AI-Driven Autonomous Construction Machinery for Enhanced Productivity and Safety

Milan Jovin[1] and Igor Pesko[1] and Vladimir Mucenski[1]

[1]Department of Civil Engineering and Geodesy, Faculty of Technical Sciences, University of Novi Sad, Serbia
mjovin@uns.ac.rs, igor.bp@uns.ac.rs, mucenskiv@uns.ac.rs

Abstract –

Construction sites remain among the least productive and most hazardous work environments. AI-driven autonomous and semi-autonomous machinery could improve productivity and safety, yet deployment is constrained by reliability and assurance under dynamic operational design domains (ODDs). This paper presents an evidence-weighted scoping review of on-site AI-enabled autonomy and robotics, reported in line with PRISMA-ScR guidance. A Scopus search (2010-2026) supplemented by snowballing identified 25 eligible peer-reviewed studies addressing productivity and/or safety outcomes. Studies were mapped into four application clusters: heavy equipment autonomy (24%), site layout and installation robots (28%), material logistics (12%), and safety monitoring AI (36%). Evidence quality was dominated by case studies and simulations (E2, 68%), with limited robust empirical testing (E3, 16%) and a smaller share of illustrative vendor reports (E1, 16%). Reported productivity benefits commonly involved cycle-time reduction, improved unit rates, and reduced rework or waste, while safety benefits centered on risk detection, exposure reduction, and compliance monitoring; however, outcomes were heterogeneous and strongly context-dependent. Recurring adoption barriers comprise ODD limitations, sensing and perception failures, workflow integration, human factors, and still unresolved liability and regulatory questions. The synthesis highlights where evidence is strongest, where validation continues thin, and what assurance-oriented considerations (risk assessment, verification and validation, and runtime monitoring) are most relevant for accountable deployment aligned with functional safety principles.

Keywords –

autonomy, construction robotics, productivity, safety, assurance, ODD, monitoring, validation

1 Introduction

The global construction industry faces a paradox: sustained demand for infrastructure projects persists alongside persistent productivity challenges and a high rate of occupational accidents [1]-[4]. Despite digital transformation in other sectors, construction still relies on labor-intensive methods, contributing to delays, cost overruns, and skilled-labor shortages [1]-[3]. AI and robotic systems offer potential productivity and safety gains, but their broad adoption is constrained by assurance: ensuring safe and reliable autonomous operation in dynamic, cluttered sites where human co-presence and sensing/perception edge cases limit the operational design domain and complicate accountability.

This paper systematically reviews AI-driven autonomous and semi-autonomous machinery in on-site construction to synthesize reported productivity and safety impacts and identify adoption barriers relevant to safety assurance and operational reliability. The review addresses four questions: (RQ1) What system categories are currently implemented on-site; (RQ2) How do they affect productivity and how is it measured; (RQ3) How do they affect safety and how is it evaluated; and (RQ4) What barriers and facilitators influence effective adoption and implementation? These four questions were formulated to cover the full adoption arc: system taxonomy (RQ1), measured productivity and safety impacts (RQ2-RQ3), and systemic barriers to deployment (RQ4), providing a basis for actionable guidance across research and practice.

To ensure conceptual clarity, this paper defines key terms related to technological intervention. An autonomous system refers to a machine or robot capable of performing tasks independently, making decisions, and adapting to environmental changes without human involvement [5]-[7]. Semi-autonomous systems require human monitoring or intervention at specific decision points and often operate in conjunction with human operators [7], [8]. AI-driven systems are those in which AI algorithms inform, optimize, or direct machinery actions, enabling advanced perception, planning, and control [9]-[10]. The scope of this paper is restricted to on-site applications, focusing on actual construction activities rather than design or planning phases.

This study is a scoping review drawing exclusively on existing academic literature; any reported productivity or safety improvements reflect the cited sources and are context-dependent.

The paper proposes a taxonomy of on-site AI-driven autonomous and semi-autonomous systems, synthesizes evidence on productivity and safety impacts and their measurement, identifies key adoption barriers and enablers, and frames the findings through an assurance-oriented perspective focused on reliability in dynamic environments.

2 Literature Review

A focused review of existing literature frames the integration of AI-driven autonomous and semi-autonomous machinery in on-site construction and summarizes reported impacts on productivity and safety. This section consolidates key themes and recurring challenges observed in actual construction site conditions, emphasizing technologies implemented directly in site operations rather than those restricted to earlier project phases such as design or controlled prefabrication environments.

2.1 Evolution and Current Landscape of AI and Automation in Construction

AI and automation in construction have evolved from basic mechanization to systems capable of perception, decision-making, and executing complex tasks with varying levels of autonomy. These progressions are driven by improvements in sensing technologies, computational power, and AI methodologies. However, construction sites present significant deployment challenges caused to their dynamic, unstructured, and human-centered nature. The Operational Design Domain (ODD) is a central concept for deployment, defining the conditions under which autonomous behavior is considered safe and effective. On construction sites, ODD boundaries are especially complex and frequently change as a result of weather, lighting, evolving layouts, mixed traffic, and ongoing human presence, which makes assurance more difficult than within controlled environments.

On-site AI and automation applications can be categorized into four primary domains, each supported by the autonomy stack of perception, planning, and control. First, heavy equipment autonomy encompasses autonomous excavators, bulldozers, loaders, and hauling trucks that perform repetitive tasks such as earthmoving and material transport. These systems typically integrate LiDAR, radar, and computer vision for perception [10], AI-based planning for path and task sequencing [10], and control mechanisms for steering, propulsion, and manipulation [10]. Major failure modes include misidentification of humans or equipment, sensor occlusion or degradation, unexpected ground conditions, and communication loss, which are critical due to the high kinetic energy and potential severity of failures [6], [13]. Second, site layout and installation robots perform tasks such as bricklaying, rebar tying, 3D printing, and assembly, often requiring high-precision sensing and Building Information Modeling (BIM)-informed planning [14], [15]. These systems are susceptible to accuracy loss from vibrations or material inconsistencies, collisions in shared workspaces, and software errors within complex logic [14], [10]. Third, material logistics utilizes Autonomous Mobile Robots (AMRs) and Automated Guided Vehicles (AGVs) for internal transport, employing navigation sensors for perception and route optimization for planning in frequently changing layouts [10], [13]. Key risks include navigation errors, load instability, and unexpected interactions in areas with dense human activity [13]. Fourth, safety monitoring AI employs computer vision to detect hazards, unsafe behaviors, and personal protective equipment (PPE) compliance from real-time video streams [14]. Reliability challenges include false alarms, missed detections, performance degradation under poor lighting or adverse conditions, and broader concerns regarding privacy and trust [14]. Across all domains, defining a comprehensive ODD and demonstrating reliable performance over diverse edge cases remain persistent barriers to scalable deployment [13], [15].

2.2 Impact on Construction Productivity

Construction productivity is typically defined as output per unit input and is evaluated at both the task level, which measures the efficiency of specific operations, and the project level, which considers schedule and cost performance. Within AI-enabled automation, frequently reported productivity metrics include unit rates such as output per hour or day, cycle time, throughput, equipment utilization, labor hours per output unit, and quality-related indicators including rework frequency, error rates, and compliance with specifications. Productivity improvements are attributed to direct effects, such as faster and more consistent execution of repetitive operations and extended operational windows, as well as indirect effects, including reduced rework, enhanced coordination, and more efficient site logistics [13], [10], [13]. Predictive analytics further contributes to productivity by identifying potential bottlenecks and equipment failures, thereby allowing proactive interventions [14]. Nevertheless, the extent of these improvements is highly context-dependent, influenced by factors such as task type, site variability, workflow integration, and the organization's level of digital readiness. Productivity gains observed in controlled or spacious environments may not be replicable in confined or highly dynamic settings [13], [15].

2.3 Enhancing Construction Safety through AI and Automation

Existing literature identifies three primary mechanisms through which AI and autonomous technologies enhance safety: reducing worker exposure by substituting hazardous tasks, improving hazard detection and monitoring via data-driven supervision, and managing risks associated with human-robot interaction in shared workspaces [2], [4]. Commonly reported safety metrics include exposure time, near-miss frequency, incident rates such as Total Recordable Incident Rate (TRIR), and fatality rates. Due to the rarity and comparability challenges of severe events across projects, surrogate indicators are frequently employed.

Exposure reduction is consistently highlighted as a primary benefit, especially for tasks performed at height, in confined spaces, near heavy equipment, or under extreme conditions [10]-[14]. Autonomous equipment can implement standardized motion control and routing practices, facilitating safer operation in mixed-traffic environments and may reduce collision risk [6], [10]. In addition to exposure reduction, AI-based monitoring systems improve safety by allowing real-time recognition of unsafe behaviors, hazard detection, and compliance verification, including personal protective equipment (PPE) monitoring and automated alerts [14], [15], [10]. Techniques such as proximity monitoring, geofencing, and predictive safety analytics are frequently cited as effective methods to reduce near misses and improve leading safety indicators [14], [15], [13], [14]. However, the deployment of these technologies introduces new hazards and assurance challenges. Operating beyond operational design domain (ODD) limits, sensor or software degradation, communication failures, and misdetections in vision-based monitoring (including false positives and false negatives) can compromise both trust and safety outcomes [13], [14], [15], [10], [13], [14]. Consequently, the literature emphasizes the need for structured safety assurance, including hazard analysis, runtime monitoring, and verification and validation through simulation, scenario-based testing, and controlled real-life deployment. These processes should be supported by rigorous risk assessment and alignment with functional safety principles to enable scalable adoption.

3 Research Methodology

This scoping review maps peer-reviewed research on AI-driven autonomous and semi-autonomous machinery in on-site construction, with a focus on reported productivity and safety impacts. The review follows PRISMA-ScR guidelines to ensure transparency and replicability [41].

3.1 Information Sources and Search Strategy

A search of the Scopus database was conducted on 2026-01-02 using combinations of terms related to artificial intelligence, machine learning, robotics, autonomy, automation, construction, on-site operations, productivity, and safety outcomes. The search was restricted to English-language journal articles and peer-reviewed conference papers published between 2010 and 2026. Additionally, reference lists of key papers were screened to identify relevant studies not captured by the initial database query.

3.2 Eligibility Criteria and Screening Process

Studies were included if they examined AI-enabled autonomous or semi-autonomous systems implemented in on-site construction tasks and reported or discussed productivity indicators or safety outcomes. Studies that focused solely on design, off-site manufacturing, general Construction 4.0 topics without specific AI or robotics applications, or technical AI developments lacking a clear on-site construction deployment context were excluded. This criterion was applied to maintain conceptual focus: digitalization and BIM-related studies subsumed under the broad Construction 4.0 label, while relevant to the wider digital transformation of the sector, do not directly report on the operational performance, reliability, or safety outcomes of on-site autonomous machinery addressed by the research questions. The screening process consisted of two stages: initial title and abstract review, followed by full-text assessment. Duplicate records were removed, and any disagreements were resolved through consensus between two reviewers.

3.3 Data Extraction and Evidence Coding

A standardized data extraction process was applied to each included study, recording system type and autonomy level, targeted task category, sensing and AI components, validation setting (field, laboratory, or simulation), reported productivity and safety metrics, as well as identified barriers and enabling factors. To ensure that conclusions reflected the strength of validation, evidence was categorized as E1 (vendor or illustrative claims without empirical confirmation), E2 (single-project case studies, simulations, or laboratory studies), or E3 (peer-reviewed evidence-based validation such as field studies or comparative evaluations). The four E1-coded sources were identified during the snowballing phase as illustrative industry reports cited within key academic papers, not through the primary peer-reviewed database query; the E1 designation explicitly flags their lower evidential strength. The interpretation of findings explicitly considered both the evidence level and the contextual specificity.

3.4 Synthesis

The extracted data were synthesized using descriptive mapping and thematic coding in alignment with the research questions. Studies were grouped by application cluster, and reported outcomes, metrics, and recurring barriers and facilitators were compared. Particular attention was given to reliability constraints within the operational design domain and to safety assurance considerations.

4 Results

This scoping review synthesizes evidence regarding the impact of AI-driven autonomous and semi-autonomous construction machinery on productivity and safety. A structured screening process identified 25 relevant studies. These studies were categorized as follows: 6 (24%) addressed heavy equipment autonomy, 7 (28%) examined site layout and installation robots, 3 (12%) focused on material logistics, and 9 (36%) investigated safety monitoring AI. The quality of evidence was distributed as 4 (16%) E1 (vendor claim or illustrative), 17 (68%) E2 (case study or simulation-based), and 4 (16%) E3 (peer-reviewed validation or empirical study).

4.1 Quantitative Impact on Productivity

Among the reviewed studies, Brosque and Fischer [10] provide one of the more structured multi-system comparisons across ten robots, while installation robot studies [14], [16] and logistics deployments [17] report measurable task-level improvements in placement accuracy, execution speed, and material flow. However, the heterogeneity of metrics, baselines, and validation settings across the 25 included studies makes meaningful numerical aggregation methodologically inappropriate; reported outcomes should be interpreted as context-specific illustrations rather than universally generalizable benchmarks.

4.2 Safety Enhancement Metrics and Assurance-relevant Findings

Safety impacts are most frequently documented through two primary mechanisms: the reduction of worker exposure to hazardous conditions by transferring high-risk tasks from humans to machines, and the enhancement of hazard identification through continuous monitoring and predictive technologies [10], [14]. Leading indicators, such as exposure time, near-miss proxies, unsafe-behavior detections, and personal protective equipment (PPE) compliance, are reported more often than outcome indicators like incident rates. This trend is partly attributable to data limitations and the infrequency of severe incidents. Exposure reduction is consistently emphasized in contexts involving fall-risk areas, confined spaces, extreme weather, and operations near heavy machinery [10], [13]. Autonomous vehicles and robotic platforms are reported to incorporate features that facilitate safer on-site movement, including controlled trajectories and maintenance of safe distances, which may reduce collision risk in mixed-traffic environments [6], [10]. AI-based monitoring systems, utilizing vision and sensor networks, are widely implemented for real-time hazard and unsafe behavior detection, PPE verification, and access control, with predictive capabilities allowing proactive interventions [14]. Geofencing is frequently used to restrict human access to autonomous operating zones, thereby reducing hazardous human-machine interactions [15]. Although pilot deployments and case studies often demonstrate reductions in near misses and improvements in situational awareness through real-time alerts and rapid corrective actions, these outcomes should be regarded as promising leading indicators rather than definitive evidence of sustained reductions in rare but severe incidents [13], [14]. Concurrently, research highlights new risks associated with autonomy and monitoring, such as software defects, sensor degradation, communication failures, and misdetections (including false negatives and false positives), all of which can undermine both safety and trust [13], [14]. These results reinforce the necessity for explicit risk assessment, alignment with functional safety standards, and assurance processes that address operational design domain limitations and edge cases [13], [14].

4.3 Qualitative Insights on Implementation and Adoption

Qualitative analyses consistently demonstrate that adoption is primarily influenced by socio-technical fit rather than technical performance alone. Workflow integration is still a significant barrier, as established planning routines, sequencing logic, and site logistics often require modification to enable reliable coordination between human crews and autonomous systems [15]. Site variability and restricted operational design domains continue to be major constraints, with system performance generally more stable in controlled or predictable settings than in environments characterized by terrain variability, obstructions, or weather-related edge cases [13]. Training and workforce acceptance are frequently identified as critical factors, encompassing the need for re-skilling in supervision, exception handling, and teleoperation. VR-based training is often cited as an effective method, with reported benefits for knowledge acquisition and safety behavior; however, adoption may be impeded by concerns regarding employment displacement or diminished control [15], [10]. Economic feasibility is typically discussed in terms of high initial costs, uncertain utilization rates, and maintenance risks, which drive interest in clearer demonstrations of return on investment and alternative models such as leasing and Robots-as-a-Service. Value is also associated with indirect benefits, including reduced rework, enhanced quality, and more predictable project execution [13], [14]. Regulatory, standards-related, and liability issues are consistently highlighted as constraints, particularly in relation to functional safety guidance and the allocation of responsibility in incidents involving self-governing decision-making [39]. Data interoperability is regarded as essential for scalable autonomy, necessitating reliable integration with BIM, GNSS, and real-time site data streams, despite challenges posed by fragmented formats and limited standardization of data exchange [15].

Table 1 provides a structured summary of the key barriers and facilitators identified across the reviewed literature, organized by category.

Table 1. Summary of key adoption barriers and facilitators for AI-driven autonomous construction machinery.

Category	**Type**	**Notes and representative sources**
Workflow integration	Barrier	Established planning routines and sequencing logic require modification to enable reliable coordination between human crews and autonomous systems [15].
ODD limitations and site variability	Barrier	System reliability degrades in environments with terrain variability, obstructions, or weather-related edge cases [13].
Workforce acceptance and training	Barrier / Facilitator	Re-skilling in supervision, exception handling, and teleoperation is required; VR-based training is frequently cited as an effective mitigation approach [15], [10], [10].
Economic feasibility	Barrier	High initial costs and uncertain ROI; leasing and Robots-as-a-Service models are cited as alternative deployment strategies [13], [14].
Regulatory, standards, and liability	Barrier	Functional safety guidance and accountability frameworks for autonomous decision-making remain underdeveloped for construction-specific applications [39].
Data interoperability	Barrier	BIM/GNSS integration challenges and fragmented data exchange formats limit scalable autonomous deployment [15].

5 Discussion

The findings demonstrate that AI-driven autonomous and semi-autonomous systems provide measurable productivity and safety benefits in on-site construction; however, the extent and generalizability of these benefits are highly context-dependent. Consistent improvements are most evident in repetitive and structured tasks, where a stable operational design domain enables reliable perception, planning, and control. This observation is consistent with previous research indicating that site variability, mixed traffic, and human co-presence impose practical constraints on autonomy and complicate assurance and accountability [13].

Regarding productivity, the evidence indicates that reported improvements are frequently associated with reduced cycle times, smoother sequencing, and enhanced material flow, often facilitated by increased placement accuracy and reduced rework in structured installation tasks [14], [13]. However, variations in baselines, validation methodologies, and reporting standards hinder direct cross-study comparisons, and numerical claims should be regarded as scenario-specific rather than universally applicable. In practice, productivity gains depend not only on technical capabilities as well as on effective workflow integration, including planning routines, work zone organization, and reliable coordination between human crews and machines [15].

For safety, the literature emphasizes exposure reduction and enhanced monitoring as the primary mechanisms of impact, while statistically robust evidence of reduced incident rates remains limited due to data availability and study timeframes [10], [14]. Vision- and sensor-based monitoring systems show potential for real-time hazard detection, unsafe-behavior recognition, and PPE compliance verification, but they also introduce operational challenges such as performance degradation under poor lighting, occlusions, and misdetections that can undermine both trust and effectiveness [14], [13], [14]. Similarly, autonomous equipment introduces new risk modes, including software defects, sensor degradation, and communication loss, and these risks are amplified when systems operate near or beyond their operational design domain [13], [14]. These findings support an assurance-oriented interpretation in which reliability under real-site variability is treated as the central bottleneck to scalable deployment [13].

Themes related to adoption underline the socio-technical nature of deployment. Workforce acceptance and training requirements consistently emerge as important factors, notably about supervision, exception handling, and teleoperation interfaces. Virtual reality (VR)-based approaches are frequently cited as practical training solutions [15], [10]. Economic feasibility is still a significant obstacle due to high initial costs and uncertainties in utilization and maintenance, leading to the need for clearer return on investment (ROI) demonstrations and alternative service models such as leasing or Robots-as-a-Service [13], [14]. Additionally, unresolved issues related to regulation, standards, and liability, as well as interoperability challenges involving BIM/GNSS integration and fragmented data exchange practices, collectively constrain certification pathways and scalable implementation [39], [15].

The adoption barriers identified in this review reflect challenges that are not exclusive to construction; assurance requirements remain underdeveloped relative to more regulated automation domains [39]. Emerging industry-specific responses - including BIM-to-robot-ready digital twin frameworks [27] and structured ODD-based deployment approaches [34] - indicate that progress is underway, but standardized certification pathways, shared interoperability protocols, and return-on-investment benchmarks remain incomplete. These observations suggest that near-term advances in construction autonomy depend less on novel technological breakthroughs and more on the systematic development of construction-specific assurance practices and evidence-based deployment frameworks [6], [7].

These discussion points suggest that near-term impact is most realistic when autonomy is deployed incrementally in bounded tasks, with explicit ODD definition, staged validation, and runtime monitoring. Future research needs to prioritize comparative field evaluations across diverse site contexts, standardized reporting of productivity and safety metrics, and assurance practices that integrate hazard analysis, verification and validation strategies, and operational monitoring aligned with functional safety principles for construction-specific autonomy.

6 Conclusion

This paper conducted an evidence-weighted scoping review of AI-driven autonomous and semi-autonomous machinery in on-site construction, synthesizing reported impacts on productivity and safety while identifying recurring adoption barriers related to safety assurance and operational reliability. The most consistent productivity and safety benefits were observed in repetitive, structured tasks where the operational design domain remains stable enough to enable reliable perception, planning, and control. However, reported outcomes were heterogeneous and often dependent on specific contexts, with limited robust data-driven validation under real-world site variability. Safety improvements were mainly attributed to exposure reduction and monitoring-based leading indicators, whereas autonomy and AI-based monitoring introduced new risk modes, including edge cases, operational design domain exceedance, sensing degradation, communication loss, and misdetections. Adoption continues to be limited by challenges in workflow integration, workforce acceptance and training, economic feasibility, interoperability, and unresolved regulatory, standards, and liability issues. Future research needs to emphasize comparative field evaluations across diverse site conditions, standardized reporting of productivity and safety metrics, and the development of construction-specific assurance practices that integrate hazard analysis, verification and validation, and runtime monitoring in accordance with functional safety principles.

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