]. In addition to minimizing waste and energy use, sensors also support environmental monitoring, ensuring

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compliance with regulations related to emissions, water usage, and air quality [13]. These capabilities position sensor technology as a key contributor to environmental sustainability in the construction industry. The widespread use of sensors in the manufacturing sector, particularly under Industry 4.0, exemplifies how they can revolutionize data acquisition, productivity, and flexibility in processes through increased automation and digitalization.

With similar goals to Industry 4.0, Construction 4.0 also aims to apply automation and digitalization technologies to revolutionize the construction industry. In their handbook, Sawhney, et al. [14] defined Construction 4.0 as a transformative framework tailored to the construction industry that integrates digital technologies to enhance the efficiency and productivity of designing, constructing, and operating built environment assets. In Construction 4.0, sensors play a crucial role in enabling smart, connected, and data-driven construction processes [14]. They enable construction production monitoring through resource and material tracking, quality control, and the integration of real-time data into Building Information Modeling (BIM) systems, thereby providing a solid approach to create Digital Twins (DTs) for digital built environment management [15–18]. Sensors also facilitate real-time monitoring of structural health, safety management, and environmental conditions, thereby ensuring safety, compliance, and sustainability [19–25]. Furthermore, they are essential for the implementation of automation and robotics in construction, providing the necessary data for machines to operate safely and effectively [26–28]. Sensor applications in Construction 4.0 have been successfully implemented in various projects, demonstrating significant benefits in safety, efficiency, and resource management. For example, in a large-scale construction project, 4D BIM was utilized to optimize logistics, reducing transportation waste and improving time efficiency on-site [29]. Additionally, in tunnel construction, Wireless Sensor Networks (WSNs) were deployed to monitor hazardous gases, temperature, and humidity. This data was integrated into a BIM model for real-time monitoring, providing early warnings of dangerous conditions and improving safety management [30]. Furthermore, the integration of Internet of Things (IoT) technologies in smart buildings has enhanced energy management and workplace safety by enabling automated monitoring of physical environments, reducing labor costs, and minimizing safety risks [30]. Overall, sensors are instrumental in enhancing the productivity, safety, and sustainability of projects in the era of Construction 4.0.

Despite the importance of sensors in the construction industry, several challenges hinder their widespread adoption. Sawhney, et al. [14] highlighted various obstacles to sensor implementation, such as the need for enhanced skills, lack of standards, data security concerns, and legal uncertainty. Additionally, other studies have explored more specific challenges associated with sensor applications. For instance, Rao et al. [31] identified issues in real-time monitoring of construction sites, including sensor location difficulties, sensor technological and physical limitations, complex data processing, and interpretation challenges. In the context of construction safety monitoring with wearable sensors, Awolusi et al. [32] pointed out challenges related to connectivity, power consumption, wearability, and interoperability. Edirisinghe [33] addressed challenges in the digitalization of construction sites, such as technology limitations, reliability, usability, and scalability. Arabshahi et al. [7] categorized the barriers in their review as cost-related, technology-related, and people-related.

Although extensive research efforts have been devoted on developing and optimizing sensors for the construction industry, their adoption in construction remains considerably low and highly concentrated on cameras, laser scanners, and Global Navigation Satellite System (GNSS) [34,35]. One of the reasons behind this situation is that existing research works have often taken a siloed approach, investigating the challenges associated with particular application purposes or types of sensors. This limited view overlooks the broad and interconnected nature of the challenges present in the construction industry and the dynamic nature of construction projects. While many challenges have been identified, the connections between them are often ignored, and these connections are key to categorizing the challenges into clear groups of barriers. Without an organized classification of these barriers, proposing solutions and future directions becomes a complex task, which in turn hinders the industry's capacity to embrace sensor technology. To this end, there is a notable gap in the literature: a comprehensive, holistic examination that considers the barriers as well as their relationships to sensor adoption in a two-fold manner—both in terms of their intended application purposes within the construction processes and the diversity of sensor technologies available. Conducting a detailed and comprehensive analysis that weaves together these aspects is crucial for a clear understanding of why the construction industry hesitates to adopt a wider array of sensor technologies—an adoption that could lead to greater efficiency, enhanced safety, and cost reductions. Therefore, this paper aims to fill this gap by utilizing a mixed approach of both quantitative and qualitative studies to delve into the challenges of developing and implementing sensors in the construction field, and then grouping them into distinct barriers while considering the relationship between the barriers. After identifying and understanding the challenges and how they are interrelated, they will be consolidated and examined as distinct barriers. By analyzing these barriers, future strategies to overcome them can be suggested, which seek actionable insights. Consequently, the research questions (RQs) for this paper are:

RQ 1. : What are the primary barriers and their relationships in the adoption of sensors within the construction industry, considering the identified gap in comprehensive, holistic examinations that consider both the application purposes and diversity of sensor technologies?

RQ 2. : What are the suggested strategies to overcome the identified barriers in sensor adoption within the construction industry, addressing the existing gap in actionable insights to enhance efficiency, safety, and cost-effectiveness?

This paper presents a systematic review of recent advancements in sensor development and optimization for construction, alongside an analysis of the challenges faced in their adoption. By integrating both quantitative and qualitative analyses, the review offers a comprehensive understanding of the barriers to sensor adoption, providing deeper insights into the issues encountered in previous studies. The expected research outcomes (ROs) include the identification and summarization of key barriers to sensor adoption, along with a detailed analysis of how these barriers are interrelated (RO1). Furthermore, the research aims to explore and identify trends and opportunities for overcoming these barriers (RO2). This will result in actionable recommendations (RO3), which include specific strategies for implementation, clearly defined research questions, and an assessment of the potential challenges in addressing these barriers.

To achieve these outcomes, a mixed-methods approach is employed. Quantitative methods, such as statistical analysis, assess chronological sensor adoption rates and their impact on construction performance, while qualitative methods, including content analysis, provide deeper insights into the nature of these barriers and opportunities for resolution. Through this approach, 11 key barriers were identified, and their chronological trends were analyzed, resulting in suggestions for future research directions and practical strategies to advance sensor adoption in the construction industry.

The rest of the paper is structured into six sections: Section 2 discusses the research design; Section 3 discusses the research method, including search protocol, databases, literature selection criteria, and the selection results; Section 4 provides literature analysis, which includes descriptive analysis, content analysis, and quantitative analysis; Section 5 is for the main discussion, where barriers are discussed in the context of their purposes and sensors applied. Research directions are suggested after the analysis of the trends of barriers; Section 6 concludes this paper with a summary of findings, limitations, and future research recommendations.

2. Research design

A systematic literature review (SLR) was selected as the most appropriate methodology for this study to ensure a thorough and rigorous synthesis of the available research. As outlined by Xiao and Watson [36], SLRs are designed to systematically collect, appraise, and synthesize relevant studies, providing comprehensive and replicable insights into the research area. Compared to other review types, such as scoping reviews or rapid reviews, an SLR offers the advantage of methodical data extraction and synthesis, which is essential for identifying research gaps, trends, and contradictions within the field of sensor adoption in the construction industry. This method was chosen over alternative approaches, such as critical or narrative reviews, to ensure adherence to a transparent and structured process as suggested by [37], offering a balanced evaluation of both quantitative and qualitative findings.

The SLR conducted in this study follows the PRISMA 2020 guidelines [38], ensuring transparent and comprehensive reporting throughout the review process. PRISMA provides a widely recognized framework designed to enhance the clarity and replicability of systematic reviews [39]. A three-stage research design diagram is drawn in accordance with the PRISMA 2020 guidelines, as shown in Fig. 1. The initial stage involved identifying relevant studies that directly corresponded to the two research questions. The second stage shifted focus to the content of

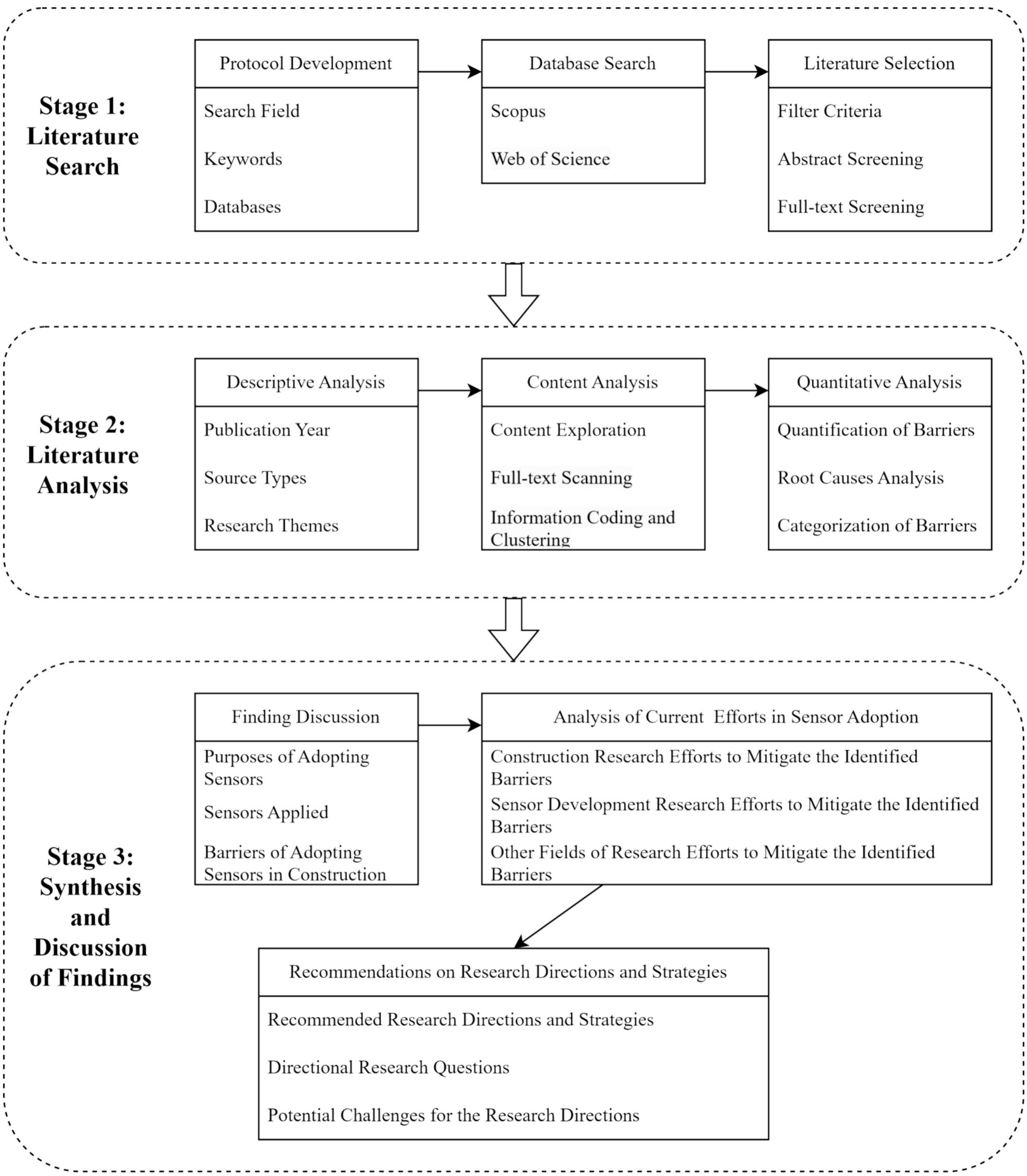

Fig. 1. Research design.

the chosen studies, with an analysis conducted to understand their characteristics and key ideas. The key characteristics and ideas from the reviewed literature focus on themes, trends, and patterns related to sensor adoption barriers, technological advancements, and challenges specific to the construction industry. Finally, the third stage aimed to utilize the insights garnered from the literature analysis to address the two research questions posed at the outset. Additionally, methodologies from Petticrew and Roberts [40] were consulted to reinforce the rigor of data collection and synthesis.

3. Literature search

3.1. Search protocol establishment

This study utilized an SLR following a search protocol developed collaboratively. This protocol, informed by recommendations from Borrego et al. [41], outlined the key elements of the SLR, including the research questions, relevant databases, keywords, and criteria for including or excluding studies. The collaborative development process ensured the protocol's validity and replicability throughout the review by allowing for iterative refinement. In addition, the protocol facilitated early discussions among the four-member author team. A total of three iterations of review and feedback from the research team were conducted. During each iteration, disagreements regarding the inclusion of studies or the interpretation of key findings were resolved through group discussions. Throughout this process, the research questions were refined to ensure they aligned with the study's objectives, focusing on addressing the key barriers to sensor adoption, exploring interrelationships between these barriers, and identifying actionable strategies for overcoming them.

The search protocol was designed to ensure comprehensive coverage of the relevant literature. The selection of search fields and keywords was based on an initial scoping review of the literature and consultations with experts in the field of construction technology and sensor systems. Keywords were chosen to capture the critical aspects of sensor adoption, including terms related to sensor technology, construction applications, barriers, and adoption trends. In accordance with methodologies from Petticrew and Roberts [40], the validation process involved cross-referencing these keywords with key studies in the field to ensure comprehensive coverage of relevant topics, ensuring the search strategy effectively identified pertinent literature for analysis. Boolean operators such as "AND" and "OR" were employed to refine and expand the search results systematically. The "AND" operator was used to ensure that all search terms appeared in the retrieved records, helping to narrow down the search to studies that specifically address all the concepts of interest. Conversely, the "OR" operator was used to broaden the search by including studies that addressed any of the individual keywords, thereby capturing a wider array of potentially relevant literature [36]. This strategic use of Boolean operators is fundamental in systematic reviews as it enhances both the precision and recall of search results, ensuring that the literature search is exhaustive without being overly restrictive. The relevance of these connectors has been well-documented in guidance for conducting systematic reviews, as they are essential for balancing comprehensiveness and specificity in literature retrieval [36,37]. By employing these Boolean connectors, the search protocol aligns with best practices for database searches in systematic reviews, ensuring a thorough identification of studies relevant to the adoption of sensing technologies in construction.

Scopus, a database known for its comprehensive coverage of leading engineering journals and conferences [42], was chosen as the primary source for scholarly articles. To capture relevant dissertations and theses, as recommended by Borrego et al. [41], the Web of Science database was also included.

The following search strings were employed:

Scopus: (construction W/3 sensor) AND (project OR management OR process OR operation OR system) AND (gap OR limitation OR issue OR problem OR challenge OR drawback OR barrier OR obstacles).

Web of Science: (construction near/3 sensor) AND (project OR management OR process OR operation OR system) AND (gap OR limitation OR issue OR problem OR challenge OR drawback OR barrier OR obstacles).

To improve the focus on relevant research, the search terms were restricted. While "sensor" and "construction" appear in various contexts, the search specifically looked for instances where these keywords appeared within three words of each other (denoted as "W/3"). This limitation aimed to capture situations where the terms were likely used in the same sentence, reducing irrelevant results. For example, this approach would identify studies mentioning "sensor for construction site monitoring" or "automatic quality assessment for construction using sensors." The search encompassed titles, abstracts, and keywords within the chosen databases.

3.2. Database search

The initial search yielded 475 articles in Scopus and 825 in Web of Science. To ensure comprehensiveness, the research team manually searched author profiles using Google Scholar to ensure comprehensiveness after the screening process, as stated in section 3.3. This step aimed to capture potentially relevant studies that were not indexed by the primary databases. Google Scholar's advantage lies in its broader scope, encompassing various resources such as books, book chapters, reports, and even unpublished materials.

3.3. Literature selection

Following the initial literature search that yielded over 1300 articles, a screening process was implemented to ensure the quality and relevance of the selected studies, as shown in Fig. 2. The authors established inclusion and exclusion criteria to guide this process, as detailed in Table 1. The inclusion criteria used in this study were carefully selected to consider only relevant and high-quality studies. First, papers that applied sensors to address construction problems were included (IC1). This criterion ensures that the selected studies directly contribute to understanding how sensors are utilized to solve practical issues within the construction industry. In addition, papers that involved sensor data in construction were considered (IC2), as analyzing such data is crucial for evaluating sensor performance and effectiveness. Studies that explored the integration of sensing networks in construction were also included (IC3), as these provide valuable insights into the broader applications of sensors in complex environments. Finally, papers aimed at improving sensor performance in construction (IC4) were selected to focus on advancements that enhance the efficiency and functionality of sensors in construction settings.

On the other hand, several exclusion criteria were applied to maintain the relevance and quality of the review. Duplicate papers were excluded (EC1) to avoid redundancy. Papers not related to construction (EC2) were filtered out to ensure that the review remained focused on the construction context. Additionally, papers that did not follow a scientific methodology were excluded (EC3) to ensure that only methodologically sound studies were included. Lastly, papers without original discussions on limitations, challenges, or future works (EC4) were excluded, as such discussions are essential for understanding the current barriers and identifying opportunities for future research.

Potential biases were considered while applying these criteria. For example, excluding papers without scientific methodology or original discussions might overlook less methodologically rigorous studies that still offer valuable insights. To mitigate this, a broader literature search and cross-verification of relevant studies were conducted to ensure important research was not excluded. In addition, the consistent application of the inclusion and exclusion criteria across all stages of the review helped minimize any selection bias.

The first stage tackled duplicate removal and topic relevance. By

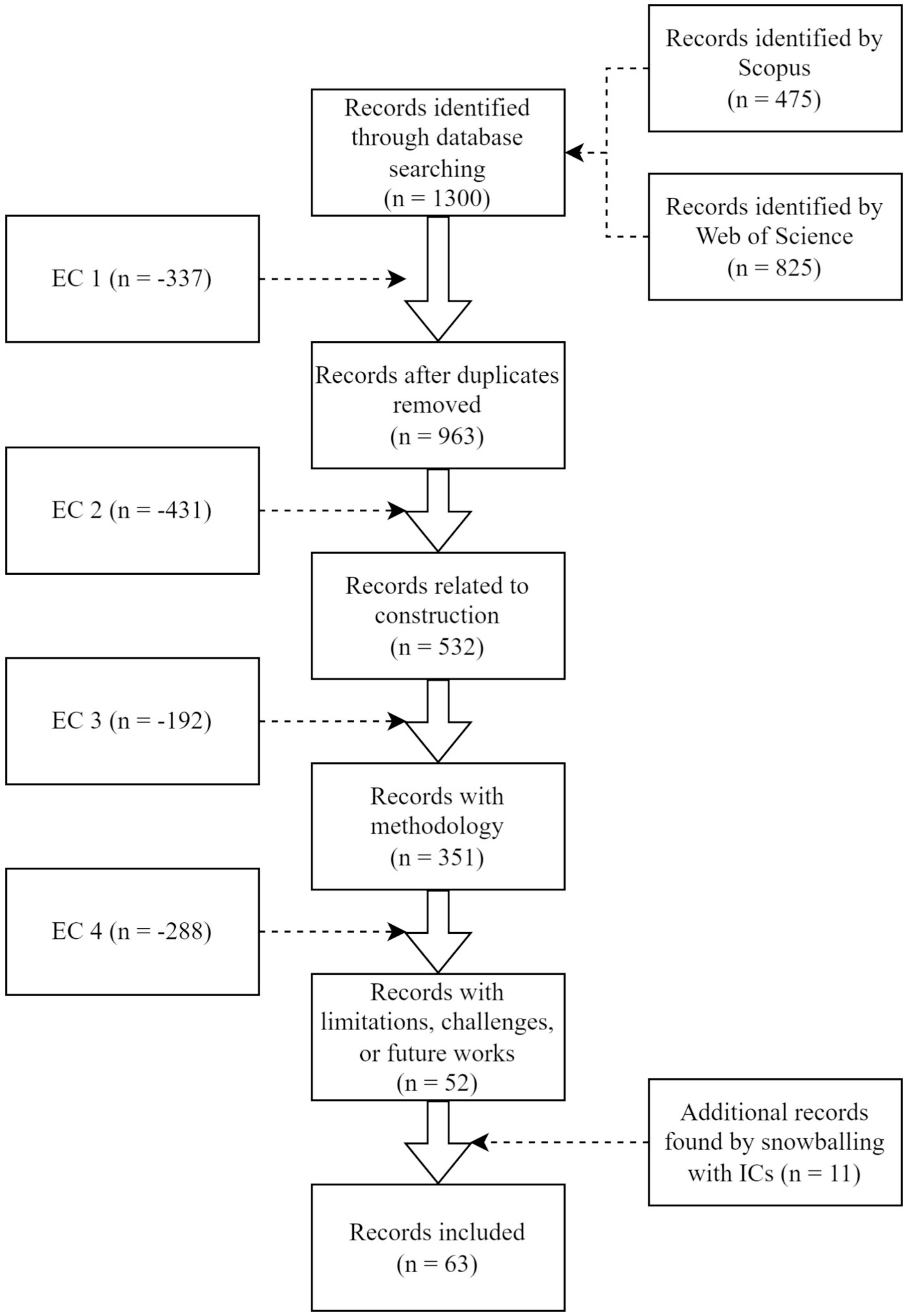

Fig. 2. Literature selection process.

Table 1
Inclusion and Exclusion Criteria of Literature Selection.

Inclusion Criteria (IC):
IC1: Papers that have applied sensors to address construction problems.
IC2: Papers that involve sensor data in construction.
IC3: Papers that consider sensing networks in construction.
IC4: Papers that aim to improve sensing performance in construction.
Exclusion Criteria (EC):
EC1: Papers that are duplicates.
EC2: Papers not related to construction.
EC3: Papers without scientific methodology.
EC4: Papers without original discussions in limitations, challenges, or future works.

applying Exclusion Criterion 1 (EC1), duplicate entries were eliminated, reducing the initial pool to 963 documents. The second stage involved a full-text analysis to assess content focus. Titles and abstracts were screened against EC 2 to focus on studies directly related to construction, resulting in 532 documents. Finally, a full-text analysis of the remaining documents ensured they employed a scientific methodology (EC3) and explicitly discussed limitations, challenges, or future directions for sensor adoption in construction (EC4). It is worth noting that some publications listed previous research as a way to highlight limitations. To avoid redundancy and focus on novel insights, studies that solely listed existing challenges (such as the comprehensive review by Arabshahi et al., [7]) were excluded based on EC4. This ensured studies offering original interpretations of the identified challenges within the field were prioritized.

To enrich the selection of relevant studies, a comprehensive snowballing technique was implemented during the full-text analysis of chosen documents. This technique involves two parts:

- Forward snowballing: Identifying additional articles that have cited the chosen documents [43].
- Backward snowballing: Examining the reference lists of the selected studies to find relevant documents not captured in the initial database search [43].

Any newly identified documents underwent the same abstract and full-text screening process as the initial set. During the snowballing process, one of the key challenges encountered was the potential bias of focusing too heavily on frequently cited papers, which might overlook less-cited but still relevant studies. To address this, the relevance of each document identified through snowballing was cross-checked by evaluating its contribution to the understanding of sensor adoption barriers. Referring to the ICs in Table 1, only documents that explicitly addressed the research questions or offered unique insights into the identified barriers were included. Additionally, the ICs and ECs required that each document provide empirical evidence or theoretical contributions related to sensor adoption in construction.

Google Scholar aided in conducting both forward and backward snowballing during the full-text analysis, ultimately contributing 11 additional documents. After applying all filtering criteria, the final selection included 63 documents, spanning from 2004 to early 2024, at which point this research was conducted. The starting point of 2004 was selected as it was the earliest that could be found during the early 2000s, when significant technological advancements in sensor technology and digital ecosystems began emerging in industries such as manufacturing and construction [44]. These documents then proceeded to the next research stage for further analysis.

4. Literature analysis

4.1. Descriptive analysis of the corpus

This section presents a chronological analysis and a thematic analysis of the selected documents. The chronological analysis showcases the distribution of selected documents across publication years, while the thematic analysis is conducted based on the classification of main themes and the categorization of sensors applied. Conducting both chronological and thematic analyses is crucial for gaining a comprehensive understanding of the literature on sensor adoption. Chronological analysis provides insights into how sensor technologies and their adoption have evolved over time, allowing for the identification of trends and shifts in the field [45]. This temporal perspective is complemented by thematic analysis, which helps uncover recurring themes, such as common barriers or strategies, across the studies [46]. By combining these two methods, the review captures both the historical progression and the core challenges in sensor adoption, providing a more holistic view of the field.

4.1.1. Chronological distribution of selected documents

Fig. 3 showcases the distribution of selected documents across publication years. Notably, the focus on sensor adoption barriers in construction has grown steadily over the past two decades, with a particularly sharp rise after 2016. This surge aligns with the growing awareness of Construction 4.0, a trend mirrored in the work of Forcael et al. [47]. This suggests a potential link between the rise in sensor-related research and a broader attempt to digitalize the construction industry.

4.1.2. Thematic analysis of the documents

To categorize the selected documents, the authors conducted a manual classification based on their primary purposes. Seven main themes emerged:

1. Construction production monitoring
2. Construction safety management
3. Structural health monitoring
4. Construction robotics and machinery
5. Digital built environment management
6. Construction sustainability monitoring
7. Construction inspection

Fig. 4 visually depicts the percentage distribution of these themes within the selected documents. This classification helps us understand the various areas where sensor technology is playing a growing role in the construction industry.

Table 2 details the various sensor types identified within the selected papers, categorized based on references from prominent works in the field. This categorization, along with the classification of the papers by their primary purpose, will provide the context needed to analyze the challenges and categorize the barriers faced in adopting sensor technology within the construction industry.

Fig. 5 presents the distribution of sensor categories. The proportions of each sensor category can be attributed to the specific demands of construction projects. Positioning and Communication Sensors make up the largest share due to the critical need for real-time tracking of workers, equipment, and materials, which is essential for ensuring safety and operational efficiency. Mapping Sensors also have a significant proportion, driven by the growing reliance on 3D site mapping for project planning and monitoring. Wireless Sensor Networks play a crucial role in enabling seamless communication between systems, accounting for their notable share. SHM sensors are slightly less common, as they are typically used for long-term monitoring of infrastructure rather than daily site operations. Physiological Sensors, which monitor worker health and safety, represent a smaller portion due to their more specialized application. Environmental Sensors hold the smallest share, likely because they are used for targeted monitoring of site-specific conditions such as air quality, which may not be required on all construction sites.

4.2. Content analysis

This research employed content analysis, a versatile method for examining a collection of texts to uncover current research trends and emerging concepts [51]. This technique can be integrated with qualitative, quantitative, or mixed methods [51]. In this paper, NVivo

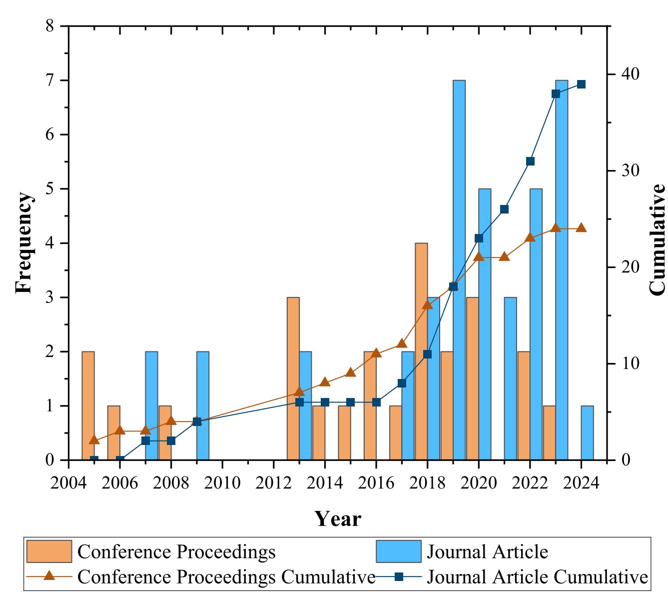

Fig. 3. Chronological distribution of selected documents.

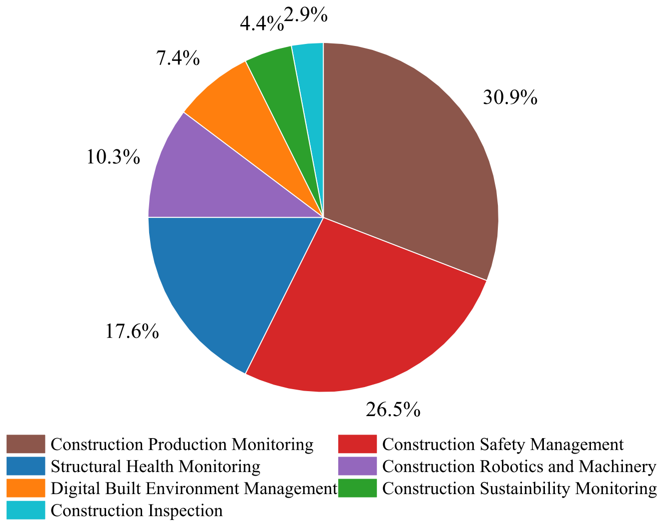

Fig. 4. Thematic analysis of the objective purposes.

software, a well-established tool for qualitative data analysis, was used for the content analysis. NVivo's effectiveness in qualitative analysis for SLRs is well-documented, as it facilitates importing, coding, editing, retrieving, and reviewing textual data [52]. Additionally, it allows for searching text for specific word combinations or patterns within the coding itself [52]. The suitability of NVivo for construction review studies is further supported by its successful application in research by Lu and Yuan [53].

To address the first research question (RQ1) on barriers to sensor adoption, the research team utilized NVivo software for content analysis. This process is based on the work carried out by Abdelmegid et al. [54] and follows the inductive coding approach proposed by Bandara, et al. [55], which follows the inductive coding approach proposed by Hilal and Alabri [52], as demonstrated in Fig. 6.

The process began by creating queries using keywords such as "gap," "limitation," "issue", "problem", "drawback", "barrier", and "challenge." NVivo then generated a list of documents containing these keywords or synonyms. These documents were meticulously scanned and defined by the authors to identify all reported barriers. Each barrier was assigned a dedicated category, which is called 'node' within NVivo. These nodes then functioned as the basis for further analysis. Each node was used to query the remaining documents, with results being manually examined and relevant information assigned back to the corresponding node. If new barriers were noticed, they were assigned new nodes and the querying process repeated. This iterative process continued until all barriers identified in the documents were captured.

To ensure the reliability of the coding process during the content analysis using NVivo, several measures were taken. First, multiple coding rounds were conducted, with initial codes being cross-checked between coders to ensure consistency. Inter-coder reliability was addressed by having two independent coders analyze the same set of data, followed by a comparison of the results. Any discrepancies in coding were discussed and resolved through consensus, ensuring a shared understanding of the themes and barriers identified. Additionally, the coding process was refined iteratively based on feedback from the coding team, further enhancing the reliability and consistency of the analysis.

Finally, a comprehensive full-text scan of the documents was conducted to verify the findings from NVivo analysis and identify any potential missing information during the iterative querying process. After the full-text scan, all identified barriers are categorized as groups. To ensure comprehensiveness, another co-author performed an additional round of scanning, validating the identified barriers and searching for any overlooked ones.

Table 2
Sensor categories.

Sensor Categories	Category Definitions	Examples
Positioning and Communication Sensors	Devices used to track the location of workers, machinery, and materials, ensuring real-time positional accuracy and communication on construction sites [31].	Tracking devices, inertial measurement units, global navigation satellite systems, short-range communication technologies, long-range communication technologies.
Mapping Sensors	Tools such as laser scanners and ground-penetrating radars that create precise 2D/3D maps of construction sites and monitor subsurface conditions for structural analysis [31].	Laser scanners, Red Green Blue (RGB) cameras, depth cameras, ground penetrating radar, sensor integration.
Wireless Sensor Network	Integrated systems of sensors that enable the real-time transmission of data across construction sites, allowing for seamless communication and data collection [48,49].	Multi-sensor network consisting of sensing, communication, and processing
Structural Health Monitoring (SHM) Sensors	Sensors designed to monitor the integrity of structures by detecting changes in strain, vibration, and other factors that could signal structural issues [49].	Fiber Optic Sensors (FOS), Conventional Resistive Strain Gauges, Thermocouples, Fatigue Sensor, Ultrasonic Sensors, Vibrating Wire Strain Gauges (VWSGs), Inclinometers, Laser Displacement Sensors
Physiological Sensors	Sensors that monitor the health and safety of workers by tracking physiological parameters like heart rate, fatigue, and stress levels in real-time [50].	Electrodermal Activity (EDA) Sensor, Skin Temperature (ST) Sensor, Photoplethysmogram (PPG) Sensor, Electrocardiogram (ECG/EKG) sensors, Electromyography (EMG) sensors, Electroencephalography (EEG), Functional Near-Infrared Spectroscopy (fNIRS), Eye-tracking
Environmental Sensors	Devices that measure environmental factors such as temperature, humidity, and air quality to ensure compliance with regulations and maintain safe working conditions on site [13].	Temperature, humidity, pressure, air quality

After this process, Table 3 summarizes the findings from the content analysis, categorizing the identified barriers into five groups: Stimulus Generation (SG), Data Acquisition (DAc), Data Transfer and Fusion (DTF), Data Processing (DP), and Data Application (DAp). This classification helps differentiate the inherent nature of each barrier, allowing for more targeted solutions based on their specific characteristics. These barriers will be discussed in section 5.1. Meanwhile, it is important to acknowledge that these categories are not entirely isolated, as some barriers may be interrelated and can potentially influence each other. The interrelationship between these barriers will be qualitatively analyzed in the discussion section (section 5).

4.3. Quantitative analysis of identified barriers

Leveraging the quantitative capabilities of NVivo, the research team was able to enumerate the identified barriers based on their frequency of occurrence within the analyzed documents. This frequency of occurrence is defined here as the count of times each barrier was noted within the selected documents, which serves to illustrate not only the

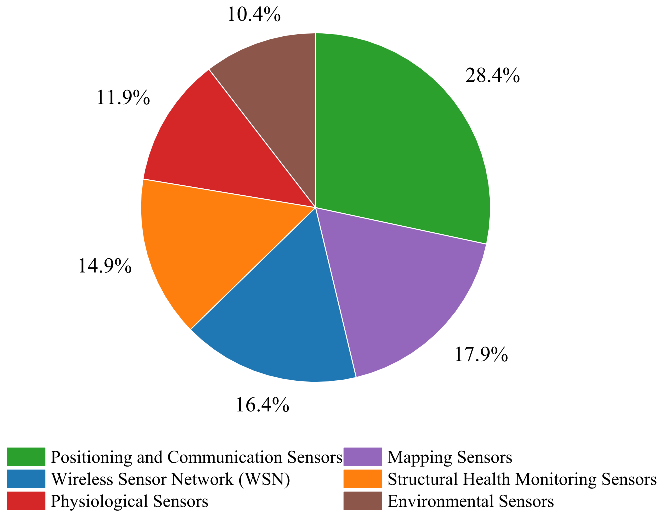

Fig. 5. Distribution of sensor categories.

prevalence of each identified barrier but also highlights those that are most pervasive across the studied literature. Table 4 presents a breakdown of this quantitative analysis, while Fig. 7 visually sorts the barriers according to how often they were reported in the selected studies. This approach provides valuable insights into the prevalence of specific challenges faced in sensor adoption for the construction industry.

Table 3
Barriers to Sensor Adoption in the Construction Industry.

Stimulus Generation (SG):
Construction Site Complexity (SG 1)
Requirement of Professional Skills (SG 2)
Data Acquisition (DAc):
Sensing Data Accuracy (DAc 1)
Sensor Durability (DAc 2)
Data Transfer and Fusion (DTF):
Sensing Data Network (DTF 1)
Multi-senser Data Fusion (DTF 2)
Data Processing (DP):
Level of Automation (DP 1)
Big Data Management (DP 2)
Computation Complexity (DP 3)
Data Application (DAp):
End User Acceptance (DAp 1)
Decision Support Integration (DAp 2)

The quantitative analysis of identified barriers reveals several key insights into sensor adoption challenges in the construction industry. Sensing data accuracy (19 %) emerged as the most frequently mentioned barrier, likely due to the critical need for reliable, high-quality data to inform decision-making processes. In construction, environmental factors such as dust, temperature fluctuations, and vibrations can affect sensor accuracy, making this a persistent issue in real-world applications. Construction site complexity (13 %) also ranked highly, reflecting the inherent challenges in deploying sensor systems in dynamic and unpredictable environments. Construction sites often involve diverse

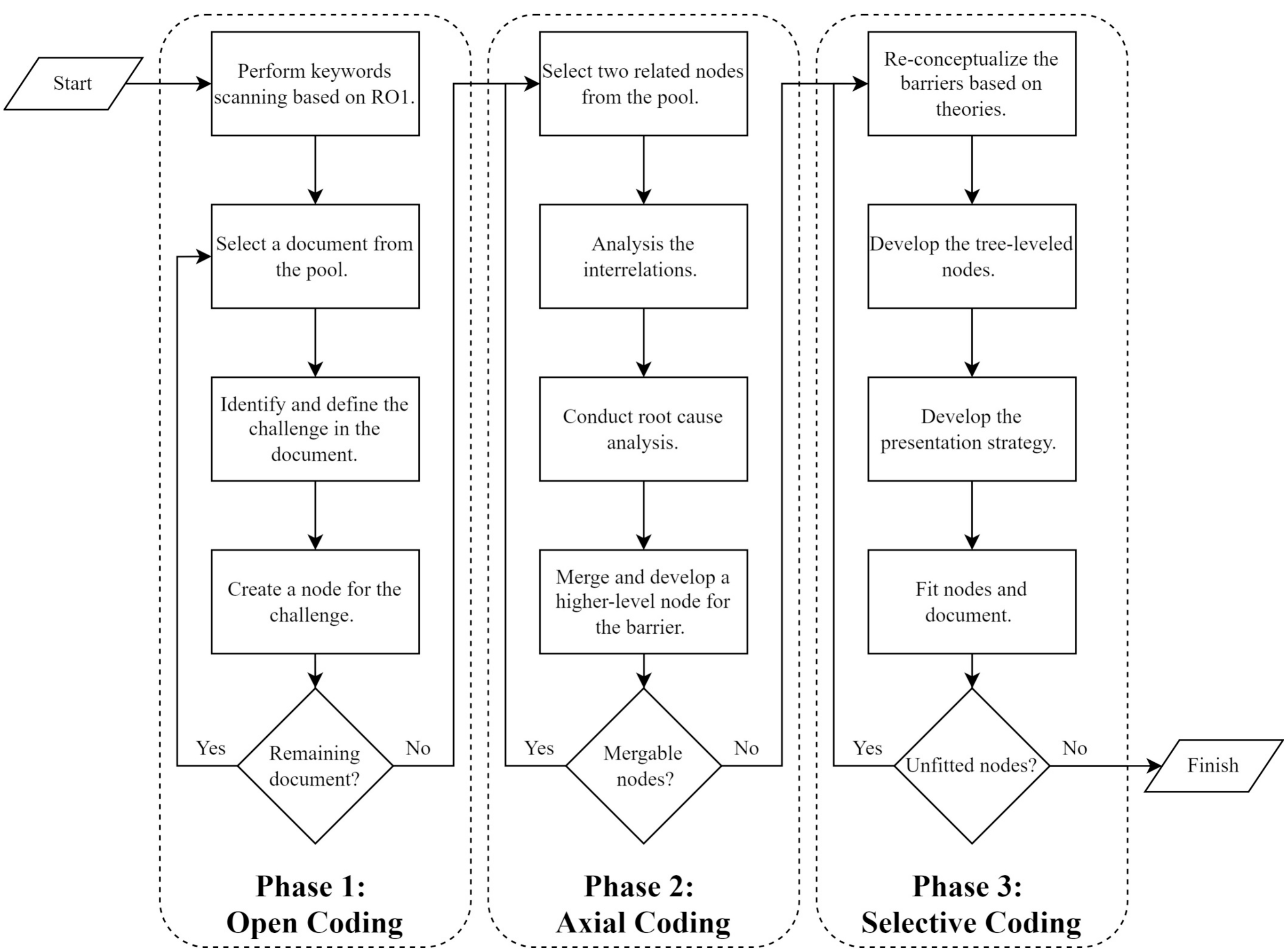

Fig. 6. Inductive coding approach using NVivo, adapted from Bandara, et al. [55].

Table 4
Barriers Mentioned by Literatures.

	SG1	SG2	DAc1	DAc2	DTF1	DTF2	DP1	DP2	DP3	DAp1	DAp2
Aksüt and Eren [56]										x	
Ansari [19]		x	x	x							
Ansari [57]		x		x							
Antwi-Afari et al. [58]	x					x					
Awolusi et al. [32]					x	x	x			x	x
Bangaru et al. [59]			x				x				
Becks et al. [60]				x							
Caron et al. [61]						x					x
Choi et al. [62]	x								x		
Costa et al. [63]					x	x	x			x	
Du et al. [64]						x		x			
Edirisinghe [33]				x						x	
Franco et al. [24]						x	x				
Golubeva et al. [65]					x		x				
Gradeci et al. [66]	x										
Harichandran et al. [67]	x										
Harper et al. [68]		x	x					x			
Hubbard and Middaugh [69]	x										
Ibrahim and Moselhi [70]									x		
Jang and Skibniewski [71]	x		x		x	x					
Jebelli et al. [72]			x							x	
Jiang and He [73]			x	x	x	x	x	x			
Johansen et al. [74]						x				x	x
Khalid et al. [75]		x						x		x	x
Kim et al. [76]		x	x								
Kim et al. [77]			x								
Koulalis et al. [17]			x			x				x	
Kwon et al. [78]			x			x					
Labossière et al. [20]	x	x			x						
Lee and Han [79]			x				x				
Li et al. [18]						x					
Liang et al. [22]		x		x	x			x	x	x	
Lim and Kim [80]			x		x						
Liu et al. [81]			x							x	
Loo et al. [15]					x						
Louis and Dunston [16]			x								
Lundeen et al. [82]	x					x			x		
Lytle et al. [83]			x								
Milivojevic et al. [25]		x					x				
Nawaz et al. [84]	x						x				
Ni [85]								x	x		
Park et al. [86]			x								
Pop et al. [87]			x								x
Rahimian et al. [21]										x	
Rahman et al. [23]		x					x			x	
Rao et al. [31]	x		x	x			x		x		
Shrestha and Behzadan [88]	x	x									x
Sudhakar et al. [89]		x		x							
Talmaki and Kamat [26]			x		x	x					
Venkatachalam et al. [90]		x									
Wang et al. [91]	x						x				x
Wang et al. [92]				x							
Wei et al. [93]	x		x			x	x		x	x	x
Xiang et al. [72]			x						x		
Xie et al. [94]			x								
Yan et al. [95]	x						x				
Yang et al. [96]	x										
Yang et al. [27]	x		x						x	x	
Yang et al. [97]			x						x		x
Yoon et al. [98]									x		
Yu et al. [28]			x								
Yuhai et al. [99]	x						x		x		
Zhang et al. [100]			x						x		

operations, multiple stakeholders, and constantly changing conditions, which complicates the implementation of standardized sensor networks. Other frequently reported barriers, such as end user acceptance (11 %) and the level of automation (11 %), highlight the human and technical factors that impact sensor integration. The need for end users to trust and effectively use sensor technologies is critical for successful adoption. Additionally, the level of automation is closely tied to both technical capabilities and workforce adaptability. In contrast, barriers like big data management (4 %) and sensor durability (6 %) were mentioned less frequently, possibly because these challenges are more specific to advanced stages of sensor adoption or are less visible in the early implementation phases. As sensor technologies mature, these barriers

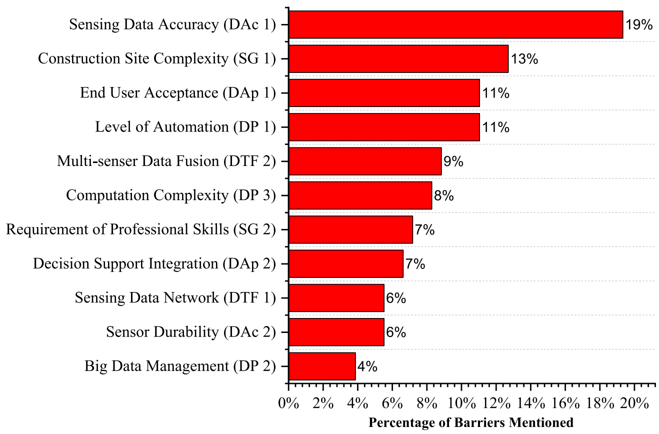

Fig. 7. Analysis of barriers to sensor adoption in the construction industry.

may become more prominent as construction firms deal with larger volumes of data and the long-term durability of sensor systems.

5. Discussion

This section delves into the identified barriers to sensor adoption in the construction industry, drawing upon the insights gleaned from the literature review, followed by key research directions that hold promise in overcoming these challenges.

5.1. Barriers to adapting sensors in the construction industry

A sensor can be defined as a device that receives a stimulus and responds with an electrical signal [101], and the signal information about sensed events of interest needs to be processed until reaching the appropriate decision-making and/or administrative point [48]. Based on this definition, five stages can be summarized as:

1. **Stimulus Generation (SG):** The process by which environmental stimuli are converted into measurable signals.
2. **Data Acquisition (DAc):** The actual capturing of data by sensors.
3. **Data Transfer and Fusion (DTF):** The process of transmitting and merging data from multiple sources.
4. **Data Processing (DP):** The analysis and interpretation of the acquired data.
5. **Data Application (DAp):** Using the processed data to make informed decisions.

Moreover, generated from the 'Objects', the 'Stimulus' needs to be captured by the 'Sensors', translated by the 'Receivers', and eventually used by the 'End Users' for 'Decision-making' (administrative point). To visualize this process, Fig. 8 is drawn by the authors to illustrate the journey of sensing information from objects to decision-making.

In addition, Fig. 9 shows the co-occurrence relationship between the identified barriers. It uses a matrix format where each axis lists the barriers identified through the research. Each cell in the matrix indicates the degree to which two barriers co-occur within the analyzed literature. Cells are color-coded to represent different levels of co-occurrence, with warmer colors typically indicating higher frequencies. This visualization helps in understanding how often certain barriers are discussed in conjunction with each other, highlighting potential interdependencies or common themes that may require integrated approaches for effective resolution.

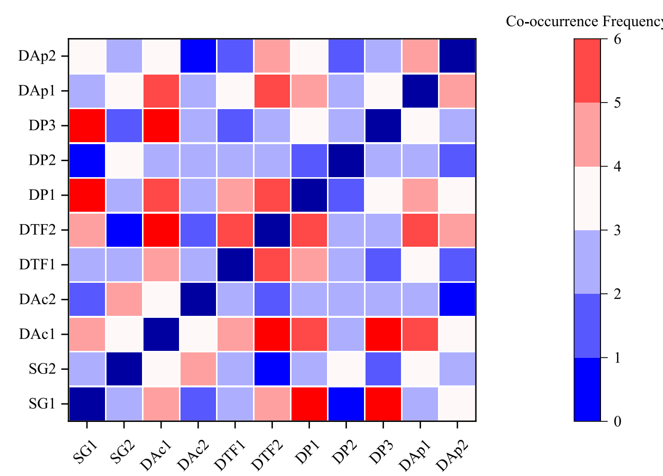

Fig. 9. Barrier co-occurrence relationship heatmap.

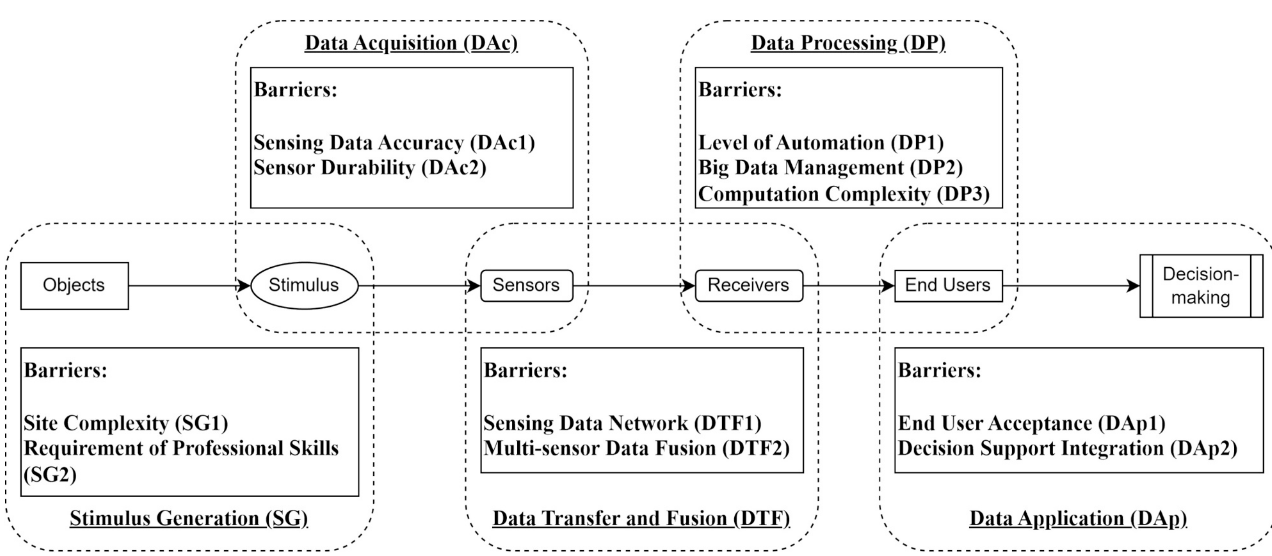

Fig. 8. Journey of sensing information from object to decision-making, with barriers in each stage.

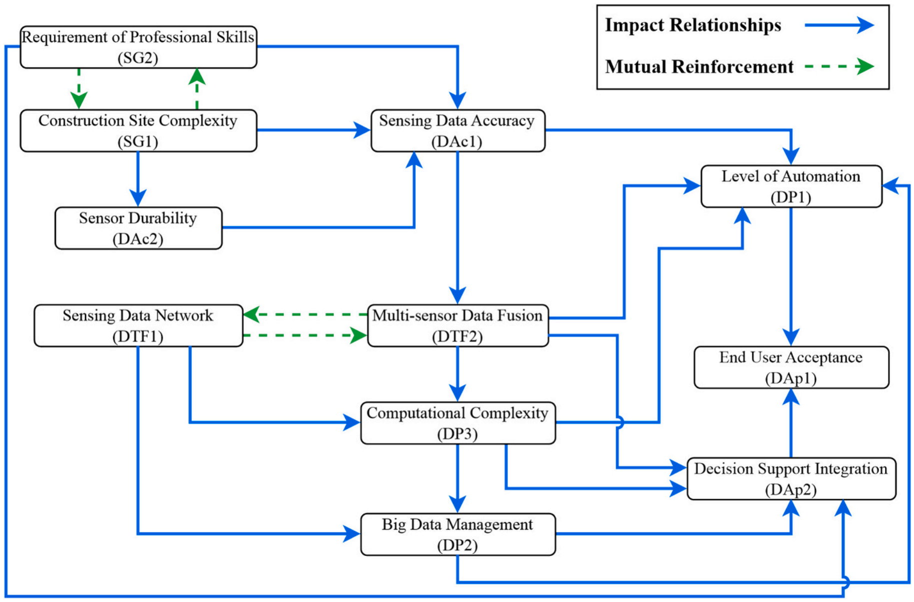

Fig. 10. Interrelationship diagram between barriers to sensor adoption in the construction industry.

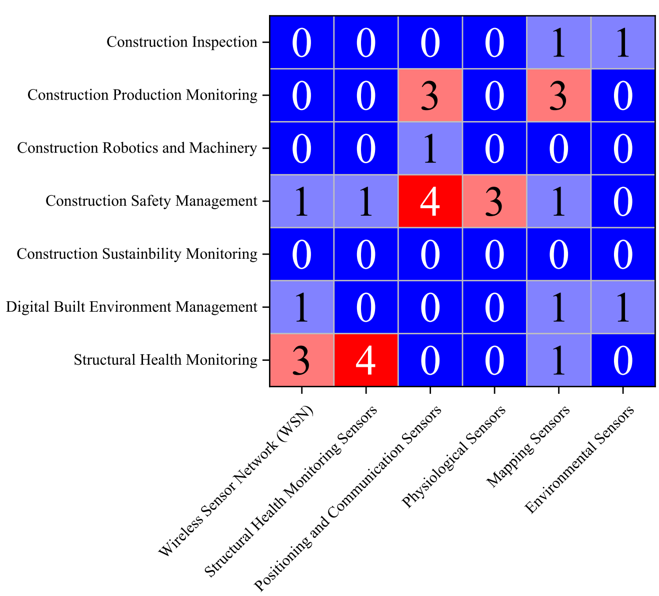

Fig. 11. Purposes and sensors applied for works that encountered the barrier of sensing data accuracy.

The co-occurrence matrix in Fig. 9 highlights several key relationships between barriers, with certain pairs of barriers frequently mentioned together in the literature. One of the most significant co-occurrences is between Sensing Data Accuracy (DAc 1) and Computation Complexity (DP 3). This suggests that challenges related to obtaining accurate sensor data are often compounded by the computational difficulties in processing that data, particularly in complex construction environments where real-time decision-making is critical. Another notable co-occurrence is between Sensing Data Accuracy (DAc 1) and Construction Site Complexity (SG 1). This pairing indicates that the variability and unpredictability of construction sites make it difficult to maintain high levels of sensor data accuracy, highlighting the need for robust sensor technologies capable of operating in challenging conditions. Additionally, the frequent co-occurrence of End User Acceptance (DAp 1) with Decision Support Integration (DAp 2) suggests that user acceptance of sensor technologies is closely linked to how well these technologies are integrated into decision-support systems. If end users perceive these systems as difficult to use or ineffective, it may hinder broader adoption, regardless of the technological benefits. These co-occurrences reveal that certain barriers are interdependent, and overcoming one may require addressing the other. To this end, an interrelationship diagram is drawn as shown in Fig. 10.

In Fig. 10, the interactions between barriers to sensor adoption in the construction industry are depicted using two types of relationships: impact relationships and mutual reinforcement. These relationships show how different barriers influence each other and create complex feedback loops. The relationships first underwent the same content analysis process in NVivo as described in Section 4.2, Content Analysis.

An impact relationship refers to a situation where one variable or factor influences the effect of another, often causing changes in outcomes or behaviors within a system [102]. These relationships are characterized by a directional influence, where addressing or changing one factor can lead to effects on another [102]. In the NVivo analysis, these impact relationships were identified by coding patterns and co-occurrence of themes across documents, revealing how frequently certain barriers are linked together in the literature. In the diagram, impact relationships are shown with blue arrows. For instance, Sensing Data Accuracy (DAc1) directly affects Multi-sensor Data Fusion (DTF2). This indicates that improving data accuracy enhances the ability to fuse data from multiple sensors, which also suggests that interventions focused on improving data accuracy can potentially lead to improvements in data fusion. Similarly, Big Data Management (DP2) is shown as impact linked to Decision Support Integration (DAp2), implying that effective data management facilitates better decision-making, a concept that can be observed and quantified through intervention. Moreover, Construction Site Complexity (SG1) influences the Requirement of Professional Skills (SG2), as more complex site environments demand higher skill levels for operating and maintaining sensor technologies effectively. These relationships suggest that addressing challenges in one barrier can have a cascading effect on related barriers, achieving the overall improvement in sensor adoption and functionality.

Mutual reinforcement occurs when two variables strengthen each other through a feedback loop, affecting their effects over time. Pearl [103] discusses this concept in his work on cyclic models and feedback systems, where variables are interdependent and enhance one another's influence. This mutual influence was captured through cross-referencing nodes in NVivo and analyzing the co-occurrence of these barriers in the literature. In the diagram, mutual reinforcement is represented by green dashed arrows. For example, Sensing Data Network (DTF1) and Multi-sensor Data Fusion (DTF2) reinforce each other: a strong data network improves data fusion, and successful data fusion makes the network more efficient. This creates a reinforcing loop where each barrier strengthens the effect of the other, leading to cumulative improvements. Similarly, Construction Site Complexity (SG1) and Requirement of Professional Skills (SG2) mutually reinforce one another, as increasing site complexity demands higher skill levels, and those skills better manage the complexities of the construction environment. These feedback loops illustrate how barriers can intensify one another in a self-reinforcing manner.

The authors acknowledge several limitations in the identified interrelationships, as they are based exclusively on the selected literature. Since these relationships are drawn from a specific set of studies, they may not fully capture the evolving nature of sensor technology or encompass the broader scope of ongoing research. Consequently, the interrelationships presented here are not static and may shift as sensor technologies progress and new barriers or facilitators emerge. This temporal limitation suggests that the findings could become outdated as advancements in technology redefine the challenges of adoption. Furthermore, the qualitative nature of the data limits the ability to conduct mathematical or statistical analyses that could provide deeper insights into the strength and dynamics of these relationships. Additionally, while these connections imply significant links between barriers, they do not establish causality due to the limited dataset. As such, the interrelationships presented should be considered an initial framework, open to further validation and refinement as the field continues to evolve.

5.1.1. Sensing Data Accuracy (DAc1)

Accuracy refers to how closely a sensor's output reflects the true value of the physical quantity it is measuring [101]. In simpler terms, it represents the difference between the sensor's reading and the actual value being measured. A more accurate sensor will have a smaller deviation from the true value to be measured.

This barrier was the most frequent one reported in the literature, which has been discussed from several perspectives. It is influenced by a variety of complex challenges, which significantly affect the performance and reliability of sensor-based applications. As shown in Fig. 11, this barrier affects sensor adoption for several key purposes in construction. These include structural health monitoring (using WSN and SHM sensors), construction safety management (using positioning, communication, and physiological sensors), and construction production monitoring (using positioning, communication, and mapping sensors). These challenges require a comprehensive approach encompassing improvements in manufacturing, environmental resilience, technological enhancements, and data management strategies.

Manufacturing and design flaws are foundational issues impacting sensor accuracy. For example, the production processes for optical fiber sensors—integral in structural health monitoring—can introduce defects that compromise their performance [19]. These processes often involve high-stress treatments such as pre-tensioning, bending, and bonding, which, while necessary for sensor functionality, can cause micro-damages that affect long-term reliability and accuracy [19]. Ensuring that these sensors are designed and manufactured with precision is crucial to mitigate such impacts and enhance their durability and effectiveness in field conditions [68,73,77,86].

Environmental conditions pose another significant challenge to sensor accuracy in construction settings. Sensors are frequently exposed to harsh conditions such as extreme temperatures, moisture, dust, and mechanical vibrations, all of which can degrade sensor components and skew data accuracy [19,78]. For instance, structural and environmental sensors must be robust enough to withstand these elements to provide reliable data, as the integrity of construction operations and safety management heavily relies on their precision [68,77,78,86,87].

Technological limitations further complicate the accuracy of sensors, particularly those used for positioning and navigation, such as GPS and IMU [16,27,72,97,100]. These sensors often face issues such as drift, signal blockage, and multipath interference, which are prevalent in cluttered urban construction sites [59]. Such challenges necessitate ongoing technological advancements and may require integrating multiple sensor technologies to compensate for individual limitations and improve overall data fidelity.

Lastly, the management of data from Wireless Sensor Networks (WSNs) introduces its own set of accuracy challenges. Issues such as signal interference, data loss during transmission, and energy management can significantly disrupt the accuracy and reliability of the collected data [31,77,78,87]. Developing robust network protocols and power management systems is essential to ensure that the data transmitted across construction sites is consistent and reliable for making informed decisions.

In recent years, with the growing interest in machine learning, data accuracy has become a prominent challenge for researchers requiring the collection of sensor data for machine learning training [17,58,79,93,95,99]. Inaccurate sensing data can lead to degraded model performance, compromised learning process, increased complexity of processing, and ultimately unreliable results. For instance, developing a computer vision model requires high-accuracy and quality images from construction sites. In this case, occlusions and clutter pose challenges not only for the training process but also for deploying the trained model [93]. Another example is training machine learning models to process and classify location-based data. In this case, inaccurate sensing data can lead to unreliable predictions of human gestures and machine locations in dynamic environments [27,59,71,72]. Additionally, finding a balance between accuracy and processing speed is a practical challenge in machine learning applications [58,93,99].

5.1.2. Construction Site Complexity (SG1)

This barrier presents two complexity issues: the diversity of entities and the signal interference caused by the site's complex nature. The former is caused by the dynamic and rapidly changing nature of the construction site, while the latter is due to the physical characteristics and limitations of sensors, specifically, the span or an input full scale (FS) of the sensor. The input FS refers to the dynamic range that a sensor can accurately convert, representing the maximum input value that can be applied without causing significant inaccuracies [101]. As shown in Fig. 12, this barrier predominantly affects construction production monitoring and safety management, while utilizing positioning and communication sensors, as well as mapping and physiological sensors.

The first major challenge arises from the dynamic and continuously changing nature of construction sites, including a variety of entities such as personnel, machinery, and materials. Adapting sensors to these conditions requires sophisticated customization and integration into various construction entities, each potentially requiring different sensor types or methods of integration [31]. Furthermore, the vast scale and physical layout of construction sites complicates sensor deployment [58,62,66,84,96]. Achieving comprehensive input FS across large, cluttered areas necessitates a significant number of sensors, which can be both expensive and labor-intensive to maintain [84,96].

Signal interference represents the second significant issue associated with this barrier, primarily due to the physical characteristics of construction sites, such as the presence of heavy machinery, which can create substantial physical and electromagnetic interference. This interference can affect the input FS of sensors by corrupting the stimulus data, thus reducing the reliability of sensor outputs [101]. Furthermore, construction sites generate vast amounts of data from a variety of sensors, including motion, environmental, and structural sensors. With the potential realization of Construction 4.0 in mind, the use of multi-sensory systems to achieve automation in construction has become a primary goal for many projects [24,32,73]. However, integrating and analyzing the vast amount of data generated by sensors requires advanced data management and analytics capabilities to ensure compatibility and the synthesis of actionable insights [48]. Meanwhile, the variety of sensing data poses a significant challenge in other aspects, as shown in Fig. 9, including level of automation (DP1), multi-sensor data fusion (DTF2) and computation complexity (DP3). The complexity of managing this data not only challenges the technical infrastructure but also demands precise coordination to avoid data overload and ensure the accuracy of the insights generated [48].

5.1.3. End-user acceptance

This barrier focuses on usability, privacy concerns, discomfort from wearable sensors, resistance to technology adoption, and regulatory challenges. To be viable, sensor technologies, such as WSNs and IoT platforms, require straightforward and powerful application access, intelligent learning capabilities, fast deployment, and robust privacy protection measures [48,101,104,105]. However, in construction, the integration of these technologies is complicated by the unique and dynamic nature of construction sites, which are less predictable and controlled compared to environments in other industries [33,106]. In addition, the transient and multi-party nature of construction projects introduces complexity in establishing consistent cybersecurity protocols. Each phase of construction might involve different subcontractors and systems, creating numerous potential vulnerabilities where sensitive data can be exposed or compromised [22].

Privacy concerns significantly influence the acceptance of sensors in the construction industry [17,21,27,32,74]. As shown in Fig. 13, technologies that might be perceived as invasive, such as physiological and mapping sensors, are met with resistance. It is important to note that all projects utilizing mapping sensors, which employed computer vision technologies, faced challenges and resistance due to concerns over data privacy. Workers often express discomfort with continuous monitoring,

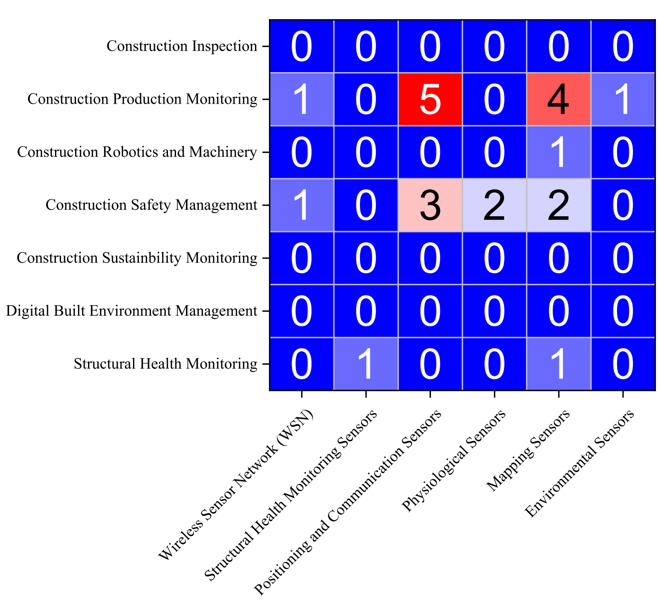

Fig. 12. Purposes and sensors applied for works that encountered the barrier of construction site complexity.

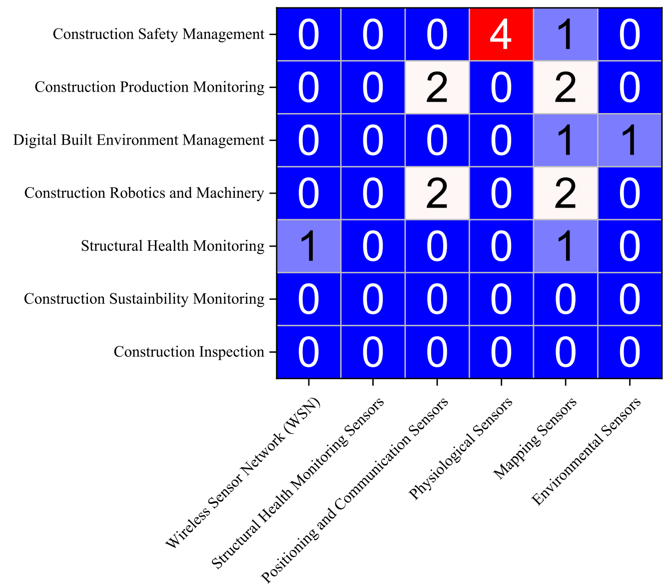

Fig. 13. Purposes and sensors applied for works that encountered the barrier of end user acceptance.

fearing surveillance and data misuse [17,27,74,93]. This discomfort is not only related to privacy but also to the physical experience of wearing the sensors [23,27,32,56,72,75]. Wearable sensors that restrict movement can be intrusive, making them less likely to be adopted despite their potential benefits for safety management and production monitoring.

Additionally, there is a broader resistance to technology adoption within the construction sector, similar to challenges faced in other industries but exacerbated by the project-based and transient nature of construction work [33]. The industry's workflow, where workers move to different sites rather than having a fixed workplace, contrasts with sectors such as manufacturing, where the environment facilitates a smoother introduction and integration of new technologies [107]. This mobile and ever-changing environment introduces complexities to standardize technology use across different projects.

Regulatory and legal challenges also play a crucial role in the adoption of sensor technologies [17,22,63]. The use of advanced sensors, particularly drones for surveillance and site inspection, requires compliance with a complex set of regulations that vary from one region to another [63]. These regulations include requirements for pilot certification, unmanned aerial vehicle (UAV) registration, flight restrictions, and stringent data privacy standards [17,22,63]. Navigating these legal requirements can be a daunting task for construction companies, often delaying or even preventing the effective use of UAVs and similar technologies on construction sites.

5.1.4. Level of automation

Integrating automation in the construction industry is challenging due to technological, logistical, and human factors [23–25,31,32,59,63,65,73,79,84,91,93,95,99]. Although the industry has seen a gradual increase in the adoption of automation tools and mobility technologies that can enhance efficiency, the transition from manual operations to automated systems is fraught with complexities. Meanwhile, the sensing data accuracy (DAc1), and the reasons behind it are barriers in site complexity (SG1), sensing data network (DTF1), and multi-sensor data fusion (DTF2). As shown in Fig. 14, this barrier mainly impacts construction safety management (using positioning and communication sensors, physiological sensors, and mapping sensors), and construction production monitoring (using mapping sensors).

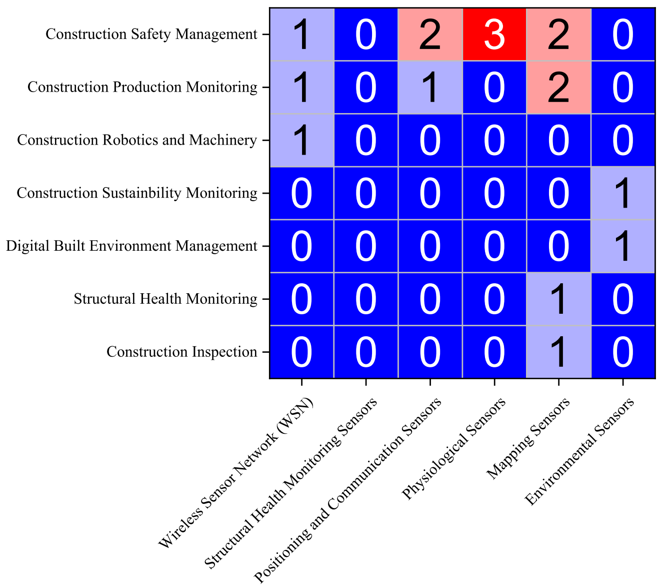

Fig. 14. Purposes and sensors applied for works that encountered the barrier of level of automation.

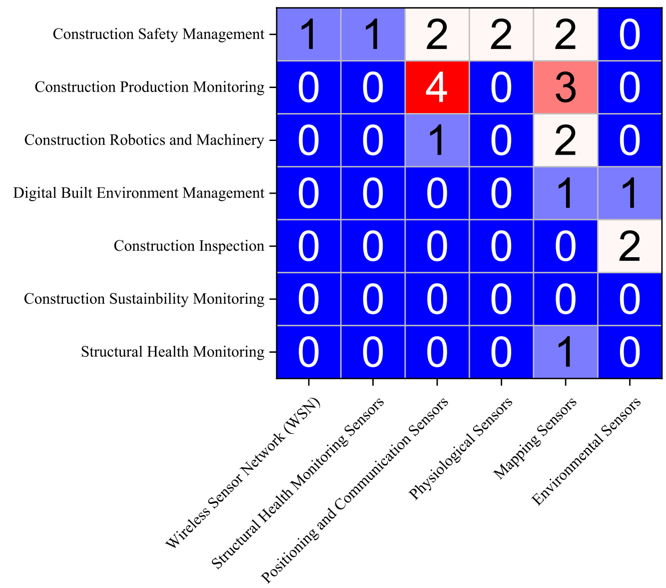

Fig. 15. Purposes and sensors applied for works that encountered the barrier of multi-sensor data fusion.

For instance, manual labeling and data entry, crucial in activities such as monitoring and recognizing different construction tasks (e.g., lifting, carrying), continue to be a significant part of the process even in environments that employ advanced sensors and data collection methods [23,31,59,63,79,84,99]. This reliance on manual methods not only introduces potential for human error but also underscores the gaps in current automation technologies, which are not yet fully capable of replacing human input in certain contexts. Similarly, the calibration of sensors, an essential step to ensure data accuracy, often requires manual intervention, as seen in practices where sensors are calibrated on official sites instead of in a controlled environment to verify their accuracy [25].

Furthermore, the practical application of automated systems in construction has demonstrated potential, particularly in enhancing operational efficiency and data reliability [31]. However, these systems still require significant manual oversight and input, particularly in data processing and integration into existing workflows [23,84]. For instance, integrating data from various sources, such as LiDAR and BIM, often remains a manual process, highlighting the ongoing challenges in achieving full automation [31].

The advancement of construction machinery and the development of smart sensors are recognized as prerequisites for autonomous construction. However, these advancements demand high levels of technical sophistication and bring forth challenges in ensuring seamless integration and operation within the dynamic and complex environment of construction sites [65,73].

5.1.5. *Multi-sensor data fusion*

Data fusion is the process of integrating multiple data sources from various sensors to produce more relevant, higher quality, and less expensive information [108]. As shown in Fig. 15, this barrier mainly impacts construction safety management (using positioning and communication sensors, physiological sensors, and mapping sensors), and construction production monitoring (using positioning and communication sensors, and mapping sensors).

The integration of multi-sensor data fusion in construction is a pivotal advancement that seeks to enhance the precision and efficiency of monitoring and controlling various construction activities. A significant barrier to effective multi-sensor data fusion is the challenge of interoperability, where different sensor technologies and data formats must be seamlessly integrated to function collectively [32,58,93]. Interoperability issues span across the physical device layer, communication protocols, and application functionalities, necessitating a sophisticated framework that ensures all components are compatible and functionally coherent [32,93]. This is critical in ensuring that data from diverse sources, such as wearable biosensors, which monitor parameters such as heart rate and body temperature, can be effectively integrated to enhance automated monitoring systems [58].

Another core aspect of multi-sensor data fusion is the performance and structuring of sensor data [61,63]. Successful data fusion requires not only the collection but also the efficient structuring and analysis of data collected from various sensors. The performance of these systems is tested in scenarios involving large amounts of sensor nodes, which are crucial for assessing the viability of these systems in real-world construction environments [61]. Moreover, the physical and operational characteristics of the construction site, such as spatial densities and distribution patterns of objects, play a significant role in determining the effectiveness of data fusion processes [63].

5.1.6. *Computational complexity*

This barrier presents multiple significant challenges due to the computational complexity required to process and analyze sensor data, compounded by the complexity of construction sites (SG1) [22,27,31,62,70,82,85,93,97–100,109]. As shown in Fig. 16, this barrier mainly impacts construction safety management (using positioning and communication sensors, and physiological sensors), and constructin robotics and machinery using mapping sensors.

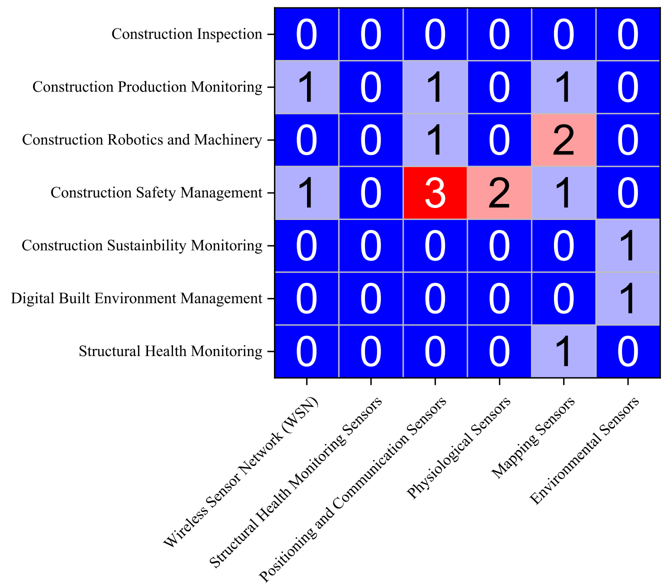

Fig. 16. Purposes and sensors applied for works that encountered the barrier of computational complexity.

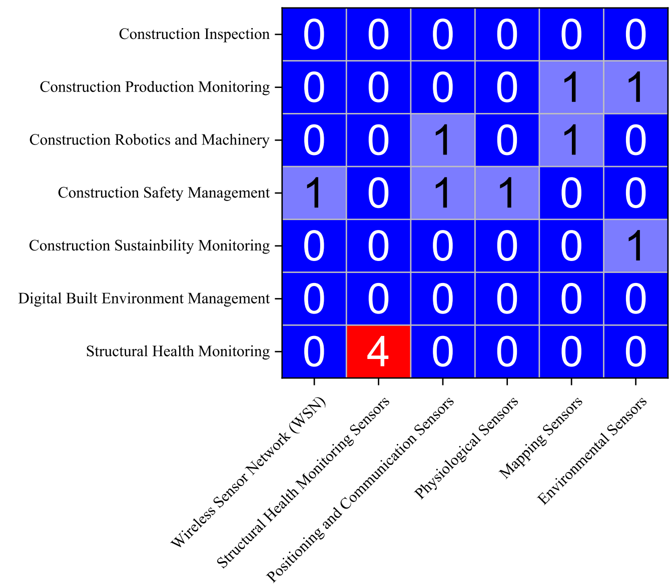

Fig. 17. Purposes and sensors applied for works that encountered the barrier of requirement of professional skills.

Various sensors, including environmental, positioning, and communication sensors, generate vast amounts of data, which require substantial computational resources to process [70,82,98,99,109]. This complexity is further exacerbated when dealing with high-resolution data from mapping sensors, where the processing and analysis can become time-consuming and impact the overall efficiency of sensors' application in construction [22,31,85,93]. Managing such large datasets demands significant storage and powerful computing capabilities, often requiring the data to be processed on high-capacity servers or cloud platforms [22,93,109].

Furthermore, the need to ensure data accuracy (DAc1) and consistency adds another layer of computational demand. Sensors must often capture data from multiple perspectives and at different times, leading to potential inconsistencies. Correcting these data for factors such as camera distortion or sensor errors to ensure high accuracy can be computationally intensive and requires sophisticated software tools and expert knowledge in data analysis and interpretation [31].

The issue of computational intensity is also present in tasks involving the fusion of different types of sensing data (DTF2), such as aligning 3D point clouds with other geometric data [85,93]. This process is computationally demanding due to the large size of the datasets involved, often necessitating the division of models and data into smaller, manageable sections for separate analysis. In addition, the real-time processing requirements for certain applications, such as tracking and analyzing construction workers' physical activity and stress levels in real time, further complicate the computational landscape, demanding efficient algorithms and robust computing infrastructure [97].

5.1.7. *Requirement of professional skills*

This barrier refers to the professional skills required for hardware handling, data analytics, and data interpretation. It spans various stages of sensor application, including installation, calibration, and data analysis [19,20,22,23,25,57,68,75,76,88–90]. As shown in Fig. 17, this barrier predominantly affects structural health monitoring when using SHM sensors. SHM sensors require high level of accuracy on determination of the object's coordinates (linear or angular) and levelness with respect to a selected reference [101]. Thus, proper placement and calibration of SHM sensors are crucial for obtaining reliable data. This process requires precision and understanding of the construction environment and sensor technology, underscoring the necessity for trained professionals.

In addition to technical skills for hardware handling, there is a growing demand for competencies in data analytics and interpretation within the construction industry [23,75]. The surge in data generated from various sensors, such as environmental and SHM sensors, calls for a skilled workforce capable of analyzing this data effectively to derive actionable insights. The industry faces a barrier in that respect, with a noticeable lack of skilled personnel to leverage the full potential of analytics, which hinders the optimization of construction processes and safety management [75].

Moreover, the use of more sophisticated technologies such as UAVs for construction inspection requires not only basic operational skills but also a deeper understanding of construction materials, processes, and safety regulations [22,68]. Training and continuous professional development are crucial, as these technologies evolve rapidly. Thus, professionals need to stay updated with the latest advancements to ensure the safe and effective use of these tools [75].

5.1.8. *Decision support integration*

Integrating decision support systems in construction is challenging due to the complexity of sensor data analytics (DTF2) and the requirements for real-time processing and interpretation (DAp1) [32,61,74,75,87,88,91,93,97]. Sensors such as positioning and communication devices, which are prevalent in the industry, provide vast amounts of data that need to be effectively integrated into decision-making processes. However, the current systems often lack the capability to provide actionable insights rapidly to the decision makers, which is crucial for dynamic construction environments [32,61]. As shown in Fig. 18, this inefficiency is particularly evident in monitoring construction production and managing safety.

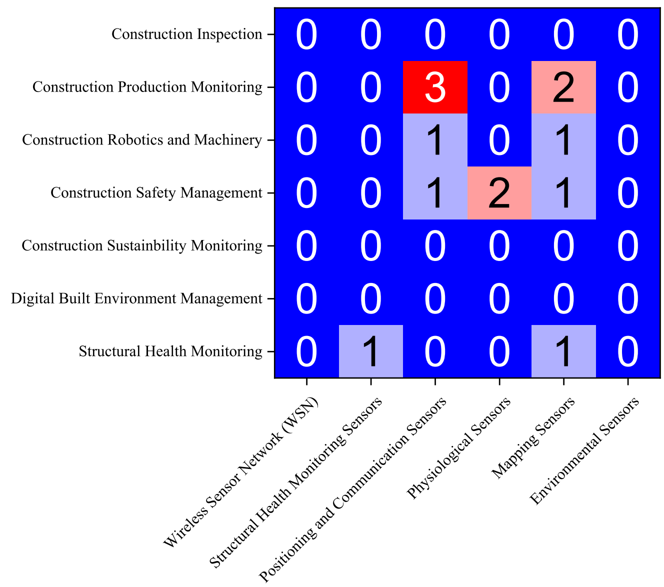

Fig. 18. Purposes and sensors applied for works that encountered the barrier of decision support integration.

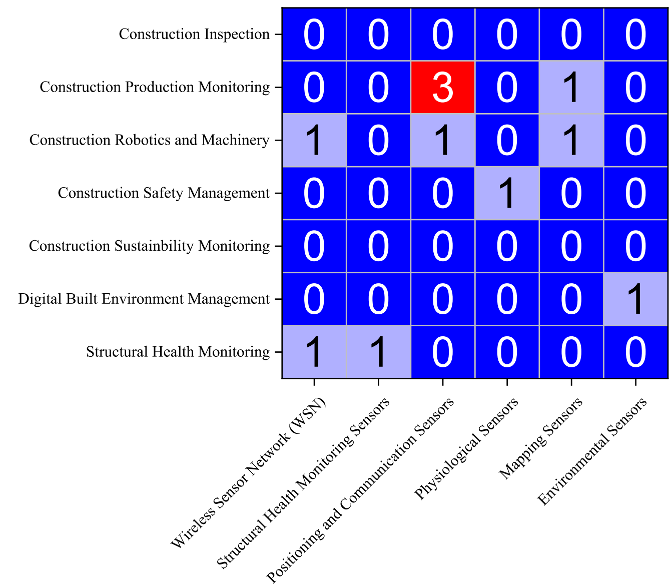

Fig. 19. Purposes and sensors applied for works that encountered the barrier of sensing data network.

The use of WSNs and IoT platforms illustrates this challenge well [32,87]. These systems do not only facilitate data collection, but also ensure that data can be quickly and accurately analyzed to support decisions related to construction safety management and production monitoring [32]. The integration of such data into decision support systems requires robust knowledge management frameworks that can handle the complexity and volume of data generated [75].

Moreover, the potential of these technologies is often hindered by data silos and the absence of efficient workflows to process sensor data [74,93]. Construction practitioners need tools that not only collect data, but also analyze and present it in formats that support timely and effective decision-making [93]. For instance, runtime dashboards that compare as-planned versus as-is schedules and costs can significantly enhance decision support but require sophisticated integration of real-time sensor data.

Additionally, the need for future enhancements in decision support systems is evident. These enhancements could include advanced software routines such as time-domain analysis and sensor diagnosis to further refine the data utility for decision-making processes [74,93,97]. Despite the availability of advanced sensing technologies such as GPS, laser scanners, and UAVs, the challenge of converting the raw sensor data into useful insights that can directly inform construction management practices remains.

5.1.9. Sensing data network

This barrier refers to the sensing data network required for the transmission of sensing data, including transmission protocol, speed, architecture, transmission method, data encryption method, and network scalability [48]. As shown in Fig. 19, this barrier predominantly affects construction production monitoring using positioning and communication sensors. Integrating and optimizing sensing data networks in construction is challenging due to technological gaps and the need for standardized protocols [15,20,22,26,32,63,65,71,73,80]. These challenges are critical for the effective management and utilization of sensor technologies in the construction environment. A primary issue is the lack of unified theoretical frameworks, system architectures, and standards in IoT platforms, which complicates the integration of the virtual and physical aspects of construction sensor networks [20,32]. Without standardized protocols that can reliably read, store, and transfer data irrespective of the sensing device's source, it becomes difficult to integrate and effectively utilize the data in broader decision-making processes.

Further complicating the integration of sensing technologies are the performance and compatibility issues of wireless sensor networks (DTF2), especially relevant in smart cities and large-scale construction sites [63,73]. These networks must handle data collection efficiently and ensure robust communication protocols that support high performance. However, current sensor technology in the construction industry faces issues such as real-time data transmission, bandwidth, and compatibility, which do not fully meet the practical application needs, thereby hindering the integration of advanced Industry 4.0 standards into construction applications [63,73].

Additionally, the physical infrastructure supporting sensors, such as GPS and Real-Time Kinematic (RTK), also poses limitations, particularly in remote or rural areas where reference stations or quality communication links may be lacking (DAc1) [22]. These environmental and infrastructure challenges can delay data processing and increase costs, restricting the effective deployment of sensing technologies in less accessible areas.

5.1.10. Sensor durability

In this sub-section, sensors durability refers to the ability to maintain the operational integrity and performance of a sensor over time [101]. Although this barrier primarily stems from the manufacturing process of sensors, it is important for the developers and researchers applying sensors in construction to note that ensuring sensor durability is crucial, given the harsh environments in which these devices typically operate. As shown in Fig. 20, this barrier predominantly affects structural health monitoring when using SHM sensors.Sensor durability is influenced significantly by design and manufacturing processes [19,57,92]. For example, optical fibers, commonly used in sensing applications, are particularly vulnerable at termination points where they are

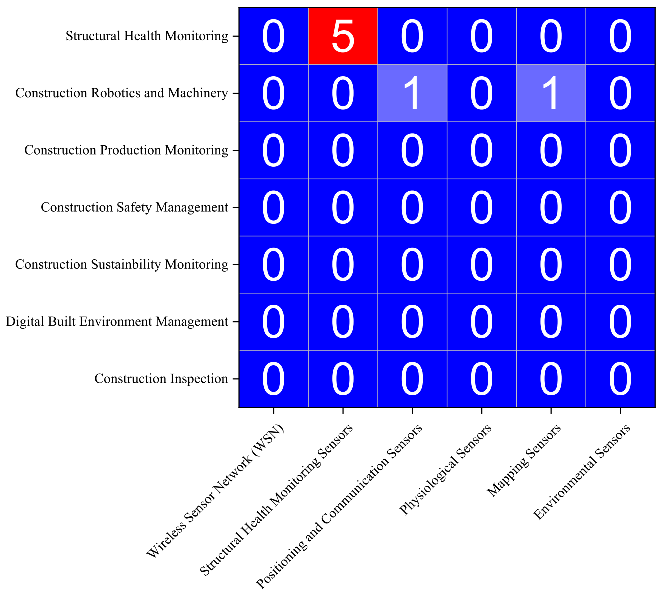

Fig. 20. Purposes and sensors applied for works that encountered the barrier of sensor durability.

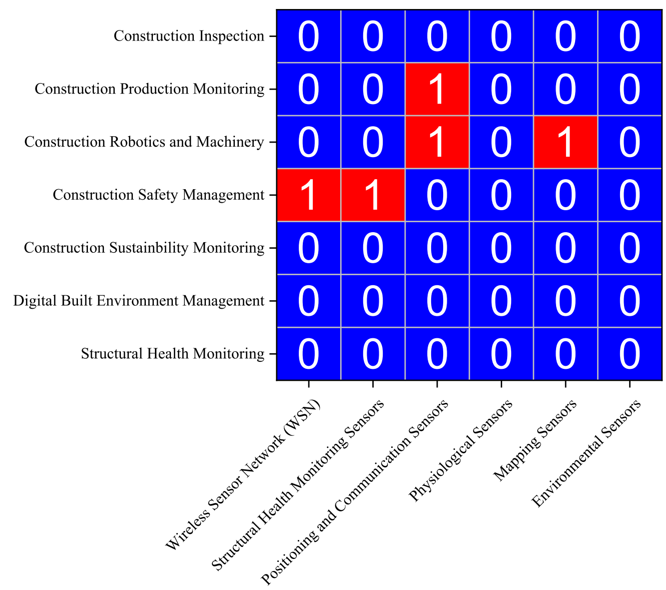

Fig. 21. Purposes and sensors applied for works that encountered the barrier of big data management.

mechanically or chemically fixed, leading to potential weaknesses [57]. Effective manufacturing practices to enhance durability include using mechanical grips that reduce stress concentrations and sealing components to protect against moisture, with materials such as stainless steel that favors corrosion resistance [19]. The manufacturing considerations are essential to ensure that the sensors can endure the challenging conditions often encountered on construction sites.

Beyond manufacturing, environmental factors heavily impact sensor performance and longevity. Sensors such as GPS and RTK, utilized on UAVs in the construction industry, face operational challenges due to susceptibility to signal interference from atmospheric conditions, tall buildings, or vegetation [22]. This interference can significantly undermine the accuracy and reliability of data, challenging their operational viability in specific environments.

Furthermore, the placement of sensors (SG2) can complicate durability issues, especially when they need to be installed in high-risk or hard-to-reach areas [31]. This issue can affect both the maintenance and reliability of the sensors. The cost of setting up extensive sensor networks can be prohibitive, particularly for smaller construction sites or in regions where the deployment of such technology is still emerging.

These challenges highlight the complexities of deploying durable sensor systems in the construction industry, where environmental, technical, and financial factors play significant roles in determining the feasibility and effectiveness of such technologies. Each aspect, from the initial design and manufacturing to the operational deployment and environmental considerations, must be carefully managed to ensure the success and sustainability of sensor applications in construction settings.

5.1.11. Big data management

The exponential increase in data volume from various sensors poses another level of difficulty in adopting sensors in the construction industry, as shwon in Fig. 21 [22,64,68,73,75,85]. This data, derived from WSN, SHM systems, and other sensor types, needs to be rapidly acquired, managed, and analyzed to be truly beneficial.

The first major challenge is establishing efficient methods to handle the vast quantities of data generated during construction projects [64]. As sensors become more integrated into construction machinery and processes, they produce an ever-increasing stream of data that needs not only to be stored, but also effectively analyzed to extract useful insights [22,68,73]. This requires robust data management systems that can handle high-frequency sampling periods without compromising the speed or accuracy of data processing.

Furthermore, the challenge extends to the need for reliable storage and data mining capabilities. The big data collected must be stored in a way that it can be accessed and analyzed quickly to support real-time decision-making in construction management, safety, and production monitoring [85]. This often necessitates significant investments in storage and computing infrastructure, as well as the development of specialized software tools for data management and analysis.

Moreover, the integration of this data into existing systems, such as BIM, further complicates data management [85]. Real-time monitoring information from sensor networks is used to evaluate the safety status of construction projects, but misjudgments can occur without access to detailed historical data from each phase of the construction cycle [85]. Therefore, effective big data management not only involves handling the current data, but also integrating it with comprehensive historical data to improve accuracy and reliability in decision-making.

5.2. Trends of the appearance of the barrier in the literature

Fig. 22 depicts the cumulative frequency of various barriers in construction research from 2005 to 2024. Barriers related to “Sensing Data Network” (DTF1) and “Sensing Data Accuracy” (DAc1) display a steady rise in frequency, emphasizing the ongoing challenges in ensuring reliable data collection and connectivity in construction environments. Meanwhile, “Sensor Durability” (DAc2) and “Multi-sensor Data Fusion” (DTF2) have maintained a moderate but consistent presence in the literature, reflecting persistent concerns over the longevity and

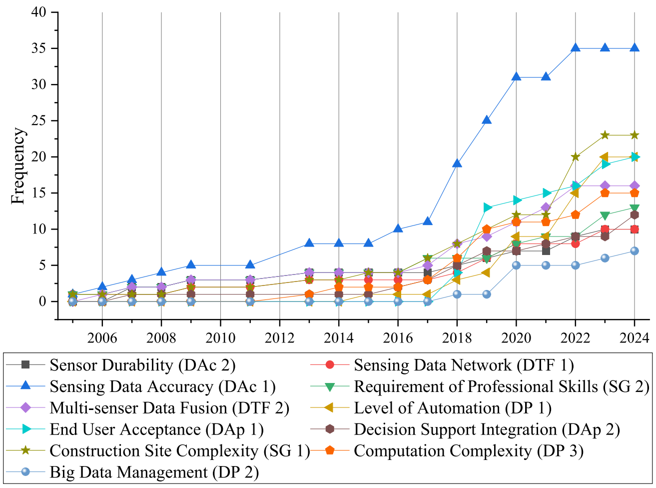

Fig. 22. Chronological trends in barriers.

integrative capabilities of sensing technologies. In contrast, “End User Acceptance” (DAp1) and “Requirement of Professional Skills” (SG2) show more modest increases. These barriers indicate critical areas where industry adoption may be lagging due to cultural and skill-related challenges. Notably, the “Level of Automation” (DP1) and “Construction Site Complexity” (SG1) have started to receive more attention in recent years, pointing to a shift in focus towards automating more complex aspects of construction as a means to address increasing site complexity.

Fig. 23 presents the stacked chronological trends of barriers from 2005 to 2024. The trends show a significant increase in attention to barriers such as sensing data accuracy, computation complexity, and end-user acceptance, particularly after 2016. This surge can be attributed to several factors. The growing adoption of advanced technologies, such as BIM, IoT, and real-time data analytics, has heightened the demand for precise and reliable sensor data. As construction projects become more complex and digitalized, the need for accurate, real-time data has intensified, pushing challenges like data accuracy and computational complexity to the forefront. Additionally, the industry’s increased focus on automation and digital decision-making tools has brought barriers related to end-user acceptance and decision-support integration into sharper focus. Ensuring that workers and managers trust and effectively use these technologies has become a critical challenge. The rapid technological advancements in construction, coupled with the rising complexity of modern projects, have also exposed new and previously underexplored barriers. Two key patterns emerge from the data: persistent concerns like data accuracy and sensor durability continue to attract steady research attention, reflecting ongoing technological challenges, while emerging areas such as big data management and decision support integration have seen rapid increases in focus. This shift highlights the growing need for sophisticated data processing and decision-making frameworks to address the practical barriers to implementing advanced technologies in construction.

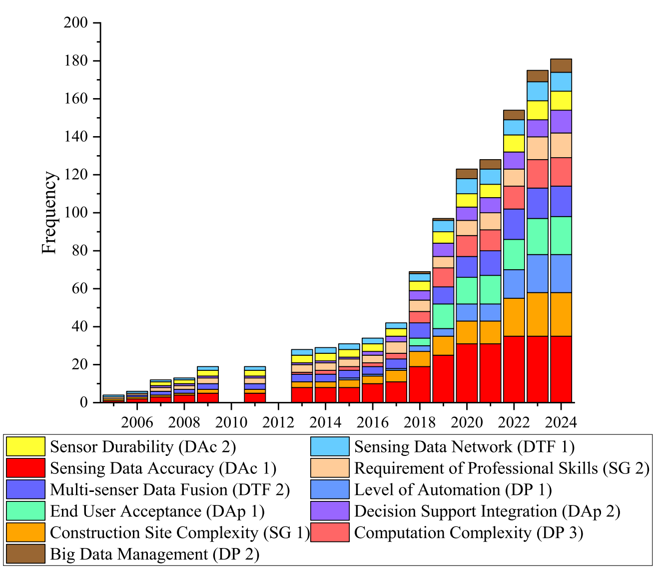

Fig. 23. Stacked chronological trend of barriers.

6. Research directions to overcome construction sensor adoption barriers

This section outlines research directions to address the barriers to sensor adoption in construction, achieved through comprehensive studies across three key areas: construction research, sensor development, and relevant fields such as manufacturing, energy, and transportation, among others. Each proposed direction includes focal points of research, supplemented by successful examples from these areas. Through this section, the authors aim to enrich the existing body of knowledge and provide insights that may encourage researchers in the construction industry to surmount the identified challenges.

6.1. Comprehensive standardization and enhanced interoperability

A fundamental barrier to sensor adoption is the lack of standardized protocols and interoperability issues among different sensor systems and platforms (DAc1, DTF1, DTF2, DP1, DP2, DP3). Unlike industries such as manufacturing, where controlled and repetitive processes allow for easy implementation of standard protocols, the construction industry operates in highly variable, project-based environments. Each construction site presents unique conditions and constraints, such as weather, terrain, building design, and the involvement of various subcontractors, all of which can impact sensor performance and data accuracy. This variability makes it difficult to develop universal standards for sensor technologies in construction. Factors like the short-term nature of projects and the fragmented nature of the industry, with numerous stakeholders possessing different technological capabilities, further complicate the creation of standardized protocols. Consequently, the construction industry requires flexible and adaptable frameworks that can be tailored to specific project conditions, in contrast to the more consistent environments in manufacturing or logistics, where stricter adherence to standardized practices is feasible.

Standardization efforts in construction must encompass hardware specifications, data formats, communication protocols, and security measures [32]. This comprehensive approach will ensure that sensor devices from different manufacturers can communicate seamlessly, reducing complexity and promoting wider adoption [17,32]. For instance, Naik [110] outlines a protocol stack for IoT systems, offering a valuable example of how such efforts can be organized, as shown in Fig. 24.

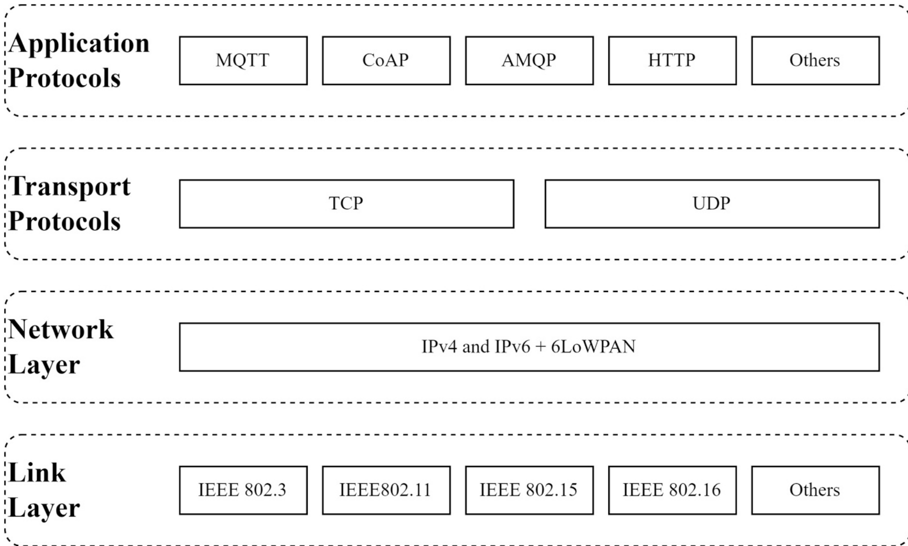

Fig. 24. Protocol Stack for IoT systems, adapted from Naik [110].

An exemplary case of standardization in construction is the framework proposed by Dave, et al. [111], which integrates Building Information Modeling (BIM) with IoT sensors using open standards to enhance the management and interaction with the built environment. This framework is demonstrated through the development of the Otaniemi3D platform, which integrates BIM and IoT data to provide insights into energy usage, occupancy, and user comfort in a campus setting. The platform uses open messaging standards and provides a proof of concept with real-world applications, showcasing the potential of this integration to improve building management and user experience.

Moreover, interoperability must extend beyond mere technical compatibility to include integrative data analytics platforms that can process and analyze data from diverse sensor sources [85]. Such platforms should support advanced data fusion techniques to enhance decision-making processes, enabling a more robust response to dynamic project conditions. As an example of such platforms in the field of energy, Kabugo, et al. [112] develop an integrative data analytics platform for a waste-to-energy plant, leveraging Industry 4.0 and IoT technologies to enhance operational efficiency and decision-making. This platform incorporates machine learning algorithms to analyze data from diverse sensor sources, enabling the creation of soft sensors that predict crucial operational parameters like syngas heating value and flue gas temperature. The case study included in their work demonstrates the platform's effectiveness in improving real-time monitoring and control within the plant, showcasing its potential to transform industrial operations through advanced data integration and analytics.

To summarize, the lack of standardization and interoperability among sensor systems remains a critical barrier to their widespread adoption in the construction industry. Without standardized frameworks, sensors from different manufacturers struggle to communicate, limiting the scalability and functionality of sensor networks. To address these issues, comprehensive protocols that allow for seamless communication and data sharing are essential. The following research questions and potential challenges explore key areas of focus for improving standardization and interoperability.

Research Questions:

- How can industry-wide standardization frameworks be effectively developed to enhance interoperability among diverse sensor systems in construction?
- What specific protocols and standards are needed to ensure seamless communication between sensors from different manufacturers, and how can they be implemented?

Potential Challenges:

- **Fragmented industry nature**: The diverse range of sensor technologies and stakeholders in construction makes it difficult to develop universally accepted standards.
- **Legacy systems integration**: Ensuring that new sensor technologies are compatible with older systems poses significant technical and operational challenges.
- **Balancing flexibility with standardization**: Creating standardized protocols that are adaptable to the varied and dynamic nature of construction projects without compromising functionality.

6.2. Data-driven decision-making enhancement

Another vital research direction is the enhancement of data-driven decision-making in construction. This involves developing integrated systems that not only collect and store data but also analyze and convert it into actionable insights through the use of Artificial Intelligence (AI). Such systems should be designed to automatically adjust to new data inputs and improve their predictive accuracies over time without human intervention [58,74]. As an example in the field of energy management, Yang, et al. [113] propose the *E*-Seq2Seq model which outperforms traditional methods in handling the security-constrained unit commitment problems by effectively integrating deep learning techniques with the unique challenges of power system operations. This proposed method not only improves decision-making accuracy but also reduces computational time, making it a significant advancement in the field of power system management.

AI and machine learning are transforming decision-making processes in the construction industry as well, by enhancing key areas such as project monitoring, scheduling, and safety [31,62]. For instance, machine learning-based systems like ALICE help optimize project schedules by analyzing multiple variables, allowing construction teams to avoid tedious planning tasks and focus on more strategic decisions [114]. Similarly, AI tools such as Buildots, which use image recognition technology to monitor progress and identify discrepancies, enable construction managers to gain real-time insights into site conditions without manual site inspections [115]. AI also plays a pivotal role in safety monitoring, with systems like Smart Vid using deep learning to predict the likelihood of accidents by analyzing site images and worker behavior, thus improving site safety while raising ethical considerations about worker surveillance [115]. These AI-driven applications provide significant benefits, such as improving project efficiency and safety, but also require careful consideration of the ethical and practical challenges they introduce.

Ethical considerations in using AI and machine learning in construction focus primarily on issues such as data privacy, surveillance, and bias [114]. AI-driven tools, like Smart Vid, which monitors worker behavior to enhance safety, raise concerns about constant surveillance and its impact on workers' privacy and autonomy [114]. Additionally, biases in AI algorithms can perpetuate unfair outcomes, especially when historical data used to train these systems reflects pre-existing biases [116]. This is particularly concerning in worker evaluations or safety prioritizations, where biased algorithms may unfairly impact certain individuals or groups. Moreover, as AI takes on more decision-making roles, there is a growing concern that human judgment may be overshadowed by AI recommendations, potentially leading to decisions that are misaligned with human values [117]. To address these challenges, transparency, the prevention of bias, and respect for worker rights must be prioritized in the implementation of AI technologies in the construction industry. These ethical considerations are critical to ensuring the responsible use of AI and machine learning in construction.

Research should also explore the development of real-time monitoring systems that utilize advanced algorithms to provide immediate feedback and early warning signals for potential issues on construction sites. This approach addresses barriers related to data management (DP2), accuracy (DAc1), and professional skills (SG2) by providing a system that enhances the usability and practicality of sensor data, thereby encouraging wider adoption among industry practitioners. In the field of transportation industrial electronics, Gou, et al. [118] introduce an intelligent, time-adaptive, data-driven method utilizing an ensemble of Extreme Learning Machine (ELM) classifiers to rapidly and accurately diagnose sensor faults in three-phase pulse width modulation inverter-fed induction motor drive systems. The method, which achieves an average diagnostic accuracy of 98 % and a decision time of 10 ms, leverages only existing system signals without additional sensors, proving robust across various operational variations and fault severities.

In summary, the use of sensors to enhance real-time decision-making in construction offers significant potential but is constrained by the challenges of data processing and analysis. Advanced analytics, such as AI and machine learning, can transform raw sensor data into actionable insights, improving site safety and operational efficiency. However, effective implementation remains challenging in dynamic environments like construction sites, with ethical considerations in AI as growing concerns. The following research questions and challenges aim to explore how these data-driven solutions can be better integrated into construction decision-making processes.

Research Questions:

- How can advanced data analytics and machine learning techniques be leveraged to improve real-time decision-making processes on construction sites?
- What are the key barriers to implementing AI-based decision-support systems in construction, and how can they be overcome?

Potential Challenges:

- **Real-time data reliability**: Ensuring accurate and timely data processing in complex and constantly changing construction environments is a challenge.
- **Resistance to AI-driven decision-making**: Many industry practitioners are accustomed to traditional methods and may resist transitioning to data-driven, AI-supported systems.
- **Data management infrastructure**: Building the infrastructure needed to handle the large amounts of data generated by sensors and making this data actionable can be resource intensive.

6.3. Sensor technology integration and user-centric innovations

Focusing on the integration of sensor technology with worker safety and construction production efficiency can address multiple barriers including end-user acceptance (DAp1), decision support integration (DAp2), and sensor durability (DAc2). This involves designing sensor technologies that are not only robust and reliable but also ergonomic and non-intrusive. Research should focus on developing sensors and sensing systems using user-centric methodologies, which can not only ensure the fulfillment of end-users' practical requirements, but also facilitate a continuous improvement process [119]. In the construction research field, notable examples of such methodologies include the safety monitoring tool by Lin, et al. [120], the educational serious game developed by Ebner and Holzinger [121], and the interior finishing material selection tool developed by Zhang, et al. [122], among others. These exemplary studies offer valuable insights that can be applicable to researchers engaged in sensor development. Furthermore, integrating sensors with digital twins and BIM can further help visualize complex data and simulate various scenarios, improving planning and decision-making processes [33,81].

In brief, ensuring that sensor technologies align with user needs and preferences is essential for successful adoption in construction. User-centric innovations can significantly enhance the usability of sensors, especially when feedback from workers and site managers is incorporated into the design and deployment process. These innovations can improve safety and efficiency on construction sites, but challenges remain in balancing complexity and usability. The following research questions and challenges highlight the need to better integrate user-focused design principles into sensor technology.

Research Questions:

- What are the effective methods for integrating sensor technology with user-centric design principles to enhance worker safety and productivity in construction?
- How can user feedback be systematically incorporated into the design and deployment of new sensor systems to ensure greater adoption and utility?

Potential Challenges:

- **Complexity vs. usability**: Designing advanced sensor technologies that are both powerful and easy to use for non-technical workers is a delicate balance.
- **Workforce resistance to new technologies**: End-users may be hesitant to adopt new sensor technologies, particularly if they are perceived as disruptive or overly complex.
- **Feedback incorporation**: Continuously integrating feedback from users to improve sensor systems may be difficult due to project timelines and resource constraints.

6.4. Training and capacity building

Overcoming barriers related to the requirement of professional skills (SG2) and the complexity of technology (DP2, DP3) requires focused efforts on training and capacity building. This research direction should aim at developing comprehensive training modules and simulation environments that use extended reality to mimic real-world scenarios. These training programs should be designed to enhance understanding and foster skills related to the deployment, maintenance, and interpretation of sensor data [75]. An example of such training programs in the field of manufacturing is the integrated application developed by Mura, et al. [123], which explores the use of augmented reality (AR) and force sensors to enhance the accuracy and efficiency of manual assembly processes. The system aims to reduce human error by providing real-time feedback and corrective instructions through AR devices, helping workers to perform assembly tasks correctly. The integration of AR with force sensing technologies enables detailed monitoring and guidance, ensuring precise adherence to assembly protocols and reducing the likelihood of errors and inefficiencies in production lines.

To conclude, one of the most significant barriers to the adoption of sensor technologies is the lack of sufficient training and capacity-building programs. Construction professionals need to be trained in deploying, maintaining, and interpreting sensor systems effectively. Incorporating technologies like extended reality (XR) into training programs can help bridge this gap, offering immersive, real-world simulations that prepare workers for using these systems. The following research questions and challenges focus on developing robust training strategies to address this issue.

Research Questions:

- What are the effective strategies for developing comprehensive training programs that enhance the skills needed to deploy, maintain, and interpret sensor data in construction?
- How can extended reality (XR) technologies be used to simulate real-world scenarios for training construction professionals in the use of sensor technologies?

Potential Challenges:

- **Scalable training programs**: Developing comprehensive training modules that can be implemented across a diverse workforce, from site workers to managers, is a major challenge.
- **Replication of real-world complexity in training**: XR and simulation-based training must accurately reflect the complexity of real-world construction sites to be effective.
- **Resource availability for ongoing training**: Ensuring consistent access to the necessary resources for continuous capacity building, particularly in smaller firms or on remote sites.

6.5. Lean construction 4.0

Lean Construction 4.0 offers a transformative approach to overcoming sensor adoption barriers in the construction industry by integrating advanced technology with Lean management principles [124]. This strategy goes beyond the simple application of Industry 4.0 technologies such as IoT, AI, and robotics, focusing also on enhancing operational and strategic outcomes through continuous improvement, waste reduction, and value maximization [124]. Distinct from traditional Construction 4.0, which is fundamentally technology-centric, Lean Construction 4.0 aligns technology deployment with lean processes to optimize the integration of people and culture, Industry 4.0-driven digital technologies, and production management philosophy. This alignment helps address challenges such as end user acceptance (DAp1), decision support integration (DAp2), level of automation (DP1), and requirement of professional skills (SG2).

As previously discussed in Section 5.1.3, the barrier of end user acceptance (DAp1) can stem from a lack of familiarity or perceived complexity. Lean Construction 4.0 addresses this challenge by emphasizing user-centric design principles that ensure technologies are intuitive and meet the real needs of end-users. By involving workers and stakeholders in the development and implementation phases, Lean Construction 4.0 fosters a sense of ownership and familiarity with the new technologies [125]. Regular training sessions and interactive workshops help demystify the technologies, reducing resistance and increasing acceptance [125].

A crucial aspect of Lean Construction 4.0 is its emphasis on standardization and interoperability of sensor technologies [126]. Developing standardized protocols ensures that different systems and devices can seamlessly communicate, enhancing data reliability and system integration [104]. This standardization is key to managing the complex data flows and integration challenges prevalent in modern complex sensing environments [48]. By standardizing data formats and communication protocols, the framework ensures seamless data integration across different platforms and systems. This interoperability allows for the efficient synthesis of data, which supports more informed decision-making and improves strategic and operational outcomes [104]. Moreover, decision support tools in Lean Construction 4.0 are designed to be adaptive, learning from past decisions to provide more accurate recommendations over time [127].

Furthermore, Lean Construction 4.0 prioritizes training and skills development to ensure that construction professionals are well-equipped to handle new technologies [128]. It supports continuous learning and capacity building through regular training programs and workshops, which prepare the workforce for current and future technological demands. This focus is critical in the modern construction sector where the technological landscape is rapidly evolving. Training programs and workshops are regularly updated and provided to all levels of staff, from site workers to management. This educational focus helps mitigate one of the industry's historical challenges: the lack of standardization in skills and knowledge across projects and regions [44].

Unlike the manufacturing sector, where lean production theory has laid a robust foundation for digitalization under Industry 4.0 [129], the construction industry has historically lacked a unified theory in design, planning, and production [44]. This absence of a standardized theory makes the adoption of Lean and digital technologies in construction particularly challenging [130], necessitating a tailored approach such as Lean Construction 4.0 to bridge these gaps. Lean Construction 4.0 supports a cultural shift towards continuous improvement and waste reduction, principles deeply embedded in lean management. This shift is not only about adopting new technologies but also about improving the strategic and operational frameworks within which these technologies operate [131]. The ultimate goal is to create a more agile, responsive, and efficient construction industry capable of handling projects of varying complexity and scale, thereby driving forward the industry's overall progression towards digital integration and improved project outcomes [129].

In summary, Lean Construction 4.0 provides a framework for integrating sensor technologies to drive efficiency, waste reduction, and continuous improvement. However, aligning sensor adoption with Lean principles presents challenges, particularly in terms of integrating decision-support systems and ensuring user acceptance. The following research questions and challenges explore how sensor technologies can be optimized to support Lean Construction 4.0 practices while

Table 5
Summary of suggested research directions, barriers to be addressed, and potential challenges.

Suggested Research Directions	Barriers to be Addressed	Potential Challenges
Comprehensive Standardization and Enhanced Interoperability	DAc1, DTF1, DTF2, DP1, DP2, DP3	• Fragmented industry nature • Legacy systems integration • Balancing flexibility with standardization
Data-Driven Decision-Making Enhancement	DP2, DAc1, SG2	• Real-time reliability • Resistance to AI-driven decision-making • Data management infrastructure
Sensor Technology Integration and User-Centric Innovations	DAp1, DAp2, DAc2	• Complexity vs usability • Workforce resistance • Feedback incorporation
Training and Capacity Building	SG2, DP2, DP3	• Scalability • Construction site complexity for replication • Resource availability for ongoing training
Lean Construction 4.0	DAp1, DAp2, DP1, SG2	• Complexity vs. Usability • Resistance to change

addressing potential barriers to adoption.

Research Questions:

- How can Lean Construction 4.0 principles, with a focus on human-centric design, be leveraged to address barriers in sensor adoption and enhance user engagement?
- How can the core production principles of Lean Construction 4.0 improve the efficiency and effectiveness of sensor technology in project management and production control?

Potential Challenges:

- **Balancing human-centric design with technological complexity**: While Lean Construction 4.0 emphasizes human-centric design, integrating advanced sensor technologies may introduce complexity that could be difficult for end-users to adopt. Ensuring that sensor systems are intuitive and user-friendly, while maintaining their technical capabilities, could pose a significant challenge.
- **Resistance to change and adoption**: Implementing Lean principles alongside sensor technologies may encounter resistance from stakeholders who are accustomed to traditional construction practices. Overcoming this resistance and fostering engagement with new systems will require both cultural shifts and training efforts.

7. Summary

Table 5 presents a summary of this section. The research directions outlined in this section provide a roadmap to overcome the critical barriers hindering sensor adoption in the construction industry. By addressing key challenges such as standardization, data-driven decision-making, user-centric design, training, and the integration of Lean Construction 4.0, these research areas present actionable pathways for the industry to advance technologically. The interconnections between barriers like data accuracy, decision support, and end-user acceptance highlight the need for collaborative solutions that incorporate technological advancements and human factors. Furthermore, addressing the ethical and practical challenges of emerging technologies such as AI, machine learning, and XR will be crucial for widespread adoption. The successful implementation of these research directions will not only improve operational efficiency but also foster a more adaptable and future-ready construction industry.

8. Conclusion

The construction industry, integral to the global economy, underutilizes sensors despite their proven return on investment and potential for operational efficiency and sustainability. This gap, significant given sensors' transformative impact in other sectors such as manufacturing, is primarily due to skepticism and traditionalism in construction practices. This paper addresses the challenges hindering sensor adoption in construction by delineating them into 11 distinct barriers and examining their interrelationships and implications on construction processes.

In discussing and mapping these challenges, the literature provides substantial support for many of the findings. For instance, the complexity of construction sites (SG 1) is highlighted by Antwi-Afari et al. [58] who emphasize the need for adaptable and resilient sensor technologies in dynamic environments. The requirement of professional skills (SG 2) is a common theme across various studies, with Ansari [57] underscoring the skill gap as a major hindrance to the adoption of advanced technologies. Similarly, issues related to sensing data accuracy (DAc 1) and sensor durability (DAc 2) are well-documented by Ansari [19], who point out the challenges posed by harsh construction environments on sensor performance. For data transfer and fusion, challenges in establishing reliable sensing data networks (DTF 1) and the complexity of multi-sensor data fusion (DTF 2) are recognized by Awolusi et al. [32], who highlights the technical difficulties in ensuring seamless communication and integration across various sensors. In terms of data processing, Rao et al. [31] and Liang et al. [22] discuss the complexities of automating processes (DP 1), managing large datasets (DP 2), and addressing computation challenges (DP 3) in real-time applications. Finally, barriers related to end-user acceptance (DAp 1) and decision support integration (DAp 2) are supported by Khalid et al. [75], who argue that these factors significantly affect the practical implementation of sensor technologies. These references provide a comprehensive foundation that reinforces the need for industry-wide solutions and targeted research to overcome these barriers.

Our research aims to not only identify and categorize these barriers but also to propose strategic directions for overcoming them. Employing a systematic literature review, we analyze recent advancements in sensor technology and the persistent barriers to their adoption in construction. This approach provides a comprehensive understanding of these barriers and informs future research directions. The findings highlight several key challenges, including the need for enhanced skills, standardized practices, and better data management systems, which align with the broader goals of revolutionizing the industry through digital technologies. Our research delineates these issues into distinct categories, facilitating targeted strategies to address them. Moreover, by providing a structured analysis of barriers and their trends over time, this paper contributes valuable insights into the evolution of sensor adoption challenges in the construction sector.

The contributions of this study are threefold: conceptual, empirical, and methodological. Conceptually, the study offers a comprehensive framework that categorizes and explores the interrelationships between barriers to sensor adoption in construction. This framework contributes to a deeper understanding of how these barriers interact, providing a foundation for future research and industry practices. Empirically, the study synthesizes findings from a broad range of literature published between 2004 and 2024, identifying key trends and patterns related to sensor adoption across multiple stages of implementation. This synthesis offers valuable insights for both academics and practitioners by highlighting areas of concern and potential opportunities for intervention. Methodologically, the study combines descriptive quantitative analysis and qualitative content analysis, providing a robust approach to systematically exploring the complex barriers to sensor adoption. The use of both analytical techniques allows for a nuanced understanding of these challenges, making the findings more applicable and relevant to real-world construction practices.

In summary, this work not only bridges the gap in the literature by providing a holistic view of the barriers to sensor adoption but also serves as a foundational reference for stakeholders aiming to enhance the efficacy and integration of sensor technologies in construction. The outcomes of this research are geared towards equipping the industry with knowledge and strategies to harness the full potential of sensors, thereby driving forward the agenda of digital transformation in construction.

This study, while comprehensive, acknowledges certain limitations that could influence its conclusions. First, despite meticulous efforts to encompass a broad range of sources, there remains the possibility that some relevant papers were not included in the review. However, the authors have made their best efforts to mitigate this by employing systematic and thorough search criteria. Second, the interpretation and categorization of challenges may carry inherent biases. To address this, the authors utilized NVivo for content analysis, carefully selecting the most frequently mentioned terms and their clusters to ensure objectivity in identifying key themes. Third, the study may not fully capture the actual usage of sensors in the construction industry as it primarily relies on published literature, which might not reflect the entirety of practical implementations. Future research should, therefore, focus on directly investigating sensor applications in the industry to provide a more comprehensive understanding of their utilization and impact.

CRediT authorship contribution statement

Zhong Wang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Vicente A. González:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **Qipei Mei:** Writing – review & editing, Visualization, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **Gaang Lee:** Writing – review & editing, Visualization, Supervision, Methodology, Formal analysis, Conceptualization.

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.

Data availability

Data will be made available on request.

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