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AUTOMATION IMPACT ANALYSIS: A CONCEPTUAL FRAMEWORK FOR TRACING SYSTEM-WIDE CONSEQUENCES OF AUTOMATION IN OFF-SITE CONSTRUCTION

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Abstract: The automation of production activities in off-site manufacturing plants has demonstrated measurable gains in cycle time, labor efficiency, and dimensional precision. Yet despite these well-documented benefits, adoption among manufacturers remains notably low, driven in part by an insufficient understanding of what automation implementation operationally entails beyond the automated station itself. Existing decision-support frameworks evaluate automation at the station level through performance comparisons, neglecting the system-wide knock-on effects that may propagate through interconnected production activities when a single station is automated. These effects, including upstream shifts in data preparation and procurement demands, downstream bottleneck migrations, workforce restructuring, and spatial reconfiguration, represent real operational costs that remain invisible in current assessment approaches. To address this gap, this paper proposes the Automation Impact Analysis (AIA) framework, a modular, system-oriented analytical structure adapted from the Change Impact Analysis methodology established in the manufacturing industry. The AIA traces how a defined automation scenario propagates through the production system by following the material flow, informational, technical, spatial, and organizational dependencies that link activities to one another, surfacing the consequential activities and responsive actions that the system must accommodate. These propagated effects are then translated into system-level performance shifts and consolidated into a total cost-benefit evaluation that brings implementation costs and operational gains into the same analytical frame. The framework provides manufacturers with a structured, auditable pathway from automation intent to informed investment decision, grounded in the realistic complexity of their production systems rather than idealized station-level projections.

Keywords: Offsite Construction; Prefabrication; Automation; Robotic; Change Analysis; Manufacturing Systems; Cost-Benefit Analysis.

1 INTRODUCTION

The construction industry is undergoing a fundamental structural shift. Mounting infrastructure demands, chronic skilled labor shortages, and persistent pressure to reduce project costs and timelines have collectively accelerated a transition away from conventional on-site building practices toward off-site construction (OSC) and factory-based prefabrication (Aghajamali et al. 2024, 2025; Noghabaei et al. 2022). This transition has demonstrated measurable performance gains across multiple dimensions, including material efficiency, labor productivity, workmanship quality, and workflow continuity, while reducing waste and compressing delivery schedules (Aghajamali et al. 2026; Metvaei et al. 2025c). Yet despite these well-documented advantages, the widespread adoption of prefabrication has remained constrained by a persistent cluster of operational and structural barriers, including prohibitive initial costs, underutilization of factory space, fragmented information flows, limited customization capacity, and continued reliance on labor-intensive conventional methods (Metvaei et al. 2025b; Pan and Pan 2019). Collectively, these challenges have tempered the transformative potential that OSC was broadly expected to deliver.

In response, researchers and industry practitioners have increasingly turned to advanced manufacturing technologies and robotic automation as viable pathways for overcoming these limitations (Metvaei et al. 2025a; Pan and Pan 2019). The automation of construction manufacturing has demonstrated tangible benefits, including reduced production cycles, minimized required workforce headcounts, enhanced dimensional precision, and lower long-term labor expenditure (Haque 2023; Lachance et al. 2023). Accordingly, the integration of automation into OSC environments introduces opportunities to strengthen operational efficiency, ensure consistency across production runs, and enable scalable manufacturing output (Islam et al. 2025). In particular, automated factories are increasingly deploying robotic systems for tasks such as structural framing, welding, insulation installation, and panel assembly, allowing manufacturers to streamline workflows and minimize human error throughout the production process (Xu et al. 2025).

However, despite the growing availability and maturity of automation solutions, their adoption among off-site manufacturers remains notably low. A primary driver of this hesitation is the industry's insufficient understanding of what automation implementation operationally entails and what its downstream consequences are across the production environment (Wang et al. 2020). Without decision-support tools capable of comprehensively evaluating different automation scenarios and their full operational implications, manufacturers are poorly positioned to anticipate and manage the transition, ultimately stalling uptake (Lachance et al. 2022).

Existing research has attempted to address this knowledge gap through decision-making frameworks operating at two distinct levels. At the strategic level, studies such as Pan and Pan (2019) examine the organizational and environmental prerequisites for automation adoption, including regulatory context, market demand, firm size, and industry interconnectedness, offering a diagnostic tool that helps individual factories assess the feasibility and business case for automation. While valuable, such frameworks are explicitly pre-adoption in scope and provide limited insight into the operational consequences that follow an automation decision. At the operational level, studies such as Orlowski (2019), Lachance et al. (2023), and Ouda and Haggag (2024) employ multi-criteria assessments and simulation modeling to evaluate automation performance. However, each of these approaches evaluates automated stations or layouts in relative isolation, without accounting for the broader production system in which they are embedded.

This distinction is consequential. Manufacturing systems are characterized by complex interdependencies, including material flows, technological dependencies, infrastructure constraints, and cause-and-effect chains linking upstream and downstream activities (Plehn et al. 2016). Automating a single station within such a system does not occur in isolation; it introduces ripple effects that propagate throughout adjacent processes and, if left unexamined, render any performance prediction fundamentally incomplete. Some of these cascading effects have begun to surface in the literature: Feldmann (2022) states that automation necessitates a shift from drawing-based work instructions to fully parameterized, machine-readable design data, thereby restructuring the required skills, software interfaces, and digital workflows at the upstream data-preparation stage. Similarly, Yang et al. (2024) note that the inherent variability of timber materials, including grain knots and environmental deformation, introduces dimensional tolerances that challenge automated execution and impose stricter requirements on upstream material selection and procurement than manual operations would demand.

Notwithstanding these observations, existing automation selection frameworks at both the strategic and operational levels fail to systematically account for the system-level knock-on effects of automating one station on adjacent processes. This represents a critical gap between current decision-support tools and the operational reality of automation implementation in OSC plants. To address this limitation, the present study proposes the conceptual Automation Impact Analysis (AIA) framework. This framework is designed to support investment decisions by modeling the realistic, system-wide consequences of automating individual production activities within an off-site manufacturing environment. The proposed framework is adapted from the modular Change Impact Analysis (CIA) methodology introduced by Bauer et al. (2020), which provides a structured method for tracing the consequences of engineering changes across interconnected factory systems. Here, the methodology is specifically calibrated to address the unique operational realities of introducing automation in prefabricated construction environments. The following sections provide a review of existing assessment frameworks, followed by the detailed introduction of the AIA framework, a discussion of its implications, and concluding remarks.

2 LITERATURE REVIEW

Manufacturing systems are inherently dynamic environments, subject to continuous change driven by technological innovation, product evolution, fluctuating demand, shifting product mix, ongoing improvement initiatives, and the routine replacement of aging equipment (Plehn et al. 2016). The elements that constitute these systems form a tightly interconnected network in which changes rarely remain localized. Depending on their scale and nature, modifications to one part of the system can propagate outward, interfering with engineering workflows, procurement processes, logistics chains, or even broader manufacturing strategy (Plehn et al. 2016). A fundamental prerequisite for successful change implementation is therefore a comprehensive understanding of all potential impacts of a given change and the activities it necessitates (Bauer et al. 2020). This understanding is equally essential for economic evaluation and informed decision-making prior to committing to any major change initiative.

The automation of production activities represents one of the most frequent changes that off-site manufacturing facilities have recently undertaken. In a timber-based panelized manufacturing facility, for instance, activities such as cutting and sawing, material feeding, framing and stud fitting, sheathing and cladding, insulation installation, building wrap application, panel turning, and intelligent storage and handling can each be automated at varying levels (Orlowski 2020). However, implementing automated stations introduces profound shifts in workload distribution, required skill profiles, process sequencing, and system resilience that extend well beyond the localized machine. Rather than simply eliminating manual tasks, automation often redirects human effort toward less visible forms of supporting work, including upstream data preparation, ongoing system maintenance, and error correction in tasks where machines lack cognitive flexibility (Boeva et al. 2023). For example, automation often requires an upstream shift from traditional drawing-based instructions to fully parameterized, machine-readable design data, which significantly increases preparation time and demands specialized digital skills (Feldmann 2022). The inherent variability of low-cost, less-processed forms of timber, commonly used in construction, further imposes stricter dimensional tolerances, complicating automated execution and elevating procurement standards beyond those required for manual operations (Yang et al. 2024). At the same time, the higher throughput associated with automated production increases physical space requirements for inventory staging and material handling, altering factory logistics and reducing the system's overall resilience to late-stage design changes (Feldmann 2022). Automation may also introduce entirely new preparatory activities, such as sub-assembling openings for timber framing machines or staging materials in precise locations for robotic blind picks, activities that constitute real operational costs yet remain invisible in station-level assessments. Despite the significance of these system-wide consequences, the existing literature on automation adoption and performance evaluation remains largely confined to station-level analyses and falls short of providing holistic insight into the full costs and benefits of automation implementation.

To understand the decision-making landscape surrounding automation, existing research has approached the problem from two distinct levels: strategic and operational. At the strategic level, Pan and Pan (2019) applied the technology-organization-environment (TOE) framework to identify nine determinants of robotics adoption in precast concrete production, including the regulatory environment, compatibility, and firm size, and to map their combined influence on the adoption decision. While this diagnostic tool effectively assesses organizational readiness and market conditions, its scope is strictly pre-adoption and does not extend to offer insights into post-implementation operational dynamics.

At the operational level, research has focused on evaluating the performance of automated machinery, though typically in isolation from the broader factory ecosystem. Orlowski (2019) employed a Multi-Criteria

Analysis (MCA) to compare manual and automated configurations in timber-panelized manufacturing across six criteria: investment cost, productivity, labor requirement, space efficiency, cross-compatibility, and health and safety. While the framework identifies where automation investment is most justified within an assembly line, it evaluates each process independently, without modeling how upgrading one station affects throughput demands or resource requirements at adjacent stages. Lachance et al. (2023) advanced the analysis by constructing a discrete-event simulation (DES) model to compare four layout types with varying automation levels for timber-frame wall production, assessing scenarios across nine key performance indicators, including worker efficiency, space efficiency, cost ratio, capacity, and productivity. Their findings demonstrated that fully robotic cell configurations outperform alternative layouts. However, the simulation compared static, predefined whole-layout alternatives rather than tracing how automating a specific activity dynamically propagates operational consequences through the rest of the production system. A comparable limitation constrains the simulation and cost-benefit analyses presented by Ouda and Haggag (2024, 2025), which similarly evaluate automation performance without accounting for system-level interdependencies.

Across both levels of analysis, current frameworks treat automation either as a localized station-level upgrade or as a predefined static layout configuration, neither of which captures the system-wide cascading effects that follow from automating a specific production activity. This represents a critical gap in the existing body of knowledge and underscores the need for a more holistic impact analysis framework, capable of tracing automation-induced changes as they propagate through the interconnected activities of an off-site manufacturing system.

3 AUTOMATION IMPACT ANALYSIS (AIA) FRAMEWORK

3.1 Framework Overview and Rationale

The Automation Impact Analysis (AIA) framework is a modular, system-oriented analytical structure designed to support decision-making around the implementation of automation in off-site construction manufacturing plants. It is adapted from the modular Change Impact Analysis (CIA) methodology proposed by Bauer et al. (2020), which provides a general-purpose structure for tracing the consequences of engineering changes across interconnected factory systems. The AIA reframes and extends the CIA logic to address the specific operational realities of automating production activities in prefabricated construction environments, where manufacturing systems exhibit tightly coupled material, informational, spatial, and organizational interdependencies.

The core premise of the AIA is that automating an individual production activity in an OSC plant does not produce effects confined to the automated station alone. Rather, it triggers a chain of consequential changes, both upstream and downstream, that alter labor requirements, data preparation workflows, material procurement standards, spatial configurations, and throughput dynamics across the broader production system. Current decision-support tools in the literature evaluate automation either as a strategic adoption question or as a station-level performance comparison, neither of which captures these system-wide hidden and secondary consequences. The AIA addresses this gap by providing a structured, traceable pathway from a defined automation scenario to its full operational and economic implications.

As illustrated in Figure 1, the proposed framework comprises four sequential modules, with each stage directly building upon the outputs of the preceding one. While engineered as a comprehensive analytical pipeline, its modular architecture permits selective application based on the required depth of analysis and the specific decision-making context. The framework navigates the adoption process through the following four core phases. Module 1 defines the automation scenario and maps its first-order impacts, producing a structured impact register. Module 2 traces how each impact propagates through the production environment, surfacing consequential activities and producing a full impact profile. Module 3 translates this profile into measurable shifts in operational performance indicators. Module 4 draws on all preceding outputs to estimate the true cost and timeline, producing a holistic implementation evaluation. The specific mechanics and objectives of each module are detailed in the following subsections.

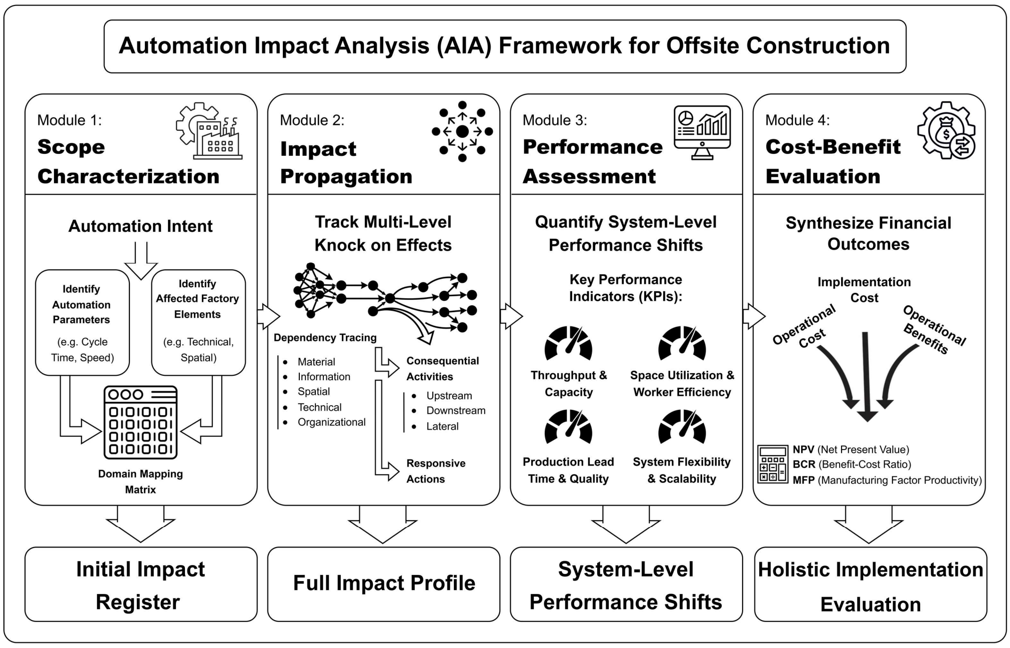

Figure 1. The Automation Impact Analysis (AIA) Framework for Off-Site Construction Manufacturing.

3.2 Module 1: Automation Scope Characterization

The first module establishes the analytical boundary of the AIA by precisely defining what is being automated, at what level, using which technology, and which factory elements are directly and immediately affected. Its purpose is to convert a general automation intent, such as "automating the framing station", into a formally characterized change scenario with clearly delineated first-order impacts. To achieve this, the module relies on specifying and linking two core data components: the change causes, defined by the selected automation technology and the operational parameters it introduces, and the directly affected factory elements at the targeted station.

The first data component requires the analyst to profile the automation configuration being introduced into the target activity. This includes documenting all technology-relevant information: the level of automation (e.g., semi-automated, fully automated, or robotic), the specific technology selected (e.g., CNC saw, robotic nailing system, automated conveyor), and its key operational parameters, such as cycle time, throughput capacity, physical footprint, material tolerance requirements, workforce requirements, and integration interfaces with existing equipment and software. These profiled parameters constitute the active drivers of change within the manufacturing system and serve as the primary inputs to the subsequent analytical steps.

The second data component requires the analyst to identify the factory elements at the targeted activity that will be directly affected by the introduced automation. A factory element is defined as any distinct object, system, or component that participates in the functioning and life cycle of the factory system and interacts with other elements through a network of relations, including material flow, information flow, and technological or infrastructural dependencies. To ensure comprehensive coverage and minimize analytical blind spots, elements can be systematically identified across the following categories, drawn from manufacturing system engineering literature (Dér et al. 2021):

- **Technical/Physical:** Equipment, tools, and process parameters
- **Human & Organizational:** Operators, managers, skill sets, and work organization

- **Spatial:** Floor area, station layout, and equipment footprint
- **Building & Infrastructure:** Building shell, utilities, and technical building services
- **Informational & Documents:** Control systems, software interfaces, data formats, and operating documents or work instructions

Once both data components are established, their relationships can be mapped using a structured tool such as a Domain Mapping Matrix (DMM), which systematically registers all affected factory elements against the automation parameters that act upon them. These relationships can further be scaled to capture quantitative attributes of the impact, including criticality, propagation probability, or constraint satisfaction.

Returning to the example of automating the framing station in a timber-based panelized manufacturing line, this structured approach ensures that the analyst registers not only the most visible first-order impacts, such as the replacement of manual nail guns with a robotic nailing gantry (technical) and the elimination of manual framing operators (human and organizational), but also less immediately apparent consequences, such as the need for machine-readable design data to replace drawing-based work instructions (informational), the increased floor area and material staging space demanded by the new equipment (spatial), and the additional electrical and compressed air capacity required for its operation (building and infrastructure).

The resulting impact register is subsequently carried forward into Module 2, where these first-order impacts are traced as they propagate through the broader production system.

3.3 Module 2: System-Wide Impact Propagation

Module 2 constitutes the analytical core of the AIA framework and represents its primary departure from existing station-level approaches. While Module 1 documents the direct, first-order impacts of automation on the target station, Module 2 takes each of those impacts and systematically traces how it travels through the broader production system, generating second-order and potentially higher-order effects at adjacent and more distant activities. Beyond identifying where these effects land, the module also determines what the affected parts of the system must do in response. To accomplish this, Module 2 operates across two analytically distinct layers: the first identifies which activities elsewhere in the system are affected, and the second specifies what each of those activities must do to accommodate the change.

3.3.1 Layer 1: Identifying Consequential Activities

The first layer works through each entry in the impact register produced by Module 1 and traces where its effects propagate within the production system. This tracing process is grounded in the interdependency links that connect activities to one another within the factory. In an OSC plant, these dependencies take several forms. Material flow dependencies arise when the output of one activity serves as the input of another. Informational dependencies exist when an activity relies on data, instructions, or digital files produced or consumed elsewhere in the system. Technical dependencies occur when activities share equipment, tooling, or process interfaces. Spatial dependencies emerge when activities compete for the same physical floor area, staging zones, or access corridors. Finally, organizational dependencies are present when activities draw on the same labor pool, skill set, or supervisory structure.

For each first-order impact, the analyst follows every dependency link connected to the affected factory element and identifies which other activities in the system may be altered as a result. Propagation can travel in three directions. Upstream propagation traces dependencies backward to activities that supply inputs (e.g., materials, components, or data) to the automated station, examining whether automation imposes new output requirements on those supplying activities. For example, if automating a framing station changes the required data format or constrains acceptable panel dimensions, then the design and data preparation activity, which is informationally linked to framing, becomes an upstream consequential activity. Downstream propagation traces dependencies forward to activities that receive the automated station's output, examining whether changes in volume, speed, or physical product characteristics alter how those activities handle, process, or inspect what they receive. Lateral propagation examines parallel activities that share resources with the automated station, identifying any effects that extend sideways across the production floor. For each propagation pathway identified, the analyst records the consequential activity, the affected factory element, and whether the impact renders a new task or an existing one to be modified or eliminated.

Several analytical tools are well-suited to support this layer. Dependency structure matrices (DSMs) help map activity-to-activity interdependencies in a structured and visual format. Cross-impact matrices allow the analyst to systematically examine each first-order change against every other production activity in the system. Causal loop diagrams are useful for capturing feedback effects that may not be immediately apparent from a linear reading of the production flow. In addition to these tools, expert elicitation through structured interviews or Delphi panels with factory managers, production engineers, and automation integrators plays an essential role in validating the propagation maps and ensuring that no consequential activity has been overlooked.

3.3.2 Layer 2: Cataloging Responsive Actions

Once consequential activities have been identified, the analyst determines the specific responsive actions required to accommodate each propagated change. This step transforms a structural map of disruptions, capturing what is affected, into an operational account of requirements, specifying what must be done. Identifying a consequential activity flags where a disruption occurs; the associated responsive action specifies the concrete resources, procedures, and investments required to bring that activity into alignment with the new automated configuration. Through expert elicitation, the analyst examines the response required at each affected activity to specify both the nature of the required intervention, such as procuring new equipment or software, adding human resources, adjusting spatial arrangements, or updating quality standards, and the type of resource consumed, such as capital, time, space, labor, or energy. It is also worth noting that responsive actions are themselves changes to the factory and may, in turn, affect other factory elements. Where a more exhaustive analysis is required, these responsive actions can be subjected to the same evaluation detailed in Modules 1 and 2, allowing the framework to map higher-order propagation pathways across the system in a recursive manner.

3.4 Module 3: Performance Impact Assessment

With the full impact profile in hand, comprising both the consequential activities and the responsive actions cataloged in Module 2, Module 3 translates this operational picture into measurable shifts in system-level performance. Its purpose is to quantify how the automation decision, when its complete system-wide effects are accounted for, alters the plant's operational performance relative to the current baseline. This system-level perspective is what distinguishes the AIA framework from existing approaches that report performance at the automated station in isolation, without accounting for the broader consequences that propagate through the rest of the production system.

To this end, the analyst selects and evaluates a set of performance indicators that collectively capture the plant's operational performance and reflect the objectives motivating the automation decision. While the specific indicators may be tailored to the context of each plant, the following represent common key performance indicators (KPIs) for OSC manufacturing environments, drawing on established performance assessment literature (Lachance et al. 2023; Orlowski 2019; Ouda and Haggag 2025).

- **System Throughput and Production Capacity:** This metric measures the number of completed panels or modules per unit of time across the entire production line. It accounts for potential bottleneck shifts identified in Module 2, takt time constraints, and any duplication of resources required to meet production targets.
- **Workforce Composition:** Rather than simply tracking total headcount changes, this indicator maps the workforce before and after automation. The assessment must separate eliminated manual roles, retained positions, and newly created jobs, such as 3D designers, programmers, or robotic maintenance staff.
- **Production Lead Time:** This captures the entire cycle from the preparation of design data to the output of the finished panel. It includes any new upstream preparatory or staging activities that were not required under the manual configuration.

- **Quality and Rework Rate:** Evaluated at the system level, this includes correctable non-conformities and permanent rejections that lead to material waste. Tracking these rates is critical because they directly influence the resilience of the overall system.
- **Space Utilization:** This measures the total floor space required by the automated setup. It incorporates the footprint of the automated station, buffer zones, material staging areas, maintenance access routes, and any displaced activities. Space utilization is typically expressed as square meters per unit of output to allow for direct comparisons between different configurations.
- **Worker Efficiency:** Defined as the output per worker per shift, determining whether the automation decision improves labor productivity across the system or simply shifts the workload from direct manual tasks to supporting roles.

Beyond these quantitative operational indicators, Module 3 also evaluates emergent system-level properties that reflect how the automation decision reshapes the plant's overall character. System flexibility captures the plant's residual capacity to accommodate design variation, late-stage changes, and product mix shifts, which may be constrained by rigid automated equipment or enhanced by programmable systems. Scalability assesses whether the post-automation configuration can support future increases in production volume or product complexity without requiring further disruptive changes to the system. Organizational readiness evaluates whether the plant's reshaped workforce structure, skill base, and management processes can reliably sustain automated operations over time.

The analytical methods used to process these indicators may vary depending on the required level of certainty and the availability of data. For qualitative assessments, where only directional tendencies such as an expected increase or decrease in a given indicator are known, cognitive mapping methods can help trace cause-and-effect relationships from the lowest operational level up to top-level performance indicators. For quantitative assessments, indicator changes can be modeled using discrete-event simulation or multi-criteria analysis tools to calculate KPIs with greater precision. To account for systemic uncertainty, probability distributions or fuzzy set approaches can be applied. Sensitivity analysis can further test the robustness of results under variations in production volume, product mix, and demand conditions.

3.5 Module 4: Total Cost-Benefit Evaluation

The final module synthesizes all preceding outputs into a unified economic evaluation that brings the full cost of automation and the full value of what it delivers into the same analytical frame. Its purpose is to determine whether the adoption of a selected technology is economically justified, and over what timeline. To achieve this, the module draws on three distinct data streams, each capturing a different dimension of the automation decision's financial consequences, and consolidates them into standard decision metrics.

Data Stream 1: Implementation Costs (One-Time). These represent the total expenses required to execute the transition and are divided into direct costs and system-induced costs. Direct costs include the acquisition, installation, commissioning, and integration of the automated equipment, which are traditionally captured in station-level evaluations (Ouda and Haggag 2025; Salmi et al. 2018). System-induced costs, by contrast, arise from the responsive actions cataloged in Module 2 and represent one-time expenditures already characterized as financial line items, such as workforce retraining, software procurement, spatial reconfiguration, new workstations, and revised procurement channels. Where relevant, the implementation timeline should also be estimated to account for any production loss incurred during the transition period.

Dara Stream 2: Operational Cost Changes (Ongoing). These represent the recurring costs that persist after the implementation is complete. Some operational costs are expected to decrease following the adoption of automation, including direct labor costs at the automated station and potentially rework and material waste costs resulting from improved dimensional precision. Conversely, others are expected to increase, including maintenance costs for automated equipment, energy consumption, design labor, setup and programming costs, and potentially higher material procurement costs driven by stricter tolerance requirements. This stream must incorporate all ongoing costs, encompassing both directly affected elements and ripple-effect responses across the system.

Data Stream 3: Operational Benefits (Ongoing). This stream captures the value generated by improved system performance. Higher system throughput leads to increased production capacity, which can result in higher revenue or the ability to meet project delivery targets faster. A reduced production lead time can improve market responsiveness and lower the carrying costs of work-in-progress inventory. Furthermore, quality improvements minimize waste, scrap costs, and customer complaints. Finally, improved worker efficiency, measured as output per worker per shift, represents a compounding productivity gain over the lifespan of the operation. Similar to the cost evaluation, this stream must account for all ongoing benefits, including both direct impacts and broader cost-saving ripple effects.

With all three streams quantified, the analyst consolidates them into standard decision metrics that allow for a direct comparison of costs and benefits. These metrics may include but are not limited to:

- **Total Cost per Unit of Product:** This metric aggregates all resource costs associated with producing one unit of output, enabling stakeholders to clearly benchmark the financial impact of competing technologies (Salmi et al. 2018).
- **Net Present Value (NPV):** This metric discounts the annual net savings (Stream 3 minus Stream 2) over the operational lifespan and subtracts the total implementation cost (Stream 1). It provides a single figure indicating whether the automation decision creates or destroys value.
- **Benefit-Cost Ratio (BCR):** This ratio expresses the return per dollar invested, offering an intuitive measure of investment efficiency.
- **Payback Period:** This estimates how long the annual net savings must accumulate before the initial investment is fully recovered. This directly informs the manufacturer's risk tolerance and financing strategy (Ouda and Haggag 2025).
- **Multifactor Productivity (MFP):** Defined as the total output per invested dollar across labor, machinery, and space costs, this provides a composite efficiency metric. It captures the combined effect of all operational changes on the overall resource productivity of the plant (Lachance et al. 2023).

Finally, non-quantifiable indicators from Module 3, such as system flexibility and scalability, should be carried forward as qualitative considerations alongside these financial metrics. A sensitivity analysis must be conducted on the key parameters driving the economic outcome, including production volume, labor wage assumptions, maintenance costs, discount rates, and equipment lifespan. This analysis reveals the conditions under which the automation decision remains viable and identifies the thresholds where it becomes uneconomical.

4 Discussion

The AIA framework offers a structured analytical workflow for evaluating automation decisions in off-site manufacturing at a level of system awareness that existing tools lack. Several characteristics of the framework merit discussion, alongside its contributions, practical implications, and limitations.

The framework's modular architecture allows it to be adapted to different decision contexts without requiring a complete end-to-end application. An early-stage screening exercise may draw on Modules 1 and 2 alone to map the scope and propagation of an automation scenario, while a full capital investment appraisal would engage all four modules. This flexibility is reinforced by the framework's technology-agnostic design. Because AIA operates on the structural logic of interdependencies rather than on the specifications of any particular machine or robot, it can be applied to any automation technology introduced at any production activity. Furthermore, the framework is scalable across multiple levels of analysis. It can evaluate a single automation scenario in isolation, compare competing alternatives side by side, or be applied iteratively to model the cumulative effects of a phased, multi-station automation strategy.

From a theoretical standpoint, the AIA addresses a gap that sits between two bodies of work, known as strategic adoption frameworks and operational assessment studies. The proposed framework in this study bridges these two domains by introducing a propagation mechanism that traces how a localized automation decision generates consequential activities and responsive actions across the full production environment. In doing so, it reframes automation evaluation from a station-level performance question to a system-level change management problem, aligning the analysis with the interconnected reality of manufacturing operations.

The practical implications of this reframing are significant. Industry discourse around automation in construction manufacturing has often been shaped by the implicit assumption that higher levels of automation yield proportionally greater benefits. The AIA challenges this assumption by making visible the system-wide costs that accompany each increment of automation. A fully automated station may deliver substantial local gains in cycle time and labor reduction, yet the responsive actions it triggers across the system, including upstream data preparation demands, workforce restructuring, spatial reconfiguration, and downstream bottleneck mitigation, may partially or substantially offset those gains when evaluated at the system level. By surfacing these hidden trade-offs, the AIA equips manufacturers to make investment decisions grounded in realistic operational consequences rather than idealized localized projections. This is particularly consequential for small and medium-sized OSC enterprises, where capital constraints require that every automation investment be justified by its true system-level return (Yang et al. 2024).

Several limitations should be acknowledged. First, the framework's analytical depth is contingent on the quality and availability of operational data. Mapping interdependencies, estimating propagation effects, and quantifying responsive actions all rely on detailed knowledge of production processes, workforce configurations, spatial layouts, and cost structures, which may not be readily available in all factories. Second, while the AIA is presented as a conceptual contribution, it has not yet been empirically validated against real-world automation transitions. The framework's central proposition, that system-level propagation effects are significant enough to materially alter the outcome of an automation investment decision, remains a theoretical claim until tested through case application. It is also unclear whether the magnitude and criticality of these hidden impacts vary with the level of automation being introduced; a semi-automated upgrade may generate fewer and less consequential effects than a fully robotic deployment, or the relationship may be non-linear. Future research should prioritize empirical validation through retrospective case studies of completed automation transitions, where actual system-level consequences can be compared against the predictions that the AIA would have generated. Extending the framework to incorporate probabilistic or fuzzy-set representations of propagation likelihood and impact severity would further strengthen its applicability in uncertain environments.

5 CONCLUSION

The Automation Impact Analysis (AIA) framework is a modular, system-oriented analytical structure designed to support automation investment decisions in off-site construction manufacturing by tracing the full operational and economic consequences of automating individual production activities. Adapted from the Change Impact Analysis methodology of Bauer et al. (2020), the framework addresses a critical gap in the existing literature, in which automation is evaluated at the station level, and the knock-on effects of introducing automation into an interconnected production environment are overlooked. Through its four-module pipeline, the AIA provides a structured pathway from a defined automation scenario to its first-order impacts, propagated consequential activities and responsive actions, system-level performance shifts, and total cost-benefit evaluation, producing an auditable chain of evidence in which every cost and benefit can be traced back to a specific interdependency and propagation pathway. For the academic community, the framework contributes a conceptual bridge between strategic adoption diagnostics and operational performance assessment, reframing automation evaluation as a system-level change management problem rather than a localized technology selection exercise. For industry practitioners, it offers a decision-support instrument that surfaces the hidden operational costs and organizational demands of automation, enabling manufacturers to move beyond idealized station-level projections toward investment decisions grounded in the realistic complexity of their production systems. The framework's modular, technology-agnostic, and scalable design allows it to be applied selectively across different decision contexts, automation technologies, and implementation strategies. Future research should prioritize empirical validation through case studies of real-world automation transitions, investigate how the magnitude of system-level propagation effects varies with the level of automation introduced, and extend the analytical machinery to incorporate probabilistic representations of propagation likelihood and impact severity.

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