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Review Article

A Scoping Review of Digital Technologies used for Automating Onsite Construction Inspection: Applications and Future Direction

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Abstract (250 words) Style Name

Construction inspection is an important aspect of project delivery in the Built Environment. However, on construction sites, the process of compliance checking is largely conducted manually. In person inspections have been found to have error rates of 20-30%. These inefficiencies have resulted in significant quality impacts, cost overruns and schedule delays. In the context of these challenges, coupled with the demand for remote inspections during the pandemic, there has been increasing research into digital technologies for the automation of construction compliance. However, to date, many developments happened in isolation focusing on narrow areas. There has been no overarching review available to consolidate the gamut of digital solutions that can be used in construction inspection, evaluate their practical applications and consider how they fit within the wider compliance workflow.

To fill this gap, this paper conducted a scoping review to identify the key digital technologies with the potential to automate inspection tasks on construction sites. The study analysed 136 papers published in the last five years to identify the development trajectories of digital solutions in construction compliance and to suggest possible directions in which certain technologies can be further applied to enhance construction compliance.

The findings reveal key inspection themes where technology can enhance construction compliance namely defect detection, dimension measurement, and alignment. Additionally, technology stack i.e. combination of hardware and software most compatible to serve each inspection purpose was analysed. The study proposes a roadmap through technology-inspection matrices to guide commercial deployment and future research in underutilised tech combinations.

Keywords: automation; construction compliance; construction inspection; digital technologies; scoping review

Highlights

- Significant relationships exist between building elements and their inspection types.
- The research mapped digital technology stacks to inspection types, revealing dominant and underused combinations
- The research bridged the gap between academic research and practical deployment through actionable technology-inspection matrices

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1 Introduction

Construction inspection is a cornerstone of regulatory compliance and quality assurance across the built environment (Halder et al., 2023). These requirements span across project phases, including design briefs, functional performance, safety laws, environmental regulations, and quality standards (Amor & Dimyadi, 2021). Failure to comply – due to limited time, resources and oversight can affect the project throughout its service lifecycle with potentially dangerous outcomes. Despite its critical role, the inspection process remains predominantly manual—labour-intensive, prone to subjectivity, and fragmented knowledge (Xu et al., 2021; Einizinab et al., 2023). This traditional inspection process has been linked to inefficiencies, cost overruns and delays (Preito et al., 2021; Shariq & Hughes, 2020; Zhang & El-Gohary, 2013), with error rates of 20-30% across various tasks (Mott et al., 2022). The errors can have severe consequences, as seen in:

- **Oscar Traynor Development Project (Ireland), 2024**: Delays and redesigns stemming from inspection-related quality issues.
- **Grenfell Tower Fire (UK), 2017**: Catastrophic loss linked to regulatory oversights and non-compliant cladding.
- **Oxgangs Primary School (Edinburgh), 2017**: Wall collapse caused by inadequate construction and missed inspections.
- **Priory Hall (Dublin, Ireland), 2011**: Evacuation due to fire safety non-compliance.

An Irish Independent Working Group reported that between 1991 - 2013, 50-80% of apartments and duplexes had at least one of three defects - fire safety, structural safety, or water ingress (Neely, 2022). These incidents have underscored the urgent need to enhance transparency, traceability, and rigour in inspection processes. Recent years have seen a surge in research into inspection automation and digital workflows (Samsami, 2024; Halder et al., 2023) such as laser scanning, computer vision, IoT sensors, robotics, BIM, point cloud and virtual reality. While several review papers (Samsami, 2024; Einizinab et al., 2023; Asgari & Rahimian, 2017) have explored digitalised inspection, they focus on isolated technologies or narrow use cases without mapping how they fit within the wider compliance workflow and evaluate their practical applications on site. A more comprehensive review is needed to classify solutions by their purpose, technological foundation, and alignment to compliance objectives. This scoping review examines the breadth of automated solutions by classifying hardware (e.g., camera, laser scanning, UAV, robotics) and software technologies (e.g., ML, AI algorithms, web platforms) used across building elements and inspection types. The study evaluates the statistical association between building elements and inspection types and analyses integrated hardware–software technology stacks and inspection types to determine highly automatable inspection tasks and underutilised technology stacks with potential for broader application.

2 Methods

This scoping review addresses three key questions:

- **RQ1**: What digital technologies are used to automate construction onsite inspection?
- **RQ2**: What types of inspections are performed using these technologies?
- **RQ3**: Which building elements are being inspected?

The **PCC (Population–Concept–Context)** framework was developed from the review questions, following JBI guidelines (Peters et al., 2020). This framework provides context to define the scope and selection criteria.

- **Population**: Construction inspections for compliance checks.
- **Concept**: Digital technologies and automation, encompassing both hardware (e.g., sensors, robots, UAVs) and software (e.g., models, algorithms, analysis).
- **Context**: Onsite inspections during the construction phase of the project.

2.1 Search Strategy & Eligibility Criteria

The review followed the JBI methodology (Peters et al., 2020), using the PCC framework to guide selection and scope. Two databases—SCOPUS and Web of Science (WoS)—were used for their comprehensive coverage of peer-reviewed engineering and construction literature (Aboiye et al., 2021; Darko et al., 2020).

Inclusion Criteria:

- Published between 2020–2025, in English
- Focused on onsite inspection activities during construction phase

Exclusion Criteria:

- Review papers, published before 2020, or non-English papers
- Studies focused on design-phase compliance, automated code checking, or semantic segmentation, dataset annotation
- Focused on robot path planning, or progress monitoring
- Non-construction industry domains (e.g., aerospace, welding, power stations, textiles)
- Focused on post-construction such as facility management, structural health monitoring, post-earthquake assessments, underwater inspections

Search terms were developed by breaking down the review questions into thematic keywords related to inspection, compliance, and digital technologies. Terms were refined and combined using Boolean operators. The final search string included groupings such as:

TITLE-ABS-KEY (inspection* OR "compliance" OR "defect detection") AND (automation OR "digital tools" OR "AI" OR "machine learning" OR "UAVs" OR "laser scanning").

Final filtering by document type and subject area excluded unrelated fields and non-peer-reviewed sources.

2.2 Selection of Sources

The study selection followed the JBI methodology (Peters et al., 2020). Search results were first exported to EndNote and then screened in Rayyan, a specialised platform for systematic screening (Mak & Thomas, 2022). Here duplicate entries were removed, and inclusion/exclusion decisions were applied on the titles and abstract level.

In a review, a minimum of two independent reviewers is ideal (Peters et al., 2020; Arksey & O'Malley, 2005). However, following Mak and Thomas (2022), a calibration exercise was conducted on 5% of the initially identified studies and reviewed independently by both authors. Upon reaching consensus, the first author screened the remaining papers. Full texts were retrieved for shortlisted studies and reviewed in full against the eligibility criteria to produce the final list of studies. As a final validation step, a subset of the included full-text articles was reviewed by the second author to ensure consistency and rigour in the selection process. A total of 136 papers were included in the final review. The process is summarised in the PRISMA flow diagram (Figure 1).

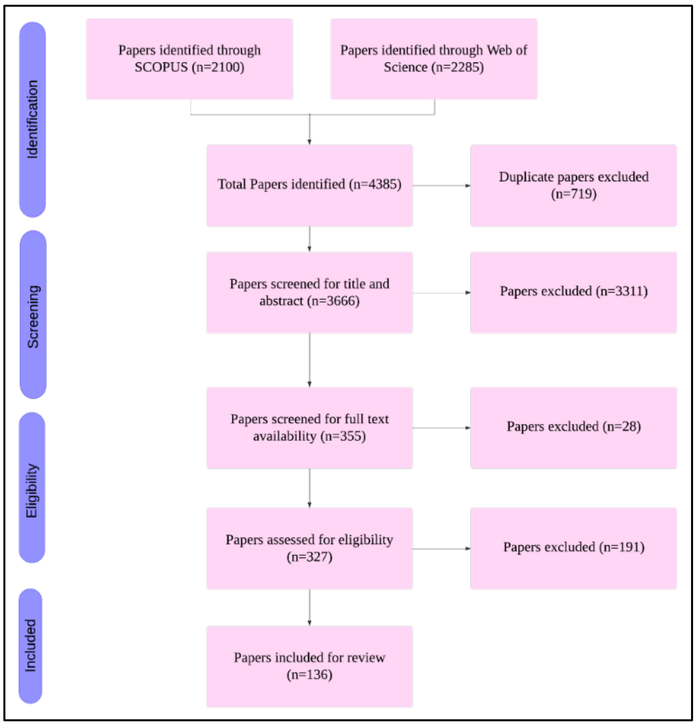

Figure 1. PRISMA flow diagram for the scoping review process.

2.3 Data Charting & Transformation

Following scoping review guidelines by Peters et al. (2015) and Arksey and O'Malley (2005), the data charting exercise was conducted alongside the full-text screening. An Excel table was used to record key characteristics of each study which included author, year, journal, location, hardware/software used, inspection purpose, building element, outcomes, and limitations. The charting exercise adopted a descriptive approach which was then modified into a structured format suitable for analysis. The charted data was processed through four transformation steps.

- **Data Cleaning** to correct typos and formatting,
- **Data Parsing** to split multi-item fields,
- **Data Normalisation** to group inspection types into: Defect, Dimension, Alignment, and Identification
- **Data Grouping** of building elements into 13 categories including building interiors, external surfaces, concrete structures, reinforcement bars, prefabricated components, steel structures, etc.

These transformations enabled consistent, scalable analysis across the dataset and supported more meaningful insights in subsequent sections.

3 Results – Key Findings

3.1 Publication & Geographic Distribution

To understand the scope and distribution of construction inspection automation, this review first mapped the journal publications and geographic origins of the studies. The journal frequency analysis, presented in Figure 2, shows that Automation in Construction is by far the leading outlet for studies in this domain, publishing 30 papers—nearly double the next most common journal, Buildings (16), followed by Journal of Construction Engineering and Management (ASCE) and Applied Sciences. In terms of geographic distribution (Figure 3), China leads in research output, contributing 48 studies, followed by South Korea (18), the USA (14), and Hong Kong (9). This suggests a concentration of research in areas driven by investments and modernisation. Notably, Europe, South America, and Africa are underrepresented indicating potential regions where further research or adoption may still be emerging.

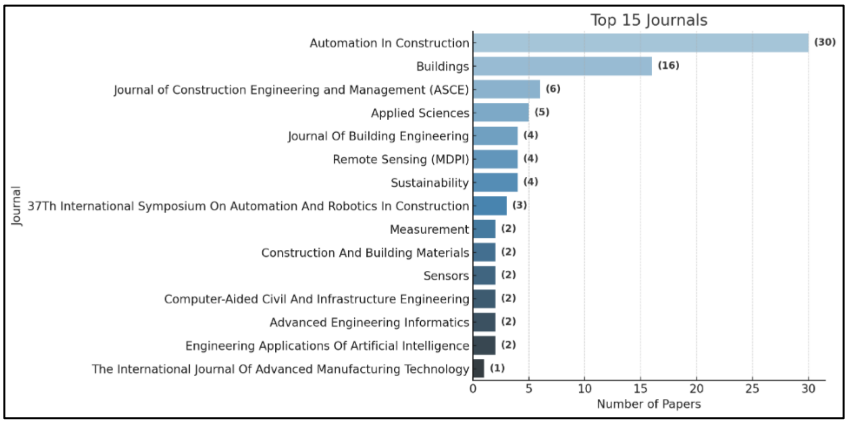

Figure 2. Journal Publication Frequency.

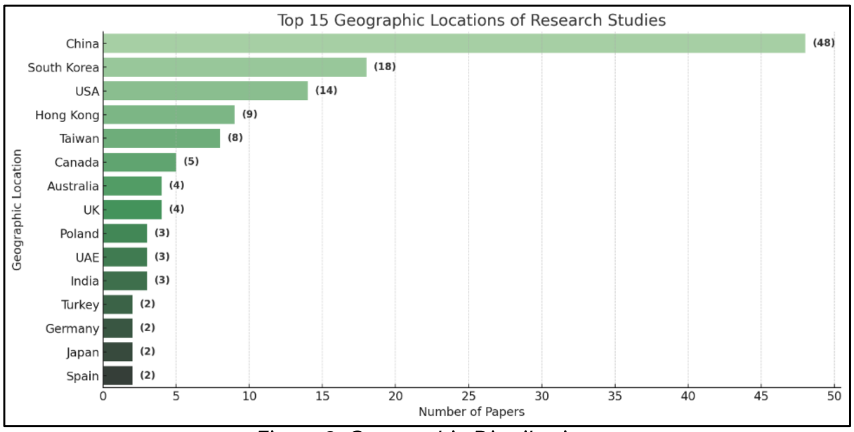

Figure 3. Geographic Distribution.

3.2 Hardware Tools

To address the first review question (RQ1), it is essential to analyse the hardware and software tools employed in the selected studies. This analysis not only provides insight into the current state of technological adoption but also reflects broader trends in the digitalisation and automation of construction inspection practices. The charts below (Figure 4 and Figure 5) present the top 15 most frequently used hardware and software/algorithmic technologies respectively, grouped by consolidated categories across all included studies.

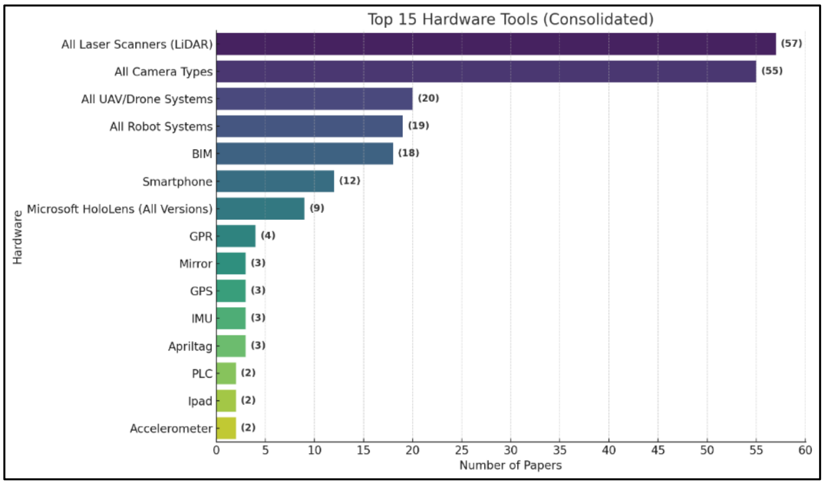

Figure 4. Hardware Frequency.

Laser scanner (LiDAR) was the most used, applied in tasks such as alignment of prefabricated wall panels (Wang et al., 2024); measuring façades (Polat & Ali, 2023) and precast concrete structures (Liang & Xu, 2023; Xu et al., 2022). Cameras followed closely used for reality capture such as industrial cameras used in capturing concrete cracks and bugholes (Liu et al., 2024); mobile GoPro cameras for capturing general construction activities or reinforcement bar details (Guo et al., 2025; Kardovskyi & Moon, 2021); stereo cameras or multi-lens cameras that capture multiple viewpoints of an activity for capturing concrete hairline cracks or indoor facility elements such as pipelines, HVAC, air ducts (Alamdari & Ebrahimkhanlou, 2024; Gao et al., 2023) as well as other types of cameras such as depth cameras (Kim et al., 2024; Kang et al., 2022) for depth perception images and RGB cameras (Yang et al., 2023; Xu et al., 2022) that captures images in the visible light spectrum, using sensors that are sensitive to the primary colours - red, green, and blue.

Other key hardware technologies identified include UAVs or drone systems, frequently used for remote or aerial inspection of facades or roofs often combined with vision-based algorithms to detect cracks or assess damages (Zhang et al., 2023; Gomez & Tascon, 2021; Tan et al., 2021). Robotic systems, such as wheeled or quadruped robots, were typically deployed for automated navigation and scanning in building interior, construction sites, or concrete structure inspections (Feng et al., 2025; Halder et al., 2023; Halder et al., 2022; Park et al., 2023).

Building Information Modelling (BIM) tools, though not physical hardware, was typically used in combination with laser scanning, cameras, Augmented Reality (AR)/Virtual Reality (VR) for scan-to-BIM methods to enable visual comparison, rule-based checking, or overlay of as-built vs. as-designed conditions (Tan et al., 2024; Polat & Ali, 2023; Zhang et al., 2023). Smartphones enabled lightweight and cost effective data collection (Liao et al., 2023; May et al., 2022), while Microsoft HoloLens, a head-mounted AR device, provided mixed-reality overlays (Dzeng et al., 2024; Chi et al., 2022). Overall, the results show that the hardware landscape is heavily oriented toward visual and spatial data acquisition, with strong support for mobile, aerial, and augmented inspection modes.

The extensive use of cameras and LiDAR systems in research reflects the industry's prioritisation of technologies of capturing physical site conditions accurately. The use of these tools highlight the need to address one of the fundamental compliance challenges of visual accuracy in detecting surface-level defects (e.g. cracks, voids, etc.) and spatial alignment (e.g. flatness, element placement, etc.) Further, the adoption of smartphones and drones as means to capture visual data reflects a demand for accessible, low-barrier technologies that are commercially available, require minimal training, and can be readily integrated into routine site operations. This trend suggests that future research in compliance automation is expected to be centred around low-barrier technologies in acquiring real-time visual data enabling timely, objective verification of construction quality and reducing the limitations of manual inspection.

3.3 Software/Algorithm Tools

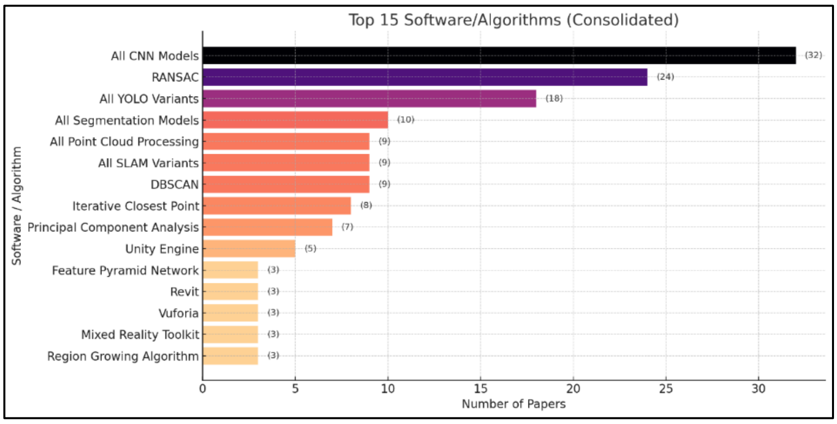

Figure 5. Software/Algorithm Frequency.

A range of AI and geometric processing models were used to automate inspection tasks. Convolutional Neural Networks (CNN) models was the most widely used tool which is a machine learning (ML) model used for image-based object or defect detection and classification. Variants of CNN included Monocular CNN-based depth estimation that enables the extraction of depth information from a single RGB image (Perez & Tah, 2023), Mask R-CNN used for instance segmentation, allowing the model to detect defects along with their precise boundaries (Chang et al., 2024), Faster R-CNN optimised for object detection with high accuracy (Lee et al., 2020) and 3D CNN that extends to volumetric calculations (Wu et al., 2023). Random Sample Consensus (RANSAC) follows closely which is used to identify patterns in messy or noisy data and acts as a smart filter to identify the real geometry of inspected elements. This model was commonly used in point cloud alignment, outlier removal, and object pose estimation (Al-Sabbag et al., 2024; Cui et al., 2024; Guo et al., 2024). Another object detection model significantly used is the You Only Look Once (YOLO) model which is a real-time object detection model that can find and classify multiple objects in a single image. Unlike traditional CNN models that may process regions one at a time, YOLO scans the entire image at once, making it much faster. Several versions of this model was used in the reviewed papers such as YOLOv3 (Ma et al., 2022), YOLOv5 (Li et al., 2024), YOLOv8 (Golpour et al., 2024), and YOLOv11 (Iqbal et al., 2025).

Other frequently used tools included segmentation model which performed semantic or instance segmentation in order to isolate particular items like cracks, walls, or pipes in images (Alamdari & Ebrahimkhanlou, 2024; Boerzel et al., 2023). Point Cloud Processing Algorithms are techniques for filtering, meshing, and geometric analysis of 3D scan data (Li et al., 2024; Kim et al., 2022). Simultaneous Localization and Mapping (SLAM) techniques assists devices to build a map of its surroundings while also figuring out where it is within that map. It is used in mobile or robotic inspection systems to track movement through a construction site (Chen et al., 2025; Becker et al., 2023). Density-Based Spatial Clustering of Applications with Noise (DBSCAN) is a tool for finding clusters or groupings in spatial data—like identifying areas with a lot of defects or grouping points in a scan that belong to the same wall or slab (Kim et al., 2021; Li et al., 2021).

Other notable tools include Iterative Closest Point (ICP) for 3D registration (Tan et al., 2024; Yuan et al., 2023), and Principal Component Analysis (PCA) for dimensionality reduction and feature extraction (Guo et al., 2024; Truong-Hong & Lindenbergh, 2022). These results demonstrate a strong reliance on computer vision, object detection, point cloud processing, and spatial reasoning, showing that inspection automation is being driven by a fusion of geometric analysis and machine learning.

The dominance of CNN, YOLO, and RANSAC indicates a shift toward automated visual reasoning and geometric verification, which directly addresses human limitations in detecting small-scale defects, assessing complex geometries, or managing the volume of inspection tasks. These algorithms allow systems to make consistent, accurate and faster decisions. Their use suggests that compliance enforcement is moving toward data-driven pattern recognition, where systems learn typical failure patterns and flag them before they escalate. For practitioners, adopting such tools can streamline repetitive checks and ensure early compliance verification with far greater coverage than manual methods.

3.4 Relationship Between Building Elements and Inspection Types

Building elements and their corresponding inspection types were analysed to address RQ2 and RQ3. As shown in Figure 6, concrete structures (29), building interiors (26), and reinforcement bars (20) were the most frequently inspected. Elements such as prefabricated components, steel structures, and temporary structures also featured significantly, whereas components like HVAC systems, pavement surfaces, and equipment were far less represented.

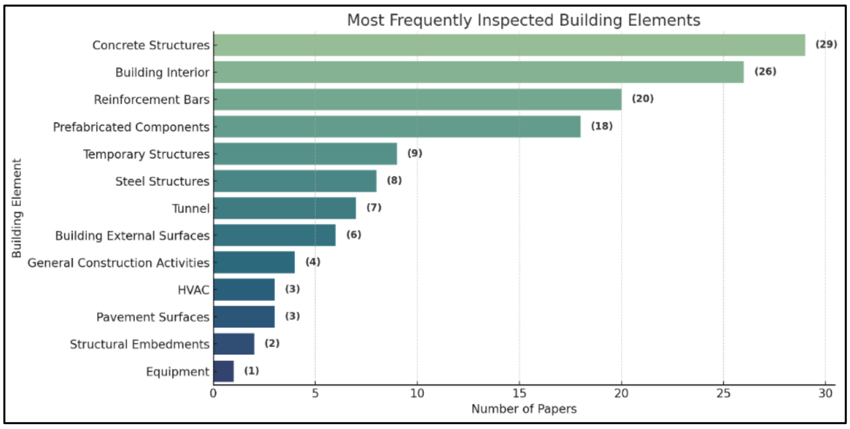

Figure 6. Building Elements Inspected.

The heatmap in Figure 7 maps inspection types—defect, dimension, alignment, and identification—to each element. This revealed key inspection preferences:

- **Defect inspections** were most prevalent in concrete structures (Al-Sabbag et al., 2024; Artus et al., 2022), building interior surfaces (Halder et al., 2023; Gomez & Tascon, 2021) such as walls, columns, and floors, due to vulnerability to cracks, spalling, and material-related damage.
- **Alignment inspections** were dominant for reinforcement bars (Chang et al., 2024; Xi et al., 2023) and interior structural components (Park et al., 2023; Govindaraju et al., 2023).
- **Dimension checks** were frequently performed on reinforcement bars (Wang et al., 2025; Wang et al., 2024), building interiors (Gao et al., 2023; Rada et al., 2023) and prefabricated elements (Li & Kim, 2021; Li et al., 2021).

- **Identification-based inspections** were limited to verifying reinforcement bar count (Wang et al., 2023; Yuan et al., 2023) in concrete structures before concrete pouring.

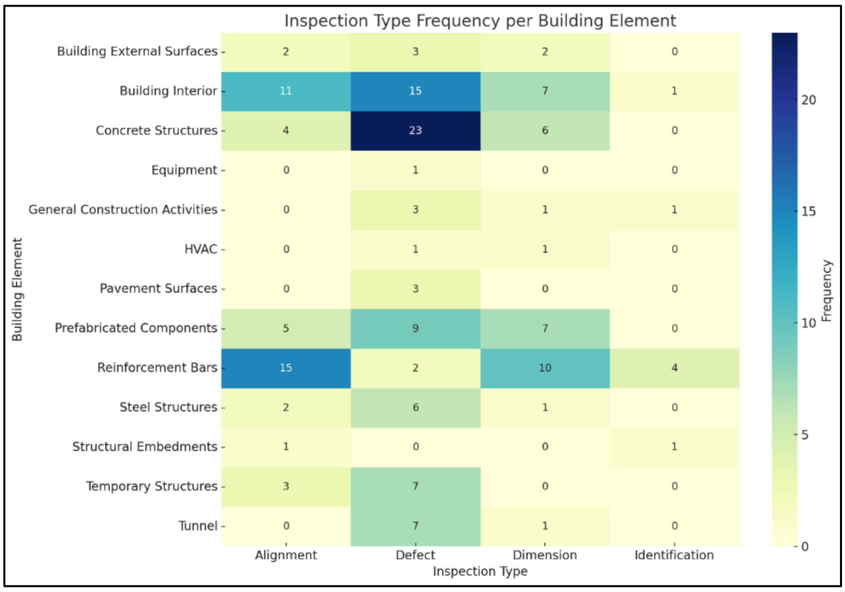

Figure 7. Inspection Type vs. Building Element Heatmap.

A Chi-square test of independence confirmed a statistically significant relationship between building elements and inspection types ($\chi^2 = 67.53$, df = 36, $p < 0.01$). This supports the observation that inspection methods are highly context-dependent, shaped by the functional role, material characteristics, and construction sequence of each element. This test showed that surfaces and façades are predominantly inspected for defects, driven by visual/aesthetic demands and exposure to the environment. Structural cores (beams, columns, slabs) are inspected mainly for alignment while interior spaces and prefabricated modules are inspected for dimensional accuracy. However, an underrepresentation of temporary structures and equipment suggests a research gap, particularly in developing adaptive, real-time inspection systems for rapidly changing site elements.

The element-wise analysis confirms that different building elements demand distinct compliance checks—such as visual defect detection for surfaces, dimensional verification for rebars or prefabricated components, or alignment checks for structural cores. This inherently supposes that different technologies are required for different inspection tasks. The element-to-inspection mapping presented in this study offers for the first time a reference point for industry to align specific compliance needs with appropriate digital tools. The onus now lies with practitioners to prioritise inspection checks based on their cost of non-compliance, current capability gaps, or the feasibility of small-scale pilot implementations. For researchers, this study provides a foundation for further inquiry into the barriers to technology adoption and highlights the need to develop strategies that actively reduce these barriers to support widespread implementation.

3.5 Tech Stack (Hardware + Software Combination) vs. Inspection Type

To understand the broader direction of technological adoption in construction inspection, it is crucial to analyse which combinations of hardware and software tools are frequently used. The analysis of consolidated technology stacks—grouped as hardware + software combinations—against inspection types revealed several dominant themes and emergent insights as shown in Figure 8.

Defect detection emerged as the most addressed inspection task in terms of frequency and diversity of technology stacks. It is supported by a variety of camera- and AI-based combinations. The leading combinations include All Camera Types + CNN Models (13), All Camera Types + YOLO Variants (10), All Laser Scanners (LiDAR) + RANSAC (4) showing predominant research investment in automating visual defect detection using AI. Alignment and Dimension inspections are more selectively addressed but show clear reliance on geometric precision technologies which suggests its demanding nature. It is used alongside 3D capture technologies and spatial analytics, particularly in structure verification, prefabrication checks, and large-scale layout validation. All Laser Scanners (LiDAR) + RANSAC is the most commonly used technology stack for alignment and dimension checking. Identification check is the least explored inspection type but shows promise in vision-based recognition for MEP systems, structural embedment, and construction assets.

The concentration of certain tech stacks around specific inspection types reflects a functional match between compliance tasks and digital tool capabilities. For instance, visual tasks like defect detection are well served by camera + CNN stacks, while alignment tasks require LiDAR + RANSAC due to their spatial accuracy. Both industry and researchers can apply this analysis to build modular inspection systems, selecting stack combinations based on the compliance outcome desired. This makes inspection not only more efficient but also more targeted and standardised.

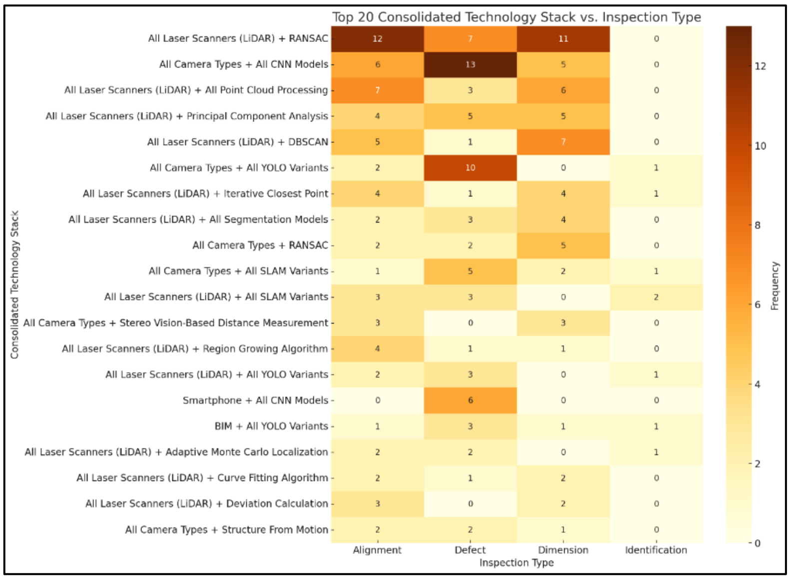

Figure 8. Technology Stack VS Inspection Type Heatmap.

4 Discussion

The preceding analysis forms the foundation for the guidance and recommendations made in this section. This section provides a strategic focus to identify scalable technologies in specific inspection areas and transition them to real world deployment.

From the analysis, it is clear that certain combinations are useful for multiple of inspection types. These technology stacks should be the focus for practitioners, researchers, and technology developers to invest in scaling and maturing current systems. Based on the analysis, the following combinations should be the focus of further real-world experimentation, pilot testing, and potential product development as shown in Table I below.

Table I. Strategic Opportunities for Deployment and Scaling.

Technology Stack	Inspection Type(s)	Recommendation
All Camera Types + CNN Models	Defect, Dimension, Identification	Scale into multi-modal vision platforms; explore deployment via smartphones, drones, and wearables.
All Laser Scanners (LiDAR) + RANSAC	Alignment, Dimension, Defect	Mature into structural verification tools integrated with BIM.
All UAV/Drone Systems + SLAM Variants	Alignment, Defect, Dimension	Ideal for external surface validation; explore further use in complex construction environments.

These versatile tech stacks could enable modular inspection systems, with software adapted per task—suitable for scalable, real-world deployment. However, while many of the identified technologies such as LiDAR scanners or SLAM-equipped UAVs offer high precision, their cost can be prohibitive for large scale implementation. This creates a disparity in adoption, suggesting a need for affordable, scaled-down solutions that maintain functionality without overwhelming capital investment.

Another key barrier to adoption is the integration of new technologies into legacy construction processes such as BIM coordination and quality control protocols. Without seamless interoperability, digital tools risk becoming isolated applications rather than embedded parts of the compliance workflow. In order to overcome this challenge, future solutions must prioritise open, interoperable design and tools should be adaptive to multiple data formats, support API development, and enable seamless integration with existing systems.

Further, a gap matrix analysis was carried out to check which of the technology stack combinations were underused but had the potential for further research. Based on a consolidated gap analysis of more than 280 technology-inspection pairings, underexplored combinations that offer high potential for future research are listed in Table 2.

Table II. Gap Matrix Analysis for underutilised technology stack combinations.

Technology Stack	Inspection Type	Potential Capabilities
UAV + SLAM	Dimension	UAVs provide rapid aerial coverage, and SLAM allows for accurate spatial reconstruction without relying on GPS. Together, they offer an effective solution for inspecting large-scale items on site.
Robot Systems + Segmentation Models	Identification	Robots can navigate complex interior environments, while segmentation models can classify and locate components like MEP fixtures, fire systems, or other assets supporting rapid compliance checks.
Laser Scanner (LiDAR) + YOLO Variants	Alignment	LiDAR captures detailed 3D geometry, and YOLO can detect object types and positions. Their combination enables automated verification of element placement against design tolerances.
Microsoft HoloLens + Point Cloud Processing	Dimension	The HoloLens provides an immersive AR interface for overlaying digital data onto physical space. Paired with point cloud algorithms, it enables real-time on-site identification and dimensional validation.

These recommendations support strategic decision-making, helping in the prioritisation of technologies that have already demonstrated effectiveness and developing new research for technology combinations that are less explored but could fill significant functional gaps in the inspection workflow automation. Current regulatory standards often lack clear provisions for automated or digitally verified inspection outputs. In jurisdictions where compliance is document-based or manually recorded, the absence of digital validation frameworks can stall innovation despite technical readiness. While large-scale policy reform may be difficult and take time, digitalising compliance documentation and enabling automated data extraction from these inspection models provide the first steps toward regulatory alignment.

In the context of the national and global construction industry, where inspection failures have had serious consequences, the guidance from this research is essential if we are to enhance quality and compliance on construction sites. The trends revealed form a call to action to move beyond academic research and focus on scaling, integrating, and commercialising solutions that work.

However, a key aspect of the practical applicability of these solutions lies in the barriers they face to implementation. These include issues of cost, integration with legacy systems, regulatory readiness, and workforce adoption. Even with effective technologies, limited user familiarity and resistance to change can hinder large scale implementation. In order to realise the full potential of these technology stacks more effort is required in developing not just the technology itself but the supporting infrastructure, policy frameworks, and skills training. By addressing these barriers, the construction industry can move from fragmented innovations to scalable, system-wide adoption of digital compliance solutions.

5 Conclusion

This scoping review explored the digital technologies used in onsite construction inspection, addressing three central research questions – “what technologies are used?”, “what type of inspection they support?”, and “which building elements are being inspected?”. Through a thorough review of 136 papers (2020–2025), the study revealed that laser scanners (LiDAR) and camera-based systems are the most used hardware, paired with AI-based algorithms like CNN, YOLO, and RANSAC. Concrete structures, building interiors, and reinforcement bars emerged as the most frequently inspected elements. Common inspection types included defect, dimension, alignment, and identification, with a significant relationship found between building elements and inspection types. The analysis shows that defect inspection is most common for concrete structures and building interior surfaces while alignment and dimension checks are common for reinforcement bars, interior structural components, and prefabricated elements.

A key contribution of the study is the technology-inspection matrix, highlighting both high-performing technology stack combinations as well as underutilised ones. Notably, combinations such as Camera + CNN models (for defect and dimension inspections) and LiDAR + RANSAC (for alignment and structural checks) showed consistent success across multiple inspection types and should be taken up for larger scale piloting and commercial deployment. Conversely, underexplored combinations like UAV + SLAM (for dimensional inspections of large-scale elements) and Robot Systems + Segmentation Models (for identification) represent high-potential avenues for future research and development. This evidence-led guidance addresses a clear gap in current literature which is a lack of strategic insight on how to take inspection automation from isolated experiments to integrated, site-ready solutions.

While this review maps the current landscape of digital inspection tools, there is potential for further research. As a scoping review, this study did not conduct critical appraisal of individual studies, and there remains a gap in understanding how these tools perform under practical, real-life constraints.

Many of the technologies identified are still at early-stage development and future research should assess their Technology Readiness Levels (TRLs), with a focus on progressing solutions from proof-of-concepts to testing in real construction site conditions. Further, subsequent reviews should aim to appraise the state of technological maturity and the industry readiness of these technology stacks. The detailed findings of this review offer a practical framework for targeted digital adoption. These insights are especially relevant given persistent issues in construction quality and compliance failures, which carry substantial societal costs in terms of safety, performance, and trust in the built environment. As digital inspection technologies mature, their potential to proactively prevent defects, reduce rework, and ensure regulatory compliance will become a key enabler in the systemic improvement of the construction sector.

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Data Availability Statement

The data supporting the findings of this study are available within the article. The raw data extraction table will be made available by the corresponding author on request.

Conflicts of 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.

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