American Journal of Applied Science and Technology

VOLUME Vol.06 Issue 08 2026
PAGE NO. 92-99

An AI-Robotics Framework for Operational Efficiency and Sustainability in Construction Management

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Received: 20 June 2026; **Accepted:** 16 July 2026; **Published:** 17 August 2026

Abstract: The construction industry is increasingly characterized by complex resource coordination, fragmented workflows, schedule uncertainty, safety constraints, and growing sustainability requirements. Artificial intelligence (AI), robotics, cloud manufacturing principles, reinforcement learning, and intelligent resource-allocation mechanisms provide an emerging technological basis for addressing these challenges. This research develops an AI-Robotics Framework for Operational Efficiency and Sustainability in Construction Management by synthesizing concepts from cloud manufacturing, resource-service composition, intelligent scheduling, reinforcement learning, multi-objective optimization, and automated negotiation. The study adopts a conceptual research and review methodology based exclusively on the supplied literature and translates its manufacturing-oriented principles into a construction-management context. The proposed framework consists of five interconnected layers: data and sensing, intelligent resource orchestration, AI decision optimization, robotic execution, and sustainability-performance feedback. The analysis indicates that operational efficiency can be improved when AI-based decision mechanisms and robotic systems are integrated rather than deployed as isolated technologies. Cloud-oriented resource coordination provides scalability, reinforcement learning enables adaptive allocation, multi-objective optimization supports simultaneous consideration of productivity and sustainability, and automated negotiation can facilitate coordination among multiple project stakeholders. The framework further emphasizes continuous feedback between construction-site operations and management decisions. Its principal contribution is a theoretically grounded architecture for integrating AI and robotics with construction-resource management while maintaining sustainability as an explicit optimization objective. The study also identifies limitations associated with interoperability, data quality, organizational readiness, computational complexity, and the transferability of manufacturing-oriented models to construction environments.

Keywords: Artificial Intelligence; Construction Robotics; Construction Management; Sustainable Construction; Cloud Manufacturing; Resource Optimization; Reinforcement Learning; Multi-Objective Optimization; Intelligent Scheduling; Digital Transformation

1. INTRODUCTION

Construction projects operate within environments characterized by temporary organizational structures, heterogeneous resources, changing site conditions, interdependent activities, and substantial uncertainty. Unlike highly standardized manufacturing environments, construction processes frequently involve changing work locations, variable material availability, weather-dependent activities, multiple subcontractors, and project-specific production configurations. These characteristics make operational efficiency difficult to achieve through static planning alone. At the same time, sustainability requires construction organizations to consider material utilization, resource consumption, productivity, and environmental performance simultaneously rather than treating sustainability as an independent post-project assessment.

Digital transformation offers an opportunity to establish more adaptive construction-management systems. Cloud-oriented manufacturing research demonstrates how distributed resources and services can be digitally coordinated, composed, and optimized. Bohu et al. describe cloud manufacturing as a service-oriented and networked production model, establishing a conceptual basis for treating distributed capabilities as digitally accessible resources (Bohu et al., 2010). This principle is particularly relevant to construction because equipment, labor, materials, subcontractor capabilities, and robotic systems can similarly be conceptualized as dynamically managed project resources.

The development of intelligent manufacturing systems further demonstrates the transition from conventional digital coordination toward more intelligent and interconnected decision environments. Bohu et al. position cloud manufacturing within an intelligent manufacturing architecture capable of supporting increasingly integrated resource and service management (Bohu et al., 2019). For construction management, this suggests that AI should not be considered merely as an analytical tool but as a decision layer capable of interpreting operational data, allocating resources, coordinating robotic activities, and continuously adjusting project execution.

The research problem addressed in this paper is therefore the absence of an integrated conceptual framework connecting AI-based decision intelligence with robotic execution and sustainability-oriented construction management. Existing concepts concerning resource allocation, service composition, reinforcement learning, and optimization provide useful foundations, but their integration into a construction-specific AI-Robotics architecture requires systematic synthesis.

The objective of this research is to develop such a framework using only the supplied literature. The study specifically examines how cloud-based resource coordination, intelligent resource allocation, reinforcement learning, multi-objective optimization, service composition, and automated negotiation can contribute to construction operations. The resulting framework is intended to provide a theoretical foundation for future empirical implementation rather than claim experimentally validated performance.

2. LITERATURE REVIEW

2.1 Cloud-Oriented Resource Coordination

Cloud manufacturing provides the conceptual foundation for treating distributed production capabilities as digitally coordinated services. Bohu et al. identify cloud manufacturing as a new model of service-oriented networked manufacturing, emphasizing the integration and accessibility of distributed manufacturing capabilities (Bohu et al., 2010). Although construction differs structurally from manufacturing, the underlying principle of resource virtualization is transferable. Construction equipment, robotic platforms, material-handling capabilities, inspection systems, and specialized subcontractor services can potentially be represented as digitally discoverable resources.

Bohu et al. subsequently examine the characteristics, technologies, and applications of cloud manufacturing, indicating that resource-service integration requires mechanisms for organizing heterogeneous capabilities within a coordinated digital environment (Bohu et al., 2012). In construction, such a mechanism could support project managers in dynamically identifying available resources according to task requirements rather than relying exclusively on manually prepared schedules.

The later development of cloud manufacturing toward an intelligent manufacturing system strengthens this theoretical trajectory. Bohu et al. argue that cloud manufacturing is evolving toward more intelligent forms of production-system organization (Bohu et al., 2019). For construction management, this evolution implies a movement from simple digital information sharing toward AI-enabled resource interpretation and decision-making.

2.2 Resource-Service Composition and Flexibility

Resource-service composition is particularly relevant to construction because individual project activities frequently require combinations of capabilities. Guo et al. investigate measurement methods for resource-service composition flexibility, demonstrating that flexibility can be treated as an evaluable characteristic rather than an informal managerial attribute (Guo et al., 2012). This provides a useful theoretical basis for evaluating whether construction resources can be recombined when project conditions change.

Zhang et al. similarly examine flexible management of resource-service composition within cloud manufacturing. Their work suggests that resource combinations must remain adaptable to changing requirements rather than being treated as fixed configurations (Zhang et al., 2010). Applied to construction, this means that a robotic system, human workforce, equipment set, and material supply chain could be dynamically recomposed around changing work-package requirements.

Fei et al. further examine cloud-manufacturing characteristics and cloud-service composition, reinforcing the importance of matching service capabilities with production requirements (Fei et al., 2011). The construction implication is that AI can serve as a matching mechanism between task requirements and available operational capabilities.

2.3 Intelligent Resource Allocation

Resource allocation represents a central connection between AI and operational efficiency. Liang et al. investigate optimal allocation of cloud-manufacturing resources, demonstrating the importance of selecting appropriate resource configurations under constrained conditions (Liang et al., 2018). Construction projects face comparable allocation problems involving machinery, labor, materials, robotic capacity, and work areas.

Gai and Qiu introduce reinforcement learning for optimal resource allocation in IoT content-centric services (Gai & Qiu, 2018). The significance of reinforcement learning lies in its ability to improve decisions through interaction with an environment. Construction sites are dynamic environments in which task durations, resource availability, and operational conditions change over time. Consequently, an adaptive decision mechanism can potentially outperform a purely static allocation strategy when sufficient data and feedback are available.

2.4 Multi-Objective Optimization

Construction management rarely has a single optimization objective. Increasing productivity may conflict with energy reduction, reducing equipment utilization may conflict with schedule performance, and minimizing resource quantities may conflict with resilience. X. Shihong et al. examine multi-objective optimization of virtual-resource scheduling in cloud manufacturing environments, providing a conceptual foundation for managing competing objectives (X. Shihong et al., 2019).

This perspective is directly relevant to sustainable construction. Instead of optimizing project duration alone, an AI-Robotics framework can conceptually optimize a vector of objectives involving productivity, resource utilization, energy consumption, material efficiency, operational risk, and schedule stability. Such an approach transforms sustainability from a supplementary criterion into an integrated decision variable.

2.5 Automated Negotiation and Multi-Actor Coordination

Construction projects involve numerous stakeholders whose objectives may differ. The work of Weidong et al. on auto-negotiation for multi-party value-conflict resolution demonstrates how computational mechanisms can support coordination when multiple parties possess potentially conflicting preferences (Weidong et al., 2020). This is important because AI-driven construction management cannot be limited to machine-level optimization. Decisions concerning equipment allocation, work sequencing, access to constrained work zones, and subcontractor resources often require coordination among multiple actors.

Osborne's work on game theory provides a theoretical foundation for understanding strategic interaction and decision-making among agents (Osborne, 2003). Within the proposed framework, game-theoretic reasoning can complement optimization by addressing situations where project participants have partially aligned but non-identical objectives.

2.6 Research Gap and Theoretical Positioning

The reviewed literature establishes strong foundations for cloud-based resource coordination, flexibility, optimization, reinforcement learning, and automated negotiation. However, the references predominantly address manufacturing, IoT services, resource scheduling, or computational decision environments rather than construction robotics and sustainability as an integrated management problem.

The principal research gap is therefore architectural rather than purely technological. The challenge is to determine how existing intelligent-resource principles can be organized into a coherent construction-management system in which AI makes adaptive decisions, robotics executes physical tasks, and sustainability metrics continuously influence resource allocation. The proposed framework addresses this gap conceptually.

3. METHODOLOGY

3.1 Research Design

This study employs a conceptual research and structured literature-synthesis methodology. The analysis is restricted to the eleven references supplied by the user. Because these references do not collectively constitute an empirical construction dataset, the study does not claim statistical validation or experimental proof. Instead, it identifies transferable concepts and constructs a theoretically grounded framework for AI-enabled construction management.

The methodology follows three analytical stages. First, the supplied literature is categorized according to technological function: cloud resource coordination, resource-service composition, adaptive allocation, optimization, and stakeholder coordination. Second, relationships among these functions are established to determine how they can form an integrated architecture. Third, the resulting architecture is translated into construction-management processes involving sensing, decision-making, robotic execution, and sustainability feedback.

3.2 Proposed AI-Robotics Architecture

The proposed framework contains five interconnected layers.

3.2.1 Layer 1: Data and Sensing

The first layer collects operational information from construction activities. Data may originate from robotic platforms, equipment sensors, site-monitoring systems, material records, task-progress information, and resource availability records. The objective is to create a continuously updated representation of the project state.

The cloud-manufacturing literature suggests the value of treating distributed capabilities within an interconnected service environment (Bohu et al., 2010). In construction, this concept can be extended from production resources to site data. The framework therefore treats information as an operational resource required by downstream AI decisions.

3.2.2 Layer 2: Intelligent Resource Representation

The second layer represents construction resources as services or capabilities. A robotic excavator, autonomous material transporter, inspection robot, crane, skilled worker, or material supplier can be described according to capability, availability, location, capacity, cost, energy demand, and task compatibility.

Service composition becomes important when one task requires multiple resources. For example, automated wall construction could require a robotic installation platform, material delivery capability, digital design information, inspection resources, and human supervision. The system should identify combinations rather than isolated resources.

3.2.3 Layer 3: AI Decision and Optimization Engine

The third layer contains AI mechanisms for resource allocation, scheduling, prediction, and optimization. Reinforcement learning can be used for adaptive decisions when the operational environment changes, while multi-objective optimization can evaluate competing performance criteria.

A simplified decision formulation can be expressed as:

Maximize:

$$F = w_1P + w_2R + w_3S + w_4E - w_5C - w_6D$$

where (P) represents productivity, (R) represents resource-utilization efficiency, (S) represents sustainability performance, (E) represents operational effectiveness, (C) represents resource cost, and (D) represents delay. The weighting coefficients (w_i) represent project-specific priorities.

The formulation is conceptual rather than an empirically calibrated construction model. Its purpose is to demonstrate that operational and sustainability objectives should be evaluated jointly.

3.2.4 Layer 4: Robotic Execution

The fourth layer converts AI decisions into physical action. Robotics provides the execution capability that distinguishes an AI-Robotics framework from an information-only construction-management platform.

For example, an AI system may identify that material delivery is becoming a bottleneck. It can reallocate an autonomous transporter, modify delivery sequencing, and communicate the revised task to a robotic platform. The robot then executes the assigned operation while reporting updated status information.

This creates a closed-loop architecture:

Sense → Analyze → Optimize → Execute → Measure → Re-optimize.

Such a loop is consistent with the broader movement toward intelligent manufacturing systems described by Bohu et al. (2019), but its construction application requires additional consideration of site variability and human supervision.

3.2.5 Layer 5: Sustainability Feedback

The final layer evaluates sustainability consequences of operational decisions. Sustainability indicators can include material utilization, equipment utilization, energy consumption, idle time, unnecessary movement, resource wastage, and task rework.

The important methodological principle is that sustainability should not be measured only after project completion. Instead, the framework integrates sustainability feedback into operational decision-making. For instance, two robotic schedules may achieve the same completion time but differ in equipment travel and energy consumption. A sustainability-aware optimizer should distinguish between them.

3.3 Adaptive Resource Allocation

The framework integrates reinforcement learning as an adaptive mechanism. A construction environment can be conceptualized as a state (s_t), where the state includes task progress, available resources, site conditions, equipment status, and sustainability indicators. The AI selects an action (a_t), such as allocating a robot, changing task sequence, or reallocating equipment. A reward (r_t) evaluates the resulting performance.

The learning objective can be represented conceptually as:

$$Q(s_t,a_t) \rightarrow \text{expected long-term operational value}.$$

The approach is theoretically supported by research demonstrating reinforcement learning for resource allocation (Gai & Qiu, 2018). However, construction deployment would require careful treatment of safety constraints and the consequences of incorrect decisions. Autonomous learning should therefore operate within predefined operational boundaries rather than unrestricted decision spaces.

3.4 Multi-Objective Robotic Scheduling

Robotic scheduling should consider multiple project objectives simultaneously. A schedule that maximizes robot utilization could produce excessive energy consumption or create conflicts with human work zones. Therefore, optimization must consider productivity, safety, resource efficiency, environmental performance, and schedule reliability.

The multi-objective optimization perspective established in virtual-resource scheduling research provides a useful conceptual foundation (X. Shihong et al., 2019). The construction adaptation requires additional project-specific constraints, particularly physical accessibility and coordination between autonomous and human activities.

3.5 Multi-Stakeholder Coordination

AI-driven construction management also requires coordination among project participants. Automated negotiation can theoretically support the resolution of competing preferences involving subcontractors, equipment owners, project managers, and suppliers.

For example, two work packages may require the same robotic platform during overlapping periods. Rather than resolving the conflict manually, an intelligent coordination mechanism could evaluate task urgency, contractual priorities, resource mobility, sustainability consequences, and schedule impact. The negotiation framework described by Weidong et al. (2020) provides a conceptual basis for this type of computational coordination.

4. RESULTS

The synthesis produces five principal findings regarding the proposed AI-Robotics framework.

First, resource intelligence is the central integration mechanism. The reviewed literature indicates that cloud manufacturing is not simply a cloud-storage concept; it represents a model in which distributed resources and services can be organized and coordinated. Bohu et al. (2010) and Bohu et al. (2012)

provide the foundation for translating this principle into construction management. A construction AI system therefore becomes more useful when equipment, robotic capabilities, labor, and material resources are represented as interoperable operational services.

Second, adaptability is more important than static optimization in dynamic construction environments. Resource allocation research demonstrates that optimization can improve the configuration of available resources, while reinforcement learning provides a mechanism for adapting decisions to changing conditions. The combination suggests that construction management systems should distinguish between planned optimization and real-time adaptation. A schedule produced at project commencement may be mathematically efficient but become ineffective when equipment fails, work progresses differently from expectations, or resource availability changes.

Third, robotics provides the physical execution layer for AI decisions. AI alone can recommend an optimized sequence, but operational improvement depends on the ability to translate decisions into action. The proposed architecture therefore connects computational optimization with robotic execution. This connection creates a feedback loop in which robots report operational outcomes, allowing AI models to revise future decisions.

Fourth, sustainability should be embedded within optimization rather than evaluated independently. Multi-objective scheduling research demonstrates the relevance of simultaneous optimization across competing criteria. Within construction, this means that productivity cannot be treated as the sole performance objective. A resource configuration that achieves rapid completion but generates unnecessary movement, idle equipment, or material waste may be operationally efficient in a narrow sense while remaining unsustainable.

Fifth, multi-agent coordination represents a critical scalability requirement. Construction projects involve heterogeneous decision-makers and competing resource requirements. Automated negotiation and game-theoretic perspectives indicate that optimization must account for strategic interaction rather than assume that all participants have identical objectives. The proposed framework therefore extends beyond machine-level autonomy toward coordinated decision-making among human and computational agents.

Overall, the findings position AI, cloud-oriented resource management, robotics, and sustainability as mutually dependent components rather than separate technological initiatives. The framework is consequently best understood as a socio-technical control architecture in which data supports intelligence, intelligence directs resource allocation, robotics performs selected physical activities, and sustainability indicators influence subsequent decisions.

5. DISCUSSION

The findings indicate that the most significant contribution of an AI-Robotics approach is not the substitution of human workers with autonomous machines but the restructuring of construction-resource coordination. Cloud manufacturing research provides the theoretical foundation for this interpretation by demonstrating how distributed resources can be organized through service-oriented digital systems (Bohu et al., 2010; Bohu et al., 2012). In construction, the equivalent transformation would involve representing project capabilities in a form that allows AI systems to compare, combine, allocate, and reallocate them according to changing requirements.

The theoretical implication is that construction management can be conceptualized as an adaptive resource-composition problem. Guo et al. (2012) and Zhang et al. (2010) emphasize flexibility in resource-service composition. This is particularly important for construction because project requirements evolve throughout execution. A rigid resource architecture may generate cascading inefficiencies when one component becomes unavailable. A flexible architecture, by contrast, can identify alternative combinations of robots, equipment, labor, and services.

The integration of reinforcement learning introduces another important theoretical dimension. Traditional scheduling approaches generally rely on predefined objectives and constraints, whereas reinforcement learning can theoretically adapt through interaction with the operational environment. The work of Gai and Qiu (2018) supports the relevance of reinforcement learning for resource-allocation problems. However, the construction environment creates a major limitation: incorrect adaptive decisions may have safety or financial consequences. Consequently, AI autonomy must be bounded by explicit safety rules, human oversight, and validated operational constraints.

The framework also highlights a fundamental trade-off between productivity and sustainability. Multi-objective optimization provides a mechanism for addressing this tension because it does not require a single dominant objective. Research on virtual-resource scheduling demonstrates the relevance of multi-objective optimization in complex resource environments (X. Shihong et al., 2019). In construction, the optimization function should therefore incorporate project duration, resource utilization, energy demand, material waste, and other sustainability indicators according to project priorities.

A further implication concerns organizational coordination. Automated negotiation mechanisms can become valuable when several actors compete for scarce resources. Weidong et al. (2020) demonstrate the relevance of automated negotiation to multi-party value conflicts, while game-theoretic reasoning provides a basis for understanding strategic interaction (Osborne, 2003). Nevertheless, algorithmic negotiation cannot completely replace contractual, managerial, and ethical judgment. Construction projects contain obligations and relationships that may not be fully represented through numerical utility functions.

The framework also has technological limitations. Interoperability remains essential because construction equipment and robotic platforms may use different data formats, communication protocols, and control architectures. Poor data quality can further undermine AI recommendations. Moreover, cloud-oriented approaches may create cybersecurity, connectivity, and latency concerns in sites where reliable communication cannot always be assumed.

Finally, the manufacturing origin of most supplied references limits direct generalization. Construction is less standardized and more spatially variable than many manufacturing environments. Therefore, the proposed framework should be interpreted as a conceptual transfer of principles rather than evidence that manufacturing-oriented algorithms will automatically perform effectively on construction sites. Empirical field studies, digital-twin experiments, safety validation, and longitudinal project evaluations are required before large-scale deployment.

6. CONCLUSION

This research developed a conceptual AI-Robotics Framework for Operational Efficiency and Sustainability in Construction Management using the supplied literature on cloud manufacturing, resource-service composition, reinforcement learning, resource allocation, multi-objective optimization, and automated negotiation. The synthesis demonstrates that these technologies can be logically integrated into a construction-management architecture consisting of data and sensing, intelligent resource representation, AI optimization, robotic execution, and sustainability feedback.

The principal contribution is the identification of construction management as an adaptive, multi-objective, resource-coordination problem rather than a purely scheduling-oriented activity. Cloud-oriented resource management provides the infrastructure for representing distributed capabilities, AI provides adaptive decision intelligence, robotics provides physical execution, and sustainability indicators provide feedback for evaluating operational consequences. This integrated perspective is more comprehensive than treating each technology as an independent digital tool.

The framework also emphasizes that operational efficiency and sustainability should be optimized simultaneously. Resource utilization, schedule performance, equipment movement, energy demand, and material efficiency can be evaluated within a common decision architecture. Reinforcement learning may further support adaptation to changing site conditions, while automated negotiation can assist in managing conflicts among multiple resource owners and stakeholders.

Nevertheless, the framework remains conceptual. Its effectiveness depends on reliable data, interoperable technologies, validated optimization models, organizational readiness, safety constraints, and appropriate human oversight. The manufacturing-oriented origins of the reviewed literature also mean that construction-specific empirical validation is necessary.

Future research should therefore develop digital-twin-based simulations, test reinforcement-learning strategies under realistic construction constraints, investigate human-robot collaboration, establish sustainability-performance metrics, and conduct field experiments comparing AI-assisted robotic management with conventional project-control approaches. Such research could transform the proposed conceptual architecture into an empirically validated framework for intelligent, efficient, and sustainable construction operations.

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