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EDITED BY

Olli Seppänen,
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REVIEWED BY

Natalia E. Lozano-Ramírez,
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Mohammad Mehdi Ghiai,
University of Louisiana at Lafayette,
United States
Gaetano Di Mino,
University of Palermo, Italy

*CORRESPONDENCE

Jiaqi Suo,
✉ suoj@purdue.edu

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The rise of digitalization in constructions: State-of-the-art in the use of sensing technology for advanced building-assistance systems

Jiaqi Suo^{1*}, Sharvari Waje², Venkata K. T. Gunturu², Akshitha Patlolla², Claudio Martani³ and Hazar Nicholas Dib⁴

¹Research Assistant. Laboratory for Future-Ready Infrastructure (FuRI Lab), School of Construction Management Technology, Purdue University, West Lafayette, IN, United States, ²Master student. School of Construction Management Technology, Purdue University, West Lafayette, IN, United States, ³Assistant Professor and Director of the laboratory for Future-Ready Infrastructure (FuRI Lab). School of Construction Management Technology, Purdue University, West Lafayette, IN, United States, ⁴Associate Professor. School of Construction Management Technology, Purdue University, West Lafayette, IN, United States

The construction sector is traditionally affected by on-site errors that significantly impact both budget and schedule. To minimize these errors, researchers have long hypothesized the development of AR-enriched 4D models that can guide workers on components deployment, assembly procedures, and work progress. Such systems have recently been referred to as Advanced Building-Assistance Systems (ABAS). However, despite the clear need to reduce the on-site errors, an ABAS has not been implemented and tested yet. This is partially due to a limited comprehension of the current wealth of available sensing technologies in the construction industry. To bridge the current knowledge gap, this paper evaluates the capabilities of current use of sensing technologies for objects identification, location, and orientation. This study employs and illustrates a systematic methodology to select according to eight criteria and analyzed in three level the literature on the field to ensure comprehensive coverage of the topic. The findings highlight both the capabilities and constraints of current sensing technologies, while also providing insight into potential future opportunities for integrating advanced tracking and identification systems in the built environment.

KEYWORDS

computer vision, location sensing, positioning, object identification, tracking, communication and control systems, orientation, building and construction management

1 Introduction

Building construction is a vital component of the US economy, representing about 4% of the national GDP in 2022 (BEA, 2023). Despite its strategic role, the construction industry is still challenged by a significant incidence of on-site errors and inefficiencies, which impact construction expenses and timelines (Jaafar et al., 2018). These challenges encompass, among others, the misplacement or misalignment of components and prolonged, inefficient searches for objects on-site, which are particularly relevant in

assembly constructions, which constitute a significant market share in the US. (García de Soto et al., 2022).

Traditionally, errors and inefficiency in the identification and placement of components in construction have been considered unavoidable. However, with recent technological advancements providing control and support to on-site constructions, this is no longer the norm. Latest advancements in sensing technologies (Kumar et al., 2015), Internet of Things (IoT), 4D virtual representation (Pan et al., 2018) and augmented reality (Yan, 2022) have created the premises for the development of AR-enriched cyber-physical 4D models to support the workers during the construction, i.e., indicating the components to be deployed according to the work plan as well as the location and mode of assembly using augmented reality, and tracking the progress of the work to automatically update the Building Information Modeling (BIM) (Chen et al., 2020; Turkan et al., 2012).

Such a construction support system has recently been referred to (Suo et al., 2023) as Advanced Building-Assistance Systems (ABAS), mutating the well-established concept of Advanced Driving-Assistance Systems (ADAS) from the automotive industry (Li et al., 2021). ABAS build on three core sensing capabilities to constantly map the movements of objects in physical construction sites; these to identify, track, and orient components in real-time. Indeed, achieving synchronization of on-site assembly processes with the 4D model first necessitates the capability to: (i) locate specific objects, e.g., identifying a particular beam intended for installation in a specific part of the construction site among numerous others; (ii) track their movements, i.e., detect when the beam is moved from its original stack to its designated location in the construction; and (iii) recognize their orientation upon placement, e.g., detecting the alignment of the beam on all axes when laid in place. These sensing capabilities play a vital role in ensuring a consistent alignment of the physical construction process with the scheduled activities outlined in a 4D virtual model (Suo et al., 2023).

Despite the clear need to reduce the on-site errors and the wealth of sensing technologies to identify, track, and orient objects, recently become available, an ABAS system has not been implemented and tested yet. This is partially due to the notorious resistance of the construction sector to adopt technological advancements (Hunhevicz and Hall, 2020), which often stems from a limited comprehension of the existing technological capabilities that could enhance the construction industry.

To cover this gap, the aim (i.e., the research question) of the present paper is to address the current lack of understanding of the state of research on Automated Building Assembly Systems (ABAS). Establishing a common understanding of the current capabilities in performing these fundamental tasks on a construction site is essential for developing a cyber-physical interface capable of automatically synchronizing the movements of physical components with their virtual counterparts. With the goal of promoting the progress of Automated Building Assembly Systems (ABAS), this paper aims to address the current knowledge gap through a systematic analysis of how sensing technologies are currently applied to recognize, locate, and orient objects.

2 Methodology

In this section, the most cutting-edge works on the use of object identification, tracking and orientation recognition are analyzed using a systematic method.

In this work, we have systematically examined the current status of research on object identification, location, and orientation by selecting, categorizing, and analyzing relevant scientific publications in these fields. We chose papers that: (1) were published within the past 20 years, i.e., since January 2003; (2) addresses objects identification, tracking, and orientation; and (3) involve technologies that could be used on a construction site, i.e., that are used or can be used in outdoor or in a non-sterile environment. The selection was run using common database for scientific publications, including Google Scholar and Scopus. Then, the chosen articles were categorized according to 8 criteria: the year of publication, the sector of application, the type and number of objects treated, the scope of the study, the sensing technology used, its state of development (i.e., the maturity of the technology) and its limitation for large scale deployment on a construction site. The choice of the criteria stems from the research question of the analysis. Therefore, some of the criteria were chosen to identify trends in the distribution of works over time, sector and objectives, and some to clarify the dependency of the applications to the state of the required technology, i.e., complexity and number of objects treated, type and maturity of the involved technology and potential barriers to implementing these solutions on a large scale, particularly in dynamic and complex environments like construction sites. The rationale for the classification of each of the criteria is reported in Table 1.

Finally, the categorized papers were analyzed to uncover patterns, trends, and areas of deficiency in the field of objects identification, location, and orientation. The analysis has been designed to delve into the relationships and potential gaps within the development of the relevant sensing technologies to ABAS. To this scope the analysis was conducted across three distinct levels:

Level 1 - For each of the eight criteria, a frequency distribution of the classifications was produced, e.g., the number of publications on object tracking. The rationale behind this level of investigation was to identify overarching trends and prevailing themes, for establishing a fundamental framework upon which more detailed analyses could be constructed.

Level 2 - A dual interpolation was conducted on the most pivotal criteria identified in the Level 1 analysis, i.e., these that provided the most indicative patterns (e.g., if the analysis of a criteria show a particular concentration of research on a specific aspect over the others, that underscore a meaningful tendency, that criteria is retained for further interpolation in level 2), to create a frequency distribution that compares the classification of one criterion against another. For example, determining the number of publications related to tracking of construction elements.

Level 3 - A triple interpolation was conducted on the most critical criteria identified in the Level 1 analysis to generate a frequency distribution that compares one classification against the other two. This resulted in a distribution that represents the frequency of specific combinations of classification characteristics. For example, providing insights into the number of works that

TABLE 1 Criteria to classify the selected publications.

Criteria	Classified in . . .
Year	accordance to the year of publication, to identify any patterns or trends over time
Sector of application	(1) building management; (2) transportation infrastructure; (3) construction sites; (4) logistics; (5) industry (which includes yards, mills, portals, and power plants); and (6) Unspecified (NA - not applicable)
Object type	(1) construction elements, such as precast walls, pipe spools, construction hard hats and steel beams; (2) Objects in Motion like trucks, mobile robots, shopping carts and vehicles; (3) Living beings, including people (e.g., construction workers, hospitals' patients) and animals; (4) Parcels, such as packages, delivery boxes, pallets, and crates; and (5) others, including metal objects, LEGO sets, and hospital equipment etc.
Number of Objects	(1) single objects [S], (2) multiple objects [M]; (3) and unspecified [NA]
Scope	tracking [T]; orientation [O]; identification [I] of the object. Or a combination of these, e.g., tracking and orientation [TO], tracking, orientation and identification [TOI]. Or not specified [NA]
Technology used	(1) location sensors, specific to location determination like ultrawide band technology; (2) Imaging-based tracking, any form of image processing and deep learning methodologies such as R-CNN (Zhao et al., 2022); (3) Identification tags - diverse forms of Radio Frequency Identification (RFID) technology; (4) Other sensors - all types of sensors apart from location (e.g., Microsoft Kinect sensor, Raspberry Pi 3B+, Optical beacons, IR channel, Optical AI sensor, Flash LADAR, TOF sensor, TSL cloud point, nanoLOC sensor node)
Maturity of technology	The works presented were classified in accordance to the Technology Readiness Level scale (TRL ¹): TRL1, Basic principles observed and reported; TRL2, Technology concept and/or application formulated; TRL3, Analytical and experimental critical function and/or characteristic proof of concept; TRL4, Component and/or breadboard validation in a laboratory environment; TRL5, Component and/or breadboard validation in a relevant environment; TRL6, System/subsystem model or prototype demonstration in a relevant environment; TRL7, System/Subsystem model or prototype demonstration in an operational environment; TRL8, Actual system completed and qualified through test and demonstration; TRL9, Actual system proven through successful mission operations
Limitations	(1) technical rigidity, (2) implementation issues, (3) measurement challenges, (4) high cost and the requirement for (5) specialized training, (6) not elsewhere included [NEI], e.g., the need for custom-built components or proprietary software compatibility in a standardized industry environment, and (7) not specified [NA]. Technical rigidity encompasses the requirement for an advanced setup, which involves a higher number of tags, an increased number of GPUs, and a clear line of sight. Implementation issued includes restrictions on object compatibility, sensitivity to environmental changes, and the need for further research. Measurement challenges comprised of limited sensor read range, tracking incapability under dynamic conditions or only when the object is static, unaccounted dynamic errors in calculations, obstacle issues during travel direction and position calculations, occlusion, and large positional errors

specifically target logistics infrastructure, using tracking technology, for TRL level.

3 Analysis of sensing technology for object identification, tracking and orientation recognition

The selected 72 articles are reported in Tables 2–4 alongside their specific classification for each of the 8 criteria. The results of the 3 levels analysis are further shown in Figures 1–5 and commented in the following text².

3.1 Level 1 analysis

Level 1 analysis (Figure 1) shows how approximately one-third of the studies selected (37%) have been conducted within the

construction sector and have been done with increasing consistency since 2019. Papers from this year on constitute 43% of the total publications in the two-decade span. The dominance of the construction sectors in the development and testing of solutions for objects identification, tracking and orientation reflects the pressing need for ABAS in this domain characterized by a complex interplay of moving machinery, materials, and personnel. Moreover, more than half the studies focus on multiple objects, as a consequence of the need in many sectors of identify and track objects among multiple others (e.g., a wooden beam out of a stock). While, over half of the studies primarily focus on two types of objects: construction elements (e.g., wooden components for balloon frame constructions) and living beings (e.g., humans on industrial or construction sites, typically for safety reasons, or animals for farming purposes). In terms of technology used, imaging-based tracking, i.e., systems using computer vision for image capturing, background subtraction, bodies detection, bodies tracking and data association (Martani et al., 2017), emerges as the mode, with Radio Frequency Identification (RFID) following closely. The preference for these technologies reflects their affordable scalability - i.e., RFID are relatively inexpensive compared to other sensing technologies and allow for affordable large-scale deployments, while imaging-based tracking is cost invariant to the volume - and resistance - i.e., RFID are resistant and often reusable tags, while imaging-based tracking does not require deployment of sensors - which are valuable attributes in many site deployments. In terms of technology maturity, over 60% of studies have used

1 Source: <https://esto.nasa.gov/trl/>.

2 Since the years are progressive, the legends for this classification characteristic is color graduated to facilitate visualizing the progression, i.e., lighter regions signify more remote years, with values increasing as the shade darkens. This is trusted to reduce the cognitive load on the reader, making it easier to focus on the data itself rather than deciphering the meaning of multiple colors.

TABLE 2 Classification of the selected articles focusing on ABAS (1/3).

References	Sector	Object type	Object number	Technology	Scope	Limitation	TRL
Jaselskis and El-Misalami, (2003)	Construction Site	Construction Elements	M	Identification tag	T	Measurement difficulties	6
Esteve-Taboada and Garcia. (2003)	NA	Others	M	Imaging-based tracking	O	Training needed	3
Song et al. (2006)	Industry	Construction Elements	NA	Identification tag	T I	Measurement difficulties	9
Goodrum et al. (2006)	Construction site	Construction Elements Living Beings	M	Identification tag	T I	Implementation difficulties Measurement difficulties	7
Ergen et al. (2007)	Industry	Construction Elements	S	Identification tag Location sensor	T I	Measurement difficulties Implementation difficulties	7
Skibniewski et al. (2007)	Construction Site	Construction Elements	NA	Other sensors	I	NEI	3
Teizer et al. (2007)	Construction Site	Objects in motion Living Beings	NA	Other sensors	T O	Measurement difficulties	9
Jang and Skibniewski, (2008)	Construction site	Construction Elements	M	Other sensors	T O	Implementation difficulties	7
Rohrig and Spieker, (2008)	Logistics	Objects in motion	S	Other sensors	T I	Measurement difficulties	7
Gao and Yuen, (2011)	NA	Objects in motion	NA	Identification tag	T	NA	6
Heißmeyer et al. (2012)	Industry	Parcels	NA	Other sensors	O	Measurement difficulties	8
Weerasinghe et al. (2012)	Construction site	Construction Elements	M	Other sensors	T I	Implementation difficulties Measurement difficulties	6
Escorcía et al. (2012)	Building management	Living Beings	M	Other sensors	T O	Training needed	7
Han and Lee, (2013)	Construction site	Living Beings	M	Imaging-based tracking	T O	Technical Rigidity	6
Arif et al. (2013)	Construction Site	Construction Elements	NA	Other sensors	T I O	Measurement difficulties	8
Turkan et al. (2014)	Construction site	Construction Elements	NA	Other sensors	T	Measurement difficulties	5
Khosrowpour et al. (2014)	Construction site	Living Beings	M	Imaging-based tracking	T I O	Measurement difficulties	7
Ren et al. (2014)	Building management	Others	M	Other sensors	T I O	Training needed	6
Galna et al. (2014)	Building management	Living Beings	M	Other sensors	T	Implementation difficulties	7
Akhavian and Behzadan, (2015)	Construction site	Construction Elements	S	Other sensors	T O	Measurement difficulties	6
Huang et al. (2015)	Industry	Objects in motion	NA	Other sensors	T	Technical Rigidity	6

technologies that are TRL 6 or above. This means that among the publications selected the vast majority used sensing technologies, at least on a prototype testing. This is not surprising as it confirms a known tendency in works addressing technology development and validation to focus on practical testing and deployments over only

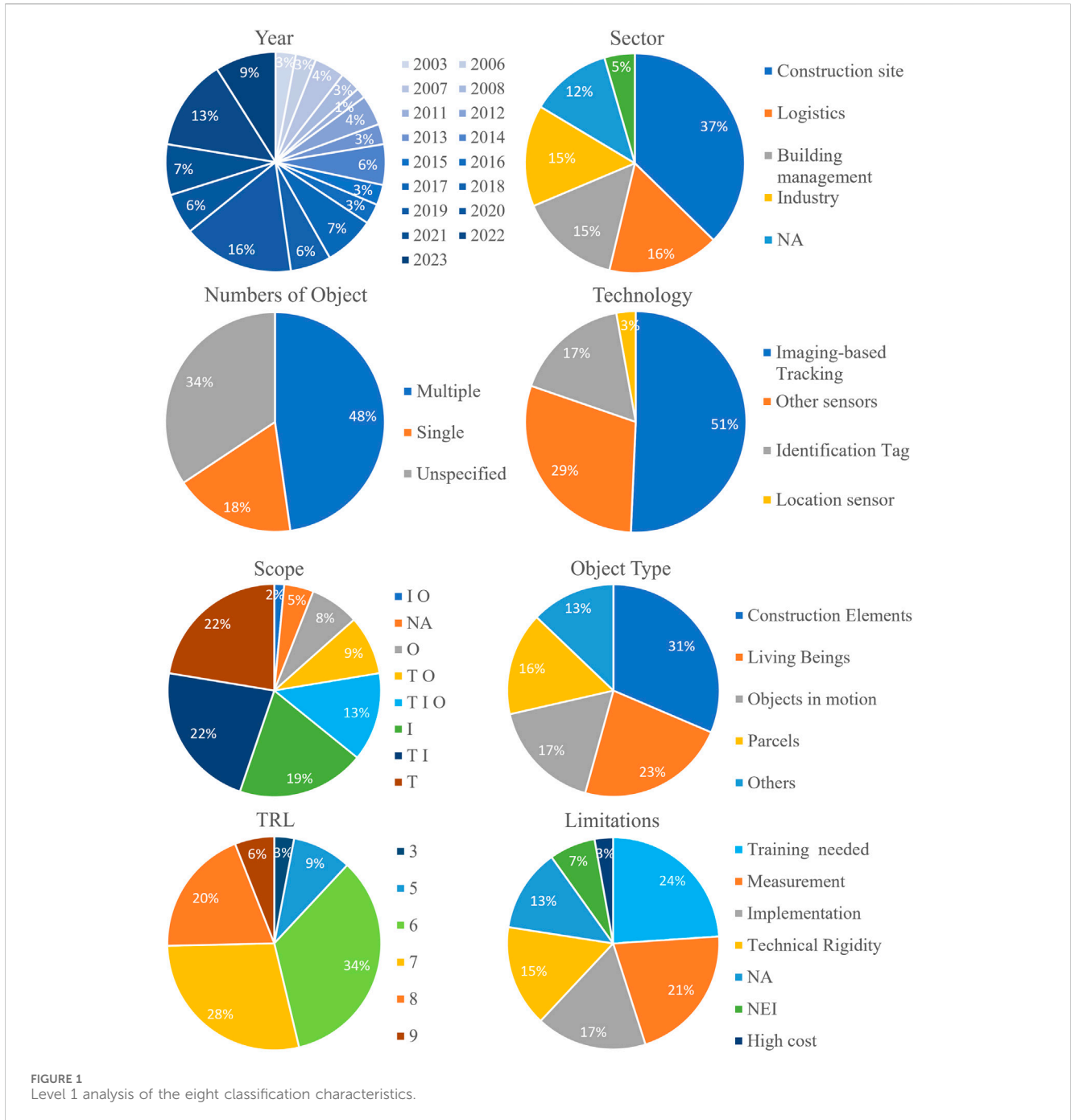
theoretical hypothesis, basic principles observation or concept formulation. Finally, an overarching limitation across various technologies, especially those involving Image-based tracking, is the need for training. Closely following this is the challenge of measurement difficulties, especially pronounced in the context of

TABLE 3 Classification of the selected articles focusing on ABAS (2/3).

References	Sector	Object type	Object number	Technology	Scope	Limitation	TRL
Contigiani et al. (2016)	Building management	Objects in motion	NA	Location sensor	T I	NA	7
Lavner et al. (2016)	NA	Living Beings	NA	Imaging-based tracking	NA	NA	5
Jeong et al. (2017)	Building management	Living Beings	S	Other sensors	I	NA	8
Shaari and Nor, (2017)	NA	Parcels	S	Identification tag	T I O	Technical Rigidity	8
Valente and Neto, (2017)	Industry	Construction Elements	S	Identification tag Other sensors	T I O	NA	7
Tao et al. (2017)	Transport	Objects in motion	M	Imaging-based tracking	T I	Measurement difficulties	7
Hamledari et al. (2017)	Construction site	construction Elements	M	Imaging-based tracking	T	Implementation difficulties	5
Brownjohn et al. (2017)	Transportation	Others	M	Others	T	Measurement difficulties	6
Kovar et al. (2018)	Transportation	Living Beings	S	Imaging-based tracking	T	Technical Rigidity	5
Lee and Marsic, (2018)	Building management	Others	M	Identification tag	T I	High cost	6
Fang et al. (2018a)	Construction site	Construction Elements Living Beings	M	Imaging-based tracking	NA	Technical Rigidity	8
Fang et al. (2018b)	Construction site	Living Beings	M	Imaging-based tracking	T I	Measurement difficulties Technical Rigidity	6
Liu et al. (2018)	NA	Living Beings	S	Imaging-based tracking	I	Training needed	8
M'hand et al. (2019)	Logistics	Objects in motion	S	Identification tag	T I	Implementation difficulties	9
Rashid and Louis, (2019)	Construction site	Construction Elements	S	Other sensors	T	NA	7
Li et al. (2019)	Logistics	Parcels	M	Imaging-based tracking	I	NA	6
Lee and Park, (2019)	Construction site	Living Beings	M	Imaging-based tracking	T	Technical Rigidity	7
Liu and Li, (2019)	Transport	Others	M	Imaging-based tracking	O	NEI	5
Huang et al. (2019)	Logistics	Parcels	M	Imaging-based tracking	T I	Training needed	6
Guven and Ergen, (2019)	Construction site	Construction Elements	M	Identification tag	T I	Technical Rigidity	7
Roddick et al. (2019)	Transport	Objects in motion	NA	Imaging-based tracking	I	Training needed	7
Hoang, (2019)	Construction site	Construction Elements	NA	Imaging-based tracking	I	Implementation difficulties	6
Roberts and Golparvar-Fard, (2019)	construction site	Construction Elements	NA	Imaging-based tracking	T	Implementation difficulties	6
Dror et al. (2019)	construction site	Construction Elements	M	Identification tag	T I O	Implementation difficulties	7
Najafi et al. (2019)	Building management	Objects in motion	NA	Imaging-based tracking	T I O	NEI	6

TABLE 4 Classification of the selected articles focusing on ABAS (3/3).

References	Sector	Object type	Object number	Technology	Scope	Limitation	TRL
Zhang et al. (2020)	Construction site	Construction Elements	NA	Imaging-based tracking	I	Training needed	5
Angah and Chen, (2020)	Construction site	Living Beings	M	Imaging-based tracking	T	Training needed	8
Nguyen et al. (2020)	Building management	Living Beings	M	Other sensors	T	Measurement difficulties	7
Wang et al. (2020)	Building management	Construction Elements	S	Imaging-based tracking	T O	Technical Rigidity	9
Zhu, (2021)	Logistics	Parcels	S	Imaging-based tracking	I	NEI	8
Malburg et al. (2021)	Logistics	Parcels	M	Imaging-based tracking	T I O	Training needed	6
Iqbal et al. (2021)	Industry	Others	M	Imaging-based tracking	I	Training needed	6
Huang et al. (2021)	NA	Living Beings	NA	Other sensors	T	Training needed	8
Sengupta et al. (2021)	Building management	Living Beings	NA	Imaging-based tracking	O	Training needed	8
Zhao et al. (2021a)	Construction site	Living Beings	S	Location sensor	O	Measurement difficulties	5
Zhao et al. (2021b)	Construction site	Construction Elements	M	Others	T I O	Training needed	5
Yan et al. (2022)	Construction site	Objects in motion	NA	Identification tag	T I	High cost	8
Thiede et al. (2022)	Industry	Parcels	NA	Other sensors	T	NEI	8
Alzahrani and Irshad, (2022)	Logistics	Objects in motion	NA	Identification tag	T	Implementation difficulties	6
Wang et al. (2022)	Industry	Others	M	Imaging-based tracking	NA	Training needed	6
Yan, (2022)	Construction site	Others	M	Imaging-based tracking	I	Implementation difficulties	6
Kim and Kim, (2022)	Logistics	Parcels	M	Imaging-based tracking	I	Implementation difficulties	6
Liang and Seo, (2022)	Construction site	Construction Elements	M	Imaging-based tracking	I	Technical Rigidity	7
Zhao et al. (2022)	Logistics	Parcels	M	Imaging-based tracking	I O	Training needed	5
Mathew and Mahesh, (2022)	Industry	Others	M	Imaging-based tracking	T I	NA	7
Jung et al. (2023)	Construction site	Construction Elements	M	Imaging-based tracking	I	Technical Rigidity	6
Han et al. (2023)	NA	Living Beings	M	Imaging-based tracking	T I O	Training needed	7
Edwards et al. (2023)	Industry	Others	NA	Imaging-based tracking	T	NA	7
Holmström et al. (2023)	Logistics	Parcels	NA	Imaging-based tracking	T I O	Training needed	6
Al Jaber et al. (2023)	NA	Objects in motion	NA	Imaging-based tracking	T I	Training needed	6
Vu et al. (2023)	Logistics	Parcels	S	Imaging-based tracking	O	Technical Rigidity	8



construction and work sites, where the dynamic and complex environment poses unique challenges to accurate measurement and tracking.

3.2 Level 2 analysis

Level 2 analysis involved a comprehensive evaluation of each criterion against all others. Among these, the most insightful results emerged from the interplay of the TRL and Scope, against the other criteria, which offer a comprehensive understanding of dynamics between technologies chosen in terms of maturity and purpose over time, sectors and objects, as well as the associated limitations.

In particular, the interpolation of the TRL with years of publication and sectors show how the maturity of the technologies chosen have remained stable over time and across fields of application. The results reported in Figure 2 clearly points that TRL 6, to 9 are consistently dominant among the works analyzed across time, without significant variations, i.e., no obvious tendency seems traceable of a progressive orientation toward either more mature or more experimental technologies in recent years. This is not surprising considering the tendency highlighted in the level 1 analysis to focus mostly on prototypes or large deployment testing over theoretical hypothesis. In particular, it is noticeable that the limited use of more experimental technologies (i.e., TRL 3, 4, and 5) is restricted to

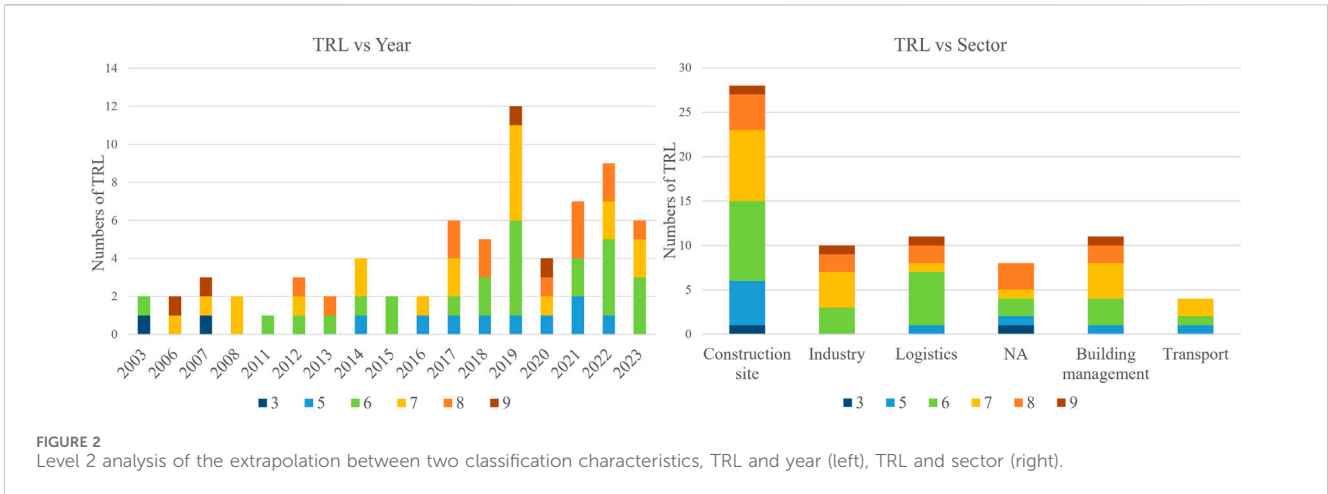


FIGURE 2 Level 2 analysis of the extrapolation between two classification characteristics, TRL and year (left), TRL and sector (right).

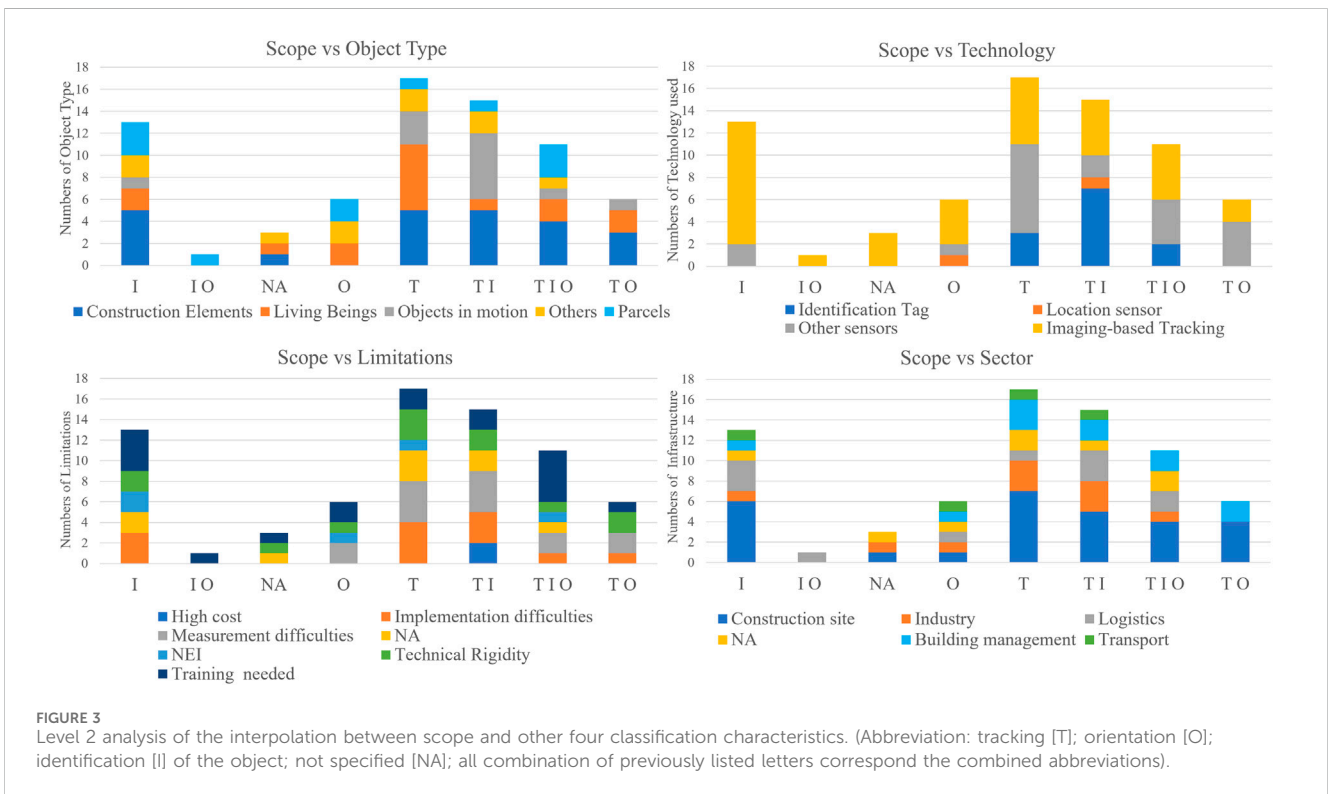
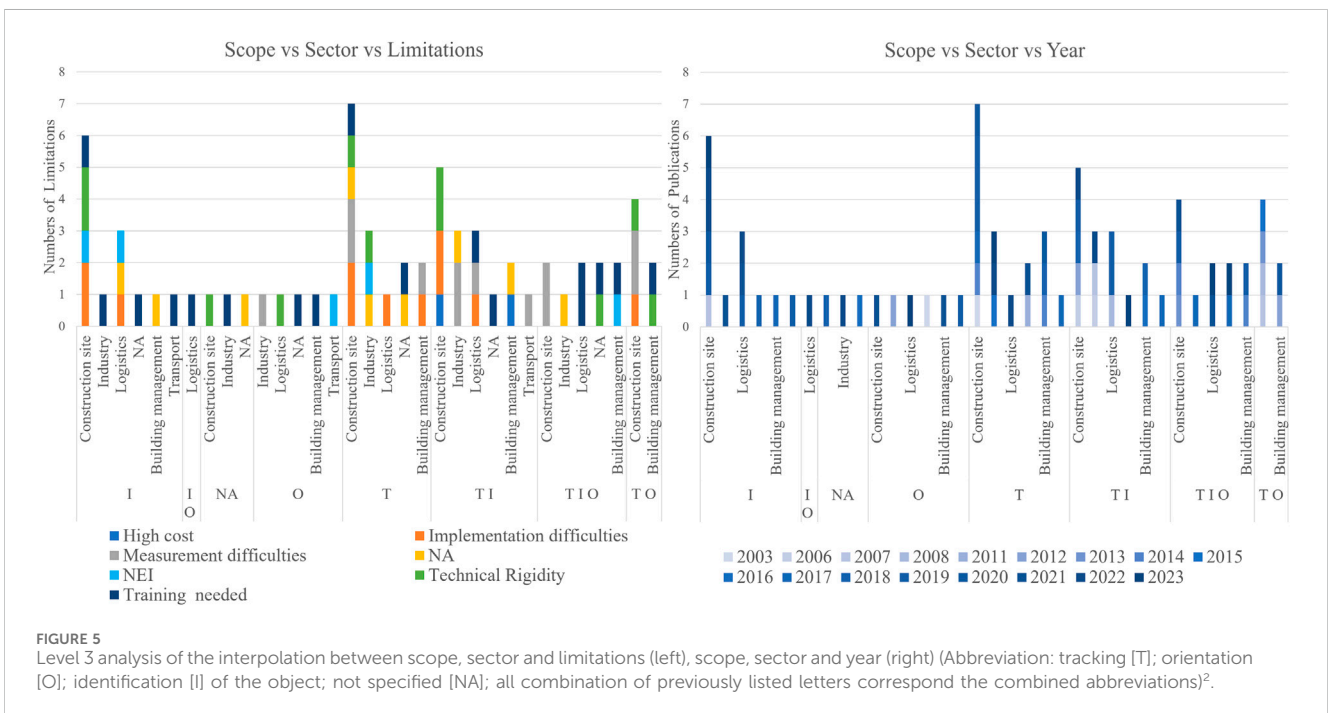
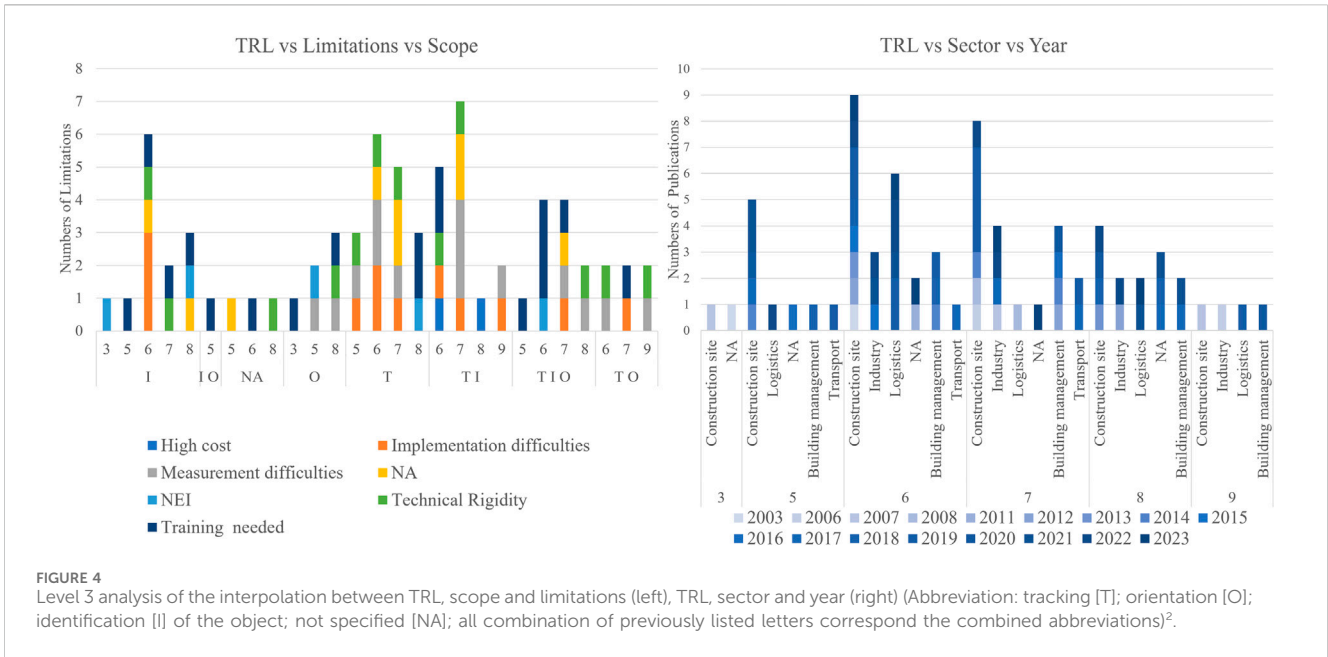


FIGURE 3 Level 2 analysis of the interpolation between scope and other four classification characteristics. (Abbreviation: tracking [T]; orientation [O]; identification [I] of the object; not specified [NA]; all combination of previously listed letters correspond the combined abbreviations).

works developed for construction sites, logistics or theoretical studies. For example, a sensor-based material tracking system for construction components has recently been presented (Jung et al., 2023), that has so far only undergone lab-based testing of its individual components to validate their functionality (i.e., TRL 4).

The Scope has been interpolated with: type of objects, technology used, limitations and sector of application. Results in Figure 3 show how the works that have objects identification as a scope are predominantly applied on construction elements, logistic parcels and living beings; using largely imaging-based tracking as a technology; and deployed mostly on construction sites for construction components identification. For instance, in a Dubai construction project, imaging-based tracking was utilized to monitor the placement and orientation of pre-fabricated

components. Cameras strategically positioned around the site, linked to AI algorithms, ensured that each component was correctly aligned according to architectural plans, thus enhancing accuracy and efficiency in the construction process (Guven and Ergen, 2019). Notably, the preference for imaging-based tracking can be attributed to its adaptability and proficiency in managing the dynamic and complex nature of construction and logistics environments. Given the multitude of objects and the non-delicate handling often observed on construction sites, the utilization of fragile sensors poses inherent risks. In this context, the robustness of imaging-based tracking systems offers a safer and more reliable alternative. In terms of limitations, a slight prevalence of training needs and implementation difficulties emerges. The works focusing on objects orientation are predominantly applied



on logistic parcels and living beings (human specifically in this case to detect hazardous movement, such as falling from height); using almost exclusively Imaging-based tracking as a technology (11/13 times); and deployed mostly on industrial sites. In terms of limitations, the main concerns come from the training needs of the imaging-based tracking. The works that have objects tracking as a scope are predominantly applied on construction elements, logistic parcels and living beings; using a mix of imaging-based technology, Identification tags and others (e.g., programmable logic control, LADAR and optical sensors); and are deployed predominantly on construction sites (18/45 times) with a large spectrum of limitations. When considering works with multiple scopes it is interesting to

notice how logistics grows in importance being the only sector involved in identification and orientation combined, and significantly present - along with building management and construction sites - both in works concerning identification and tracking and identification, orientation and tracking together.

3.3 Level 3 analysis

Also in the level 3 analysis, the most informative findings were uncovered by exploring the interaction between TRL and Scope with the other criteria (illustrated in Figures 4, 5 respectively). Figure 4

indicates a prevalence of technologies within TRL 6-8 across various scopes, with a relatively limited presence of more mature technologies at TRL 9. Several limitations could account for this trend. Works centered on identification, tracking, and their combination are significantly impacted by implementation challenges, technical rigidity, and measurement difficulties, while, works related to orientation often face challenges due to high costs. The need for extra training is ubiquitous across sectors, being a prevalent constraint in systems integrating Imaging-based tracking. These limitations frequently hinder these technologies from reaching the level of successful commercial systems, i.e., TRL 9. Additionally, it is noteworthy, as depicted in [Figure 4](#) (right), that research endeavors spanning different sectors and TRLs have notably intensified over the past 7 years. While this trend is expected, the substantial acceleration in research activities within this field in recent years is striking. This trend is particularly evident in logistics, where only 1 out of 11 studies took place before 2016.

[Figure 5](#) indicates that the construction research dominates, along with logistic, in works related to identification, tracking and a mix of the two. However, these applications face two main challenges: implementation complexities and technical rigidity. As an example, construction sites contend with issues such as dust, vibrations, and ever-changing environments, all of which can disrupt sensitive tracking devices. Another example details a residential building in New York that uses a cloud-based security system, allowing for remote monitoring and management, which enhances tenant security and operational efficiency ([Sengupta et al., 2021](#)). These implementation challenges are crucial as they can result in significant consequences. Construction projects often operate within tight budgets and schedules, where errors or inefficiencies can lead to substantial financial and time losses. For instance, misplacing a component due to tracking or identification errors can cause delays lasting several days. In terms of year of publication, also in [Figure 5](#) (right) it is possible to appreciate the steep increase in works across various sectors and scopes in recent years. In this case the phenomenon is particularly evident in the construction sector, where 16 out of 23 studies, primarily focusing on Identification, tracking, or a combination of both, were conducted after 2016.

3.4 Contribute to the research question

In line with the research question presented in the introduction, this study contributed in covering the current gap in understanding the state of research on ABAS through a systematic literature review. The findings over the three levels analysis helped identifying the current trends, capabilities and limitations in the use of sensing technologies for recognizing, locating, and orienting objects that could be used for the development of in ABAS systems. Detailed conclusions from the results are provided in the next sections.

4 Conclusion

This study addresses the current lack of understanding of the state of research on ABAS by providing a comprehensive analysis of existing technologies, their applications, and the challenges they

face. By identifying critical areas for improvement and potential future research directions, this paper contributes to the development of more effective and efficient ABAS solutions, ultimately promoting progress in the field. Specifically, based on all three levels of analysis, several notable conclusions can be drawn.

- Research in this domain has accelerated vigorously in recent years. Since 2019, there has been a discernible surge in identification and orientation research, not limited to the construction sector but also in building management, logistics and manufacturing industry. This growing trend highlights the urgent demand for innovative solutions across these sectors, emphasizing safety, productivity, and operational efficiency. The inherent challenges of each sector, like the complex nature of construction sites or the dynamic environment of logistics, are driving a shift towards the use of Imaging-based tracking techniques that are greatly adaptable to multifaceted environments.
- The construction sector stands out as one of the dominant areas among the research sectors involved. This prevalence is logically justified by the dynamic nature of construction environments, which involve intricate interactions among moving machinery, materials, and personnel. The research emphasis in this sector is unsurprising considering the significant advantages that integrating a proficient ABAS can offer, such as enhancing safety protocols, streamlining operations, and improving overall cost efficiency.
- The technologies utilized are characterized by a high level of maturity across various sectors. TRL 6 or above consistently dominates over time, showing no clear trend indicating a shift towards either more mature or experimental technologies. In particular, there is a consistent prevalence of TRL 5-7 overtime, albeit coupled with a modest presence of TRL 8 and 9. Current limitations in the use of highly impactful technologies, particularly visual technology across sectors, appears to possibly be responsible for the limited amount of TRL 9 applications.
- Five main limitations emerge to be recurrent across all applications and all sectors: works focused on identification, tracking, and their combination encounter significant obstacles related to implementation challenges, technical rigidity and measurement difficulties, while, initiatives involving orientation often encounter challenges due to high costs. In the aspect of technical rigidity, key challenges involve the need for multiple high-frequency RFID tags for precise tracking in warehouse automation systems, and the necessity for numerous GPUs for efficient real-time data processing in complex simulations. Regarding implementation issues, difficulties arise in machine vision systems that fail to recognize objects with diverse surface textures or colors, environmental monitoring systems providing inaccurate readings under extreme weather conditions. Measurement challenges are exemplified by GPS systems with limited range and accuracy in densely built urban areas. The necessity for additional training seems to be widespread. This is a common limitation of systems incorporating visual technologies, impacting projects across various scopes and sectors.

The practical challenges of implementing sensing technologies on construction sites are particularly noteworthy. Construction sites present unique challenges such as harsh environmental conditions, dynamic and cluttered workspaces, and the need for integration with existing workflows and safety protocols. These factors can significantly impact the performance and reliability of sensing technologies. Additionally, the high costs associated with the deployment and maintenance of these technologies pose a barrier to widespread adoption. Further exploration of these practical implications is crucial for advancing the field.

Future research should focus on overcoming the identified limitations, particularly in improving the technical robustness and implementation feasibility of sensing technologies. Addressing the current challenges and tailoring solutions to specific industry needs could yield significant breakthroughs in the coming years. Recent advancements in AI-related Imaging-based tracking (Hamledari et al., 2017; Nguyen et al., 2020) are poised to overcome many of these limitations. It is foreseeable that upon overcoming the existing training challenges linked to Imaging-based tracking, the possibilities for identification, tracking, and orientation in the construction sector will greatly broaden. Combined with the advancement of augmented reality-enriched 4D models, this could facilitate the creation of Advanced Building-Assistance Systems (ABAS) capable of guiding workers in component deployment, assembly procedures, and work progress. Future research on several key areas would be needed, including.

- Enhancing the robustness of sensing technologies to ensure reliable performance across diverse and challenging environments.
- Evaluating and reducing the costs associated with these technologies to make their implementation more economically viable. This includes a thorough cost-benefit analysis to determine the financial feasibility and identify potential cost-saving measures.
- Developing strategies to make the implementation of these technologies more feasible and cost-effective.
- Creating user-friendly interfaces and systems that minimize the need for extensive training.

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Author contributions

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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