

Evaluation of Technical Readiness Level for Intelligent Construction Robots

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Abstract –

This paper presents a systematic review of intelligent construction robots and their readiness for real-world deployment. Intelligent construction robots are defined as software-based or physically embodied agents that operate in a Perception–Reasoning–Action loop—sensing the environment, reasoning over observations and/or human commands, and executing actions through control or actuation. Using a structured search of Web of Science, the ASCE Library, and Scopus, 134 peer-reviewed journal and conference papers were identified and analyzed. A construction-oriented Technology Readiness Level (TRL) assessment framework was developed by adapting the classic TRL model and prior civil engineering TRL studies to evaluate technical maturity and deployability. Results reveal a step-up maturation trajectory: after an extended plateau near mid-level readiness, the literature shows accelerated growth in 2017–2025 with increasing dispersion in study quality. Only two studies achieved TRL 9 field validation, while most 2025 studies clustered at TRL 8. Findings highlight a persistent “valley of death” barrier between validation and deployment and motivate multi-condition field testing, safety assurance, and workflow integration to advance site-ready robotics.

Keywords –

Construction Robotics; Technical Readiness Level; Artificial Intelligence; Deep Learning; Reinforcement Learning

1 Introduction

The adoption of construction robots is increasingly necessary given the industry’s severe labor shortage. Since 2023, the construction labor gap has reached 546,000 workers [1]. This sustained scarcity of skilled labor slows project delivery and substantially increases costs. A recent poll found that more than 90% of contractors report difficulty hiring qualified workers,

which in turn raises operating expenses [2].

One prominent response is increased automation and robotics. Automated construction methods can reduce repetitive manual work by 25–90% and cut workers’ exposure to hazardous activities by 72%, while improving accuracy and reducing rework [3]. Accordingly, construction robotics has been widely recognized as both necessary and productive [4,5]. Early diffusion, however, was constrained by high capital costs, the inherently unstructured nature of jobsites, and limited sensing and cognition in robotic platforms [6]. Today, simultaneous advances in artificial intelligence (AI), sensing, and building information modeling (BIM) are enabling a resurgence—from single-purpose tools toward more capable autonomous systems that can execute complex tasks. These developments are ushering in a new era of intelligent construction robots that can perceive, reason, and act autonomously to perform high-quality craft operations.

With rapid technological progress, construction robots increasingly leverage advanced perception and decision-making methods, including deep learning and reinforcement learning. Many successful prototypes have been demonstrated across a wide range of tasks, such as ceiling installation [7,8], window installation [9], drywall installation [10], inspection [11], welding [12], and human–robot interactive operations [13,14]. However, although these systems often show strong performance in high-fidelity simulation or controlled laboratory environments, the field still lacks a systematic evaluation framework that enables industry managers and decision-makers to assess the technical readiness of these technologies for deployment on real construction sites.

To address this gap, this paper adapts the widely used NASA Technology Readiness Level (TRL) framework [15] for construction robotics products and applies it to systematically evaluate the technical readiness of current intelligent construction robotics research. We analyze 134 papers published from 2017 to 2025 on intelligent construction robots and use the adapted framework to quantify their readiness levels. We further examine overall trends in readiness and product evolution to

characterize research progress, identify roadmaps, and highlight key challenges that must be addressed to accelerate real-world deployment.

2 Technical Readiness Level Framework

As mentioned in the Introduction section, this paper is theoretically supported by the classic TRL framework proposed by Nasa (15 Mankins 1995), which is shown in Table 1.

Table 1 Original TRL framework [15]

TRL Level	Definition (Operational Environment)
TRL 1	Basic principles observed and reported
TRL 2	Technology concept and/or application formulated
TRL 3	Analytical and experimental critical function and/or characteristic proof-of-concept
TRL 4	Component and/or breadboard validation in laboratory environment
TRL 5	Component and/or breadboard validation in relevant environment
TRL 6	System/subsystem model or prototype demonstration in a relevant environment (ground or space)
TRL 7	System prototype demonstration in a space environment
TRL 8	Actual system completed and “flight qualified” through test and demonstration (ground or space)
TRL 9	Actual system “flight proven” through successful mission operations

In this framework, the general hierarchy is from proposing the concept - component validation - system validation in controlled environments - system validation in true environment (space). It also fits the development of construction automation products. For construction robotics, it will also generally go through the similar phases: conceptualization (TRL)- prototyping in the lab- test in the field.

To understand how the traditional TRL scheme can be fit for construction technology development, the

authors referred to two sources:

1) The core of development in NASA TRL: The authors conceptualized and abstracted the essence of TRL to three phase: conceptualization - prototyping in lab -test in the field. For construction robotics, it will also generally go through the similar phases: conceptualization (TRL)- prototyping in the lab- test in the field.

2) The previous work adapting TRL to civil engineering or construction related technologies. The following two representative TRL schemes were discovered, as shown in Table 2 and 3:

Table 2 TRL for construction and civil engineering [16]

TRL Level	Definition (Operational Environment)
TRL 1	Basic principles and research: Scientific principles observed
TRL 2	Applied Research: Application formulated and potential identified
TRL 3	Proof of Concept: Critical function validated in separate elements
TRL 4	Lab Validation (Low Fidelity): Component validation in a laboratory environment
TRL 5	Lab Validation (High Fidelity): Integrated components demonstrated in a laboratory environment
TRL 6	Prototype (Relevant Environment): Prototype demonstrated in a relevant environment
TRL 7	Prototype (Operational Environment): Prototype demonstrated in an operational environment
TRL 8	System Proven: Technology proven in an operational environment
TRL 9	Implementation: Technology refined and adopted

For a more abstract type, the following example on construction material development was also used in Table 3 [17].

Table 3 An abstract version of TRL for Civil Engineering [17]

TRL Phase	Construction-Specific
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		Definition
TRL (Concept)	1–3	Chemical formulation of the biocomposite (liquid wood) and basic mechanical testing (tension/compression) on small samples.
TRL (Validation)	4–5	"Component Testing: Producing standard construction shapes (profiles, boards) and testing them for fire resistance, water absorption, and UV stability in a lab."
TRL (Demonstration)	6–7	"Pilot Projects: Installing the material in a non-critical real-world structure (e.g., a park bench, facade cladding, or small shelter) to monitor weathering over 1–2 years."
TRL (Deployment)	8–9	"Standardization: The material is included in national building codes (e.g., Eurocodes) and is available in commercial catalogs for structural use."

As summarized in Table 4, we aggregate the nine original TRL levels into four tiers to better reflect the typical development trajectory of construction robotics. Tier 1 (TRL 1–3) emphasizes conceptualization, including knowledge integration across disciplines (e.g., construction engineering, robotics, sensing, and AI) to clarify potential technological solutions to a construction-domain problem. Tier 2 (TRL 4–5) corresponds to component-level validation, where key subsystems are tested to verify that individual components can perform their intended functions within the proposed system architecture. Tier 3 (TRL 6–7) focuses on system-level prototyping and validation, in which integrated robotic systems are demonstrated and evaluated as complete solutions. Finally, Tier 4 (TRL 8–9) addresses deployment in relevant environments, where systems with established performance through prior validation are implemented and assessed under jobsite-representative conditions.

Building on these tier definitions, this paper proposes a TRL assessment framework specifically tailored to intelligent construction robotics (Table 4). This framework utilizes two primary criteria: Test Environment and Model Performance. The Test Environment (rated 1–6) evaluates the physical context of deployment, ranging from low-fidelity simulations to real-world construction sites. Simultaneously, Model

Performance (rated 1–3) assesses the accuracy of perception and reasoning. To ensure reliability, if a robot's performance falls below 60% for any given rating, the overall TRL is downgraded by one level.

The specific criteria for each factor are as follows:

- Test Environment: 6 (field deployment on real-world construction sites); 5 (construction-similar lab environments); 4 (simplified lab environments); 3 (high-fidelity simulations); 2 (low-fidelity simulations); and 1 (non-construction environments with no direct task applicability).
- Model Performance: 3 (near-perfect; such as >95% object identification accuracy); 2 (moderate; such as 80% accuracy in human state inference); and 1 (low; such as ~60% accuracy in object identification).

Table 4 TRL for intelligent construction robots

TRL Level	Definition (Operational Environment)
TRL 1	Basic principles and research: Scientific principles observed
TRL 2	Applied Research: Application formulated and potential identified
TRL 3	Proof of Concept: Critical function validated in separate elements
TRL 4	Lab Validation (Low Fidelity): Component validation in a laboratory environment, such as perception results in general datasets or trajectory planning in simplified simulation environment
TRL 5	Lab Validation (High Fidelity): Integrated components demonstrated in a laboratory environment, such as perception results in task-relevant dataset or motion planning in high-fidelity simulation or simulations with task-relevant elements
TRL 6	Prototype (Relevant Environment): Prototype demonstrated in a relevant environment, such as integrated intelligent system in high-fidelity and task-relevant simulations
TRL 7	Prototype (Operational Environment): Prototype demonstrated in an operational environment, such as embodying all elements in a robot to perform construction tasks in simplified

	environment
TRL 8	System Proven: Technology proven in an operational environment, such as embodying all elements in a robot to perform construction tasks in lab environment that has all construction task elements but less cluttered
TRL 9	Implementation: Technology refined and adopted

However, it should be noted that the authors also considered the performance of the demonstrations. For example, if a lab prototyping of intelligent robot was demonstrated (TRL7) but the performance does not show its capabilities to perform high-quality construction tasks, the authors will rate this as TRL 6.

3 Data from Literature Review

This paper reviews intelligent construction robots that integrate deep learning (DL), reinforcement learning (RL), and other AI methods to perceive site conditions, interpret human intent or task specifications, and execute goal-directed actions. In this review, “intelligent robots” refers to agents: software-based or physically embodied, that operate in a Perception–Reasoning–Action loop: they sense the environment, reason over observations and/or commands, and generate actions through control or actuation [18].

Using this inclusive definition, the review covers two categories that are essential for understanding methodological progress in the field. First, it includes robots without physical embodiment (e.g., simulation-based or purely computational agents). Because construction robotics hardware deployments were relatively sparse prior to 2020, a substantial portion of foundational research validated learning-based perception and control using simulated platforms; these studies are therefore included for their algorithmic contributions and their role in establishing DL-based robotic control pipelines. Second, the review includes automated construction equipment under a broad robotics lens—ground robots, robotic manipulators, unmanned aerial vehicles, and sensorized construction machinery such as excavators or other articulated equipment. When such systems are equipped with environmental sensing, DL-driven reasoning modules, and actuation/control capabilities, they satisfy the criteria of intelligent construction robots.

The literature search was conducted across three major scholarly repositories: Web of Science (WoS), the American Society of Civil Engineers (ASCE) Library, and Scopus. The search was executed on August 10, 2025 and limited to publications from 2017 through 2025 to

emphasize the most recent wave of advances in DL-enabled construction robotics. Although neural-network-based work in construction robotics predates this window (e.g., studies appearing as early as 2017), the selected timeframe reflects the rapid acceleration in DL architectures, data-driven control, and foundation-model capabilities that have materially changed the state of practice. The review scope was restricted to peer-reviewed journal articles and conference proceedings written in English. Searches were performed over titles, abstracts, and author keywords using three keyword groups combined with Boolean “AND”: (i) robot-related terms (“robot” OR “robotic”), (ii) the domain term (“construction”), and (iii) learning-related terms, with “deep learning” as the primary keyword supplemented by “neural networks,” “reinforcement learning” (given its growing role in robot control and long-horizon decision-making), and “large language model” (included because it is DL-based and increasingly leveraged for robotic reasoning and human–robot interaction).

Studies were excluded if the search terms appeared incidentally but the content was not substantively related to construction robotics or DL/RL methods, and review papers were also removed to avoid duplicating secondary syntheses. After screening and applying these criteria, 134 publications were retained for analysis (Appendix I). The year-by-year distribution shows a sustained rise in output over 2017–2025 (Figure 1), indicating expanding research attention at the intersection of robotics, construction, and learning-based methods. In terms of publication venues, Automation in Construction emerged as the dominant journal outlet, followed by leading conference proceedings including the *Construction Research Congress (CRC)* and the *International Conference on Computing in Civil Engineering (IC3E)*. Additional high-frequency sources included the *Journal of Computing in Civil Engineering* and the *Journal of Field Robotics*, underscoring both the construction-engineering and robotics communities’ increasing engagement with DL-enabled construction automation.

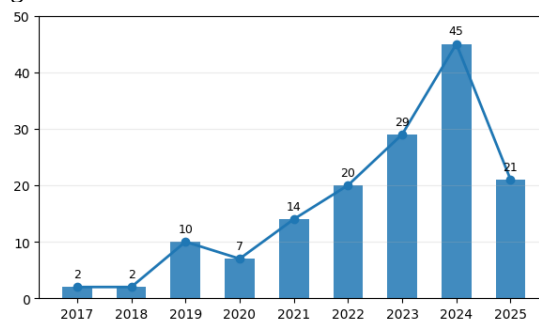


Figure 1. Publication trends and major publication venues.

4 Results

The TRL has largely improved from 2017 (averagely TRL3) to 2025 (averagely TRL 6.7). There are two studies testing the robotic products on construction sites and reached TRL 9. However, the majority does not show readiness to be directly deployed on construction sites. \

The authors also observed the large variation of the TRL in the prototypes or systems, all mean, median, and mode were used to show the patterns. The results are shown in Table 5.

To provide easier understanding of the trend, the visualization of the table is performed. The result is shown in Figure 2.

Table 5 Average TRL for intelligent construction robot studies 2017-2025

	Mean	Median	Mode
2017	3	3	3
2018	5	5	5
2019	5.625	5	5
2020	5.571	5	4.5
2021	6.25	5.5	5
2022	6	5	5
2023	6.444	6	6
2024	5.641	6	5
2025	6.667	7	8

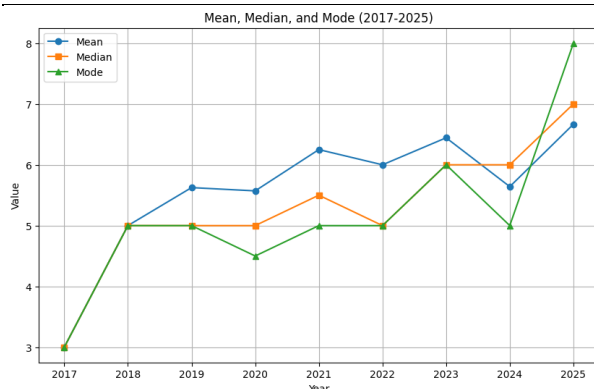


Figure 2. Average TRL for intelligent construction robot studies 2017-2025.

As can be seen in Figure 2, the TRL for intelligent construction robots illustrates a classic "step-up" maturation trajectory, characterized by a distinct phase of stabilization followed by a recent period of volatile growth. The jump from 2017 to 2018 established a solid baseline around a value of 5.0, where the technology or metric sat for several years with minimal deviation, suggesting a period of consistency or stagnation. However, beginning in 2021 and accelerating into 2023–

2025, the data shows a breakout from this plateau. The divergence between the Mean, Median, and Mode in these later years indicates varying performance; specifically, the high Mode (8.0) in 2025 suggests that while the most common outcome is now high-performing, the lower Mean (6.667) indicates that significant low-performing outliers are still dragging the average down. This indicated the variation in the quality of research.

In addition, from the innovation perspective, the average TRL from 2020-2025 stabilized around 6. Innovation management to describe this as the difficulty of moving from TRL 4–6 (Research/Validation) to TRL 7–9 (Commercialization/Deployment) [19][20]. The "stagnation" seen in your data (flatline at 5.0 for years) is the textbook statistical signature of a project stuck in this valley. However, the majority of studies in 2025 has reached TRL 8, suggesting the completion of a full-scale robot embodiment in a construction-relevant lab environment.

In addition, the authors performed stratified analysis to further explore the reasons behind the TRL trend. The intelligent robots are categorized to: manipulators (robot arm and hand), soft robots, self-made robots (assembled from scratch), industrial equipment (modified excavator and cranes), combined robots (off-the-shelf solution modified), mobile robots, UAV, and 3D printing machines. The max and mode TRL were both used for each category, as shown in Figure 3.

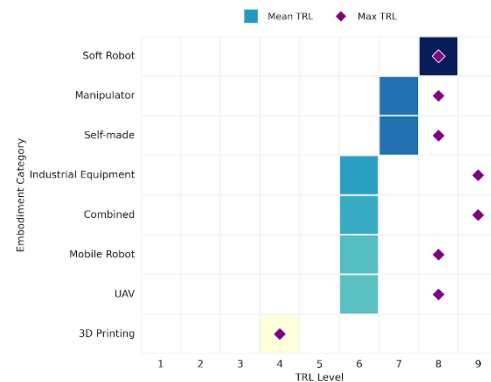


Figure 3. Stratified TRL analysis with eight robot types.

As illustrated in Figure 3, most construction robot categories now possess near-field-ready configurations. 3D printing remains the primary outlier with limited site deployability for intelligent systems. This is largely because 3D printing trajectories are typically pre-programmed to prevent structural defects and ensure material integrity, with relatively few studies successfully integrating adaptive, ML-based control. Conversely, both industrial equipment and combined robotic systems demonstrate viable prototypes for direct on-site deployment. It is important to note that while these specific categories reach high maturity, the high

volume of simulation-based research across the broader field pulls the aggregate mean TRL toward lower validation levels, highlighting how sample composition can mask the operational progress of specific sub-sectors.

5 Conclusions

This paper systematically reviewed 134 publications on intelligent construction robots and assessed their technical readiness for on-site deployment. Intelligent construction robots were defined broadly as software-based or physically embodied agents that implement a Perception–Reasoning–Action loop—sensing the environment, reasoning over observations and/or human commands, and executing actions through control or actuation [18]. Building on the classic Technology Readiness Level (TRL) framework [15], and informed by prior TRL adaptations in civil engineering research [16][17], this study developed a domain-appropriate, methodologically rigorous readiness assessment tailored to the realities of construction environments.

The readiness trends reveal a “step-up” maturation pattern rather than smooth linear progress. The TRL metrics show an extended period of stabilization around mid-level readiness (approximately TRL 5) through the late 2010s, followed by a clear breakout beginning around 2021 and accelerating through 2023–2025 (Figure 2). In the most recent years, the widening spread among central tendency measures (mean, median, and mode) indicates uneven progress across the literature: although the most common outcome has shifted to high maturity (mode near TRL 8 in 2025), the average remains noticeably lower, implying that a subset of studies still lag behind and pulls down overall performance. This dispersion suggests increasing variation in methodological rigor, validation quality, or the extent of real-world testing as the field scales.

Consistent with innovation management theory, the evidence also suggests that the field has faced a persistent transition barrier between research validation and deployment. Across 2020–2025, the average TRL hovering around ~6 aligns with the well-documented difficulty of moving from TRL 4–6 (research/validation) into TRL 7–9 (commercialization/deployment), often described as the “valley of death” in technology maturation [19][20]. In this context, the earlier multi-year plateau near TRL 5 can be interpreted as a statistical signature of technologies that demonstrate feasibility but struggle to secure the field access, integration pathways, safety assurance, and robustness needed for sustained deployment.

The readiness evaluation indicates that full site-ready maturity remains uncommon. Only two studies achieved TRL 9, meaning robotic systems were validated in real construction settings under varied conditions sufficient to

represent real-world variability. Most of the remaining work clustered below that threshold, reflecting persistent barriers such as unstructured environments, safety constraints, limited access to field trials, and challenges in generalization across tasks, sites, and work practices. At the same time, the evidence points to rapid progress: by 2025, the dominant maturity level shifted to TRL 8, indicating that many systems are approaching deployability through late-stage validation and near-field testing, even if they have not yet demonstrated sustained performance across diverse live jobsite conditions.

Overall, the findings suggest the field has moved from early-stage feasibility demonstrations around 2017 (typically TRL ~3) to near-deployment prototypes within less than a decade, underscoring the accelerating impact of deep learning, reinforcement learning, and AI-enabled perception and planning. The primary gap is no longer proof-of-concept capability, but robust translation to the field—especially generalization, safety assurance, and integration into work-zone operations and workflows. Future research should therefore prioritize multi-site, multi-condition field evaluations, standardized benchmarking protocols, and human-centered deployment procedures that ensure reliability and safety while delivering measurable gains in productivity, constructability, and reduced disruption to construction operations.

Overall, to address the lack of a standardized technical maturity baseline in current literature, this study employs the TRL framework as a vital “first-pass” screening tool. By establishing this technical baseline, we provide a curated starting point for the research community and industrial decision-makers to identify viable candidates for adoption. However, we acknowledge that TRL is a high-level metric with inherent limitations; it does not, on its own, guarantee safety, generalization, or robustness across diverse construction environments, which are all important operational factors to consider for a technology adoption decision. In this paper, the authors position TRL as a preliminary filter that allows stakeholders to judiciously apply resource-intensive evaluations: such as safety audits and cross-environment generalization tests, to a more targeted subset of technologies. This tiered framework bridges the gap between laboratory-based technical maturity and field-proven technical maturity.

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