

A Systematic Data-Driven Framework for Integrating AI and Robotics in Construction

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ABSTRACT: The construction industry faces unique challenges in adopting automation technologies due to its labor-intensive and dynamic nature, where processes from design to construction are nonlinear and interdependent. Although automation technologies from other industries have been adapted for construction, they often fail to align with the industry's distinctive characteristics. To address the need, this study develops a data-driven framework which can integrate automation solutions, including artificial intelligence (AI) and robotics. By incorporating concepts such as human information processing and automation taxonomies, the framework adopts a workforce-centric approach to enhance automation adoption. A key feature of this framework is its ability to capture and analyze critical moments in construction phases, freezing specific stages for deeper analysis. This capability allows for improved decision-making, task allocation, and collaboration between human workers and automated systems. Unlike traditional automation frameworks that apply static models, this approach considers the real-time interactions between workforce, machines, and processes, ensuring automation is implemented in a way that aligns with construction's inherent variability. The results suggest that structuring automation through a dynamic and data-driven framework facilitates a more effective transition toward AI-integrated construction. Future research will explore how to expand this framework to include entire project phases, ensuring adaptability across varying construction workflows. By leveraging AI and robotics within a structured automation framework, this study provides a foundation for advancing automation adoption, workforce collaboration, and innovation in construction while addressing the industry's complex and evolving challenges.

1. INTRODUCTION

The construction industry plays a vital role in supporting economic growth and infrastructure development, closely aligning with Sustainable Development Goal (SDG) 9: Industry, Innovation, and Infrastructure, which emphasizes the need for resilient infrastructure and innovation ("Goal 9 | Department of Economic and Social Affairs" n.d.). To promote the goal, automation has long been seen as a key driver in increasing productivity and improving safety in construction by reducing labor-intensive tasks and enhancing efficiency (Liang et al. 2021). For example, construction automation involves replacing human operators with robots to reduce costs and time while enhancing quality and efficiency (Ardiny et al. 2015). On the other hands, various human-robot collaboration systems have been proposed (Ardiny et al. 2015): 1) teleoperated systems, where human operators interpret data and control machines (Zhang et al. 2023); 2) programmable machine applications that allow human operators to choose tasks from preprogrammed functions (Prieto et al. 2024); and 3) intelligent systems, where unmanned robots perform construction tasks semi- or fully-automatically (Jud et al. 2021). While research and development activities in human-robot collaboration have become more active in assisting human workers with dangerous and repetitive tasks (You et al. 2018),

fully autonomous systems are also envisioned, along with the development of Artificial Intelligence (AI) technology and intelligent machines, as a long-term goal (Bryson et al. 2005; Czarnowski et al. 2020).

However, due to the distinct nature of construction, where product design, process design (e.g., engineering, scheduling), and production phases (e.g., construction) are deeply interconnected, benchmarking automation directly from other industries presents limitations when applied to the construction industry. Unlike manufacturing, where products, production sites, and tasks tend to be standardized and repeatable, construction projects are inherently variable. Each project often differs in design, location, and execution, contributing to significant complexity in planning and operations (Everett and Slocum 1994). Additionally, product design is often not fully implemented before process design, process design is frequently adjusted during production, and even product design may change during production (e.g., change orders). Furthermore, the construction industry remains a workforce-centric environment (Barbosa et al. 2017), necessitating a gradual, step-by-step approach to automation adoption that recognizes the importance of human expertise, involvement, and interactions within the workforce.

To address this need, this study proposes a framework that integrates automation technologies with human information processing to facilitate automation adoption in construction. This framework provides adaptive solutions aligned with the industry's unique challenges. Specifically, it focuses on unifying automation, AI, and robotics into a cohesive system. We expect that the framework will initiate the process of enabling informed decision-making, optimizing task allocation, and enhancing human-automation collaboration. By analyzing data and fostering cooperation between humans and machines, the framework leverages a data-driven approach that incorporates cognitive processes. Ultimately, this framework suggests a pathway for the construction industry to move beyond traditional automation practices and embrace AI and robotics across all phases of a project.

2. RESEARCH BACKGROUND

The rapid advancement of automation technologies necessitates the development of comprehensive frameworks to recognize prior and ongoing industry applications, establish the state of the art, and identify knowledge gaps for future implementation. A structured and hierarchical framework is crucial for understanding how different elements, particularly automation technologies, interconnect and influence construction processes (Slaughter 1997). Additionally, such frameworks play a critical role in documenting industry adoption trends, categorizing automation applications, and standardizing industry practices (Ahmed and Kassem 2018). They provide the necessary infrastructure for systematically organizing, retrieving, and applying industry knowledge based on a common vocabulary (Bowmaster and Rankin 2019). As automation in construction continues to evolve, these frameworks become increasingly important in analyzing industry complexities, guiding adoption strategies, and ensuring seamless integration of new technologies into construction workflows. By systematically mapping the relationships between various automation technologies and their practical applications, these frameworks help bridge the gap between research, development, and real-world industry adoption, ensuring that innovations align with the evolving needs of construction.

Automation in construction has progressed from relatively simple mechanical processes to more complex human and robot collaboration systems designed to improve safety and efficiency. Advancements in AI and machine learning allows the human-robot collaboration systems to perform more sophisticated tasks, significantly reducing the need for construction workers in hazardous or repetitive activities (You et al. 2018). On the other hand, studies have shown that construction automation benefits greatly from a framework that classifies various levels and types of automation (Statsenko et al. 2023; Su et al. 2023). It also improves the categorization of tasks performed by both machines and humans, enabling a more structured and effective implementation of automation technologies in construction (Klarin and Xiao 2024).

Despite significant progress in construction automation, existing frameworks have primarily focused on task-based classifications and have not fully integrated the dynamic nature of the construction industry into their models. One early study identified several goals for adopting automation in construction, such as reducing labor intensive tasks, increasing work speed, and improving both quality and safety (Demsetz 1989). This task identification framework specifically focused on selecting tasks that would benefit the most

from automation and on allocating subtasks between humans and machines based on their respective capabilities. Another study classified 85 different construction automation and robot technologies by evaluating various attributes, including the materials used, the phases of construction during which the technologies were applied, and the geometries of the tasks (Slaughter 1997).

Recent frameworks have attempted to address some of these challenges. For example, one study developed a Building Information Modeling (BIM) adoption framework that tackles the lack of a comprehensive classification system for BIM integration in the construction industry (Ahmed and Kassem 2018). This organizes BIM adoption into awareness, intention, and decision-making stages and can be used to analyze adoption both at the organizational and market levels. Another study proposed a technology classification framework that assesses construction technology innovation based on development timing, application areas, technology types, and innovation phases (Bowmaster and Rankin 2019). Some literature review papers have introduced classifications based on their reviews (Jacques de Sousa et al. 2024; Klarin and Xiao 2024; Statsenko et al. 2023). However, these studies often fail to consider the unique characteristics and demands of the construction industry.

While previous frameworks focus on specific technologies or phases of automation, a significant gap remains in the development of a systematic and data driven framework that comprehensively integrates automation technologies. Addressing this gap is essential for advancing construction automation in a manner that aligns with the industry's dynamic and workforce centric nature. This study introduces a novel framework that incorporates automation solutions, including AI and robotics, while integrating human information processing and automation taxonomies. By fostering more effective collaboration between human workers and automated systems, this framework provides a structured and adaptable pathway for analyzing and adopting automation in construction practices.

3. FRAMEWORK DEVELOPMENT FOR INTEGRATING AUTOMATION IN CONSTRUCTION

To develop an integrated framework for automation in construction, this research identifies and synthesizes key attributes of automation, including human information processing, hierarchical control levels, physical automation, and cognitive automation. Subsequently, the syntax of the integrated automation framework is mapped to the construction hierarchy.

3.1 Key Attributes of Automation

3.1.1 Human information processing

In automated systems, decisions are derived from various functions that replicate human information processing, shown in Figure 1. Automation can be divided into four primary functional types: information acquisition through sensing, information analysis for continuous perception and retrieval in working memory, decision and action selection, and action implementation (Parasuraman et al. 2000). These stages collectively transform physical inputs into cognitive processes and, ultimately, physical outputs. In these stages, devices that convert physical input into data are called sensors, while those that convert information into physical outputs are referred to as actuators. Meanwhile, processors handle perception and decision making, mimicking human cognitive functions through algorithmic design (Czarnowski et al. 2020). Understanding this parallel between human information processing and machine automation is essential for identifying how construction tasks can be effectively automated.

Figure 1 illustrates this process, showing how sensory inputs are transformed into data, analyzed within working memory, and used to make decisions, which then drive physical actions. This structured framework highlights the integration of human cognitive processes with machine automation in construction tasks, underlining the importance of this synergy for achieving optimal system performance. These concepts of automation taxonomy and human information processing serve as foundational principles for the framework developed in this study. By aligning construction tasks with specific stages of human cognitive processing and corresponding automation functions, the framework systematically identifies opportunities for targeted automation interventions.

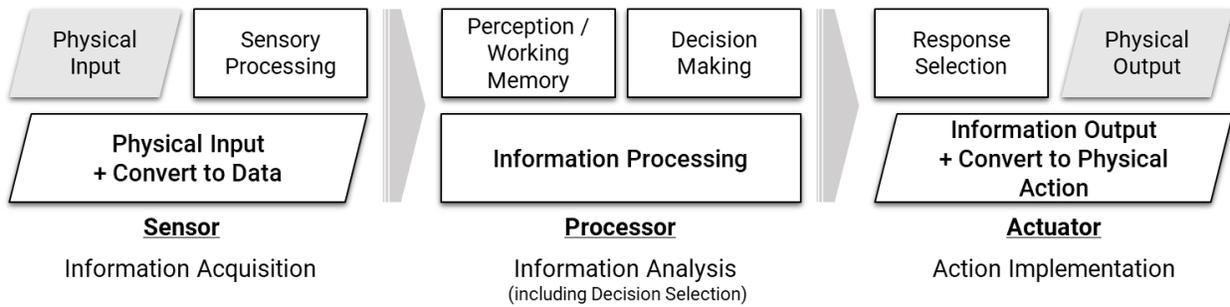


Figure 1: Human information processing at a machine standpoint

3.1.2 Hierarchical Control Levels in Automation

Automation in construction can be better understood through a hierarchical system, as outlined in Groover's study (Groover 2016). This model defines control levels ranging from the most fundamental, which consists of sensors and actuators, to the highest level, which involves enterprise-wide decision making and strategic oversight. The hierarchical distribution of automation responsibilities ensures that higher levels demand greater human cognitive involvement, particularly in tasks such as decision making and system monitoring.

At the foundational levels, individual machines such as sensors and actuators perform physical tasks. As one moves higher in the hierarchy, processors assume responsibility for cognitive functions, including perception and decision making. This stratified control system facilitates efficient communication between human operators and machines, ensuring the seamless flow of data and coordination throughout the automation process.

Figure 2 illustrates this hierarchical control structure, showcasing the interaction between processors and lower level automation components, such as sensors and actuators. By systematically managing data flow between human and machine, this structure optimizes both physical and cognitive task execution within construction projects. This hierarchical approach enhances operational efficiency, allowing for a more integrated and dynamic application of automation in construction.

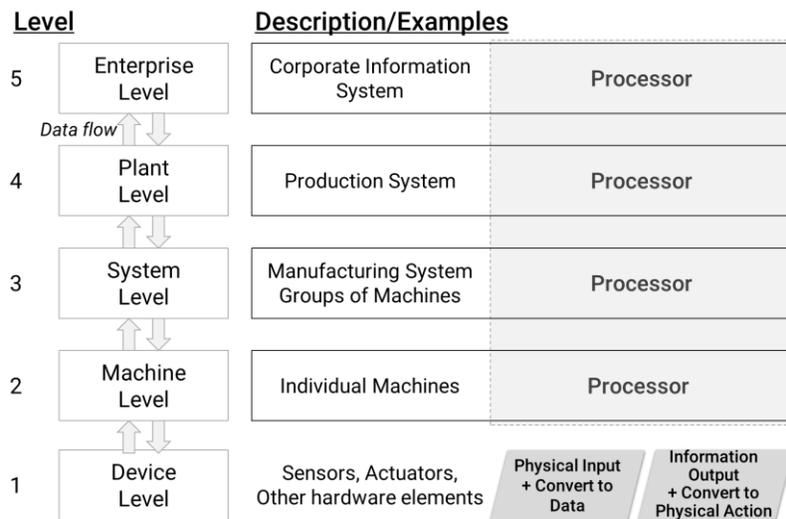


Figure 2: Adapted representation of levels of control for automation (adapted from Groover, 2016)

3.1.3 Integration of Physical and Cognitive Automation

Automation in construction must address both physical and cognitive tasks that have traditionally been performed by human workers. Physical automation replaces tasks that rely on human muscle power, such as lifting, transporting, or repetitive manual work. Cognitive automation, on the other hand, delegates decision making, sensory processing, and reasoning tasks, such as planning and problem solving, to machines. Effective integration of these two aspects is essential for achieving full automation in construction. For example, models such as the Square of Possible Improvements evaluate levels of both physical and cognitive automation by plotting them within a two dimensional coordinate system (Slaughter 1997). This effort enables a systematic assessment of automation capabilities, highlighting areas where human and machine strengths can be leveraged.

However, with advancements in artificial intelligence, cognitive automation has evolved beyond predefined rule-based processes. AI powered systems can now analyze complex data, adapt to changing conditions, and make autonomous decisions (Russell and Norvig 2016). Traditionally, machines excelled in repetitive, hazardous, or precision based physical tasks, while humans outperformed in cognitive tasks that required adaptability, creativity, and problem solving. This distinction is now shifting, accelerating the need for an integrated framework where AI and robotics work collaboratively (Bock and Linner 2015). As construction projects continue to grow in complexity and variability, a well-balanced integration of physical and cognitive automation has become more critical than ever. This synergy ensures that automation enhances safety, efficiency, and adaptability, ultimately transforming the way construction tasks are executed.

3.2 Development of the Automation Framework

The proposed framework synthesizes four key attributes of automation: human information processing, hierarchical control levels, physical automation, and cognitive automation. As depicted in Figure 1, the model of human information processing establishes a foundation for automating cognitive tasks by mimicking human decision-making processes. Meanwhile, the hierarchical control levels illustrated in Figure 2 provide a structured system for task allocation between human operators and machines, ensuring seamless collaboration.

Automation operates along a continuum, ranging from low levels (manual tasks) to high levels (fully automated tasks) (Groover 2016). Achieving optimal performance within this continuum requires strategic task allocation that considers the capabilities of both humans and machines alongside the current state of available technologies. The framework acknowledges that automation significantly reduces human intervention in repetitive and time-consuming tasks but emphasizes the ongoing necessity of human and machine collaboration. While machines enhance efficiency by performing routine and hazardous tasks with precision, human oversight remains essential for tasks that require adaptability, creativity, and real time decision making (Brynjolfsson and McAfee 2017). This collaboration ensures that automation is not only efficient but also responsive to the complexities of construction projects.

Below the sensor-actuator level, we incorporate foundational elements such as orthopedics and cellular processes (Everett and Slocum 1994), which are essential to physical systems. At higher levels, cognitive tasks such as information analysis and decision making are performed, enabling a structured approach to optimizing automation. With advancements in AI, this integration allows machines to learn from real time data, adjust to dynamic construction environments, and enhance decision making processes (Russell and Norvig 2016). This ensures the framework's applicability across diverse construction processes, addressing both routine physical tasks and complex cognitive challenges.

3.3 Application of the Framework in Construction

To adapt the proposed automation attributes to the construction context, a multi level organizational structure is utilized. This structure reflects the dynamic nature of construction tasks, and Figure 3 demonstrates how tasks are allocated between humans and machines, leveraging their respective strengths. The figure also highlights the correspondence between machine functions and worker roles,

particularly in bridging physical and cognitive domains. This mapping ensures that tasks are performed efficiently while maintaining flexibility in dynamic construction environments.

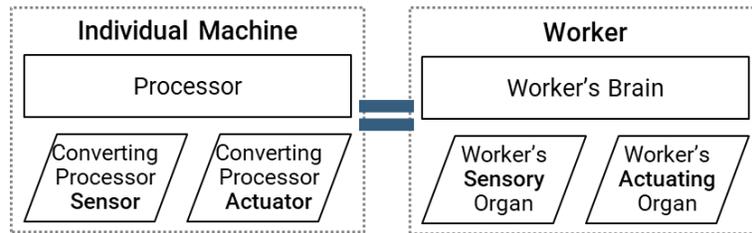


Figure 3: Worker level implication: correspondence between a machine and a worker

The syntax of automation is mapped directly to the construction hierarchy. Physical elements correspond to orthopedics and cell levels, individual machines represent workers, and higher control levels correspond to roles such as foremen, division managers, and project managers. At lower levels, machines or workers handle routine and repetitive tasks, while at higher levels, humans manage cognitive intensive responsibilities such as decision making and system oversight, ensuring adaptability and strategic alignment. With advancements in artificial intelligence, automation is expanding beyond task execution to decision support systems that enhance project management and operational planning (Barbosa et al. 2017). Figure 4 illustrates this integration, showing how control levels are applied across construction management, from task execution to high level planning and coordination (Everett and Slocum 1994; Groover 2016; Parasuraman et al. 2000).

This multi level approach provides a structured framework for optimizing task allocation and system management across a diverse range of construction activities. By aligning human and machine capabilities with their respective strengths, it ensures operational efficiency while fostering seamless collaboration. Additionally, the increasing adoption of AI driven construction analytics and robotics is transforming how machines interact with real time project data, allowing for continuous process optimization (Bock and Linner 2015). This structured adaptation allows for better integration of automation, AI, and robotics into the construction industry to enhance adaptability, scalability, and decision making across various construction phases.

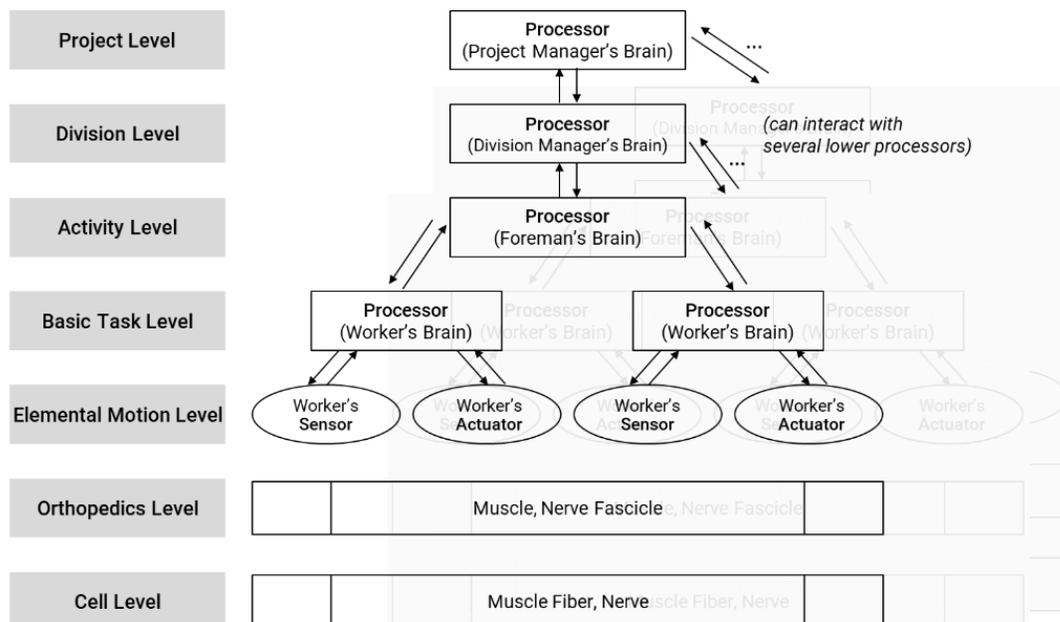


Figure 4: Framework for Integrating Automation in Construction

4. FINDINGS AND DISCUSSIONS

4.1 Automation, AI, and Robotics in Construction

In construction, there is a distinction between cognitive automation (AI) and physical automation (robotics), which is evident in Figure 4. Different levels of work require varying degrees of human and machine involvement, with AI predominantly assisting in decision-making at higher levels, while robotics plays a more active role in execution at lower levels. At higher levels of an organizational structure, such as those managed by foremen and division managers, cognitive tasks predominate. These tasks benefit from AI and advanced decision-making algorithms, enabling systems to analyze complex data, optimize schedules, allocate resources, and enhance real-time decision-making. In this context, AI-driven processors collaborate with human decision-makers, providing data-driven insights that improve operational efficiency. AI-powered systems such as autonomous scheduling tools and predictive analytics models are increasingly used to enhance decision-making by foreseeing potential risks, delays, or resource constraints.

Conversely, at lower levels, where construction workers and field operators interact directly with the environment, physical automation takes precedence. These tasks involve direct physical execution, such as operating machinery, handling materials, and assembling structures. Robotics enables workers to offload physically demanding or hazardous tasks, allowing machines to take over repetitive labor-intensive activities while maintaining precision and efficiency. In addition, modern AI driven robotics, such as robotic arms that adjust in real time based on environmental conditions, are further blurring the boundary between cognitive and physical automation. These hybrid systems integrate both autonomous decision making and physical execution, demonstrating the growing need for an integrated framework that seamlessly combines AI, robotics, and automation technologies to optimize construction workflows.

This distinction and emerging overlap between AI-driven cognitive automation at higher levels and robotics-driven physical automation at lower levels highlights the dual nature of automation in construction. The proposed framework serves as a comprehensive roadmap for integrating these technologies, ensuring that automation is not just about execution but also about intelligent decision-making and adaptability in complex construction environments.

In addition to distinguishing between cognitive and physical automation, the framework supports coordination among multiple agents, whether human, machine, or hybrid, to function as an integrated unit. Rather than allocating tasks strictly at the individual level, it enables grouping processors and actors by role, skill, or task function to operate collaboratively as modular units. For example, a team of two workers and a foreman can be considered a coordinated group whose combined functions may be supported or substituted by an advanced AI and robotics system, such as a humanoid robot equipped with both decision-making and execution capabilities. This group-based approach creates new opportunities to improve, upgrade, or reconfigure task teams in a way that enhances collaboration, flexibility, and system-level performance.

4.2 Optimizing Task Allocation in Human-Machine Collaboration

Task allocation is a fundamental aspect of a mixed work environment where humans and machines collaborate. The MABA-MABA principle ("men are better at, machines are better at") provides a guiding framework for determining how tasks should be distributed between human operators and machines. Traditionally, this principle evaluates tasks based on feasibility, technology availability, and project-specific needs (Fitts et al. 1951). However, modern AI-driven automation is shifting this paradigm by enabling dynamic, real-time task allocation based on real-time data and predictive insights (Russell and Norvig 2016).

Traditionally, machines excel at performing repetitive, hazardous, or time-sensitive tasks. Their ability to operate under strict parameters makes them ideal for tasks such as heavy lifting, precision operations, and working in hazardous environments. Conversely, humans excel in cognitive tasks that require creativity, adaptability, and complex problem-solving. The emerging trend of AI-driven automation systems allows for

a more adaptive approach, where AI continuously monitors construction site conditions and reallocates tasks dynamically based on environmental changes, workload distribution, and predictive analytics.

In the proposed framework, physical automation handles low level tasks on site, while cognitive automation focuses on high level information processing. By enabling AI driven adaptability, task allocation becomes a continuous and dynamic process, ensuring that both human and machine contributions are optimized throughout the entire project lifecycle. For example, AI powered safety monitoring systems with sensors on site can detect hazardous conditions in real time and alert workers to prevent accidents.

4.3 Integrating Data-Driven Framework: Delivering the Right Data at the Right Time

The success of automation in construction heavily depends on the ability to deliver the right data to the right systems or personnel at the right time. Whether dealing with processors, sensors, or actuators, timely data exchange is critical for ensuring that all automated components work in harmony. This can be achieved when the data framework is well mapped to the specific needs of each project, ensuring seamless integration and coordination across all automation levels. Figure 4 outlines the hierarchical view of task allocation in automation and emphasizes the importance of maintaining efficient data flow throughout all levels. However, the effectiveness of this hierarchy is heavily dependent on well structured data frameworks that can anticipate workflow disruptions, optimize decision making, and enable real time adjustments.

For example, certain construction issues require coordinated decision making at different levels of the hierarchy. On-site safety monitoring, for instance, involves low-level sensors detecting hazardous conditions, while mid-level processors analyze data and trigger automated responses, such as alerting workers or adjusting machine operations to prevent accidents. Other issues, such as change orders, require synchronization across low, mid, and high levels. At the low level, sensors track material availability and on-site progress, while mid-level processors evaluate feasibility and constraints. At the high level, AI-driven decision-making systems assess broader project impacts, optimize scheduling, and reallocate resources dynamically to minimize delays. By grouping and managing specific sets of tasks across multiple levels, the framework enhances efficiency, adaptability, and coordination throughout the project lifecycle, ensuring that both human and automated decision-making processes remain synchronized.

5. CONCLUSIONS AND FURTHER RESEARCH

This study introduces a data-driven automation framework that optimizes task allocation, decision-making, and workflow integration in the construction industry. It bridges the gap between physical and cognitive automation, ensuring efficient collaboration between human workers and AI-driven systems. Through structured task allocation, it strategically assigns responsibilities to machines and humans, improving efficiency, adaptability, and safety. A core distinction in this framework is the relationship between AI-driven cognitive automation and robotics-driven physical automation, while also integrating them into a cohesive system. Cognitive automation, mainly powered by AI, enhances decision-making, risk assessment, and resource optimization, while physical automation, mainly driven by robotics, executes labor-intensive tasks and expanded information inputs and outputs. By synchronizing these two forms of automation, the framework enables dynamic and adaptive coordination between AI-powered decision support at higher levels and robotic execution at lower levels, providing seamless, intelligent automation across all phases of construction.

Furthermore, we expect that this framework has the potential to contribute to advanced construction methods, such as 3D printing, modular construction, and robotic fabrication. By mapping and grouping specific tasks within the workflow, it can identify configuration patterns that allow for focused and integrated automation strategies. These specific configurations can be tailored to optimize task execution, enhance coordination between AI-driven decision-making and robotic systems, and improve overall efficiency. This structured task segmentation enhances precision in automation, enabling better synchronization of automated systems and expanding scalability in digital construction techniques.

To further validate and enhance the proposed framework, future research should incorporate real-world case studies that demonstrate its impact on efficiency, coordination, and innovation in actual construction

projects. For example, case studies will help ground the framework in practice, revealing both its strengths and areas for refinement. Several practical limitations must also be acknowledged, including the assumptions of consistent data availability, seamless integration with existing systems, and workforce readiness to adopt new technologies. Future study can address these limitations through phased implementation strategies, comprehensive training programs, and robust data governance to ensure the framework's successful translation into diverse construction environments.

However, while this framework focuses on capturing a static representation of task allocation and automation by freezing a moment in time, it does not yet fully incorporate one of the most critical dimensions—time itself. Construction projects are inherently dynamic, with workflows, resource demands, and automation needs evolving continuously. Future research should explore how to integrate temporal factors into the framework, enabling time-based adaptability, process reconfiguration, and predictive automation adjustments. Finally, extending the framework to map entire project lifecycles will further advance the integration of Automation, AI, and Robotics in construction, promoting a more adaptive, efficient, and intelligent industry-wide transformation.

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