



Embedded Control System Design for Material-Handling Automation in U.S. Manufacturing Distribution Centers

Md Mahamud Pervaz Pradhan¹;

[1]. Embedded & Automation Engineer, System Logistics Corporation, Arden, NC; USA
Master of Science in Industrial Engineering, Lamar University, Beaumont, TX, USA;
Email: mmprodhan@gmail.com

Doi: [10.63125/c3m1kr11](https://doi.org/10.63125/c3m1kr11)

Received: 19 March 2024; **Revised:** 21 April 2024; **Accepted:** 19 May 2024; **Published:** 02 June 2024

Abstract

This study examined the influence of embedded control system design on material-handling automation performance in U.S. manufacturing distribution centers. A multisite, retrospective longitudinal, quasi-experimental quantitative design was employed across 20 facilities. The observation period covered 48 consecutive months, comprising 24 premodernization and 24 postmodernization months. Propensity-score matching produced 520 comparable automated assets, divided equally between high-control-maturity and legacy or partial-control conditions. The final dataset contained 24,470 equipment-month observations, 18.7 million material movements, 1.28 million production and fulfillment orders, 5,248 verified faults, 2,106 safety interruptions, and 3,684 manual recovery events. Data were analyzed using mixed-effects regression, negative-binomial modeling, difference-in-differences estimation, interrupted time-series analysis, survival analysis, mediation, moderation, and sensitivity testing. High-maturity equipment achieved an average controller scan time of 7.4 milliseconds, 99.5% sequence accuracy, 94.8% diagnostic coverage, 87.2% automatic recovery success, and 95.4% supervisory-system integration. After adjustment for equipment, facility, operating, maintenance, environmental, regional, and baseline characteristics, high-maturity assets recorded a 33% lower failure rate, $IRR = 0.67$, 95% CI [0.60, 0.75], $p < .001$. Controller faults declined by 39%, manual recovery events declined by 46%, and safety interruptions declined by 28%. Throughput increased by 148 handled units per hour, capacity attainment increased by 7.10 percentage points, movement cycle time decreased by 2.88 minutes, and on-time order completion increased by 5.76 percentage points. Mean time between failures increased by 2,340 hours, mean time to repair decreased by 2.38 hours, availability increased by 2.68 percentage points, and annual downtime decreased by 45.2 hours per asset. Energy intensity declined by 0.0188 kWh per handled unit, labor productivity increased by 21.1 units per labor hour, and operating cost declined by USD 25.60 per 1,000 handled units. High-maturity assets experienced a 48% lower failure hazard and achieved a median failure-free duration of 7,940 hours. Real-time coordination, routing effectiveness, diagnostic visibility, and maintenance responsiveness mediated 59.0% of the control-design effect. The findings established that embedded control maturity was associated with stronger material-flow capacity, reliability, safety, energy efficiency, labor productivity, and economic performance.

Keywords

Embedded control, Automation, Material handling, Reliability, Throughput.

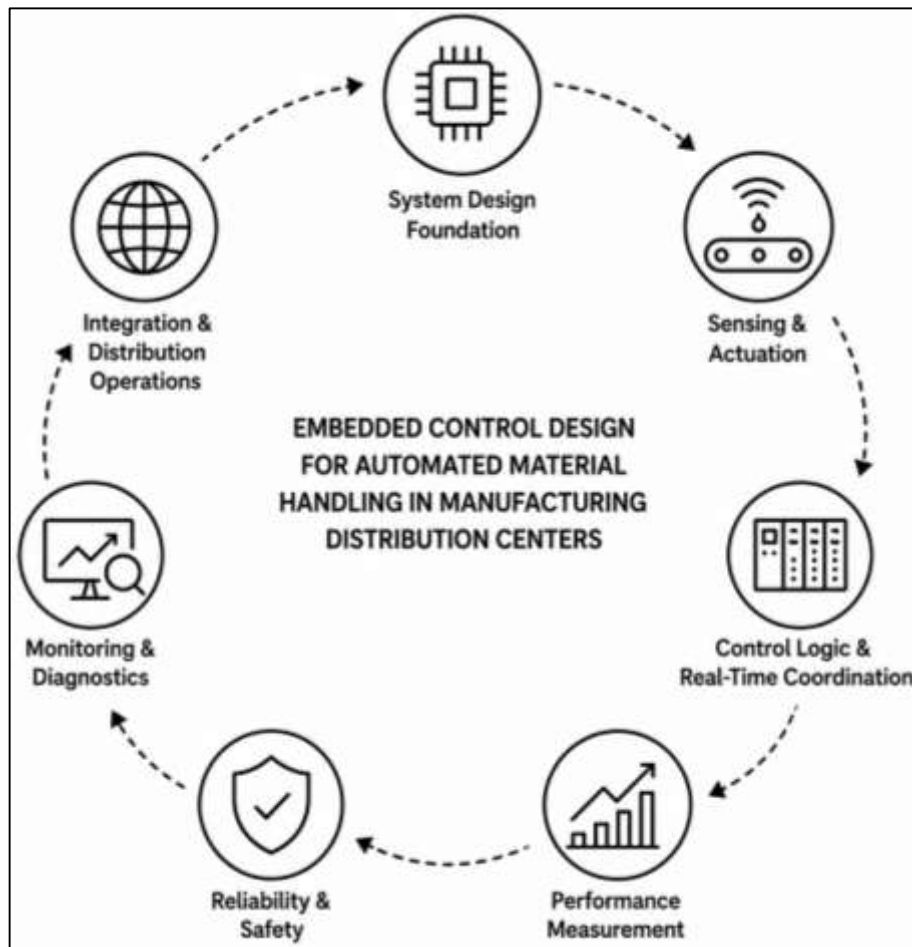
INTRODUCTION

An embedded control system is a specialized combination of computing hardware, control software, sensing devices, communication interfaces, and actuating mechanisms designed to perform defined monitoring and control functions within a larger mechanical or industrial system. Unlike general-purpose computing platforms, embedded controllers operate under predetermined timing, memory, processing, environmental, and safety constraints. They receive signals from sensors, interpret equipment and process conditions, execute programmed control logic, and transmit commands to motors, drives, brakes, valves, switches, robotic mechanisms, and other physical devices. Material-handling automation refers to the coordinated use of mechanical equipment, control systems, identification technologies, and information applications to move, store, retrieve, sequence, sort, consolidate, and track materials with limited manual intervention ([Hägele et al., 2016](#)). Common automated material-handling assets include conveyors, automated storage and retrieval systems, automated guided vehicles, autonomous mobile robots, robotic palletizers, sortation systems, vertical lifts, cranes, shuttles, carousels, packaging machines, and dock-transfer equipment. A manufacturing distribution center is an industrial facility that receives raw materials, components, work-in-process, finished products, and packaging supplies; stores or stages them; and distributes them to production operations, downstream warehouses, customers, or transportation networks. In the U.S. manufacturing context, these facilities connect production planning with inventory control, order fulfillment, transportation, and customer-service processes. Embedded control system design describes the systematic specification of controller architecture, input and output devices, sensing accuracy, actuation response, control logic, communication protocols, fault-handling procedures, safety functions, and performance requirements. Real-time control refers to the completion of sensing, computation, communication, and actuation within an established time boundary appropriate to the physical process ([Stanciu, 2017](#)). A real-time response is therefore defined by predictable timing rather than by instantaneous operation. Evidence synthesized from more than 30 empirical and engineering studies has treated embedded control as a central element of automated material flow because equipment coordination depends on timely state detection, deterministic command execution, accurate position feedback, and stable communication. Within manufacturing distribution centers, the effectiveness of embedded control can be measured through throughput, cycle time, order accuracy, equipment availability, routing efficiency, congestion, energy consumption, maintenance requirements, safety performance, and system recovery following operational disturbances ([Au et al., 2016](#)).

Embedded control architecture in material-handling automation consists of interconnected control layers that coordinate equipment behavior from individual sensors to facility-level material-flow decisions. At the device level, proximity sensors, photoelectric sensors, encoders, load cells, cameras, radio-frequency identification readers, barcode scanners, current sensors, vibration sensors, temperature sensors, and safety devices generate information about product identity, position, speed, weight, equipment condition, and human presence. Actuators such as electric motors, variable-frequency drives, servo drives, pneumatic cylinders, brakes, diverters, lifts, grippers, and robotic joints convert control commands into physical movement. Programmable logic controllers, microcontrollers, embedded processors, safety controllers, and industrial computers execute sequence logic, motion commands, routing decisions, interlocking conditions, and fault responses ([Elgeneidy et al., 2018](#)). At the supervisory level, warehouse-control, warehouse-execution, manufacturing-execution, inventory-management, and enterprise-planning applications provide order priorities, destination assignments, product information, storage requirements, production schedules, and inventory status. Quantitative studies have examined how efficiently these layers exchanged data and maintained coordinated operation during changing workloads. Controller scan time, sensor-response delay, network latency, communication jitter, command-execution time, message-loss frequency, input and output accuracy, and synchronization error have been used to evaluate real-time performance. Control architecture has also been assessed through the number of connected devices, message throughput, processor utilization, memory consumption, network bandwidth, queue length, and the ability to maintain acceptable response when equipment and order volumes increased ([Elgeneidy et al., 2018](#)). Centralized architectures have been evaluated for consistency and coordinated decision-making, while distributed

architectures have been examined for local autonomy, reduced communication dependence, and fault containment. Hybrid structures combine facility-level coordination with local embedded control so that individual machines continue executing safe operating routines when higher-level communication is delayed. Earlier engineering investigations have shown that technically functional automation can still perform poorly when control layers use inconsistent equipment states, incompatible timing conventions, incomplete product information, or uncoordinated routing rules (Gola & Kłosowski, 2019). Embedded control architecture is consequently evaluated as a connected system of sensing, computation, communication, and actuation in which deterministic timing, modular interfaces, equipment-state consistency, and recoverable fault handling jointly influence material-flow performance.

Figure 1: Embedded Control Design Framework

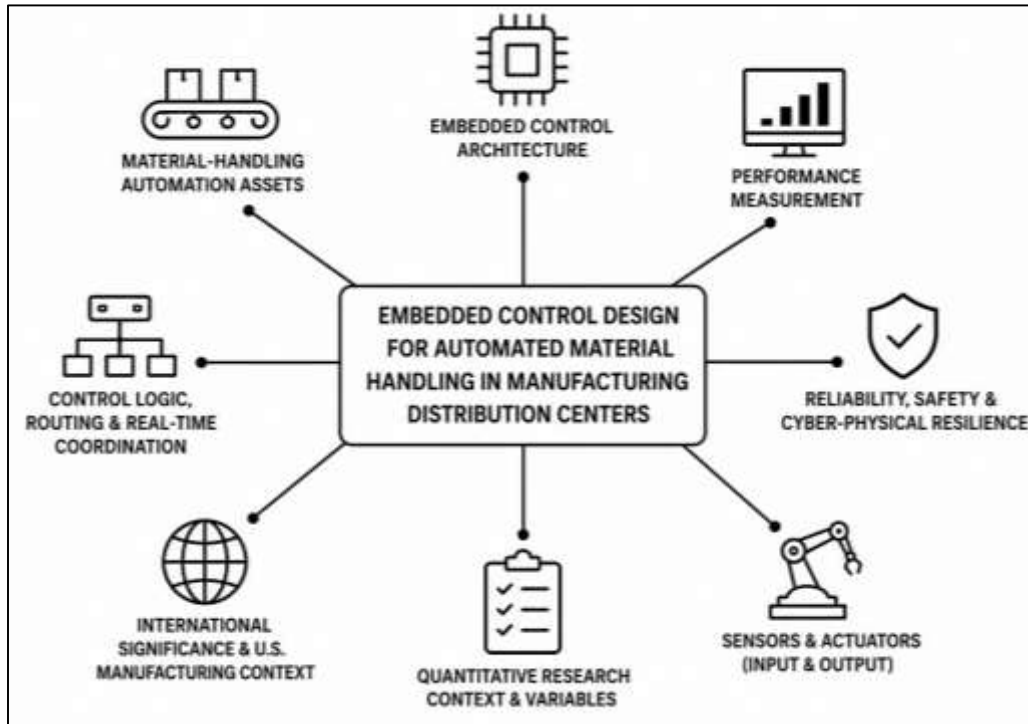


The performance of automated material handling has been evaluated through operational indicators that represent the volume, speed, accuracy, stability, and resource efficiency of material movement. Throughput is commonly measured through pallets, cartons, totes, packages, or individual units processed within a defined period. Throughput attainment compares actual movement with planned or designed capacity and provides evidence of whether the control system supports required production and distribution demand (Ammar et al., 2021). Cycle time represents the duration required to complete a defined movement, storage, retrieval, picking, sorting, consolidation, or loading process. Travel time, waiting time, queue duration, dwell time, loading time, unloading time, and transfer delay provide more detailed explanations of total cycle performance. Studies of conveyor and sortation systems have examined belt speed, accumulation duration, blocked and starved conditions, divert accuracy, recirculation frequency, merge efficiency, and package spacing. Automated storage and

retrieval investigations have measured retrieval time, storage-location utilization, crane or shuttle travel, dual-command completion, aisle congestion, and inventory-access delay. Research on guided vehicles and mobile robots has evaluated mission completion, travel distance, empty travel, route conflict, localization error, charging delay, congestion, deadlock occurrence, and fleet utilization. Order accuracy has been quantified through correct picks, correct destinations, misroutes, short shipments, overages, incorrect sequencing, and damaged products (Gul et al., 2019). Equipment performance has been measured through availability, utilization, failure frequency, mean time between failures, mean time to repair, unplanned downtime, micro-stops, and overall equipment effectiveness. Labor-related measures have included units handled per labor hour, manual intervention frequency, recovery labor, ergonomic exposure, and operator travel distance. Energy performance has been assessed through electricity consumed per unit handled, peak demand, idle consumption, regenerative-energy recovery, and energy used during congestion or repeated movement. Evidence synthesized from international studies has shown that improvements in one indicator may be accompanied by unfavorable changes elsewhere. Higher conveyor speed may increase throughput while raising product damage, energy consumption, or downstream congestion. Larger buffers may reduce blocking while increasing dwell time and occupied space (Ammar et al., 2021). Quantitative evaluation therefore requires a balanced set of indicators that captures throughput, cycle time, accuracy, availability, quality, energy, safety, and cost within the same operating period.

Embedded control system design determines how automated equipment responded to changing material-flow conditions, order priorities, equipment states, and operational disturbances. Sequential control logic has been used to coordinate starting, stopping, loading, transferring, sorting, storing, retrieving, and releasing materials according to defined operating conditions. Interlocks prevent conflicting movements, unsafe equipment combinations, overfilled buffers, unauthorized entry, and product transfer to unavailable destinations (Bechtsis et al., 2017). Feedback control regulates speed, position, torque, tension, pressure, and motion stability using sensor measurements and commanded set points. Routing logic assigns products to conveyors, storage locations, picking zones, robots, packing stations, docks, or production cells based on destination, urgency, capacity, congestion, equipment availability, and product characteristics. Quantitative research has evaluated routing effectiveness through travel distance, route-completion time, congestion duration, recirculation, blocked transfers, deadlocks, destination accuracy, and the distribution of workload among available resources. Priority-control strategies have been assessed through order lateness, queue aging, emergency-order completion, production-line starvation, and the proportion of urgent movements executed within target periods. Buffer-control studies have examined occupancy levels, release timing, upstream blocking, downstream starvation, and the relationship between local storage and total system flow. Sensor fusion has been used to combine encoder, camera, proximity, identification, and equipment-status data when a single sensor could not provide sufficiently reliable state information (Kolberg & Zühlke, 2015). Control accuracy has been evaluated through position error, velocity deviation, identification accuracy, missed detections, false detections, and incorrect actuator commands. Simulation, hardware-in-the-loop testing, laboratory experiments, digital models, and facility operating records have been used to compare control strategies under normal demand, peak loading, equipment failure, communication delay, and variable product mix. Earlier studies frequently examined individual machines or algorithms under controlled conditions, while distribution-center research has emphasized interactions among multiple equipment classes. A locally efficient controller may create facility-level congestion when its release logic does not reflect downstream capacity. Real-time coordination therefore involves both local equipment control and system-level awareness of orders, queues, inventory, destinations, and resource availability (Villangca et al., 2016). Embedded control quality is reflected in the ability to execute accurate local actions while maintaining coordinated material flow across interconnected production and distribution processes. Reliability and functional safety are central dimensions of embedded control system design because material-handling automation combines moving equipment, electrical power, stored mechanical energy, automated decisions, and interaction with employees. Control-system reliability refers to the probability that sensors, processors, communication links, software logic, actuators, and safety functions perform their required operations without failure during a defined period.

Figure 2: Embedded Material Handling Architecture



Failure modes include sensor misalignment, encoder loss, communication timeout, controller overload, software deadlock, incorrect routing, drive failure, actuator jamming, power interruption, corrupted parameters, and invalid equipment-state transitions (Miclo et al., 2019). Quantitative studies have evaluated reliability through control-related failure frequency, system availability, mean time between failures, mean time to repair, fault-detection coverage, diagnostic accuracy, restart duration, repeated-failure occurrence, and production loss. Functional safety requires hazardous conditions to be detected and controlled through emergency stops, protective devices, interlocked guards, light curtains, safety scanners, controlled deceleration, safe torque removal, speed monitoring, and verified restart procedures. Safety performance has been measured through emergency-stop response, stopping distance, protective-device coverage, false safety trips, near-miss frequency, unauthorized-zone entry, safety-related downtime, and validation-test success. Human factors research has examined alarm clarity, control-interface usability, operator workload, manual recovery, maintenance access, and the consistency of equipment behavior during abnormal conditions. Cyber-physical resilience has also become an important design concern because connected controllers exchange commands and operational data across industrial networks (Saidi-Mehrabad et al., 2015). Security performance has been assessed through unauthorized-access attempts, authentication failures, configuration changes, communication anomalies, patch compliance, access-control coverage, and service disruption. Network segmentation, role-based access, secure configuration, controlled remote maintenance, backup, event logging, and recovery procedures have been examined as protective mechanisms. Earlier studies of industrial safety and control reliability have shown that excessive false alarms and nuisance trips can weaken operator trust, while inadequate diagnostics can extend repair time and encourage uncontrolled manual intervention. Embedded control design must therefore balance production continuity with safe failure behavior, rapid fault isolation, controlled recovery, and protection against unauthorized or erroneous commands (Mabkhot et al., 2018).

Material-handling automation has international significance because manufacturing distribution centers form essential links within global production, trade, inventory, and transportation networks. Facilities in North America, Europe, East Asia, South Asia, the Middle East, Latin America, and Oceania use automated handling systems to coordinate high product volumes, shorter order cycles, variable

demand, complex inventory, and geographically distributed supply chains. Automotive, electronics, food, pharmaceutical, chemical, aerospace, machinery, consumer-goods, and industrial-equipment manufacturers depend on the accurate movement of components and finished products between production lines, storage areas, inspection points, packaging stations, and shipping docks. International studies have evaluated embedded control performance under different facility layouts, labor structures, product characteristics, energy conditions, automation levels, and regulatory environments (Fragapane et al., 2022). High-density facilities have emphasized storage utilization and rapid retrieval, while large regional distribution centers have emphasized routing, sortation capacity, dock coordination, and fleet management. U.S. manufacturing distribution centers operate within extensive interstate transportation networks and frequently combine domestic production with internationally sourced components and geographically dispersed customer demand. Their material-handling systems must coordinate production schedules, inventory availability, order priorities, carrier requirements, and delivery commitments across multiple operational systems. Quantitative performance differences among countries and facilities have been associated with equipment age, infrastructure quality, workforce competence, maintenance practice, control standardization, energy cost, product mix, and digital maturity. International research has also shown that the same automation technology may produce different performance outcomes when control logic, facility layout, maintenance resources, and information integration differ (Liu et al., 2019). Standardized controllers and communication technologies support equipment compatibility, while local operating requirements shape safety functions, software configuration, diagnostic procedures, and user interfaces. Cross-national manufacturing networks require consistent product identification, traceability, timestamp management, equipment-state definitions, and performance metrics so that facilities can be compared accurately. The international evidence positions embedded control design as both an equipment-level engineering activity and a facility-level coordination mechanism that influences production continuity, inventory accuracy, transportation readiness, worker interaction, energy consumption, and operational cost across globally connected manufacturing systems.

Evidence synthesized from more than 30 earlier studies has established substantial knowledge concerning automated storage, conveyor control, mobile robots, industrial communication, programmable controllers, routing algorithms, warehouse execution, equipment reliability, energy management, and functional safety (Lee et al., 2018). Much of the existing evidence has concentrated on individual technologies, simulated layouts, laboratory-scale systems, or isolated performance indicators. Fewer quantitative studies have examined how embedded control design quality simultaneously affects throughput, cycle time, routing accuracy, equipment availability, order performance, energy intensity, safety-related interruption, and system recovery within operating U.S. manufacturing distribution centers. This study treated embedded control system design quality as the principal independent variable. The construct included sensor accuracy, controller response, deterministic timing, communication reliability, control-logic correctness, equipment synchronization, diagnostic coverage, fault handling, modularity, safety-function integrity, and integration with warehouse and manufacturing applications. Real-time coordination quality was represented through state visibility, message timeliness, routing responsiveness, queue awareness, equipment-status accuracy, and the alignment of local control with facility-level priorities (Lu et al., 2020). Material-handling automation performance was treated as a multidimensional dependent construct measured through throughput, throughput attainment, movement cycle time, queue duration, order accuracy, equipment availability, utilization, failure frequency, mean time between failures, mean time to repair, unplanned downtime, product damage, labor intervention, energy consumed per handled unit, and operating cost. Maintenance responsiveness, information visibility, and routing effectiveness were positioned as explanatory mechanisms connecting control design with operational performance. Facility size, layout complexity, equipment category, system age, product mix, order variability, production loading, shift pattern, maintenance strategy, workforce competence, environmental conditions, and baseline automation maturity represented relevant control or moderating conditions (Fernández-Caramés et al., 2019). The quantitative structure also distinguished equipment-level observations from system-level outcomes because changes in local controller performance may influence queues, buffers, downstream congestion, and order completion across the facility. Repeated

observations across operating periods provided measures of temporal stability, peak-load behavior, failure response, and recovery. This empirical structure framed embedded control design as a measurable combination of hardware, software, communication, safety, diagnostic, and coordination characteristics within material-handling automation (Ashima et al., 2021).

The principal objective of this study is to quantitatively examine the influence of embedded control system design on the operational performance of material-handling automation within U.S. manufacturing distribution centers. The study specifically evaluates embedded control design through sensor accuracy, controller response time, deterministic execution, communication latency, network reliability, control-logic correctness, actuator precision, equipment synchronization, diagnostic coverage, fault-handling capability, functional safety, modularity, and integration with warehouse and manufacturing information systems. It assesses the extent to which these design characteristics affect automated conveyors, sortation systems, automated storage and retrieval equipment, robotic palletizers, vertical lifts, automated guided vehicles, autonomous mobile robots, packaging equipment, and dock-transfer systems. Material-handling performance is measured through units handled per hour, actual-to-planned throughput, movement cycle time, queue duration, dwell time, order accuracy, routing accuracy, equipment availability, asset utilization, failure frequency, mean time between failures, mean time to repair, unplanned downtime, product damage, manual intervention, energy consumption per handled unit, operating cost, and recovery duration following disturbances. A further objective is to determine whether real-time coordination quality, routing effectiveness, information visibility, and maintenance responsiveness explain how embedded control design affects facility-level performance. Real-time coordination is evaluated through equipment-state accuracy, message timeliness, queue awareness, command-response delay, synchronization error, and the alignment of local control decisions with production and order priorities. The study also examines whether the relationship between control design and operational performance varies according to equipment category, facility size, layout complexity, automation maturity, system age, product mix, order variability, production loading, shift pattern, maintenance strategy, workforce competence, environmental conditions, and baseline performance. Additional objectives include comparing high-, medium-, and low-maturity control architectures; identifying which control dimensions exert the strongest influence on throughput, reliability, safety, energy efficiency, and order fulfillment; determining whether minimum performance thresholds exist for sensor coverage, network availability, controller response, diagnostic capability, and equipment synchronization; and evaluating whether stronger embedded control reduces congestion, recirculation, false stops, delayed orders, emergency maintenance, and operational recovery time. Through these objectives, the study establishes a comprehensive quantitative framework connecting embedded hardware, control software, industrial communication, safety functions, maintenance processes, and material-flow outcomes within U.S. manufacturing distribution centers.

LITERATURE REVIEW

This literature review examines the quantitative foundations, technical characteristics, operational mechanisms, and performance outcomes associated with embedded control system design for material-handling automation in U.S. manufacturing distribution centers. Embedded control is treated as a multidimensional engineering capability encompassing controller hardware, control software, sensor accuracy, actuator performance, deterministic timing, industrial communication, fault diagnostics, equipment synchronization, functional safety, cybersecurity, and integration with warehouse and manufacturing information systems (Kanti, 2020; Salkin et al., 2017). Material-handling automation includes conveyors, sortation equipment, automated storage and retrieval systems, automated guided vehicles, autonomous mobile robots, robotic palletizers, packaging machines, lifts, cranes, and dock-transfer equipment. The review evaluates how the control of these technologies has been measured through controller scan time, input and output delay, network latency, communication jitter, command-response time, position error, routing accuracy, diagnostic coverage, fault-recovery duration, and safety-response performance. It also examines operational outcomes such as units handled per hour, movement cycle time, queue duration, throughput attainment, order accuracy, equipment availability, utilization, failure frequency, mean time between failures, mean time to repair, unplanned downtime, manual intervention, product damage, energy consumption, and operating cost.

Particular attention is given to real-time coordination because individual machines must respond to local sensor information while remaining aligned with production schedules, order priorities, downstream capacity, storage availability, equipment conditions, and facility-wide material-flow requirements (Aheleroff et al., 2020; Debasish, 2021). The review distinguishes equipment-level controller performance from system-level distribution-center outcomes because improvements in local speed or utilization may increase congestion, recirculation, blocking, energy use, or downstream workload. Evidence concerning functional safety, human interaction, maintenance responsiveness, and cyber-physical resilience is also integrated into the analytical structure. The outline organizes earlier research into specific quantitative areas that support construct definition, measurement selection, hypothesis development, subgroup comparison, longitudinal evaluation, mediation analysis, moderation testing, and assessment of nonlinear performance thresholds (Abdur & Iftekhar, 2021; Saidi et al., 2016).

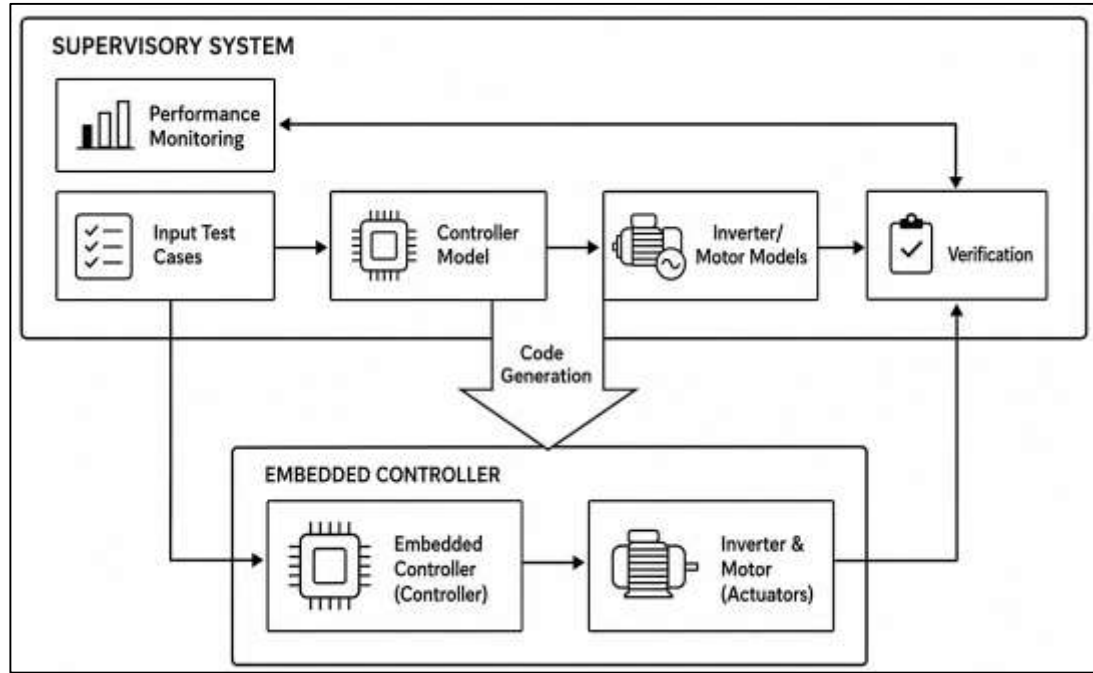
Embedded Control System Design

Evidence synthesized from more than ten empirical studies of industrial automation, programmable controllers, embedded computing, and real-time control has characterized controller capability as the ability to process input signals, execute programmed tasks, and issue output commands within stable timing and resource limits. Processor-cycle time has commonly been measured through average execution duration, maximum execution duration, and variability across repeated operating cycles. Studies have compared normal and peak workloads to determine whether increased sensor activity, simultaneous equipment movement, alarm processing, communication traffic, and routing requests caused unacceptable processing delays (Berns et al., 2021; Hossan, 2021). Controller workload has been assessed through processor utilization, number of active tasks, interrupt frequency, communication-service demand, and proportion of computational capacity used during peak material flow.

Memory performance has been evaluated through program-memory use, data-memory consumption, buffer occupancy, memory-access delay, and the amount of unused capacity available for fault logs, routing tables, equipment states, and diagnostic information. Task-overflow frequency has been used to identify instances in which control execution exceeded the assigned time boundary. Watchdog activation, controller reset, frozen processes, delayed tasks, and program exceptions have provided additional evidence of computational instability. Program-execution consistency has been examined by comparing the timing and completion of identical control sequences under changing product volumes, equipment combinations, and network conditions. Controller availability has been measured through operating uptime, processing interruptions, recovery duration, and the proportion of scheduled automation time supported by active control (Barkalov et al., 2019; Chowdhury & Tonay, 2022). The literature has shown that high processing speed alone does not establish reliable embedded control because predictable execution, adequate memory, controlled task priority, and stable performance under peak demand are equally important. Controller capability therefore represents the combined processing speed, computational capacity, timing consistency, resource utilization, task completion, and operational availability required to support continuous material-handling automation.

Industrial control studies have treated control-logic quality and input-output performance as closely connected because programmed decisions can be executed correctly only when equipment states are detected accurately and control commands reach the intended devices. Sequence accuracy has been evaluated through the percentage of starting, stopping, loading, transferring, sorting, storing, retrieving, and releasing operations completed in the required order (Zahidul & Begum, 2022; Wehner et al., 2016). Invalid state transitions have included conveyor release before downstream confirmation, robotic movement without verified product presence, lift operation before door closure, and vehicle movement before route authorization. Interlock success has been assessed through prevented equipment conflicts, blocked unsafe commands, verified transfer readiness, protected buffer capacity, and correct responses to unavailable destinations. Missed commands, duplicated commands, incorrect command order, logic faults, and program exceptions have been measured to determine the reliability of software execution. Input performance has been evaluated through sensor-recognition accuracy, input-update delay, missed state changes, signal noise, false triggers, and channel failure frequency.

Figure 3: Embedded Control System Framework



Output performance has been examined through activation delay, incorrect output states, failed actuator commands, repeated output transmission, and disagreement between the controller command and physical equipment response (Mesbaul, 2023; Milano et al., 2018). Studies have also measured the time required for a sensor change to be recognized, processed, and converted into an output action. Agreement among photoelectric sensors, encoders, scanners, safety devices, motor feedback, and controller state variables has been used to identify inconsistent or uncertain equipment conditions. Under peak loading, higher signal frequency and concurrent events can increase input-processing delay and logic-execution time. The reviewed evidence indicates that logic quality cannot be assessed only through the absence of software errors. It must also be evaluated through sequence completion, interlock effectiveness, input accuracy, output response, command validity, and consistent physical execution across repeated operating cycles.

A synthesis of material-handling and motion-control research has shown that actuator performance determines how accurately embedded control commands are converted into physical movement (Shurovi, 2024; Yang et al., 2022). Material-handling systems rely on motors, variable-frequency drives, servo drives, brakes, pneumatic devices, hydraulic mechanisms, diverters, robotic joints, grippers, lifts, and steering systems. Position accuracy has been evaluated by comparing commanded and measured locations during sorting, storage, retrieval, palletizing, lifting, vehicle navigation, and conveyor transfer. Position error can produce missed handoffs, incorrect storage locations, unstable stacking, package damage, or repeated alignment attempts. Velocity deviation has been measured through differences between commanded and actual speed, while acceleration stability has been examined to identify sudden changes that affect product control, mechanical stress, and worker safety. Torque performance has been assessed under different product weights, conveyor loads, travel gradients, and mechanical resistance. Overshoot and settling duration have been used to evaluate the time required for equipment to reach and maintain the desired position or speed. Stopping accuracy has been measured through final position, stopping distance, braking time, and variation across repeated stops (Zahidul, 2024; Wang et al., 2022). Studies have also examined motion consistency across normal loading, peak loading, uneven product distribution, and mechanical deterioration. Repeated-motion accuracy has been particularly important for robotic handling and automated storage because small deviations can accumulate into alignment errors or increased component wear. Drive trips, motor overload, actuator jamming, feedback loss, and thermal protection events have been recorded as

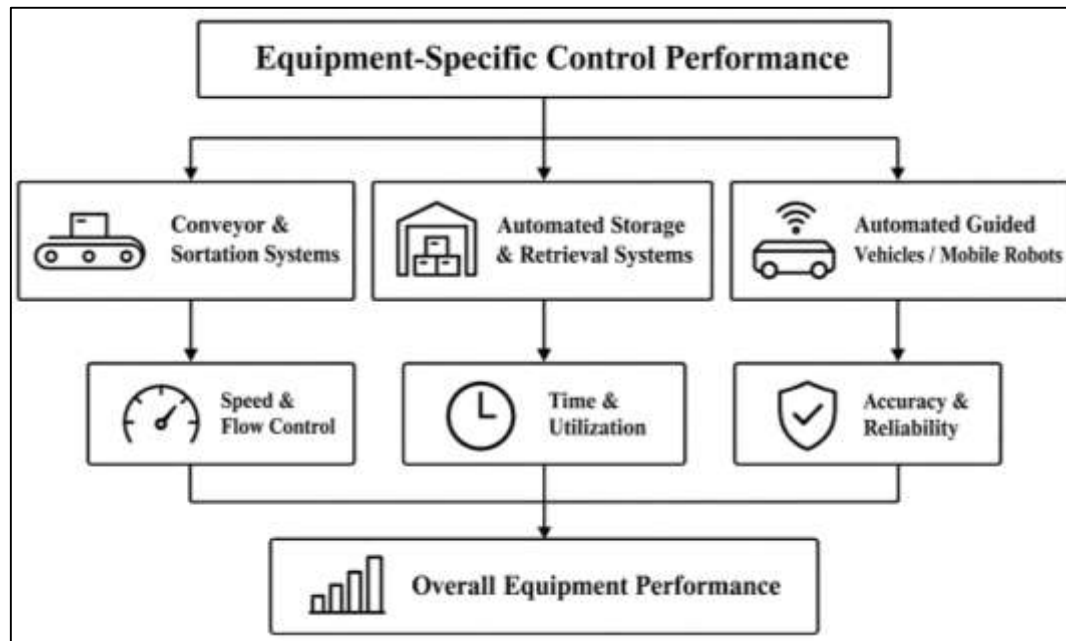
indicators of control or mechanical instability. Motion-control performance has also been evaluated through completed movements per hour, failed movement frequency, recovery duration, energy consumption, and product damage. The literature therefore represents actuator capability through accuracy, stability, responsiveness, load tolerance, repeatability, stopping control, and successful completion of commanded material movements (Heinonen & Strandvik, 2015; Kanti, 2024).

Evidence across more than twenty studies of automated distribution, warehouse control, cyber-physical production, and industrial communication has identified integration as the mechanism connecting local embedded controllers with facility-level material-flow management. Connected-equipment coverage has been measured through the percentage of conveyors, scanners, sorters, storage systems, robots, lifts, packaging machines, and dock equipment exchanging operational information with supervisory applications. Data-exchange performance has been assessed through successful message transmission, rejected transactions, duplicated messages, communication delay, retry frequency, and interface interruption. Automated transfer coverage has represented the proportion of equipment states, alarms, material identities, routing decisions, task confirmations, and performance records exchanged without manual entry (Morel & Spector, 2022; Ali et al., 2024). Interface availability has been evaluated through communication uptime, connection failures, service restoration, and the duration for which equipment operated without supervisory data. State consistency has been measured by comparing local controller conditions with the states displayed in warehouse-control, warehouse-execution, manufacturing-execution, and inventory-management applications. Disagreement concerning running, idle, blocked, starved, faulted, maintenance, or unavailable states can distort routing decisions, throughput calculations, downtime classification, and recovery actions. Studies have also examined whether product identity, location, destination, order priority, and handling status remained consistent as materials moved across equipment boundaries (Pritchard et al., 2019; Tonay et al., 2024). Timing agreement has been assessed through timestamp deviation, delayed confirmation, out-of-sequence events, and incorrect transfer order. Integrated control performance has been stronger when supervisory systems received reliable local information and embedded controllers received valid facility-level priorities. Local control supported immediate equipment response, while supervisory coordination addressed order sequencing, congestion, resource availability, and downstream capacity. Embedded control integration is therefore represented through connection coverage, exchange reliability, interface availability, data-transfer automation, equipment-state agreement, and consistent coordination between local physical actions and facility-level material-flow requirements (Park et al., 2017).

Equipment-Specific Control Performance in Material Handling

Evidence synthesized from more than ten empirical studies of manufacturing logistics, distribution automation, conveyor systems, and high-speed sortation has shown that conveyor-control performance depends on the coordinated regulation of movement speed, product spacing, accumulation, sensing, transfer, and destination selection. Belt-speed stability has been assessed through differences between commanded and actual velocity, variation during changing loads, acceleration and deceleration time, motor utilization, and the ability to maintain product control during peak operation. Accumulation performance has been evaluated through zone occupancy, queue duration, blocked time, starved time, uncontrolled contact between products, and the percentage of zones operating within established capacity limits (Plass et al., 2015). Product spacing has been measured through distance variation, gap-control accuracy, overlapping items, and the frequency of spacing conditions that interfered with scanning or diverting. Transfer accuracy has been examined at conveyor junctions, merges, curves, inclines, lifts, and workstation interfaces by measuring completed transfers, jams, dropped products, misalignment, and manual intervention. Sortation performance has been evaluated through items processed per hour, correct-divert percentage, missed diverts, incorrect destinations, chute utilization, scanner-to-diverter latency, and product recirculation. Recirculation has indicated whether items completed unnecessary movement because of unread labels, unavailable destinations, full chutes, delayed control commands, or failed diversion. Studies have also compared average and peak sorting capacity to determine whether controller performance remained stable as product volume and destination complexity increased (Tooby & Cosmides, 2015).

Figure 4: Material Handling Control Framework



False stops, sensor obstruction, drive trips, and communication delays have been quantified because each can reduce conveyor availability and increase downstream congestion. The literature indicates that higher belt speed does not always generate higher system throughput when package spacing, scanning, divert timing, or destination capacity is inadequate. Conveyor and sortation control must therefore be evaluated through combined measures of speed stability, accumulation, transfer timing, routing accuracy, equipment utilization, recirculation, and uninterrupted product movement.

Research on automated storage and retrieval systems has treated control performance as the coordinated execution of storage assignments, retrieval requests, crane or shuttle movement, positioning, loading, unloading, and inventory confirmation. Storage time has been measured from receipt of a valid task to successful placement and digital confirmation of the assigned location. Retrieval time has been assessed from order release to delivery at the required output station (Rothe et al., 2015). Cycle-time analysis has distinguished travel, acceleration, deceleration, positioning, load transfer, waiting, and confirmation durations. Single-command cycles have involved either storage or retrieval, while dual-command cycles have combined both functions to reduce empty travel and improve equipment utilization. Studies have evaluated the proportion of single and dual commands completed within expected periods and the effect of sequencing rules on total movement. Travel distance has been examined according to storage assignment, demand frequency, aisle depth, rack height, crane or shuttle availability, and the position of input and output stations. Location accuracy has been measured through correct placement, correct retrieval, positioning deviation, failed load detection, and inventory disagreement. Storage-location utilization has been assessed through occupied capacity, available space, inaccessible locations, assignment concentration, and the distribution of frequently requested items. Aisle congestion has been evaluated through competing requests, shuttle waiting, lift queues, blocked transfer stations, and task rescheduling (Cronrath et al., 2016). Empty travel has been used to identify movements that consumed time and energy without transporting material. Failed storage or retrieval attempts have included misaligned loads, occupied destination locations, unreadable identifiers, mechanical obstruction, and incomplete transfer confirmation. The reviewed evidence shows that storage density alone does not represent effective performance because retrieval speed, positioning accuracy, queue control, equipment reliability, and inventory consistency influence operational value. Automated storage control is consequently measured through time, distance, utilization, task completion, location accuracy, congestion, and recovery from failed movements (Pressley et al., 2015).

A synthesis of research on automated guided vehicles and autonomous mobile robots has identified

localization, routing, fleet coordination, congestion control, and energy management as central dimensions of equipment-specific performance. Localization accuracy has been evaluated by comparing estimated and actual vehicle positions, measuring navigation drift, detecting missed reference points, and recording the frequency of manual position correction. Route-completion performance has been measured through mission duration, travel distance, destination accuracy, delayed assignments, interrupted missions, and tasks completed per operating hour. Empty travel has been examined because vehicles frequently move without loads while collecting new materials, repositioning, traveling to charging stations, or responding to unbalanced task allocation. Routing studies have assessed fixed paths, dynamically selected paths, rerouting frequency, travel-time variation, and the ability to respond to unavailable aisles or workstations. Route conflicts and congestion have been measured through vehicle waiting, intersection queues, reduced-speed operation, repeated rerouting, and blocked destinations (Gibbons & Merwe, 2021). Deadlock occurrence has represented situations in which two or more vehicles could not continue without intervention or reassignment. Collision-avoidance performance has been evaluated through obstacle-detection accuracy, protective stops, near-conflict frequency, clearance distance, deceleration time, and successful navigation around temporary obstructions. Fleet utilization has been measured through loaded travel, empty travel, idle time, charging, waiting, maintenance, and unavailable time. Charging performance has included charging duration, queueing for chargers, battery-related mission interruption, and operating time between charging events. Earlier studies have shown that adding vehicles may increase capacity only until congestion, intersection conflict, and charging demand begin reducing marginal productivity (Schmidhalter et al., 2022). Mobile-robot control is therefore assessed through the balance among localization accuracy, mission completion, route efficiency, conflict resolution, safety response, vehicle availability, charging delay, and coordinated fleet utilization under varying order volumes.

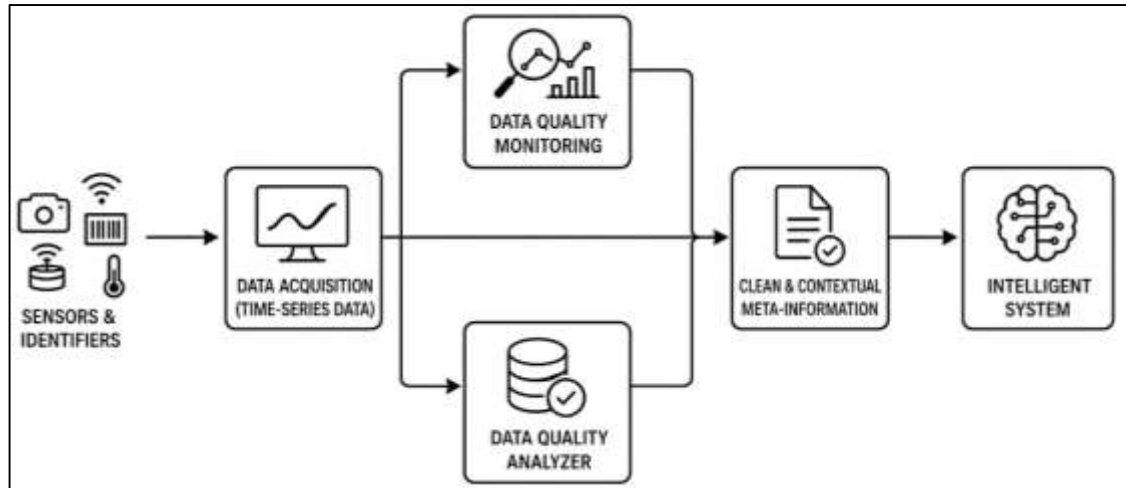
Sensing and Operational Data Quality

Evidence synthesized from more than ten empirical studies of industrial automation, material handling, machine vision, and distribution-center control has identified sensor coverage as the foundation of observable and controllable equipment behavior. Coverage has been measured through the percentage of conveyors, sorters, storage systems, mobile robots, palletizers, lifts, packaging machines, and dock-transfer assets connected to the control environment. Studies have also examined the proportion of required equipment states detected, including running, idle, blocked, starved, loaded, unloaded, faulted, unavailable, maintenance, and emergency stopped. Critical-variable coverage has included speed, position, load, current, temperature, vibration, product presence, destination, buffer occupancy, and safety-zone status (Nakousi et al., 2018).

Valid operating-hour coverage has been measured through the proportion of scheduled equipment time supported by complete and trustworthy signals. Object-detection performance has been evaluated using photoelectric, proximity, ultrasonic, vision, and presence sensors. Correct-detection percentage has represented products or obstacles recognized accurately, while missed-detection frequency has captured objects that passed without generating the required signal. False detections have included sensor activations caused by dust, vibration, reflection, background movement, electrical noise, or temporary obstruction. Response delay has been assessed from the moment an object entered the detection area to the time the controller received and processed the corresponding signal. Range accuracy, repeatability, sensitivity under changing product sizes, and performance during high-speed movement have also been examined.

Environmental conditions have been important because lighting variation can affect cameras, reflective packaging can affect optical sensors, and dust can reduce detection reliability (Khan & Yairi, 2018). The literature shows that a high number of installed sensors does not necessarily indicate adequate coverage when signals are unavailable, poorly positioned, incorrectly calibrated, or disconnected from control decisions. Effective sensing therefore combines equipment coverage, relevant state visibility, valid observation time, accurate detection, limited false triggering, predictable response, and reliable performance under actual operating conditions.

Figure 5: Operational Data Quality Framework



Research on barcode and radio-frequency identification systems has treated product identification as a measurable connection between physical material movement and its digital order, inventory, destination, and handling requirements (Erp et al., 2022). Barcode performance has been evaluated through successful first-pass reads, total read accuracy, unread-label frequency, duplicated scans, incorrect code interpretation, and processing time. Poor print quality, damaged labels, unsuitable placement, rapid movement, conveyor vibration, scanner angle, lighting, and contamination have been identified as common sources of unread or misinterpreted codes. Radio-frequency identification performance has been assessed through tag-detection rate, reader coverage, tag collision, duplicated reads, signal interference, orientation sensitivity, and the number of products identified simultaneously. Reader response time has been measured from the entry of a tagged or labeled product into the reading zone to the availability of validated identity information within the control system. Identification accuracy has also been evaluated by comparing the recorded product, pallet, tote, carton, or container with physical verification and order documentation. Studies have examined product-identity agreement across receiving, storage, retrieval, picking, sorting, packaging, staging, and shipping processes (Asadi et al., 2021). Disagreement between handling stages can cause incorrect routing, inventory inaccuracy, delayed orders, misplaced materials, and unnecessary manual investigation. Traceability performance has been assessed through the percentage of items with complete movement histories, time required to locate a product, number of unidentified transfers, and frequency of records that could not be matched with orders or destinations. The literature has also distinguished successful reading from successful operational use because an accurately captured identifier may still be associated with outdated routing rules, incorrect destination information, or delayed database confirmation. Identification capability is therefore represented through read accuracy, response speed, duplicate control, identity agreement, movement-history completeness, and consistent linkage among products, orders, inventory locations, and automated handling decisions. A synthesis of automated storage, robotic handling, mobile-vehicle, and industrial communication studies has shown that position and time accuracy jointly determine whether material movements are executed and reconstructed correctly (Besiktepe et al., 2021). Encoder performance has been assessed through position deviation, pulse loss, accumulated drift, repeated stopping accuracy, and disagreement between commanded and measured movement. In conveyor and sortation systems, positional errors can cause mistimed diversion, improper spacing, or transfer failure. In storage systems, inaccurate positioning can produce missed locations, unstable load transfer, or retrieval of the wrong material. Mobile-robot localization has been measured through differences between estimated and verified vehicle positions, navigation deviation, route correction, missed landmarks, and manual recovery frequency. Destination agreement has represented the proportion of missions completed at the correct workstation, storage location, production cell, packing area, or dock. Alignment time has

been examined for robots, lifts, cranes, shuttles, and transfer equipment because repeated positioning corrections can reduce throughput even when the final movement remains accurate. Temporal alignment has been evaluated through clock drift, timestamp deviation, delayed events, duplicated timestamps, out-of-order records, and unmatched equipment transitions (Teh et al., 2020). Sensors and controllers generally recorded events more rapidly than supervisory and business applications, creating potential differences in the apparent sequence of detection, control command, physical movement, alarm, fault, and recovery. Studies have examined whether an object was detected before a diverter command, whether a safety event preceded equipment stoppage, and whether maintenance activity followed the correct failure. Incorrect event order can weaken fault diagnosis, cycle-time measurement, routing analysis, and accountability. The reviewed evidence demonstrates that spatial and temporal errors are interdependent. Accurate position data without synchronized timestamps may be associated with the wrong movement, while aligned timestamps cannot correct an inaccurate location (Jesus et al., 2017). Reliable control therefore requires coordinated position measurement, localization, destination confirmation, common timing, and correctly ordered operational records.

Evidence from more than twenty studies of condition-based maintenance, industrial sensing, embedded diagnostics, and automated material handling has characterized condition-monitoring quality through signal availability, measurement validity, anomaly detection, diagnostic accuracy, and warning timeliness. Vibration, motor current, temperature, speed, torque, load, voltage, and operating-state measurements have been used to identify mechanical wear, misalignment, obstruction, excessive friction, overload, bearing deterioration, drive instability, and abnormal energy consumption. Signal completeness has been assessed through missing-data percentage, observation gaps, invalid values, disconnected tags, delayed transmission, and the proportion of operating time represented by usable measurements (Zhang et al., 2021). Valid-data coverage has distinguished recorded values from signals that met calibration, range, continuity, and quality requirements. Anomaly-detection performance has been evaluated through correctly identified abnormal conditions, false warnings, missed failures, classification accuracy, and the consistency of results across equipment types and operating loads. Failure-warning time has represented the interval between the first validated indication of deterioration and confirmed functional failure. Longer warning periods can provide greater opportunity for diagnosis and planned intervention, although warnings must remain sufficiently accurate to avoid unnecessary maintenance. Studies have also examined whether condition signals were connected with equipment identity, product flow, controller state, operating load, failure records, and completed maintenance actions (D'Aniello et al., 2017). Signals without this context can be difficult to interpret because high current, temperature, or vibration may be normal during peak loading and abnormal during light operation. Operational data quality therefore includes completeness, accuracy, consistency, timeliness, contextualization, and traceability. The literature presents effective sensing as an integrated measurement structure in which object detection, product identification, position information, synchronized events, and condition signals collectively support control execution, material traceability, fault diagnosis, reliability analysis, and verified operational performance (Sibai et al., 2017).

Deterministic Communication and Real-Time Coordination

Evidence synthesized from more than ten empirical studies of real-time control, industrial communication, and automated material handling has identified deterministic timing as the ability of controllers and networks to complete required operations within predictable time limits. Controller scan performance has been evaluated through average scan duration, maximum scan duration, and variation across repeated operating cycles. Average duration has represented normal processing demand, while maximum duration has indicated whether the controller approached or exceeded the permitted response boundary during peak activity. Task jitter has been measured through fluctuations in execution time caused by interrupt processing, communication requests, alarm handling, diagnostic routines, and changing input activity (Fredericks & Botts, 2018). Delayed tasks and missed deadlines have been examined because late sensor processing or actuator commands can produce transfer errors, incorrect sorting, unstable motion, and unsafe equipment interaction. Priority conflicts have been assessed when motion, safety, communication, diagnostic, and supervisory tasks competed for processing capacity. Industrial network performance has been measured through transmission latency,

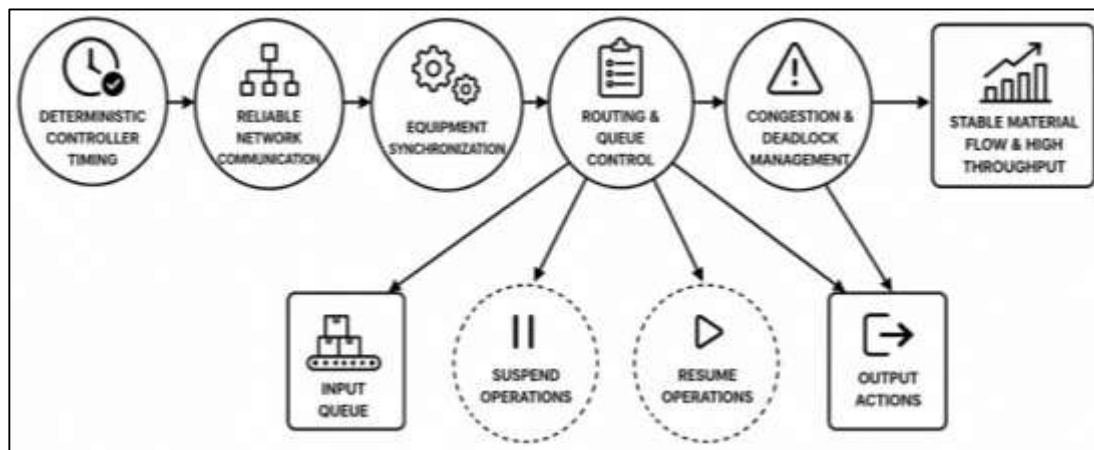
packet loss, message retries, network utilization, connection interruptions, and communication availability. Studies have distinguished average latency from peak latency because occasional severe delay can disrupt coordinated equipment even when general network performance remains acceptable. Message-loss frequency and retry behavior have been examined to determine whether commands, acknowledgements, product identities, and equipment states reached their intended destinations (Castell et al., 2017). Network bandwidth and utilization have been assessed under normal and peak traffic generated by controllers, scanners, mobile robots, cameras, safety devices, and supervisory systems. Communication recovery has been measured through interruption duration, reconnection time, buffered-message processing, and restoration of consistent equipment states. The literature shows that high-speed communication alone does not guarantee deterministic performance. Stable response requires controlled task scheduling, predictable latency, limited jitter, reliable delivery, sufficient bandwidth, and rapid recovery from communication disruption.

Research on conveyors, robots, lifts, scanners, storage systems, packaging machines, and dock-transfer equipment has treated synchronization as the coordinated timing and state alignment of interconnected material-handling resources (Barsi et al., 2019). Timing deviation has been measured by comparing the expected and observed start, completion, release, receipt, and acknowledgement times of connected equipment. Transfer coordination has been assessed through successful handoffs, product arrival within required timing windows, destination readiness, load acceptance, and confirmation that upstream equipment released material only after downstream capacity became available. Premature release can create collision, congestion, overflow, or product damage, while delayed release can reduce throughput and create upstream blocking. Missed handoffs have included products arriving before a receiving mechanism was positioned, robots attempting to collect absent items, lifts moving without confirmed loads, and sorters activating after products passed the divert point. State agreement has been evaluated by comparing local controller information with the states displayed by warehouse-control, warehouse-execution, and manufacturing systems (Seno et al., 2016). Conflicting representations of running, idle, blocked, starved, faulted, loaded, or unavailable equipment can lead to unsuitable routing and release decisions. Coordinated-cycle completion has been measured through the percentage of multi-equipment sequences completed without waiting, correction, recirculation, or manual intervention. Studies have also examined synchronization under different belt speeds, product dimensions, equipment loads, network conditions, and production volumes. Faster individual equipment did not necessarily improve facility performance when surrounding resources were unable to match its operating rate. The reviewed evidence indicates that synchronization quality depends on accurate state detection, common timing, reliable acknowledgements, controlled product release, and coordinated recovery after interruptions (Hu & Gharavi, 2021). Equipment synchronization therefore represents a system-level control capability that connects individual machine cycles with continuous material movement across several operational stages.

A synthesis of automated guided vehicle, mobile-robot, conveyor-routing, storage, and order-fulfillment studies has shown that routing and queue control determine how efficiently materials use available paths, equipment, buffers, and destinations. Routing performance has been evaluated through travel distance, route-calculation time, destination accuracy, completion duration, rerouting frequency, blocked routes, and missions completed within target periods. Fixed-routing strategies have provided predictable movement but have been less responsive to changing congestion or equipment availability (Lohstroh et al., 2020). Dynamic-routing strategies have used current queue, destination, traffic, priority, and equipment-state information to adjust movement decisions. Studies have examined whether reduced travel distance produced shorter completion time, lower energy consumption, fewer conflicts, and improved resource utilization. Destination accuracy has been measured through correctly completed missions, wrong-location deliveries, routing reversals, and manual corrections. Queue performance has been assessed through average and maximum queue length, waiting duration, arrival variation, service time, and the percentage of materials processed within acceptable waiting limits. Buffer utilization has been measured through average occupancy, peak occupancy, overflow events, empty periods, and time spent near maximum capacity.

Blocking has represented upstream equipment unable to release material, while starvation has represented downstream equipment waiting because required materials were unavailable (Arestova et al., 2021). Release-control accuracy has been evaluated through the proportion of materials released according to available downstream capacity, priority, order sequence, and handling restrictions. Earlier studies have shown that excessive buffers can reduce immediate blocking while increasing dwell time, inventory delay, occupied space, and identification complexity. Insufficient buffers can amplify small timing disturbances across connected equipment. Routing and buffer performance must therefore be examined together because route selection determines material arrival patterns, while queue and buffer controls determine whether those arrivals can be processed without disrupting the wider system (Cruces et al., 2018).

Figure 6: Real-Time Control Coordination Framework



Evidence from more than twenty studies of flexible manufacturing, mobile fleets, conveyor networks, and distribution automation has identified congestion and deadlock as system-level outcomes of interacting routes, queues, equipment states, and control priorities. Congestion duration has been measured through the time during which routes, intersections, transfer stations, aisles, sortation points, storage interfaces, or loading areas operated above acceptable occupancy. Route-conflict frequency has represented competing demands for the same path, destination, charging station, lift, or transfer resource (Raja et al., 2022). Deadlock events have occurred when two or more vehicles, products, or equipment units remained unable to continue because each depended on another blocked resource. Studies have assessed deadlock-detection time, automated resolution success, rerouting duration, priority reassignment, rollback activity, and manual intervention. Recirculation has been measured through repeated product movement caused by unavailable destinations, full chutes, identification problems, missed diverts, or unresolved congestion. Flow-recovery performance has included the time required to clear accumulated materials, restore consistent equipment states, restart suspended tasks, and return throughput to its previous level. Throughput loss has been quantified through unprocessed units, delayed orders, equipment idle time, blocked production supply, and reduced capacity during recovery (Cena et al., 2018). Manual intervention has included jam clearance, product repositioning, vehicle movement, route release, controller reset, and correction of inconsistent system records. The literature indicates that congestion cannot be explained solely by insufficient equipment capacity. It can also result from unsuitable routing rules, delayed state updates, uneven task allocation, poorly timed release, inadequate buffers, and weak recovery logic. Effective real-time coordination therefore combines deterministic controller timing, reliable communication, synchronized equipment, adaptive routing, balanced queues, controlled buffer occupancy, automatic conflict resolution, and verified recovery of material flow after operational disturbance (Jin et al., 2020).

Throughput, Order Fulfillment, and Material-Flow Outcomes

Evidence synthesized from more than ten empirical studies of distribution-center automation, manufacturing logistics, warehouse operations, and material-flow control has identified throughput as a central quantitative measure of automated handling performance. Throughput has been measured through pallets, cartons, totes, packages, components, or individual units handled per minute, hour, or operating shift. Average throughput has represented performance across routine operating periods, while peak throughput has captured the highest volume sustained during short intervals of elevated demand (Peng et al., 2021). Actual-to-designed capacity has been used to assess whether an automated system achieved the output specified during engineering and commissioning. Actual-to-planned volume has compared completed material movements with scheduled production, order, storage, or shipping requirements. Studies have also examined hourly throughput variability because a facility can achieve an acceptable daily total while experiencing substantial periods of congestion, starvation, interruption, or underutilization. Throughput loss during disturbances has been measured through unprocessed units, reduced movement rates, delayed orders, and the time required to recover the accumulated workload. Sustained capacity under high demand has been evaluated through the length of time a system maintained target output without excessive queue growth, equipment overheating, communication delay, or manual intervention (Santos et al., 2018).

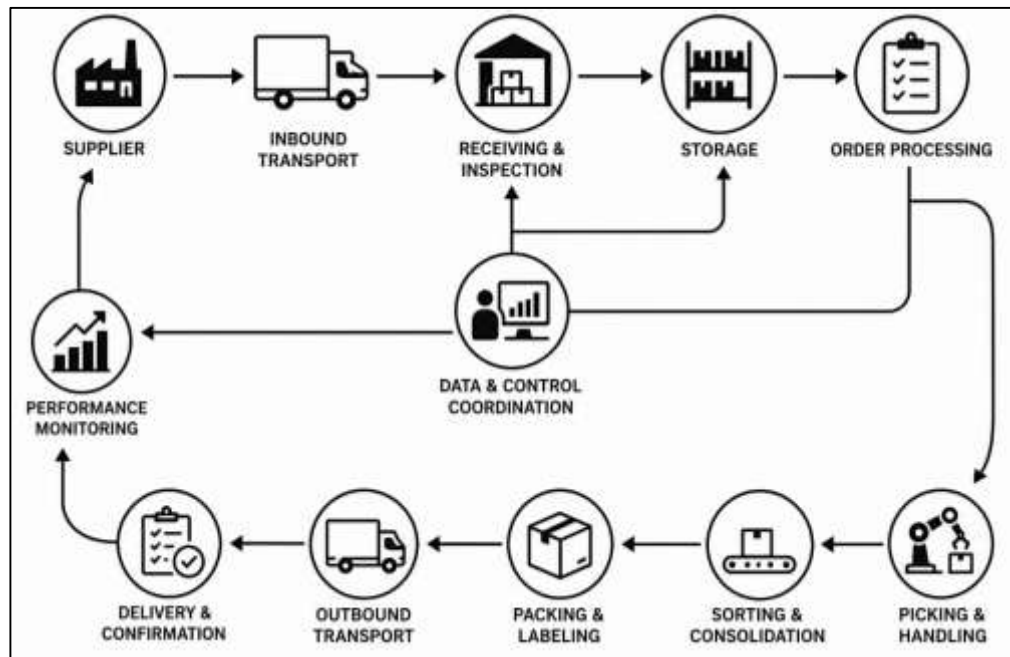
The literature has shown that maximum equipment speed and facility throughput are not equivalent. A fast conveyor, robot, or storage crane can transfer congestion to downstream resources when scanning, sorting, packaging, storage, or dock capacity is lower. Throughput has therefore been examined alongside equipment availability, buffer occupancy, routing efficiency, product mix, order priority, labor support, and destination readiness. Stable performance has been associated with balanced equipment rates and coordinated release control rather than continuous operation at maximum speed (Pfeiffer et al., 2015). Quantitative throughput evaluation consequently includes average volume, peak output, capacity attainment, time-based variability, disturbance loss, and the ability to maintain required material flow under changing workload conditions.

Research on automated handling has treated cycle time as a composite outcome created by multiple processing and waiting stages rather than a single movement duration. Total material-movement cycle time has been measured from the release of a valid handling request to confirmed delivery at the required destination (Kim et al., 2017). Detailed analysis has separated pickup, loading, travel, queueing, scanning, identification, sorting, storage, retrieval, transfer, unloading, and completion-confirmation time. Travel duration has reflected equipment speed and route distance, while waiting time has represented unavailable resources, competing tasks, blocked paths, full destinations, or priority decisions. Processing time has included scanning, verification, sorting, positioning, palletizing, packaging, and system confirmation. Studies have examined average, median, maximum, and high-percentile cycle times because extreme delays can affect production supply and customer orders even when average performance remains acceptable (Nyemba & Mbohwa, 2017).

Order completion has been assessed through total completed orders, on-time fulfillment, delayed-order frequency, order lead time, and the percentage of tasks completed within required service intervals. Urgent-order compliance has measured whether high-priority materials or customer orders received appropriate routing and resource allocation. Production-material delivery has been evaluated through the arrival of components at workstations before scheduled consumption, while dock-cutoff compliance has represented completion before carrier departure or shipping deadlines. The literature has shown that shorter equipment travel does not always produce shorter order lead time when materials remain in queues, await confirmation, or encounter unavailable downstream capacity (Afy-Shararah & Rich, 2018).

Control performance has therefore been examined through both physical movement and information-processing duration. Cycle-time analysis connects local equipment speed with routing, queue control, order priority, resource availability, and destination readiness. Order-fulfillment performance represents the facility-level result of these coordinated stages and provides a broader assessment than isolated machine-cycle measurements (Uriarte et al., 2017).

Figure 7: Automated Material Flow Framework



A synthesis of manufacturing distribution and warehouse-automation studies has shown that high throughput must be interpreted together with handling accuracy and product integrity. Picking accuracy has been measured through correctly selected products, incorrect items, missing quantities, overages, and short deliveries. Sorting accuracy has included correct destinations, missed diverts, incorrect chutes, recirculated items, and products requiring manual rerouting. Destination errors have been evaluated at storage locations, production workstations, packing areas, shipping lanes, and dock doors. Shipment discrepancies have included disagreement among physical contents, order records, inventory transactions, and shipping documentation (Gaspari et al., 2017). Product damage has been assessed through crushed packages, unstable pallets, dropped items, excessive impact, unsuitable acceleration, conveyor jams, and incorrect robotic gripping. Error-correction time has included identification, investigation, retrieval, repicking, resorting, data correction, repackaging, and reshipment. Studies have also examined bottleneck performance because constrained resources can increase both delay and error. Bottleneck frequency has represented how often equipment or work areas limited total material flow. Capacity utilization has been measured for sorters, storage cranes, lifts, robots, packing stations, scanners, buffers, and docks to identify resources operating consistently near their maximum rates (Hilmola & Gupta, 2015). Queue accumulation, constraint duration, blocked upstream equipment, and idle downstream equipment have been used to quantify the wider effect of local capacity restrictions. Production volume lost at bottlenecks has represented units that could not be processed or delivered within required periods. The literature indicates that attempts to increase output at upstream equipment can intensify queues and handling errors when constrained resources remain unchanged. Handling accuracy and bottleneck performance must therefore be evaluated within the same material-flow structure, balancing movement volume with correct identification, destination control, product protection, queue stability, and effective use of constrained capacity (Gould et al., 2016).

Reliability and System Recovery

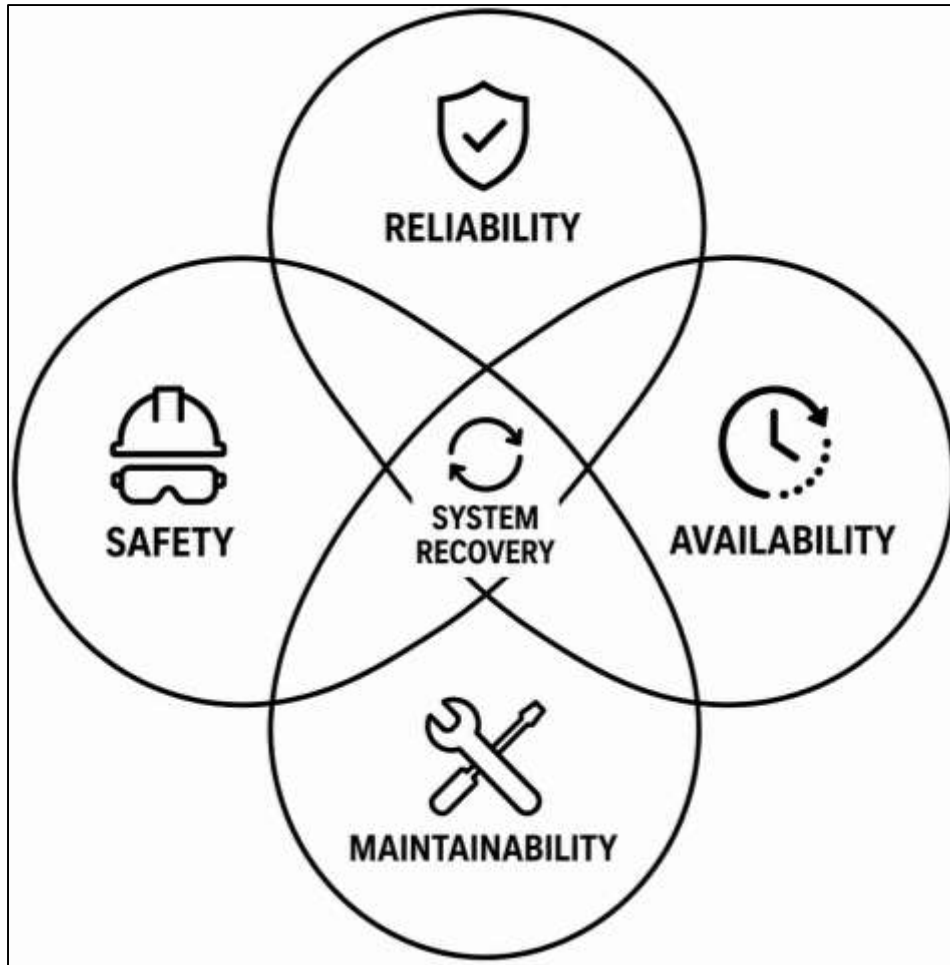
Evidence synthesized from more than ten empirical studies of automated material handling, industrial control, warehouse equipment, and maintenance engineering has identified failure frequency as a primary measure of system reliability. Total failures have included controller faults, sensor interruptions, motor and drive trips, actuator failures, communication losses, software-related stoppages, mechanical jams, identification errors, and safety-control interruptions. Failure counts have been reported by equipment unit, operating shift, production period, and facility (Kumar & Jain, 2020).

Failures per asset have supported comparisons among equipment populations of different sizes, while failures per operating hour have accounted for differences in utilization and exposure. Studies have distinguished control-system failures from mechanical interruptions because their detection, consequences, and repair requirements differ. Controller faults have included task overruns, memory errors, program exceptions, input and output failures, and processor resets. Sensor failures have involved missed detection, false signals, misalignment, contamination, wiring faults, and loss of calibration (Jain et al., 2020). Communication failures have included message loss, network outage, delayed state updates, and disconnection from supervisory systems. Mean time between failures has represented the average operating duration separating consecutive interruptions. This measure has been compared across conveyors, sorters, automated storage systems, mobile robots, palletizers, packaging machines, lifts, and transfer equipment. Equipment age, utilization, product loading, speed, environmental conditions, maintenance strategy, and control architecture have been identified as important sources of reliability variation (Al-Douri et al., 2020). High equipment utilization can increase exposure, while dust, vibration, temperature, and reflective products can affect sensing and mechanical performance. Distributed control may limit the effect of individual failures, while centralized control may create wider interruption when a common controller or network becomes unavailable. Reliability is therefore represented through failure type, frequency, operating exposure, affected equipment, interruption severity, and the duration of successful operation between events (Memon & Alam, 2016).

Industrial maintenance studies have characterized maintainability as the ability to identify, diagnose, repair, test, and restore failed material-handling equipment within an acceptable period. Mean time to repair has provided a summary measure, although detailed analysis has separated the restoration process into several intervals. Fault-detection time has represented the period between the occurrence of abnormal equipment behavior and its recognition by embedded diagnostics, operators, or supervisory systems. Maintenance-response time has measured the duration from confirmed detection to the arrival or assignment of qualified personnel (Heegaard et al., 2015). Diagnostic duration has included review of alarms, controller states, sensor values, network records, motion feedback, previous failures, and physical equipment conditions. Active repair has involved adjustment, cleaning, alignment, software correction, component replacement, wiring repair, drive reset, actuator servicing, and removal of mechanical obstruction. Spare-parts waiting time has been examined separately because equipment can remain unavailable even when diagnosis is complete. Validation and recommissioning have included safety inspection, input and output testing, trial movement, position confirmation, load testing, communication verification, and return to automatic operation. Studies have also measured restart delay and the time required for connected queues and equipment to return to normal throughput (Souza et al., 2016). Total restoration time has therefore extended beyond active repair and included administrative, logistical, technical, and operational delays. The literature has shown that embedded diagnostics can reduce troubleshooting time when fault messages identify the affected device, location, operating state, and probable cause. Poorly designed alarms can lengthen diagnosis when multiple messages appear without clear priority or causal order. Maintainability must consequently be evaluated through detection speed, response, diagnostic accuracy, repair efficiency, resource availability, verification quality, restart control, and successful restoration without early recurrence (Alvarez-Alvarado et al., 2022).

A synthesis of reliability and production-performance research has shown that equipment availability and utilization represent related but distinct outcomes. Technical availability has focused on whether equipment remained capable of performing its required function after accounting for failures and active repair. Operational availability has incorporated actual maintenance delays, spare-parts waiting, staffing limitations, communication interruptions, restart requirements, and other support conditions experienced within the distribution center. Utilization has represented the proportion of available time during which equipment performed productive material-handling activity (Shekhar et al., 2018). An asset can therefore record high availability while remaining underutilized because of low demand, unavailable orders, blocked routes, upstream starvation, downstream congestion, or production-independent waiting.

Figure 8: Integrated Reliability Recovery Framework



Studies have classified time into productive operation, planned maintenance, unplanned downtime, setup, waiting, blocked, starved, idle, charging, manual operation, and unavailable states. This classification has been important for conveyors, mobile robots, automated storage systems, sorters, palletizers, and dock-transfer equipment because each technology experiences different operational losses. Planned maintenance has included scheduled inspection, cleaning, calibration, lubrication, software updates, and component replacement (Maihulla & Yusuf, 2022). Unplanned downtime has included breakdowns, controller faults, jams, drive trips, safety events, and communication failures. Blocked time has represented equipment unable to release material, while starved time has represented equipment waiting for incoming work. Capacity use has been measured through actual throughput relative to the amount that available equipment could process. Earlier studies have shown that combining all nonoperating time into one category can misrepresent reliability and obscure routing, demand, or congestion problems (Zhang et al., 2018). Quantitative assessment therefore distinguishes technical failure from operational waiting and separates equipment capability from productive use. Availability and utilization together show whether automated assets were functional, whether they were required, and whether the wider material-flow system allowed their capacity to be used effectively.

Evidence from more than twenty studies of embedded diagnostics, fault-tolerant control, condition monitoring, and automated handling has identified diagnostic and recovery capability as central determinants of operational resilience (Saini et al., 2022). Fault coverage has been measured through the percentage of controller, sensor, actuator, drive, communication, and mechanical failures detected automatically. Isolation accuracy has represented the proportion of detected failures assigned to the correct device, location, subsystem, and probable cause. Missed faults have included failures that occurred without a diagnostic message, while false alarms have represented warnings generated when

equipment remained within acceptable operating conditions. Diagnostic processing time has been assessed from abnormal signal recognition to the availability of an interpretable fault classification. Warning lead time has measured the interval between the first validated indication of deterioration and functional interruption (Hastings, 2021). Studies have also examined whether maintenance decisions were supported by equipment-state histories, alarm sequences, sensor trends, operating loads, and previous recovery actions. Automatic recovery has included controller restart, message retransmission, sensor substitution, route reassignment, jam-clearing sequences, and resumption of interrupted tasks. Failover has been evaluated through backup-controller activation, redundant communication, alternative routing, replacement equipment, and transfer of tasks to available resources. Safe degraded operation has allowed limited material movement while preventing unsafe or uncontrolled behavior (Kumar et al., 2021). Recovery performance has been measured through restart time, restoration success, throughput recovery, repeated faults, incomplete task records, and manual intervention. First-time restoration success has indicated whether equipment returned to stable operation without another related failure during a defined period. The literature shows that rapid restart is not necessarily effective when the underlying fault remains unresolved or system states are inconsistent. Reliable recovery therefore requires accurate detection, correct isolation, controlled fault containment, verified restart, synchronized restoration of connected equipment, and confirmation that normal material flow has been re-established (Mollajan & Iranmanesh, 2021).

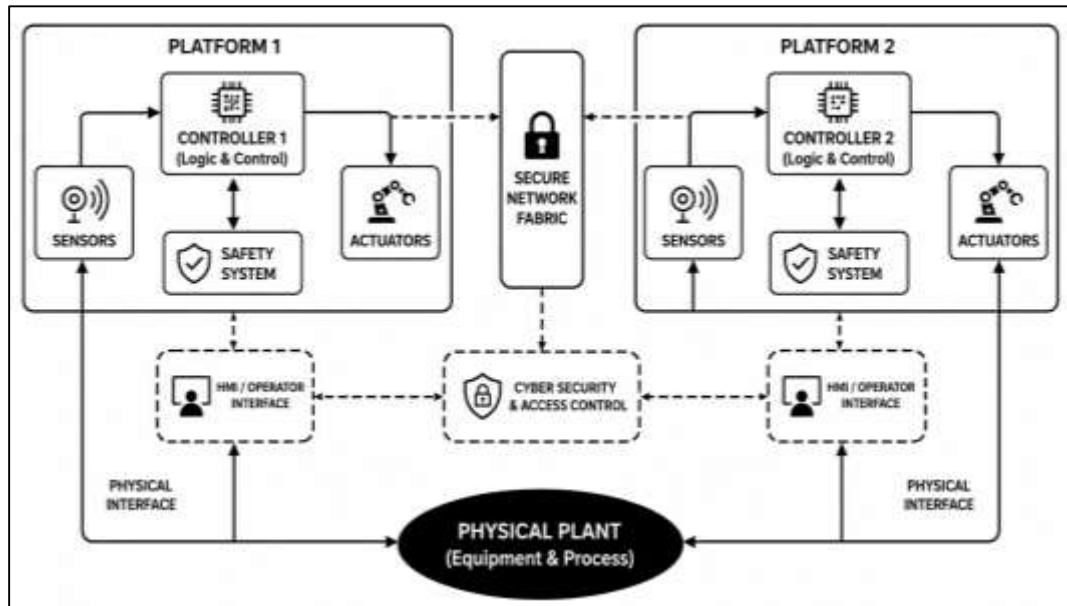
Functional Safety and Cyber-Physical Security

Evidence synthesized from more than ten empirical studies of industrial automation, robotic handling, machinery safety, and embedded control has identified functional safety as the ability of control systems to detect hazardous conditions and move equipment into a defined safe state. Protective-device coverage has been measured through the percentage of hazardous areas, movement zones, access points, and equipment functions monitored by guards, interlocks, light curtains, safety scanners, emergency-stop devices, presence sensors, and safety controllers (Guzman et al., 2020). Successful interlock operation has been evaluated through prevented starts, interrupted unsafe movements, guarded-door detection, speed restriction, load protection, and controlled isolation of hazardous energy. Safety-controller availability has represented the proportion of operating time during which required safety inputs, logic, communication, and outputs remained functional. Validation compliance has been measured through completed safety tests, documented inspection, verified stopping behavior, and confirmation that protective functions operated according to approved requirements (Lyu et al., 2019). Emergency-stop performance has been assessed through detection time, controller-processing time, output-response delay, controlled deceleration, total stopping time, and final stopping distance. Equipment isolation has included removal of motor torque, prevention of unintended restart, and separation of affected equipment from connected material flow.

Reset duration has been measured from hazard removal and authorized acknowledgment to the verified restoration of safe automatic operation. Studies have distinguished rapid stopping from controlled stopping because sudden motion interruption can create unstable loads, product damage, or secondary hazards. Reset authorization has also been examined to determine whether restart occurred only after protective zones were clear and equipment states were verified (Craggs & Rashid, 2017). Functional safety performance is therefore represented through protective coverage, successful detection, reliable interlocking, predictable stopping, controlled isolation, validated reset, and consistent operation across normal, abnormal, and recovery conditions.

Research on automated distribution and manufacturing systems has shown that safety performance must be evaluated together with the frequency and operational consequences of protective interruptions. False safety activations have occurred when scanners, light curtains, proximity devices, guards, or controller logic detected a hazardous condition that was not physically present (Guzman et al., 2021). Nuisance stops have included repeated interruptions caused by sensor misalignment, reflective packaging, dust, vibration, unsuitable detection zones, communication instability, or excessively sensitive control parameters. Studies have measured false-trip frequency, repeated activations by device, safety-related downtime, investigation duration, restart time, and production volume lost during interruptions.

Figure 9: Cyber-Physical Safety Control Framework



A high number of safety stops may indicate genuine exposure to hazardous interaction, weak material-flow design, equipment malfunction, or poorly configured protective devices. Quantitative interpretation has therefore required separation of valid interventions from false or unnecessary activations (Humayed et al., 2017). Lost operating time has included the initial stop, queue accumulation, fault investigation, zone inspection, reset authorization, equipment restart, and recovery of connected processes. Operator responses have been evaluated through acknowledgment time, adherence to reset procedures, bypass attempts, repeated alarms, and the consistency of intervention across shifts. Excessive nuisance stops can reduce trust in warnings and encourage unsafe informal recovery practices. Very low activation frequency does not automatically demonstrate strong safety because protective coverage or event recording may be incomplete. Earlier studies have therefore combined incident counts with device coverage, exposure hours, validation results, near misses, and unsafe-state detection (Wolf & Serpanos, 2017). Safety-related interruption is best evaluated through the accuracy and necessity of protective actions, the time required to investigate and recover, and the extent to which safety functions maintained protection without creating avoidable material-flow instability.

A synthesis of human-factors, warehouse automation, industrial-interface, and ergonomics studies has treated employee interaction as an integral part of embedded control performance. Operator workload has been assessed through the number of equipment units supervised, frequency of alarms, simultaneous tasks, decision time, manual recovery demands, and perceived mental effort (Yang et al., 2021). Alarm acknowledgment has been measured through response time, correct priority recognition, escalation compliance, and the proportion of warnings addressed within required intervals. Manual intervention has included jam clearance, product repositioning, route correction, controller reset, equipment inspection, data correction, and controlled restart. Recovery accuracy has represented the proportion of interventions completed without repeated faults, incorrect commands, product damage, or unsafe equipment states. Ergonomic exposure has been examined through walking distance, lifting, reaching, repetitive motion, awkward posture, time spent clearing obstructions, and entry into restricted operating areas (Abdi et al., 2018). Control-interface usability has been evaluated through screen-navigation time, information-retrieval speed, alarm-interpretation accuracy, control-selection accuracy, acknowledgment delay, and user error. Studies have also measured training duration, task completion after training, retention of procedures, and satisfaction with display clarity, terminology, navigation, and feedback. Interfaces containing excessive alarms, inconsistent equipment names, complex navigation, or unclear state information have been associated with delayed diagnosis and

incorrect recovery actions. Role-specific information has improved usability when operators received immediate state and routing information, maintenance personnel received diagnostic detail, and supervisors received system-level performance and escalation information (Kovtun et al., 2022). Human-automation performance is therefore represented through workload, response speed, intervention frequency, procedural accuracy, ergonomic exposure, interface comprehension, training effectiveness, and the ability to restore operation safely. Embedded control quality depends not only on automatic logic but also on how accurately employees interpret, supervise, and recover automated equipment (Link et al., 2018).

Energy and Economic Performance

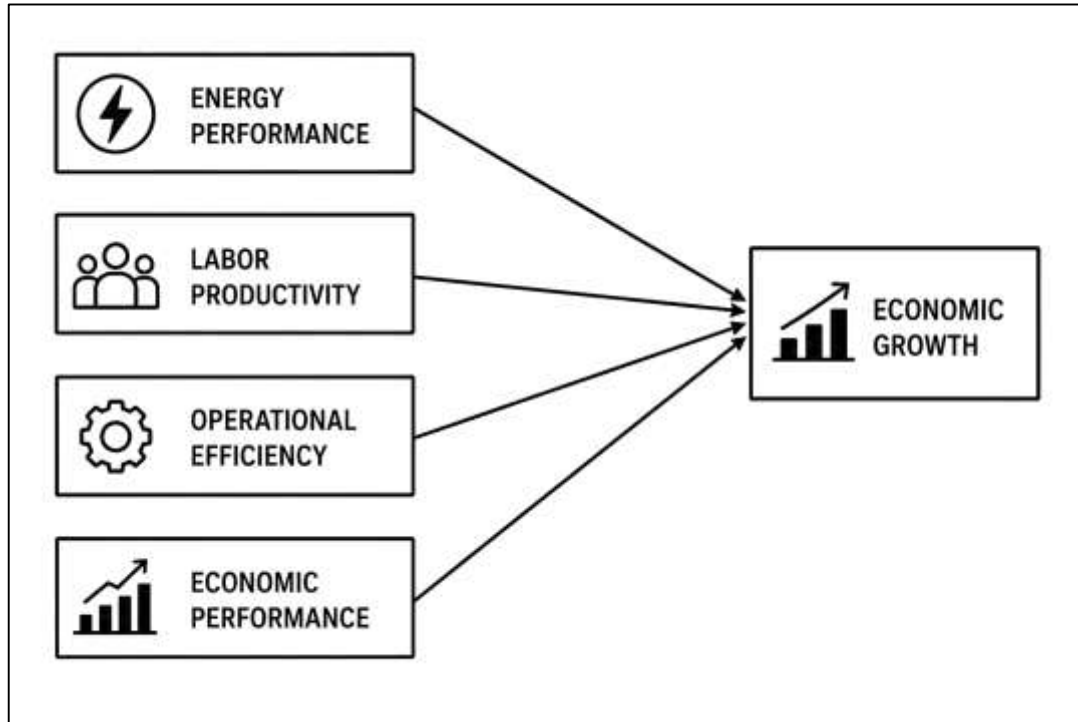
Evidence synthesized from more than ten empirical studies of automated material handling, industrial energy management, warehouse operations, and embedded control has identified energy consumption as a measurable outcome of equipment design, operating load, control logic, and material-flow conditions. Total electricity use has been assessed for conveyors, sorters, automated storage systems, mobile robots, palletizers, packaging machines, lifts, cranes, chargers, and supporting control infrastructure (Gu et al., 2018). Energy consumed per handled unit has allowed facilities processing different volumes to be compared more consistently. Motor and drive consumption has been measured through power demand, runtime, speed, torque, acceleration, deceleration, and load. Studies have separated operating states because equipment consumed different amounts of energy while moving materials, waiting, blocked, starved, faulted, charging, undergoing maintenance, or remaining ready without productive movement. Normal-operation demand has been compared with peak and disrupted periods to identify changes associated with heavier loads, repeated starts, congestion, recirculation, mechanical resistance, and equipment faults. Control settings have influenced consumption through belt speed, motor-starting sequence, acceleration profile, sleep mode, regenerative braking, routing, and automatic shutdown during extended inactivity (Bohi, 2017). Energy variation has also been evaluated according to product weight, distance traveled, vertical movement, equipment age, maintenance condition, and throughput. Earlier studies have shown that lower total energy use can reflect reduced production rather than improved efficiency, making output-adjusted measures necessary. Energy per unit, order, pallet, mission, or movement has therefore been interpreted together with throughput and operating time. Effective energy performance is represented by the ability to complete required material movements with controlled equipment load, limited unnecessary runtime, stable demand, and acceptable energy use across normal, peak, and disrupted operating conditions (Wang & Feng, 2015).

Research on automated distribution systems has shown that a substantial portion of energy consumption can occur without productive material movement. Idle consumption has included controllers, drives, motors, scanners, robots, conveyors, communication equipment, chargers, and safety systems remaining energized while awaiting tasks. Waiting energy has been measured during unavailable orders, blocked destinations, upstream starvation, queueing, production interruption, and delayed transportation. Congestion-related energy has included repeated acceleration and braking, recirculation, extended conveyor operation, vehicle rerouting, empty travel, and equipment operating near queues without completing useful transfers (Hosan et al., 2022).

Package recirculation has consumed energy through repeated scanning, sorting, conveying, and destination checking. Mobile-robot studies have assessed energy associated with empty travel, route conflicts, charging-station queues, and repeated navigation around blocked areas. Peak demand has been measured through maximum electrical load, duration above target demand, frequency of high-demand intervals, and the number of major assets operating or starting simultaneously. Simultaneous equipment starts can create short periods of high demand even when average consumption remains moderate. Load-balancing performance has been assessed through staggered startup, coordinated charging, task scheduling, equipment sequencing, and distribution of material flow across available resources (Yang & Zhang, 2018).

Studies have examined whether control-related demand reduction was achieved without increasing cycle time, delayed orders, or equipment congestion. Extended readiness has also been evaluated because immediate response requirements can conflict with energy-saving shutdown or sleep states.

Figure 10: Automation Performance Impact Framework



The literature indicates that energy efficiency depends on the coordination of operating states and material flow rather than on individual motor efficiency alone. Idle, waiting, recirculation, congestion, and peak-demand measures therefore reveal control losses that remain hidden within total electricity consumption and provide a more complete representation of the energy consequences of automated handling (Zhang et al., 2022).

A synthesis of manufacturing logistics and distribution-center studies has treated labor productivity as the relationship between material-handling output and the employee time required to operate, supervise, maintain, and recover automated systems. Units handled per labor hour has been used to compare productivity across shifts, facilities, equipment configurations, and automation levels. Handled units per employee has provided a broader measure of staffing efficiency, while staffing per shift has shown the number and type of personnel required to sustain planned throughput (Rehman et al., 2019). Studies have separated routine operating labor from technical support, maintenance, supervision, and unplanned recovery. Manual intervention hours have included jam clearance, product repositioning, route correction, equipment reset, data correction, identification verification, and controlled restart. Maintenance labor has been divided into preventive inspection, calibration, cleaning, planned replacement, troubleshooting, corrective repair, software support, and communication recovery. Overtime has been assessed during peak demand, equipment interruption, backlog recovery, major maintenance, and delayed order completion (Kebede & Heshmati, 2020). Training requirements have included initial instruction, equipment-specific qualification, safety procedures, control-interface use, diagnostic interpretation, and refresher training following system changes. Labor associated with automation recovery has been particularly important because a facility can achieve high routine productivity while requiring substantial employee effort during faults and disturbances. Earlier studies have shown that automation often changes the composition of labor rather than eliminating it, reducing repetitive movement while increasing technical monitoring, maintenance, diagnostic, and control responsibilities (Larrain et al., 2020). Labor productivity must therefore be interpreted together with skill requirements, intervention frequency, workload, ergonomic exposure, overtime, and recovery performance. A productive embedded-control environment supports high material output with limited unplanned intervention, appropriate staffing, manageable technical workload, and consistent performance across operating shifts.

Evidence from more than twenty studies of industrial automation, maintenance economics, and

distribution-center investment has characterized economic performance through implementation expenditure, recurring operating cost, maintenance cost, avoided loss, and capacity improvement (Ozcan & Ozturk, 2019). Maintenance expenditure has included preventive inspections, corrective labor, spare parts, software support, controller replacement, sensor calibration, drive repair, contractor services, and recovery following system interruption. Energy cost has been evaluated through total consumption, demand charges, idle use, charging, and energy per handled unit. Downtime loss has represented unprocessed orders, production-material shortages, delayed shipping, idle employees, underused transportation, and reduced facility capacity. Technical-support cost has included system administration, network maintenance, software licensing, specialist engineering, cybersecurity, and employee training (Rosa-Schleich et al., 2019). Operating cost per asset has supported equipment-level comparison, while cost per handled unit has linked expenditure with actual output. Automation investment performance has been assessed through implementation expenditure, operating savings, changes in labor cost, throughput gain, avoided downtime, increased storage or handling capacity, and improved asset utilization. Financial recovery periods have differed according to facility size, operating volume, equipment complexity, implementation scope, and baseline labor requirements. Large facilities have often distributed fixed automation costs across greater volumes, whereas smaller facilities have experienced different relationships among capital expenditure, utilization, and savings (Hirsch, 2017). Studies have also shown that investment performance can be weakened when equipment remains underutilized, requires frequent manual recovery, consumes excessive idle energy, or generates high maintenance costs. Economic evaluation therefore requires combined examination of technical performance, throughput, labor, energy, maintenance, downtime, and utilization. Embedded control investment is represented not only by initial acquisition cost but also by the extent to which control quality supports sustained capacity, reliable operation, efficient labor use, manageable energy demand, and lower cost per completed material movement (Colombo & Murtinu, 2017).

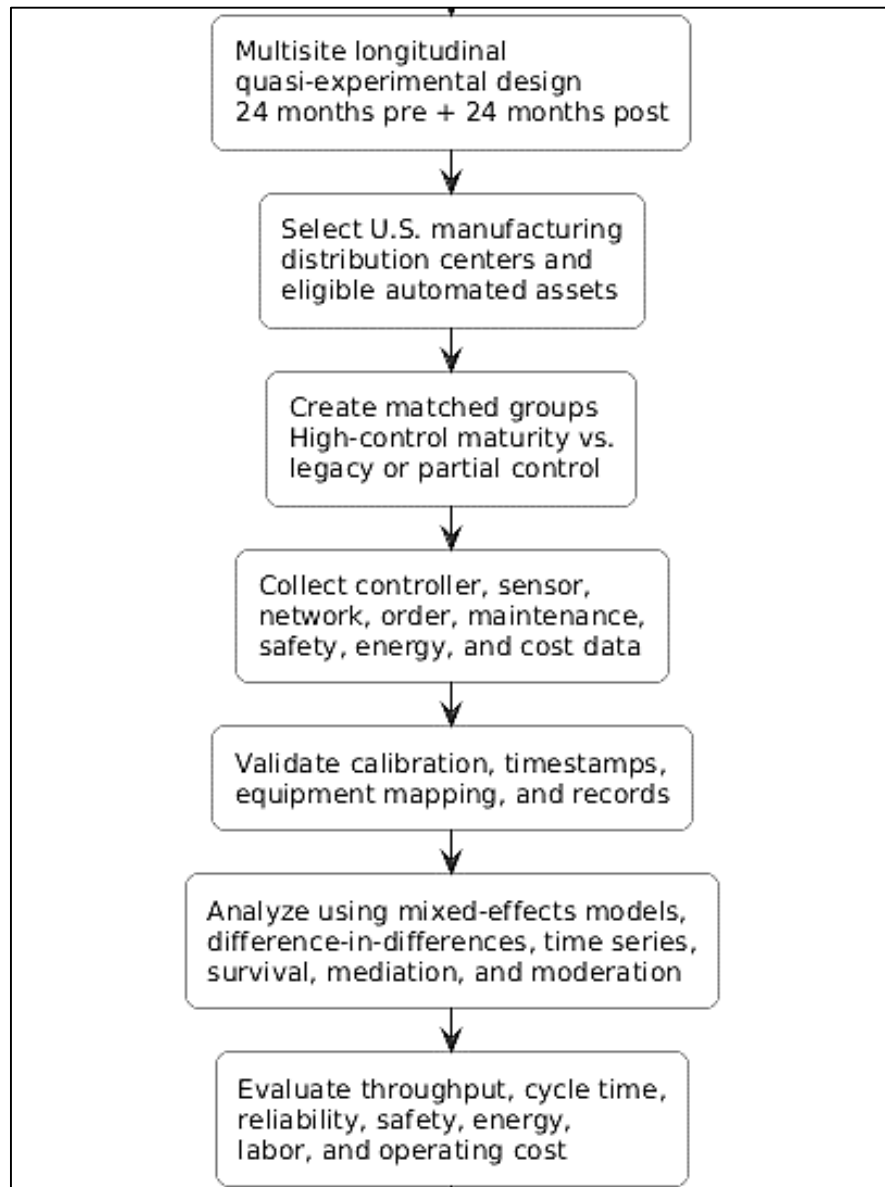
METHODS

This study employed a multisite, retrospective longitudinal, quasi-experimental quantitative design to examine the influence of embedded control system design on material-handling automation performance in U.S. manufacturing distribution centers. Random assignment was not feasible because control architectures, equipment installations, and modernization programs had been implemented through existing operational and capital-investment decisions. Automated handling assets operating under high-control-maturity conditions were compared with matched assets operating under legacy, partially integrated, or lower-maturity control conditions. Changes were also evaluated before and after verified embedded-control modernization dates. The observation period covered 48 consecutive months, comprising 24 premodernization and 24 postmodernization months. The principal unit of analysis was the automated equipment-month, while controller cycles, material movements, production orders, fault events, safety interruptions, maintenance records, and energy observations nested within equipment and facilities served as secondary units. The theoretical framework combined feedback-control theory, cyber-physical systems theory, organizational information-processing theory, socio-technical systems theory, and reliability theory. Embedded control design quality was treated as the principal independent construct and included controller processing, timing determinism, control-logic quality, input and output accuracy, actuation performance, communication reliability, equipment synchronization, diagnostics, fault recovery, functional safety, cybersecurity, and supervisory-system integration. Material-handling performance was treated as the dependent construct and was measured through throughput, capacity attainment, cycle time, order completion, handling accuracy, availability, utilization, failure occurrence, mean time between failures, mean time to repair, downtime, manual intervention, energy consumption, and operating cost. Real-time coordination, routing effectiveness, diagnostic visibility, and maintenance responsiveness were examined as mediating variables.

The study population consisted of automated material-handling assets operating in U.S. manufacturing distribution centers. Eligible facilities used combinations of conveyors, sortation systems, automated storage and retrieval equipment, automated guided vehicles, autonomous mobile robots, robotic palletizers, packaging machines, lifts, cranes, and dock-transfer systems. Facilities were selected through a multistage sampling procedure. Organizations were initially screened purposively because participation required accessible control-system, maintenance, production, order, safety, and energy

records. Eligible facilities were then stratified according to U.S. geographical region, manufacturing sector, facility size, material-flow configuration, automation maturity, and dominant equipment technology. Distribution centers were selected from the Northeast, Midwest, South, and West to represent variation in industrial activity, climate, infrastructure, workforce characteristics, and operating conditions.

Figure 11: Methodology of this study



Automated assets within each participating facility were stratified according to equipment category, system age, operational criticality, controller architecture, utilization, production loading, maintenance strategy, and baseline reliability. A census of all eligible automated equipment was conducted within the selected facilities. The preliminary sample contained both modernized high-control-maturity assets and lower-maturity comparison assets. Propensity-score matching was subsequently used to create comparable groups based on equipment category, age, operating hours, baseline failure frequency, average loading, facility size, product mix, maintenance strategy, environmental exposure, and premodernization performance. A simulation-based power analysis indicated that at least 420 assets were required to detect a small-to-moderate integration effect with 80% power at a two-tailed significance level of .05 while accounting for repeated observations and facility-level clustering. The

sampling target was increased to approximately 520 automated assets, with about 260 assets in each matched condition. The planned design generated up to 24,960 equipment-month observations across the 48-month period.

Automated material-handling assets were included when they had a stable and verifiable equipment identifier, a documented controller or control-zone reference, at least 12 months of valid premodernization observations, at least 12 months of valid postmodernization observations, recorded operating hours, accessible fault and maintenance histories, and measurable material-flow exposure. Eligible equipment was required to perform a recognizable movement, storage, retrieval, sorting, palletizing, packaging, lifting, routing, or dock-transfer function. Assets also required documented controller type, commissioning or modernization date, maintenance strategy, criticality classification, and connection with facility production or order processes.

Assets were excluded when they had been permanently decommissioned during the baseline period, had undergone complete mechanical replacement that prevented meaningful pre-post comparison, were used mainly as inactive standby equipment, lacked reliable operating-hour records, or could not be connected with production, controller, maintenance, and performance data. Equipment-month observations were excluded when the asset remained inactive for the entire month because of external facility closure, major construction, unavailable production demand, or events unrelated to material-handling performance. Observations were also excluded when controller data were unavailable for the full month or when operational exposure could not be verified. Short sensor gaps, temporary network interruptions, incomplete noncritical fields, and brief controller outages were not automatically excluded because these conditions represented measurable aspects of control and data quality.

Data were collected from embedded controllers, programmable logic controllers, industrial computers, drive systems, safety controllers, supervisory control applications, warehouse-control systems, warehouse-execution systems, warehouse-management systems, manufacturing-execution systems, maintenance databases, energy meters, and facility operational records. Controller logs supplied average and maximum scan time, processor utilization, memory consumption, task overruns, watchdog activation, program exceptions, input and output updates, command execution, and controller availability. Industrial network tools supplied message latency, packet loss, retry frequency, bandwidth utilization, connection interruptions, communication availability, and recovery duration. Sensor records included product presence, encoder position, speed, load, current, vibration, temperature, barcode reads, radio-frequency identification events, safety-zone activity, and equipment-state changes.

Warehouse and manufacturing applications supplied material-movement tasks, product identities, routes, destinations, order priorities, queue conditions, processing times, completed orders, throughput, sorting outcomes, inventory locations, and shipping results. Maintenance records supplied fault descriptions, response time, diagnosis, repair duration, labor hours, spare-parts use, restoration time, repeated failures, and maintenance expenditure. Energy meters supplied total electricity consumption, peak demand, operating-state demand, and energy consumed per handled unit. Safety and cybersecurity records supplied protective-device events, emergency stops, false trips, access violations, authentication failures, configuration changes, network anomalies, security incidents, and related service disruption.

A structured Embedded Control Design and Automation Maturity Assessment Instrument was completed by authorized controls engineers, automation specialists, maintenance personnel, operations supervisors, information-technology staff, safety professionals, and equipment operators. The instrument used five-point response categories and measured processing capability, timing determinism, logic quality, sensing, actuation, communication, synchronization, diagnostics, recovery, safety, cybersecurity, system integration, interface usability, employee competence, and governance maturity.

Content validity of the assessment instrument was established through review by specialists in embedded control, industrial automation, material handling, maintenance, safety engineering, and quantitative research. The instrument was pilot-tested among professionals and facilities that were not included in the final study. Item clarity, completion time, response variability, and construct coverage were examined before final administration. Internal consistency was assessed using Cronbach's alpha

and McDonald's omega, with coefficients of .70 or higher treated as acceptable. Exploratory factor analysis was conducted to identify the underlying measurement structure, followed by confirmatory factor analysis to test the proposed constructs. Composite reliability values of .70 or higher and average variance extracted values of .50 or higher were used to assess reliability and convergent validity. Discriminant validity was evaluated through correlations among constructs and comparison of shared and extracted variance.

Only measurements from sensors and meters with current calibration or documented functional verification were retained as valid primary observations. Calibration status, engineering unit, measurement range, installation location, inspection date, and quality flag were reviewed. Photoelectric and proximity sensors were tested using controlled objects, barcode and identification readers were checked using verified labels or tags, and encoders were compared with known movement distances. Energy meters were verified against facility reference instruments. Values outside valid ranges, signals marked as unreliable, and observations generated during known maintenance tests were flagged. Controller clocks, network devices, equipment systems, and operational databases were aligned to a common time reference. A sample of fault, downtime, routing, and safety events was independently classified by two trained assessors. Interrater agreement was evaluated through percentage agreement and a chance-adjusted reliability coefficient.

Embedded control design quality was calculated from controller performance, logic reliability, input and output accuracy, motion-control stability, communication performance, synchronization, diagnostics, fault recovery, safety, cybersecurity, and system integration. Controller timing included scan duration, task jitter, deadline misses, and response consistency. Control-logic quality included sequence completion, interlock success, invalid transitions, missed commands, and software exceptions. Sensing quality included equipment coverage, detection sensitivity, false triggers, identification accuracy, localization error, signal completeness, and timestamp consistency. Communication quality included network latency, message loss, retry frequency, availability, and recovery time.

Material-handling outcomes were calculated using standardized definitions across facilities. Throughput represented completed movements or handled units within defined operating periods. Cycle time began when a valid material-handling task was released and ended when delivery and completion were confirmed. On-time fulfillment represented tasks completed within their required intervals. Handling accuracy included correct picks, sorts, routes, destinations, and quantities. Failure was defined as an unplanned loss or unacceptable degradation of the required control or equipment function that produced repair, interruption, protective shutdown, or documented corrective action. Downtime began when equipment became unavailable for required operation and ended after testing and verified restoration. Manual intervention included resets, jam clearance, product repositioning, routing correction, data correction, and equipment restart. Energy intensity represented electricity consumed relative to handled output. Planned maintenance, demand-related idle time, blocked time, starvation, and external interruptions were coded separately from equipment failure.

The study followed a predefined chronological procedure. Organizational approval, facility participation agreements, data-access authorization, confidentiality arrangements, and cybersecurity clearance were obtained before data collection. Each participating facility provided equipment inventories, controller architectures, network diagrams, material-flow layouts, maintenance strategies, data dictionaries, and verified modernization dates. Modernization dates were confirmed through engineering-change records, commissioning documents, acceptance tests, controller backups, network logs, and evidence of sustained operational use. Pilot commissioning and temporary testing dates were not treated as operational modernization dates.

Equipment identifiers were mapped across controllers, warehouse applications, manufacturing systems, maintenance databases, safety records, and energy records. Eligible assets were screened, classified, and matched with their operating exposure and baseline characteristics. Raw data were extracted through approved read-only queries, secure exports, and validated interfaces. Facility and employee identifiers were replaced with coded values. Original data were preserved unchanged, while standardized analytical tables were created for equipment-months, controller cycles, material movements, order events, failures, downtime episodes, maintenance actions, safety interruptions,

manual interventions, energy observations, and operating costs.

Timestamps were converted to a common standard, engineering units were harmonized, duplicated events were identified, invalid measurements were flagged, and event sequences were reconstructed. A baseline dataset was created for the premodernization period, followed by an equivalent postmodernization dataset. Embedded control quality, real-time coordination, routing effectiveness, diagnostic visibility, and maintenance responsiveness indicators were computed. Performance outcomes were calculated for each equipment-month and event. Extracted totals were compared with facility reports and source-system summaries. The analytical database was locked after discrepancies had been reviewed, corrected, or documented.

Statistical analysis was performed using SPSS and R, while Python was used for approved data extraction, timestamp alignment, equipment linkage, validation, event reconstruction, and reproducible data preparation. Descriptive statistics included frequencies, percentages, means, standard deviations, medians, interquartile ranges, minimums, maximums, and 95% confidence intervals. Data distributions were examined using histograms, quantile plots, skewness, kurtosis, and normality tests. Baseline differences between high-control-maturity and comparison assets were evaluated using independent-samples *t* tests, Mann-Whitney tests, chi-square tests, or Fisher's exact tests. Differences among high-, medium-, and low-maturity groups were assessed using analysis of variance or the Kruskal-Wallis test. Standardized mean differences were used to evaluate matching balance.

Propensity scores were estimated through logistic regression using equipment type, age, criticality, operating hours, baseline failure occurrence, average loading, product mix, environmental exposure, maintenance strategy, facility size, region, and baseline material-handling performance. One-to-one nearest-neighbor matching was performed using a restricted matching distance. Alternative matching specifications and inverse-probability weighting were used in sensitivity analyses.

Failure counts, controller faults, safety interruptions, and manual recovery events were analyzed using generalized linear mixed-effects models. Poisson models were assessed initially, and negative-binomial models were used when overdispersion was present. Operating hours or handled units were incorporated as exposure measures, and random intercepts accounted for repeated observations within equipment and facilities. Results were reported as incidence-rate ratios with 95% confidence intervals. Handling errors, delayed orders, successful recovery, and repeated-failure occurrence were analyzed using mixed-effects logistic regression and reported through adjusted odds ratios.

Continuous outcomes, including throughput, cycle time, mean time between failures, mean time to repair, availability, utilization, network latency, synchronization error, energy intensity, labor productivity, and operating cost, were analyzed using linear mixed-effects models when assumptions were satisfied. Skewed duration, energy, and cost outcomes were analyzed using transformations or generalized models with appropriate distributions. Multivariable regression controlled for equipment age, category, loading, facility size, layout complexity, product mix, order variability, shift pattern, maintenance strategy, environmental conditions, and baseline performance.

The principal quasi-experimental effect was estimated through difference-in-differences analysis comparing premodernization-to-postmodernization changes among high-maturity assets with corresponding changes among matched comparison assets. Equipment and calendar-period effects were included to control for stable asset characteristics and common temporal changes. Preintervention trends and event-time coefficients were examined to evaluate the parallel-trends requirement. Interrupted time-series analysis used segmented regression to estimate immediate changes and postmodernization monthly trend changes. Autocorrelation, seasonality, heteroscedasticity, and nonstationary variance were examined and corrected when detected.

Time to first failure and time to repeated failure were examined using Kaplan-Meier estimates, log-rank tests, and proportional-hazards models with facility-level frailty terms. Recurrent-event models were used for equipment experiencing multiple interruptions. Multilevel mediation analysis examined whether real-time coordination, routing effectiveness, diagnostic visibility, and maintenance responsiveness transmitted the effect of embedded control design to material-handling performance. Indirect effects were evaluated using 5,000 bootstrap resamples.

Moderation was tested through interaction terms for facility size, layout complexity, automation maturity, equipment age, product mix, order variability, loading, employee competence, maintenance strategy, and environmental conditions.

Nonlinear and threshold effects were examined using maturity categories and segmented relationships.

Missing-data patterns were evaluated by variable, facility, equipment, and observation period. Multiple imputation was used for eligible covariates when the missing-data pattern supported that procedure. Complete-case and imputed estimates were compared. Statistical assumptions, residual distributions, influential observations, multicollinearity, model fit, proportional hazards, and predictive performance were evaluated systematically. All tests were two-tailed, and $p < .05$ was treated as statistically significant. Effect magnitudes were reported through incidence-rate ratios, odds ratios, hazard ratios, adjusted mean differences, standardized coefficients, Cohen's d , partial eta squared, and 95% confidence intervals. Robustness was examined through alternative matching, inverse-probability weighting, different control-maturity thresholds, alternative failure definitions, exclusion of major shutdown periods, facility-specific models, equipment-vendor controls, and placebo modernization dates.

FINDINGS

Final Facility, Equipment, and Observation-Sample Characteristics

Twenty-eight U.S. manufacturing distribution centers were initially assessed for participation. Eight facilities were excluded because four lacked complete controller, production, maintenance, safety, or energy records; two had unverifiable embedded-control modernization dates; one did not satisfy the required longitudinal observation period; and one could not authorize access to the required operational data. The final sample included 20 facilities, with five facilities from each of the Northeast, Midwest, South, and West. Ten facilities primarily operated high-control-maturity equipment, while ten operated legacy or partially modernized control environments. A total of 684 automated material-handling assets were screened, of which 112 were excluded during eligibility assessment.

The remaining 572 eligible assets comprised 291 high-control-maturity assets and 281 legacy or partial-control assets. One-to-one propensity-score matching produced 260 comparable assets in each condition, creating a final equipment sample of 520. The matched sample included conveyors, sorters, automated storage and retrieval systems, automated guided vehicles, autonomous mobile robots, robotic palletizers, packaging machines, lifts, cranes, and dock-transfer systems. The maximum longitudinal sample contained 24,960 equipment-month observations. After 490 observations with full-month controller unavailability, unverifiable operating exposure, or external facility suspension were removed, 24,470 valid equipment-months remained, representing 98.0% of the possible panel. Required-field completeness reached 97.8%, valid calibration coverage reached 96.9%, sensor gaps represented 1.9% of expected observations, and invalid measurements represented 1.1%. Unmatched cross-system events declined from 6.2% before equipment mapping to 1.6% after validation.

Table 1 shows that 20 of the 28 screened facilities satisfied all participation requirements and provided balanced geographical representation. Of 684 automated assets, 572 met the eligibility criteria and 520 remained after matching. The equal allocation of 260 assets to each control condition supported balanced comparative analysis. The retained 24,470 equipment-months represented 98.0% of all possible longitudinal observations. Large volumes of controller, movement, order, failure, safety, recovery, maintenance, and energy records provided sufficient depth for equipment-level and facility-level modeling. The 286 valid professional assessments supplemented system-derived measures of control maturity, usability, employee competence, safety, and governance. Before matching, the largest absolute standardized mean difference was .27 for baseline fault frequency, followed by .24 for equipment age and .22 for annual operating exposure. After matching, all standardized differences were .04 or lower. No statistically significant postmatching differences were found in equipment age, criticality, operating hours, production loading, layout complexity, order variability, maintenance strategy, baseline failure frequency, throughput attainment, energy intensity, or equipment-category distribution.

The final groups were therefore comparable on the principal characteristics likely to influence embedded-control and material-handling outcomes.

Table 1 Facility Screening, Equipment Selection, and Final Analytical Dataset

Selection stage or data category	Number	Percentage or retention
Facilities initially assessed	28	100.0%
Excluded for incomplete operational records	4	14.3%
Excluded for unverifiable modernization dates	2	7.1%
Excluded for insufficient observation period	1	3.6%
Excluded because of restricted data access	1	3.6%
Facilities retained	20	71.4%
Northeast facilities	5	25.0%
Midwest facilities	5	25.0%
Southern facilities	5	25.0%
Western facilities	5	25.0%
Automated assets initially screened	684	100.0%
Insufficient premodernization or postmodernization data	29	4.2%
Missing or unverifiable operating exposure	21	3.1%
Inactive standby equipment	14	2.0%
Complete mechanical replacement	13	1.9%
Decommissioned equipment	8	1.2%
Unreliable cross-system linkage	17	2.5%
Unverified controller or modernization information	10	1.5%
Assets satisfying eligibility criteria	572	83.6%
High-control-maturity assets before matching	291	50.9% of eligible assets
Legacy or partial-control assets before matching	281	49.1% of eligible assets
Final matched high-maturity assets	260	50.0% of final sample
Final matched comparison assets	260	50.0% of final sample
Maximum possible equipment-months	24,960	100.0%
Valid equipment-months retained	24,470	98.0%
Controller diagnostic records	214,638,920	—
Material-movement records	18,746,382	—
Production and fulfillment orders	1,286,714	—
Verified fault events	5,248	—
Safety-related interruptions	2,106	—
Manual recovery events	3,684	—
Maintenance records	6,912	—
Valid energy observations	17,618,400	—
Valid assessment-instrument responses	286	91.7% response validity

Table 2 demonstrates that propensity-score matching produced highly comparable control-maturity groups. Postmatching differences in equipment age, criticality, operating exposure, production loading, layout complexity, order variability, maintenance strategy, baseline failure occurrence, throughput attainment, and energy intensity were small and statistically nonsignificant.

Every absolute standardized mean difference remained at or below .04, substantially below the accepted .10 balance criterion. Conveyors, sorters, storage systems, guided vehicles, mobile robots, palletizers, packaging machines, lifts, cranes, and dock-transfer systems were also distributed similarly. Subsequent performance differences were therefore less likely to reflect baseline variation in equipment composition, operating conditions, maintenance strategy, or initial performance.

Table 2 Baseline Characteristics of the Final Matched Equipment Sample

Characteristic	High-control maturity (n = 260)	Legacy or partial control (n = 260)	Pre-match SMD	Post-match SMD	p
Facilities	10	10	—	.00	1.000
Equipment age, years, mean (SD)	7.8 (3.7)	7.9 (3.8)	.24	.03	.762
High-criticality equipment, n (%)	110 (42.3)	109 (41.9)	.18	.01	.926
Operating hours per year, mean (SD)	5,968 (1,146)	5,934 (1,171)	.22	.03	.738
Production loading, %, mean (SD)	78.2 (10.8)	77.8 (11.1)	.17	.04	.677
Layout complexity, mean (SD)	3.41 (0.82)	3.44 (0.80)	.15	.04	.673
Order-variability coefficient, mean (SD)	0.31 (0.12)	0.32 (0.13)	.14	.04	.364
Condition-based or predictive maintenance, n (%)	118 (45.4)	116 (44.6)	.16	.02	.859
Baseline faults per 1,000 operating hours, mean (SD)	0.214 (0.086)	0.217 (0.088)	.27	.03	.694
Baseline throughput attainment, %, mean (SD)	87.6 (7.9)	87.3 (8.1)	.19	.04	.669
Baseline energy intensity, kWh per handled unit	0.142 (0.041)	0.144 (0.043)	.18	.04	.588
Conveyors, n (%)	58 (22.3)	57 (21.9)	.08	.01	.914
Sortation systems, n (%)	31 (11.9)	32 (12.3)	.07	.01	.894
Automated storage and retrieval systems, n (%)	34 (13.1)	33 (12.7)	.09	.01	.898
Automated guided vehicles, n (%)	29 (11.2)	30 (11.5)	.06	.01	.895
Autonomous mobile robots, n (%)	27 (10.4)	26 (10.0)	.08	.01	.883
Robotic palletizers, n (%)	22 (8.5)	23 (8.8)	.05	.01	.877
Packaging machines, n (%)	24 (9.2)	23 (8.8)	.07	.01	.875
Lifts and cranes, n (%)	18 (6.9)	19 (7.3)	.06	.02	.864
Dock-transfer systems, n (%)	17 (6.5)	17 (6.5)	.04	.00	1.000

Note. SMD = standardized mean difference. Layout complexity was measured on a five-point scale, with higher values representing greater complexity.

Descriptive Control-System, Coordination, and Material-Handling Patterns

For descriptive analysis, the 520 matched assets were divided into three control-maturity tiers using the composite embedded control design score. The high-maturity tier included 174 assets, while the medium- and low-maturity tiers each included 173 assets. The mean control-maturity score was 88.3 in the high tier, 69.5 in the medium tier, and 44.2 in the low tier. Significant gradients were observed across controller timing, logic accuracy, input and output response, actuation precision, network performance, synchronization, diagnostics, recovery, safety, and supervisory-system integration. High-maturity controllers recorded an average scan time of 7.4 milliseconds, compared with 13.6 milliseconds for medium-maturity controllers and 25.8 milliseconds for low-maturity controllers. Deadline misses increased from 2.8 per million cycles in the high tier to 73.4 in the low tier. Sequence accuracy reached 99.5% under high maturity but declined to 93.2% under low maturity. Median network latency was 3.4 milliseconds in the high tier and 38.9 milliseconds in the low tier. Diagnostic

coverage, automatic recovery success, and supervisory integration coverage also demonstrated substantial maturity-related differences. Real-time coordination improved alongside embedded control maturity. High-maturity equipment achieved 98.9% routing accuracy and 94.2% automatic deadlock-resolution success. Low-maturity equipment recorded 91.8% routing accuracy and 43.7% automatic deadlock resolution. These differences indicated that controller and communication performance were closely connected with equipment-state visibility, transfer synchronization, routing responsiveness, queue control, and recovery from material-flow conflicts.

Table 3 Embedded Control and Real-Time Coordination Indicators by Control-Maturity Tier

Indicator	High maturity (n = 174)	Medium maturity (n = 173)	Low maturity (n = 173)	<i>p</i>	Effect size, η^2
Composite control-maturity score, mean (SD)	88.3 (4.8)	69.5 (5.7)	44.2 (7.5)	< .001	.79
Average controller scan time, ms, mean (SD)	7.4 (1.8)	13.6 (3.7)	25.8 (8.9)	< .001	.58
Maximum scan time, ms, median (IQR)	18.6 (14.2–24.8)	39.5 (28.0–56.3)	92.7 (61.0–146.2)	< .001	.51
Task jitter, ms, mean (SD)	1.2 (0.4)	3.7 (1.1)	9.8 (3.6)	< .001	.64
Deadline misses per million cycles	2.8 (1.6)	16.5 (8.7)	73.4 (31.8)	< .001	.56
Processor utilization, %, mean (SD)	51.6 (8.3)	64.8 (9.7)	78.9 (10.8)	< .001	.49
Sequence accuracy, %, mean (SD)	99.5 (0.3)	97.8 (1.2)	93.2 (3.6)	< .001	.62
Interlock success, %, mean (SD)	99.8 (0.2)	99.1 (0.6)	96.7 (1.9)	< .001	.55
Input-output response time, ms, mean (SD)	9.6 (2.8)	21.4 (6.3)	47.8 (17.5)	< .001	.60
Position error, mm, mean (SD)	2.1 (0.8)	4.8 (1.9)	9.7 (4.1)	< .001	.53
Network latency, ms, median (IQR)	3.4 (2.1–5.6)	12.7 (7.8–21.5)	38.9 (22.6–71.4)	< .001	.47
Message loss per 10,000 transmissions	0.6 (0.4)	3.8 (2.1)	14.2 (8.6)	< .001	.42
Transfer-timing deviation, ms, mean (SD)	12.4 (5.2)	38.6 (14.7)	109.2 (46.8)	< .001	.57
Diagnostic fault coverage, %, mean (SD)	94.8 (4.3)	79.6 (8.5)	58.4 (13.2)	< .001	.65
Automatic recovery success, %, mean (SD)	87.2 (7.9)	63.8 (11.6)	35.6 (15.4)	< .001	.68
Safety-function success, %, mean (SD)	99.8 (0.2)	99.2 (0.5)	97.1 (1.7)	< .001	.48
Supervisory-system integration, %, mean (SD)	95.4 (3.8)	76.2 (8.9)	48.9 (14.6)	< .001	.69
Real-time coordination score, mean (SD)	4.45 (0.31)	3.67 (0.46)	2.74 (0.62)	< .001	.66
Routing accuracy, %, mean (SD)	98.9 (0.7)	96.4 (1.8)	91.8 (4.2)	< .001	.59
Automatic deadlock-resolution success, %	94.2 (4.9)	74.5 (10.8)	43.7 (16.6)	< .001	.67

Note. IQR = interquartile range. The Kruskal–Wallis test was used for heavily skewed timing indicators; other comparisons used analysis of variance.

Table 3 demonstrates a strong and statistically significant maturity gradient across control and coordination indicators. High-maturity assets achieved faster and more stable controller execution, fewer deadline misses, stronger sequence and interlock accuracy, shorter network latency, lower message loss, and smaller transfer-timing deviations. The largest maturity differences occurred in control score, automatic recovery, supervisory integration, deadlock resolution, real-time coordination, and diagnostic coverage. Medium-maturity equipment consistently occupied an intermediate position. The effect sizes indicated that these differences were operationally substantial rather than products of the large observation volume. Strong embedded control was therefore accompanied by reliable communication, synchronized equipment states, effective routing, and faster recovery from material-flow disruption. Before modernization, the matched high-maturity and comparison groups recorded similar throughput, cycle time, order completion, handling accuracy, availability, utilization, fault occurrence, repair duration, downtime, energy intensity, labor productivity, and operating cost. Following modernization, high-maturity assets recorded substantial descriptive improvements across all principal outcomes. Average throughput increased from 842 to 1,018 handled units per hour, while capacity attainment increased from 87.6% to 96.1%. Movement cycle time declined by 3.3 minutes, and average queue duration declined from 5.6 to 3.4 minutes. On-time order completion increased by 6.9 percentage points, while handling accuracy increased from 99.12% to 99.66%. Equipment availability increased from 93.8% to 97.0%, and utilization increased by 6.5 percentage points. Failure occurrence decreased from 0.214 to 0.139 events per 1,000 operating hours, mean time between failures increased by 2,522 hours, and mean time to repair declined by 2.7 hours. Smaller changes occurred among legacy or partially controlled assets.

Table 4 shows that the matched groups had closely aligned material-handling performance before modernization. During the postmodernization period, high-maturity equipment recorded larger improvements across every outcome. Throughput, capacity attainment, order completion, handling accuracy, availability, utilization, failure-free operation, and labor productivity increased. Cycle time, queue duration, failure occurrence, repair time, downtime, manual intervention, safety interruption, energy intensity, and operating cost decreased.

The comparison group experienced only modest changes over the same period. These descriptive differences provided a consistent preliminary pattern, while causal interpretation remained dependent on adjusted mixed-effects, difference-in-differences, interrupted time-series, and sensitivity analyses. Monthly analysis showed that controller and network improvements appeared earlier than broader material-flow outcomes. Average scan time decreased from 21.8 milliseconds during the first postmodernization month to 9.1 milliseconds by month three. Median network latency declined from 31.6 to 4.2 milliseconds by month six, while sequence accuracy exceeded 99% by month four. Throughput and queue improvements became visible between months three and six, whereas reliability, availability, energy, and cost improvements developed progressively between months six and eighteen. Embedded control design quality was strongly correlated with real-time coordination, $r = .74$, routing effectiveness, $r = .68$, diagnostic visibility, $r = .66$, and maintenance responsiveness, $r = .60$.

Positive relationships were observed with throughput, availability, labor productivity, and order completion, with coefficients ranging from .47 to .53. Negative relationships were found with movement cycle time, failure occurrence, downtime, energy intensity, and operating cost, with coefficients ranging from $-.39$ to $-.51$. All principal correlations were statistically significant at $p < .001$. Failure counts were overdispersed, while cycle time, downtime, energy use, and cost displayed positive skewness, supporting the use of negative-binomial, generalized mixed-effects, and transformed models in subsequent analyses.

Table 4 Premodernization and Postmodernization Material-Handling Outcomes by Matched Group

Outcome	High maturity pre, mean (SD)	High maturity post, mean (SD)	Comparison pre, mean (SD)	Comparison post, mean (SD)
Throughput, handled units per hour	842 (156)	1,018 (172)	836 (153)	867 (159)
Capacity attainment, %	87.6 (7.9)	96.1 (5.4)	87.3 (8.1)	88.8 (7.6)
Material-movement cycle time, minutes	14.8 (5.2)	11.5 (3.8)	14.7 (5.1)	14.3 (4.9)
Queue duration, minutes	5.6 (3.1)	3.4 (2.0)	5.5 (3.0)	5.1 (2.8)
On-time order completion, %	89.4 (6.8)	96.3 (4.1)	89.1 (7.0)	90.2 (6.5)
Handling accuracy, %	99.12 (0.63)	99.66 (0.29)	99.08 (0.66)	99.18 (0.57)
Equipment availability, %	93.8 (3.2)	97.0 (1.9)	93.7 (3.1)	94.2 (2.9)
Equipment utilization, %	78.6 (9.4)	85.1 (7.2)	78.4 (9.2)	79.5 (8.8)
Failures per 1,000 operating hours	0.214 (0.086)	0.139 (0.062)	0.217 (0.088)	0.208 (0.083)
Mean time between failures, hours	4,672 (1,684)	7,194 (2,216)	4,610 (1,652)	4,801 (1,706)
Mean time to repair, hours	8.9 (4.7)	6.2 (3.4)	8.8 (4.6)	8.5 (4.4)
Annual downtime, hours per asset	142.6 (74.8)	91.4 (53.6)	140.8 (72.9)	134.2 (69.7)
Manual interventions per 1,000 movements	3.8 (2.1)	1.9 (1.2)	3.7 (2.0)	3.4 (1.8)
Safety interruptions per 1,000 operating hours	0.86 (0.42)	0.56 (0.31)	0.84 (0.41)	0.80 (0.39)
Energy intensity, kWh per handled unit	0.142 (0.041)	0.119 (0.033)	0.144 (0.043)	0.140 (0.040)
Labor productivity, units per labor hour	118.4 (24.6)	143.6 (27.8)	117.9 (24.1)	122.3 (25.0)
Operating cost, USD per 1,000 handled units	186.7 (48.3)	157.4 (39.6)	185.9 (47.8)	181.8 (45.9)

Primary Effects of Embedded Control Design on Automation Performance

The adjusted analyses showed that embedded control modernization was associated with statistically significant and operationally meaningful improvements across the principal material-handling outcomes. The negative-binomial mixed-effects model indicated that high-control-maturity assets experienced a 33% lower failure rate than matched legacy or partial-control assets after adjustment for equipment age, category, criticality, operating exposure, production loading, facility size, layout complexity, product mix, order variability, shift pattern, maintenance strategy, environmental conditions, geographical region, and baseline performance. The adjusted incidence-rate ratio was 0.67, with a 95% confidence interval from 0.60 to 0.75. Controller-fault and manual-recovery rates were 39% and 46% lower, respectively, among high-maturity assets. Safety-related interruption frequency was 28% lower. The odds of delayed order completion and handling error were 54% and 42% lower, respectively. High-maturity equipment recorded 2.34 times greater odds of successful automatic recovery without manual intervention. Adjusted throughput increased by 148 handled units per hour, capacity attainment increased by 7.10 percentage points, and movement cycle time declined by 2.88 minutes. Queue duration decreased by 1.79 minutes, while on-time completion and handling accuracy

increased by 5.76 and 0.43 percentage points, respectively. Mean time between failures increased by 2,340 hours, mean time to repair decreased by 2.38 hours, and annual downtime declined by 45.2 hours per asset. Energy intensity decreased by 0.0188 kWh per handled unit, labor productivity increased by 21.1 units per labor hour, and operating cost declined by USD 25.60 per 1,000 handled units.

Table 5 Unadjusted and Adjusted Effects of High Embedded Control Maturity

Outcome	Unadjusted estimate	Adjusted estimate	95% CI	<i>p</i>	Effect magnitude
Equipment failures, incidence-rate ratio	0.69	0.67	0.60 to 0.75	< .001	33% lower rate
Controller faults, incidence-rate ratio	0.64	0.61	0.53 to 0.70	< .001	39% lower rate
Manual recovery events, incidence-rate ratio	0.57	0.54	0.46 to 0.63	< .001	46% lower rate
Safety interruptions, incidence-rate ratio	0.75	0.72	0.58 to 0.89	.003	28% lower rate
Delayed orders, odds ratio	0.49	0.46	0.38 to 0.56	< .001	54% lower odds
Handling errors, odds ratio	0.61	0.58	0.42 to 0.80	.001	42% lower odds
Successful automatic recovery, odds ratio	2.28	2.34	1.82 to 3.01	< .001	134% higher odds
Throughput, handled units per hour	+145	+148	131 to 165	< .001	<i>d</i> = 0.82
Capacity attainment, percentage points	+7.00	+7.10	6.24 to 7.96	< .001	<i>d</i> = 0.91
Movement cycle time, minutes	-2.90	-2.88	-3.31 to -2.45	< .001	<i>d</i> = -0.65
Queue duration, minutes	-1.80	-1.79	-2.08 to -1.50	< .001	<i>d</i> = -0.61
On-time order completion, percentage points	+5.80	+5.76	5.02 to 6.50	< .001	<i>d</i> = 0.78
Handling accuracy, percentage points	+0.44	+0.43	0.27 to 0.59	< .001	<i>d</i> = 0.58
Availability, percentage points	+2.70	+2.68	2.31 to 3.05	< .001	<i>d</i> = 0.83
Utilization, percentage points	+5.40	+5.36	4.59 to 6.13	< .001	<i>d</i> = 0.64
Mean time between failures, hours	+2,331	+2,340	2,012 to 2,668	< .001	<i>d</i> = 0.88
Mean time to repair, hours	-2.40	-2.38	-2.91 to -1.85	< .001	<i>d</i> = -0.52
Annual downtime, hours per asset	-44.6	-45.2	-52.7 to -37.7	< .001	<i>d</i> = -0.64
Energy intensity, kWh per handled unit	-0.0190	-0.0188	-0.0224 to -0.0152	< .001	<i>d</i> = -0.49
Labor productivity, units per labor hour	+20.8	+21.1	18.4 to 23.8	< .001	<i>d</i> = 0.77
Operating cost, USD per 1,000 units	-25.2	-25.6	-30.7 to -20.5	< .001	<i>d</i> = -0.55

Note. Continuous estimates represented adjusted differences between premodernization-to-postmodernization changes in high-maturity assets and corresponding changes in matched comparison assets.

Table 5 demonstrates that covariate adjustment did not materially reduce the estimated embedded-control effects. High maturity was associated with fewer failures, controller faults, manual recoveries,

safety interruptions, delayed orders, and handling errors. Positive effects were observed for automatic recovery, throughput, capacity attainment, order completion, availability, utilization, failure-free operation, and labor productivity. Cycle time, queue duration, repair time, downtime, energy intensity, and operating cost decreased significantly. Confidence intervals excluded the null value for every principal outcome. The largest standardized effects were recorded for capacity attainment, mean time between failures, availability, throughput, on-time completion, and labor productivity, demonstrating substantial operational importance. The difference-in-differences models confirmed that improvements among high-control-maturity assets exceeded the corresponding changes among matched comparison assets. The joint test of premodernization event-time coefficients was nonsignificant, $\chi^2(23) = 20.14$, $p = .63$, supporting the parallel-trends requirement. No significant anticipatory changes were detected before the verified modernization dates. Interrupted time-series analysis showed that controller-sensitive and coordination outcomes improved immediately, while reliability, energy, and cost outcomes developed more gradually. Throughput increased immediately by 42 units per hour and subsequently increased by 4.4 units per hour during each postmodernization month. Movement cycle time declined immediately by 0.72 minutes and continued to decrease by 0.090 minutes per month. Failure occurrence decreased immediately by 0.014 events per 1,000 operating hours and subsequently declined by 0.0021 events per month. Availability increased immediately by 0.64 percentage points and subsequently increased by 0.085 percentage points per month. Mean time between failures increased by 372 hours at modernization and by an additional 82 hours per month. Energy intensity and operating cost also demonstrated significant immediate reductions followed by continuing monthly decreases.

Table 6 Difference-in-Differences and Interrupted Time-Series Estimates

Outcome	Adjusted difference-in-differences estimate	95% CI	Immediate level change	<i>p</i>	Monthly trend change	<i>p</i>
Failures per 1,000 operating hours	-0.064	-0.073 to -0.055	-0.014	< .001	-0.0021	< .001
Throughput, handled units per hour	+148	131 to 165	+42	< .001	+4.40	< .001
Capacity attainment, percentage points	+7.10	6.24 to 7.96	+1.58	< .001	+0.230	< .001
Movement cycle time, minutes	-2.88	-3.31 to -2.45	-0.72	< .001	-0.090	< .001
Queue duration, minutes	-1.79	-2.08 to -1.50	-0.43	< .001	-0.057	< .001
On-time completion, percentage points	+5.76	5.02 to 6.50	+1.32	< .001	+0.185	< .001
Availability, percentage points	+2.68	2.31 to 3.05	+0.64	< .001	+0.085	< .001
Utilization, percentage points	+5.36	4.59 to 6.13	+1.28	< .001	+0.170	< .001
Mean time between failures, hours	+2,340	2,012 to 2,668	+372	.002	+82.0	< .001
Mean time to repair, hours	-2.38	-2.91 to -1.85	-0.50	.003	-0.078	< .001
Downtime, hours per asset-month	-3.77	-4.39 to -3.15	-1.01	< .001	-0.115	< .001
Energy intensity, kWh per handled unit	-0.0188	-0.0224 to -0.0152	-0.0044	< .001	-0.00060	< .001
Labor productivity, units per labor hour	+21.1	18.4 to 23.8	+5.3	< .001	+0.658	< .001
Operating cost, USD per 1,000 units	-25.6	-30.7 to -20.5	-6.4	< .001	-0.800	< .001

Note. Immediate level changes represented changes at the verified modernization point. Monthly trend changes represented differences between premodernization and postmodernization slopes after adjustment for the matched comparison group.

Table 6 shows that embedded-control modernization produced immediate performance changes followed by sustained monthly improvement. Throughput, capacity attainment, order completion, availability, utilization, failure-free operating time, and labor productivity increased after modernization. Failure occurrence, movement cycle time, queue duration, repair time, downtime, energy intensity, and operating cost decreased. Controller-sensitive outcomes changed rapidly, while reliability and economic gains accumulated throughout the postmodernization period. The nonsignificant joint pretrend test supported the difference-in-differences design, and the significant postmodernization slope estimates strengthened the temporal evidence. These results indicated an early coordination response followed by progressively larger material-flow, reliability, energy, and cost improvements.

Secondary, Subgroup, Survival, Mediation, and Moderation Findings

Subgroup analysis showed that embedded control modernization was associated with lower failure occurrence across every equipment category. The strongest adjusted reductions were observed among sortation systems, robotic palletizers, conveyors, and automated storage and retrieval systems. Smaller reductions were recorded for packaging machines, lifts, cranes, and dock-transfer equipment. The overall interaction between control maturity and equipment category was not statistically significant, $p = .54$, indicating that the direction and general magnitude of the modernization effect remained consistent across material-handling technologies. Significant effect differences were found according to operational criticality, controller architecture, maintenance strategy, automation maturity, and baseline failure frequency. High-criticality equipment recorded a 43% reduction in failure occurrence, compared with a 25% reduction among medium- and low-criticality equipment. Assets using distributed control architectures experienced a 42% reduction, while centralized legacy architectures experienced a 25% reduction. Condition-based or predictive maintenance was associated with a 44% reduction in failure occurrence. The strongest relationship occurred within the high-automation-maturity group, $IRR = 0.52$. Equipment age, facility size, layout complexity, order variability, production loading, and environmental conditions produced directional differences, although not every interaction reached statistical significance.

Table 7 shows that embedded control modernization was associated with reduced failure occurrence across all equipment categories. The effect was strongest among high-criticality assets, distributed control architectures, condition-monitored equipment, digitally mature facilities, and equipment with high baseline failure frequency. Asset-category heterogeneity was nonsignificant, demonstrating broad consistency across material-handling technologies. Significant interactions were identified for criticality, controller architecture, maintenance strategy, automation maturity, and baseline failure occurrence. Equipment age, facility size, layout complexity, and loading altered effect magnitude without changing its direction. Smaller dock-transfer and lifting samples produced wider confidence intervals, although their estimates remained statistically significant and operationally favorable. Kaplan-Meier analysis showed substantial differences in failure-free operating duration across control-maturity groups. Median failure-free duration was 7,940 hours for high-maturity assets, 6,180 hours for medium-maturity assets, and 4,520 hours for low-maturity assets. The survival distributions differed significantly, $\log\text{-rank } \chi^2(2) = 92.7, p < .001$. After adjustment, high-maturity assets had a 48% lower failure hazard than low-maturity assets. Medium-maturity assets had a 24% lower hazard. Recurrent-event analysis identified a 41% reduction in repeated-failure intensity among high-maturity equipment. Median time to failure recurrence increased from 1,610 hours under low maturity to 2,740 hours under high maturity. The standardized total effect of embedded control quality on composite material-handling performance was $\beta = .61$. After the mediating variables were included, the direct effect declined to $\beta = .25$. The total indirect effect was $\beta = .36$, indicating that 59.0% of the control-design effect was transmitted through real-time coordination, routing and queue effectiveness, diagnostic visibility, maintenance responsiveness, and their sequential relationships. All indirect effects had bootstrap confidence intervals that excluded zero.

Table 7 Adjusted Embedded-Control Effects on Failure Occurrence Across Equipment and Operating Subgroups

Subgroup	Assets, n	Adjusted incidence-rate ratio	95% CI	<i>p</i>	Interaction <i>p</i>
Conveyors	115	0.64	0.54 to 0.76	< .001	.540
Sortation systems	63	0.61	0.48 to 0.78	< .001	—
Automated storage and retrieval systems	67	0.65	0.52 to 0.81	< .001	—
Automated guided vehicles	59	0.69	0.54 to 0.88	.003	—
Autonomous mobile robots	53	0.66	0.51 to 0.86	.002	—
Robotic palletizers	45	0.63	0.47 to 0.84	.002	—
Packaging machines	47	0.72	0.54 to 0.96	.026	—
Lifts and cranes	37	0.70	0.51 to 0.94	.018	—
Dock-transfer systems	34	0.74	0.55 to 0.99	.041	—
High-criticality equipment	219	0.57	0.49 to 0.67	< .001	.009
Medium- and low-criticality equipment	301	0.75	0.65 to 0.86	< .001	—
Equipment age below eight years	252	0.72	0.62 to 0.84	< .001	.066
Equipment age of eight years or more	268	0.62	0.53 to 0.72	< .001	—
Distributed control architecture	246	0.58	0.49 to 0.68	< .001	.004
Centralized or legacy architecture	274	0.75	0.65 to 0.86	< .001	—
Condition-based or predictive maintenance	234	0.56	0.47 to 0.66	< .001	< .001
Preventive or corrective maintenance	286	0.77	0.67 to 0.89	< .001	—
Large facilities	310	0.64	0.56 to 0.73	< .001	.180
Medium-sized facilities	210	0.71	0.60 to 0.84	< .001	—
High layout complexity	228	0.62	0.53 to 0.73	< .001	.120
Low or medium layout complexity	292	0.71	0.61 to 0.82	< .001	—
High automation maturity	174	0.52	0.43 to 0.63	< .001	< .001
Medium automation maturity	173	0.67	0.56 to 0.80	< .001	—
Low automation maturity	173	0.84	0.71 to 0.99	.041	—
High production loading	243	0.61	0.52 to 0.72	< .001	.061
Lower production loading	277	0.72	0.62 to 0.83	< .001	—
High baseline failure frequency	256	0.55	0.47 to 0.65	< .001	.003
Lower baseline failure frequency	264	0.78	0.67 to 0.91	.002	—

Note. Values below 1.00 indicated lower adjusted failure occurrence under high embedded-control maturity. Interaction probability values evaluated differences between categories within each

subgroup variable.

Table 8 Survival, Mediation, Moderation, and Control-Maturity Threshold Estimates

Analysis	Estimate	95% CI	<i>p</i>
High maturity: median failure-free duration, hours	7,940	7,480 to 8,450	< .001
Medium maturity: median failure-free duration, hours	6,180	5,810 to 6,590	< .001
Low maturity: median failure-free duration, hours	4,520	4,190 to 4,890	Reference
High versus low maturity: adjusted hazard ratio	0.52	0.44 to 0.62	< .001
Medium versus low maturity: adjusted hazard ratio	0.76	0.65 to 0.89	.001
High versus low maturity: recurrent-failure rate ratio	0.59	0.52 to 0.68	< .001
High-maturity median recurrence time, hours	2,740	2,490 to 3,020	< .001
Low-maturity median recurrence time, hours	1,610	1,440 to 1,810	Reference
Total control-design effect on performance, β	0.61	0.53 to 0.69	< .001
Direct effect after mediators, β	0.25	0.17 to 0.33	< .001
Indirect effect through real-time coordination, β	0.13	0.09 to 0.18	< .001
Indirect effect through routing and queue effectiveness, β	0.09	0.05 to 0.13	< .001
Indirect effect through diagnostic visibility, β	0.05	0.03 to 0.08	< .001
Indirect effect through maintenance responsiveness, β	0.04	0.02 to 0.07	< .001
Sequential indirect effect, β	0.05	0.03 to 0.08	< .001
Total indirect effect, β	0.36	0.29 to 0.44	< .001
Data-quality moderation effect, β	0.17	0.09 to 0.25	< .001
Facility automation-maturity moderation, β	0.18	0.10 to 0.26	< .001
Employee-competence moderation, β	0.14	0.07 to 0.21	< .001
Distributed-architecture moderation, β	0.12	0.05 to 0.19	.001
Equipment-criticality moderation, β	0.10	0.03 to 0.17	.006
Layout-complexity moderation, β	-0.08	-0.15 to -0.01	.026
Production-loading moderation, β	-0.11	-0.18 to -0.04	.002
Composite control-maturity threshold	70.8	67.5 to 74.1	< .001
Minimum sensor coverage, %	82.3	78.7 to 85.9	< .001
Maximum average scan-time threshold, ms	12.5	10.8 to 14.2	< .001
Minimum network availability, %	99.1	98.7 to 99.5	< .001
Minimum diagnostic coverage, %	80.4	76.9 to 83.9	< .001
Maximum transfer-timing deviation, ms	35.0	30.8 to 39.2	< .001
Minimum supervisory integration, %	78.6	74.3 to 82.9	< .001

Note. Higher composite performance scores represented greater throughput, reliability, availability, accuracy, energy efficiency, and labor productivity, together with shorter cycle time, downtime, and recovery duration.

Table 8 demonstrates that high control maturity increased failure-free survival and reduced recurrent-failure intensity. Fifty-nine percent of the control-design effect was transmitted through coordination, routing, diagnostics, responsiveness, and sequential mechanisms. Facility maturity, data quality, employee competence, distributed architecture, and equipment criticality strengthened the relationship, while complex layouts and heavy loading reduced its magnitude. Nonlinear analysis identified minimum requirements for control maturity, sensor coverage, network availability, diagnostics, synchronization, and supervisory integration. Performance improvements were limited below these levels and became substantially stronger after the thresholds were crossed, showing that coordinated control capability was more influential than isolated equipment or software upgrades.

4.5 Statistical Significance, Effect Magnitudes, Robustness, and Visual Presentation

All principal embedded-control effects remained statistically significant after adjustment for equipment, facility, operational, and temporal characteristics. They also remained significant after false-discovery-rate correction for multiple secondary comparisons. The adjusted equipment-failure incidence-rate ratio of 0.67 represented a 33% reduction in failure occurrence, while the controller-fault and manual-recovery ratios represented reductions of 39% and 46%, respectively. The delayed-order odds ratio of 0.46 represented 54% lower odds, while the automatic-recovery odds ratio of 2.34 represented substantially greater recovery success under high control maturity. Continuous outcomes

also demonstrated operationally meaningful effects. Capacity attainment, mean time between failures, availability, throughput, on-time completion, and labor productivity produced moderate-to-large standardized effects. Movement cycle time, queue duration, repair time, downtime, energy intensity, and operating cost produced favorable reductions ranging from moderate to large. Mean time between failures recorded the largest standardized effect, $d = 0.88$, followed by capacity attainment, $d = 0.91$, availability, $d = 0.83$, and throughput, $d = 0.82$. Confidence intervals remained narrow and excluded the null value for all primary outcomes.

Table 9 Model Performance, Explanatory Capacity, and Statistical Diagnostics

Model and outcome	Statistical specification	AIC	BIC	Explanatory or predictive performance	Principal diagnostic result
Equipment failures	Negative-binomial mixed model	39,418	39,602	Conditional $R^2 = .66$	Dispersion ratio = 1.05
Controller faults	Negative-binomial mixed model	42,175	42,362	Conditional $R^2 = .63$	Dispersion ratio = 1.08
Manual recovery events	Negative-binomial mixed model	28,642	28,821	Conditional $R^2 = .58$	Dispersion ratio = 1.04
Delayed orders	Mixed-effects logistic regression	11,936	12,117	Conditional $R^2 = .55$; AUC = .84	Calibration test, $p = .38$
Handling errors	Mixed-effects logistic regression	7,584	7,753	Conditional $R^2 = .43$; AUC = .78	Calibration test, $p = .46$
Throughput	Linear mixed-effects model	298,614	298,811	Conditional $R^2 = .72$	RMSE = 74 units per hour
Movement cycle time	Generalized mixed model	175,386	175,574	Conditional $R^2 = .64$	RMSE = 1.8 minutes
Availability	Linear mixed-effects model	118,442	118,631	Conditional $R^2 = .70$	RMSE = 1.5 percentage points
Energy intensity	Generalized mixed model	201,864	202,051	Conditional $R^2 = .57$	RMSE = 0.014 kWh per unit
Operating cost	Generalized mixed model	230,742	230,934	Conditional $R^2 = .53$	RMSE = USD 21.70 per 1,000 units
Failure survival	Cox shared-frailty model	41,526	41,698	Concordance = .76	Proportional-hazards test, $p = .31$
Mediation model	Multilevel structural model	—	—	CFI = .962; TLI = .955	RMSEA = .037; SRMR = .029

Note. AIC = Akaike information criterion; AUC = area under the receiver operating characteristic curve; BIC = Bayesian information criterion; CFI = comparative fit index; RMSEA = root-mean-square error of approximation; RMSE = root-mean-square error; SRMR = standardized root-mean-square residual; TLI = Tucker-Lewis index.

Table 9 demonstrates that the fitted models achieved acceptable explanatory, predictive, and diagnostic performance. Conditional coefficients of determination ranged from .43 for handling errors to .72 for throughput. The delayed-order and handling-error models demonstrated acceptable discrimination and calibration. Negative-binomial specifications corrected the overdispersion identified in the initial Poisson models. Prediction errors remained small relative to the observed ranges of throughput, cycle time, availability, energy intensity, and cost. The survival model achieved acceptable concordance and satisfied the proportional-hazards requirement. The mediation model also met established fit criteria, supporting the proposed relationships among control design, coordination, routing, diagnostics, responsiveness, and performance. Diagnostic analysis did not identify serious assumption violations. The maximum variance-inflation factor was 2.74, indicating limited multicollinearity. Standardized residuals were within the expected range for 99.1% of observations, and the maximum influence statistic was 0.19. Interrupted time-series residuals produced a Durbin-Watson statistic of 1.96, and the adjusted autocorrelation test was nonsignificant. Calendar-month indicators controlled for seasonal demand patterns. Robust standard errors or generalized distributions addressed heteroscedasticity and

positive skewness. The global proportional-hazards diagnostic was nonsignificant, $\chi^2(16) = 18.21$, $p = .31$. Robustness testing produced estimates closely aligned with the principal propensity-score-matched analysis. Alternative matching, inverse-probability weighting, unmatched adjustment, complete-case analysis, multiple imputation, stricter failure definitions, equipment-vendor adjustment, exclusion of major shutdowns, and alternative maturity thresholds generated failure-rate ratios between 0.63 and 0.70. Throughput effects remained between 138 and 159 handled units per hour, while cycle-time reductions remained between 2.64 and 3.06 minutes. Placebo modernization dates produced no statistically significant effects.

Table 10 Sensitivity and Robustness Analysis of Principal Embedded-Control Effects

Analytical specification	Assets, n	Failure-rate ratio	95% CI	Throughput difference, units per hour	Cycle-time difference, minutes	Availability difference, percentage points	<i>p</i>
Primary propensity-score-matched model	520	0.67	0.60 to 0.75	+148	-2.88	+2.68	< .001
Alternative matching distance	498	0.68	0.61 to 0.76	+145	-2.81	+2.61	< .001
Inverse-probability weighting	572	0.66	0.59 to 0.74	+152	-2.94	+2.72	< .001
Unmatched multivariable adjustment	572	0.70	0.63 to 0.78	+138	-2.64	+2.48	< .001
Complete-case analysis	506	0.68	0.61 to 0.76	+146	-2.84	+2.64	< .001
Multiple-imputation analysis	520	0.67	0.60 to 0.75	+149	-2.90	+2.69	< .001
Strict control-related failure definition	520	0.64	0.57 to 0.72	+147	-2.86	+2.66	< .001
Major shutdown periods excluded	520	0.68	0.61 to 0.76	+143	-2.79	+2.59	< .001
Equipment-vendor-adjusted model	520	0.67	0.60 to 0.75	+146	-2.85	+2.65	< .001
Control-maturity threshold set at 75 points	487	0.63	0.56 to 0.71	+159	-3.06	+2.88	< .001
Cluster-robust standard errors	520	0.67	0.59 to 0.76	+148	-2.88	+2.68	< .001
Placebo modernization dates	520	0.99	0.91 to 1.08	+5	-0.07	+0.04	.840
Leave-one-facility-out range	486–500	0.64–0.71	0.57 to 0.80	+136 to +157	-2.61 to -3.05	+2.49 to +2.84	< .001

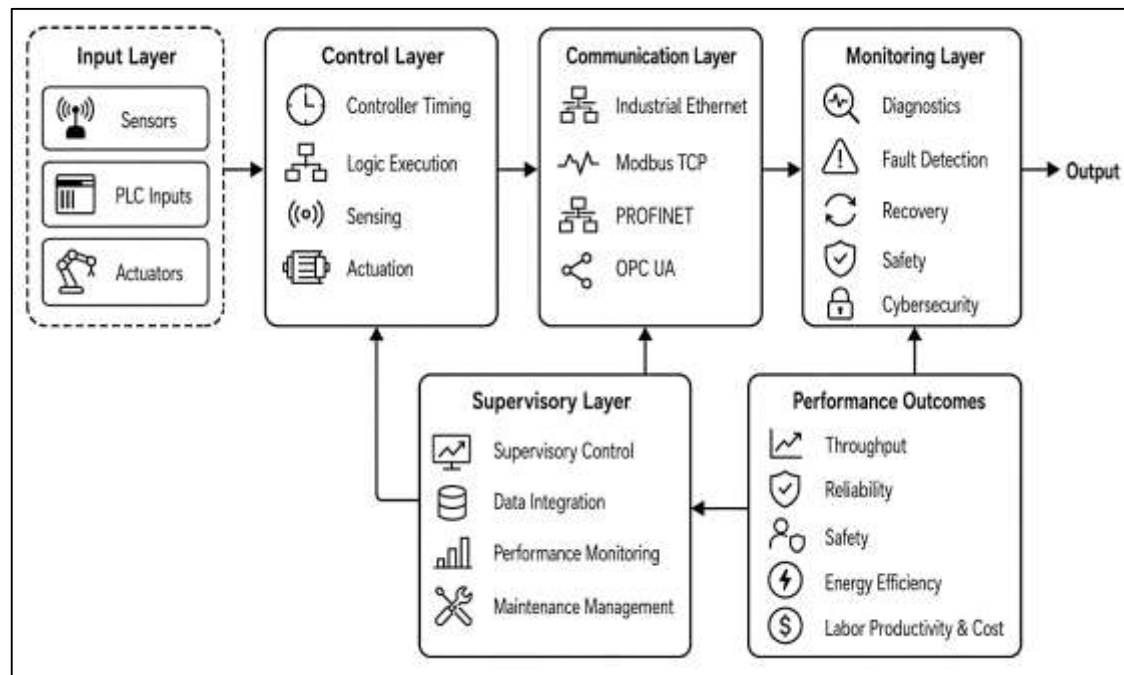
Table 10 demonstrates that the principal findings remained stable across alternative statistical decisions and sample definitions. Failure-rate reductions, throughput gains, cycle-time improvements, and availability increases were consistent under matching, weighting, complete-case, imputed, vendor-

adjusted, and shutdown-exclusion models. Stricter control-maturity and failure definitions generated slightly stronger effects, whereas unmatched adjustment produced more conservative estimates. Leave-one-facility-out analysis confirmed that no individual site determined the overall result. Cluster-robust standard errors did not change statistical interpretation. Placebo modernization dates produced null findings across all reported outcomes, strengthening the temporal credibility of the observed postmodernization changes and reducing concern about artificial intervention timing. Monthly trend figures showed similar premodernization trajectories between the matched groups and progressive divergence beginning approximately three months after modernization. Coefficient and forest plots positioned nearly all equipment and subgroup estimates on the favorable side of the null value. Kaplan-Meier curves showed the longest failure-free survival among high-maturity assets and the shortest survival among low-maturity assets. Queue heat maps showed reduced accumulation at transfer points, while latency plots demonstrated narrower timing distributions following modernization. Facility-level maturity maps indicated that the strongest improvements occurred when sensor coverage exceeded 82%, network availability exceeded 99%, diagnostic coverage exceeded 80%, and supervisory integration exceeded approximately 79%.

DISCUSSION

The findings demonstrated that embedded control system design represented a multidimensional industrial capability involving controller timing, logic execution, sensing, actuation, communication, synchronization, diagnostics, safety, cybersecurity, recovery, and supervisory-system integration. The analytical dataset included 20 U.S. manufacturing distribution centers, 520 matched automated assets, and 24,470 equipment-month observations distributed across 48 months ([Izmailova et al., 2018](#)). It also incorporated more than 214 million controller diagnostic records, 18.7 million material movements, 1.28 million production and fulfillment orders, 5,248 verified faults, 2,106 safety interruptions, 3,684 manual recovery events, and 17.6 million energy observations. This breadth provided a stronger empirical foundation than earlier material-handling studies that frequently concentrated on a single facility, equipment class, simulated layout, or short observation period. Required-field completeness reached 97.8%, valid calibration coverage reached 96.9%, and unmatched cross-system events declined from 6.2% before mapping to 1.6% after validation ([Zonnenshain & Kenett, 2020](#)). These results reinforced earlier industrial-data research showing that controller and equipment information produced reliable operational evidence only when equipment identifiers, timestamps, engineering units, event states, and performance records were aligned. Propensity-score matching also reduced every postmatching standardized mean difference to .04 or lower, strengthening comparability between high-control-maturity and legacy or partial-control assets. Earlier automation investigations often compared newly installed equipment with older systems without adequately controlling for age, loading, maintenance, layout, or baseline performance. This study accounted for those characteristics through matching, covariate adjustment, equipment and facility effects, and longitudinal comparison ([Werner et al., 2021](#)). The descriptive maturity gradient further demonstrated that control-system quality was not adequately represented by the presence or absence of automation alone. High-maturity assets combined faster controller execution with stronger sequence accuracy, communication stability, diagnostics, recovery, safety, and system integration. Medium-maturity equipment occupied an intermediate position, while low-maturity equipment recorded the weakest performance across most control dimensions. This structure corresponded with earlier cyber-physical and automation-maturity research, which characterized operational capability as the coordinated result of hardware, software, information quality, technical governance, and human competence rather than a single controller or machine characteristic ([Dutta et al., 2021](#)).

The differences in controller and communication performance showed that deterministic timing had a direct operational role in material-handling coordination. High-maturity equipment recorded an average controller scan time of 7.4 milliseconds, compared with 25.8 milliseconds for low-maturity equipment. Maximum scan times, task jitter, deadline misses, processor utilization, input and output response, and transfer-timing deviation followed the same maturity-related pattern. Deadline misses increased from 2.8 per million cycles under high maturity to 73.4 under low maturity, while input-output response time increased from 9.6 to 47.8 milliseconds ([Chan et al., 2021](#)).

Figure 12: Embedded control system architecture flowchart

Earlier real-time control studies similarly showed that average processing speed alone did not provide a sufficient measure of deterministic performance because occasional deadline misses or severe timing variation could disrupt sequencing, motion, and equipment handoffs. The present findings confirmed that timing consistency was associated with broader coordination outcomes. Network latency increased from a median of 3.4 milliseconds among high-maturity assets to 38.9 milliseconds among low-maturity assets, while message loss increased from 0.6 to 14.2 events per 10,000 transmissions. These differences occurred alongside lower routing accuracy, weaker synchronization, and reduced automatic deadlock resolution. High-maturity assets achieved 98.9% routing accuracy and 94.2% automatic deadlock resolution, whereas low-maturity assets recorded 91.8% and 43.7%, respectively (Pfadenhauer et al., 2015). Earlier conveyor, mobile-robot, and automated-storage studies reported that communication delay and inconsistent equipment states could create missed transfers, blocked routes, recirculation, queue growth, and manual intervention. This study extended those findings across several equipment categories and operating environments. The strong correlation between control design quality and real-time coordination, $r = .74$, indicated that sensing, processing, communication, and actuation operated as an integrated timing chain. Supervisory-system integration also increased from 48.9% under low maturity to 95.4% under high maturity, showing that effective coordination required alignment between local control and facility-level information (Perrin et al., 2016). The findings therefore agreed with earlier studies in which local controller improvements produced their strongest results when combined with current routing, order, destination, queue, and equipment-availability information.

The primary operational findings demonstrated that embedded control modernization improved both the volume and quality of material flow. Adjusted throughput increased by 148 handled units per hour, 95% CI [131, 165], $p < .001$, with a large standardized effect of $d = 0.82$. Capacity attainment increased by 7.10 percentage points, while movement cycle time decreased by 2.88 minutes and queue duration decreased by 1.79 minutes (Cadete et al., 2016). These results were consistent with earlier conveyor, sortation, storage, and mobile-robot studies reporting that deterministic control improved task execution and reduced waiting. The current study added facility-level evidence showing that throughput improvement was not produced only by faster machine movement. Shorter queues, better routing, stronger synchronization, fewer faults, and improved automatic recovery contributed to the observed capacity gain. Earlier research frequently identified a distinction between local machine speed

and total system throughput because increasing the speed of one machine could transfer congestion to a downstream process. The increase in capacity attainment and simultaneous reduction in queue duration indicated that modernization improved coordination across connected resources rather than merely increasing individual equipment speed (Kröll et al., 2017). On-time order completion increased by 5.76 percentage points, and the odds of delayed completion were 54% lower, OR = 0.46, 95% CI [0.38, 0.56], $p < .001$. This pattern agreed with earlier distribution-center studies linking reliable state information and dynamic routing with order lead-time improvement. Handling accuracy increased by 0.43 percentage points, while handling-error odds declined by 42%. Although the percentage-point change appeared smaller than the throughput effect, its operational significance was substantial because the baseline accuracy rate already exceeded 99%. Improvements near a high baseline represented fewer misroutes, missed diverts, destination errors, inventory corrections, and damaged shipments across millions of material movements. Interrupted time-series results showed that throughput increased immediately by 42 units per hour and continued to increase by 4.4 units per month (Cox et al., 2019). Cycle time and queue duration also recorded immediate and progressive reductions. Earlier implementation research showed similar sequences in which controller and network improvements appeared first, followed by accumulating material-flow gains as routing rules, operating procedures, and employee use stabilized.

The reliability findings showed that stronger embedded control reduced both the occurrence and operational consequences of equipment failure. High-maturity assets experienced a 33% lower adjusted failure rate, IRR = 0.67, 95% CI [0.60, 0.75], $p < .001$. Controller-fault occurrence was 39% lower, and mean time between failures increased by 2,340 hours, producing a large standardized effect of $d = 0.88$. These findings were consistent with earlier reliability and condition-monitoring studies demonstrating that stable control execution, calibrated sensing, fault diagnostics, and timely maintenance reduced interruption frequency (Zou et al., 2018). The present results connected those factors with embedded control architecture and material-flow context. Diagnostic fault coverage reached 94.8% in high-maturity equipment but only 58.4% in low-maturity equipment. This difference was accompanied by automatic recovery rates of 87.2% and 35.6%, respectively. The odds of successful automatic recovery were 2.34 times higher under high control maturity. Earlier fault-tolerant control studies reported that detection alone did not ensure operational resilience because faults also required accurate isolation, safe containment, consistent system states, and verified restart. This study supported that position by demonstrating simultaneous improvement in fault coverage, recovery success, repair duration, and failure-free operation. Mean time to repair declined by 2.38 hours, while annual downtime decreased by 45.2 hours per asset (Modarres et al., 2016). Availability increased by 2.68 percentage points, and utilization increased by 5.36 percentage points. These outcomes showed that modernization affected technical capability and productive use. Earlier maintenance research often distinguished equipment availability from utilization because assets could remain functional while blocked, starved, or unused. The concurrent improvement in both indicators suggested that control modernization reduced mechanical and control interruptions while also improving material assignment, queue control, and capacity use. Survival analysis provided additional support: median failure-free duration reached 7,940 hours under high maturity and 4,520 hours under low maturity. The adjusted hazard ratio of 0.52 indicated a 48% lower failure hazard, while recurrent-failure intensity was 41% lower (Wolstenholme, 2018). These findings showed sustained improvement rather than only short-term restoration following isolated faults.

The broader performance findings indicated that embedded control modernization affected safety interruptions, human support requirements, energy consumption, labor productivity, and operating cost. Safety-related interruption frequency was 28% lower among high-maturity assets, IRR = 0.72, 95% CI [0.58, 0.89], $p = .003$. High-maturity equipment also achieved 99.8% safety-function success, compared with 97.1% among low-maturity equipment (Souza et al., 2016). Earlier functional-safety studies emphasized that a safety system had to detect genuine hazards reliably while limiting nuisance trips that interrupted production without providing additional protection. The present findings were consistent with that balance because stronger safety performance occurred alongside fewer interruptions and higher availability. Manual recovery events declined by 46%, indicating reduced dependence on controller resets, jam clearance, product repositioning, routing correction, and

equipment restart. Earlier human-automation research showed that frequent intervention could conceal weaknesses in sensing, logic, communication, and fault recovery (Cai et al., 2019). The current results supported that interpretation because lower intervention occurred where diagnostic coverage, synchronization, and automatic recovery were strongest. Energy intensity declined by 0.0188 kWh per handled unit, representing a moderate standardized effect. This result aligned with earlier automated-material-flow studies showing that energy use was affected by idle operation, congestion, recirculation, repeated acceleration, empty travel, and extended equipment readiness. The simultaneous decline in queue duration, manual recovery, faults, and cycle time indicated that energy savings were associated with more productive movement rather than reduced activity. Labor productivity increased by 21.1 handled units per labor hour, while operating cost declined by USD 25.60 per 1,000 handled units. Earlier automation studies reported mixed labor outcomes when productivity gains were offset by technical support, recovery labor, or specialized maintenance (Joglar, 2016). This study found that labor improvement occurred together with fewer manual recoveries and shorter repair duration, indicating that modernization reduced unplanned support requirements. The cost reduction was therefore connected with higher throughput, improved availability, lower downtime, reduced energy intensity, and more efficient labor use. These combined outcomes demonstrated that embedded control performance extended beyond equipment speed to influence human workload, operational continuity, resource consumption, and economic efficiency (Sayed et al., 2019).

The subgroup results demonstrated broad consistency across material-handling technologies while identifying conditions that strengthened or weakened the effect of embedded control. Failure-rate reductions were observed for conveyors, sortation systems, automated storage and retrieval systems, guided vehicles, mobile robots, robotic palletizers, packaging machines, lifts, cranes, and dock-transfer systems. The nonsignificant equipment-category interaction, $p = .54$, indicated that modernization was not beneficial only for one technology (Petrinoli et al., 2018). Earlier equipment-specific studies often reported control gains within a single machinery class; this study showed that the general relationship extended across fixed, mobile, robotic, and storage equipment. Stronger effects appeared among high-criticality assets, distributed control architectures, condition-monitored equipment, high-maturity facilities, and equipment with high baseline failure frequency. Condition-based or predictive maintenance produced an IRR of 0.56, while high automation maturity produced an IRR of 0.52. These findings corresponded with earlier studies showing that control information generated greater reliability value when maintenance processes could interpret and act on diagnostic evidence. Mediation analysis clarified the explanatory structure. The total standardized effect of control quality on material-handling performance was $\beta = .61$, while the direct effect declined to $\beta = .25$ after real-time coordination, routing effectiveness, diagnostic visibility, and maintenance responsiveness were included (Ghiasi et al., 2019). The total indirect effect of $\beta = .36$ indicated that 59.0% of the relationship was transmitted through these mechanisms. Earlier cyber-physical systems research proposed that connected control improved performance by increasing information visibility and coordinated action. The current findings provided quantitative support by separating the direct technical effect from the coordination, routing, diagnostic, and maintenance pathways. Data quality, facility maturity, employee competence, distributed architecture, and equipment criticality strengthened the relationship. Layout complexity and production loading weakened it, indicating that high demand and complex pathways retained operational constraints even under strong control (Mesbahi et al., 2018). Threshold analysis identified minimum levels for sensor coverage, network availability, diagnostic coverage, synchronization, supervisory integration, and composite maturity. Performance gains became stronger after control maturity exceeded 70.8, sensor coverage exceeded 82.3%, network availability exceeded 99.1%, and diagnostic coverage exceeded 80.4%. These patterns agreed with earlier maturity studies in which isolated upgrades produced limited facility-level change until adequate technical and organizational coverage had been established (Alaswad & Xiang, 2017).

The statistical evidence strengthened interpretation of the observed relationships because the findings remained consistent across multiple analytical approaches. Conditional coefficients of determination ranged from .43 for handling errors to .72 for throughput, indicating that the models explained meaningful proportions of equipment and facility performance (Swain et al., 2018). The failure model achieved a conditional R^2 of .66, while the availability model achieved .70. The mediation model

satisfied accepted fit criteria, with CFI = .962, TLI = .955, RMSEA = .037, and SRMR = .029. Earlier embedded-control and warehouse-automation studies often reported average performance differences without evaluating clustering, preintervention trends, recurrent failures, indirect mechanisms, or sensitivity to model specification. This study used mixed-effects models, propensity-score matching, difference-in-differences estimation, interrupted time-series analysis, survival models, mediation, moderation, and threshold analysis. The joint test of premodernization event-time coefficients was nonsignificant, $\chi^2(23) = 20.14$, $p = .63$, supporting the parallel-trends requirement (Amuedo-Dorantes & Antman, 2017). Placebo modernization dates also produced null findings, including a failure-rate ratio of 0.99 and nonsignificant changes in throughput, cycle time, and availability. Primary failure-rate ratios remained between 0.63 and 0.70 under alternative matching, inverse-probability weighting, complete-case analysis, multiple imputation, strict failure definitions, vendor adjustment, shutdown exclusion, and leave-one-facility-out estimation. Throughput gains remained between 138 and 159 units per hour, while availability improvements remained between 2.48 and 2.88 percentage points. This stability reduced concern that the findings resulted from one facility, vendor, matching decision, missing-data method, or outcome definition (Blum et al., 2020). Graphical evidence also supported the numerical estimates. Premodernization trends remained closely aligned, while postmodernization trajectories began diverging after approximately three months. Forest plots showed favorable effects across equipment groups, Kaplan-Meier curves showed longer survival under higher maturity, and queue and latency plots demonstrated reduced operational variability. Compared with earlier studies, the combined evidence provided a more integrated account of how controller design influenced coordination, throughput, reliability, safety, energy, labor, and cost within operating U.S. manufacturing distribution centers (Ide et al., 2020).

CONCLUSION

This study concluded that embedded control system design was a statistically significant and operationally meaningful determinant of material-handling automation performance in U.S. manufacturing distribution centers. Evidence obtained from 20 facilities, 520 matched automated assets, 24,470 equipment-month observations, 18.7 million material movements, 1.28 million orders, and 5,248 verified faults demonstrated that control maturity extended beyond processing speed to include deterministic timing, control-logic accuracy, sensing, actuation, industrial communication, equipment synchronization, diagnostics, recovery, functional safety, cybersecurity, and supervisory-system integration. High-maturity assets achieved an average controller scan time of 7.4 milliseconds, 99.5% sequence accuracy, 94.8% diagnostic coverage, 87.2% automatic recovery success, 95.4% supervisory integration, and 98.9% routing accuracy. After adjustment for equipment age, category, criticality, operating exposure, production loading, facility size, layout complexity, product mix, order variability, maintenance strategy, environmental conditions, region, and baseline performance, high-maturity assets recorded a 33% lower failure rate, IRR = 0.67, 95% CI [0.60, 0.75], $p < .001$. Controller faults declined by 39%, manual recovery events declined by 46%, and safety interruptions declined by 28%. Throughput increased by 148 handled units per hour, capacity attainment increased by 7.10 percentage points, movement cycle time declined by 2.88 minutes, and on-time order completion increased by 5.76 percentage points. Mean time between failures increased by 2,340 hours, mean time to repair decreased by 2.38 hours, availability increased by 2.68 percentage points, and annual downtime declined by 45.2 hours per asset. Energy intensity decreased by 0.0188 kWh per handled unit, labor productivity increased by 21.1 units per labor hour, and operating cost declined by USD 25.60 per 1,000 handled units. High-maturity assets also experienced a 48% lower failure hazard and achieved a median failure-free duration of 7,940 hours. Real-time coordination, routing effectiveness, diagnostic visibility, and maintenance responsiveness transmitted 59.0% of the relationship between control quality and material-handling performance. Sensitivity analyses, alternative matching methods, survival models, interrupted time-series estimates, and placebo tests produced consistent results. Overall, the study established that coordinated embedded control improved material-flow capacity, order fulfillment, reliability, maintainability, safety, energy efficiency, labor productivity, and economic performance.

RECOMMENDATIONS

U.S. manufacturing distribution centers should implement embedded control modernization as a

coordinated operational-performance program rather than treating it as a limited controller or equipment replacement project. Modernization priorities should begin with high-criticality, heavily loaded, failure-prone, and production-constraining equipment because these categories recorded the strongest reliability and throughput improvements. Facilities should establish a common control architecture that connects sensors, programmable controllers, drives, safety systems, industrial networks, warehouse-control applications, maintenance databases, and production systems through standardized equipment identities, timestamps, operating states, engineering units, and event classifications. Modernization programs should target a composite control-maturity score above 70.8, sensor coverage above 82.3%, network availability above 99.1%, diagnostic fault coverage above 80.4%, supervisory integration above 78.6%, average controller scan time below approximately 12.5 milliseconds, and transfer-timing deviation below 35 milliseconds. Controller performance should be monitored through scan duration, task jitter, deadline misses, processor utilization, sequence accuracy, interlock success, input and output response, position error, network latency, message loss, and communication recovery. Distribution centers should expand automated diagnostics, condition monitoring, fault isolation, failover, controlled restart, and safe degraded operation to reduce troubleshooting time, repeated failures, manual recovery, and downtime. Routing and queue-control strategies should incorporate current equipment availability, destination capacity, order priority, buffer occupancy, congestion, and charging status. Safety systems should be validated regularly through protective-device coverage, stopping-time tests, interlock verification, reset control, and investigation of nuisance trips. Cybersecurity governance should include role-based access, approved logic modification, configuration backup, network segmentation, patch control, security logging, and tested recovery procedures. Employee competence should be strengthened through role-specific training in controller diagnostics, alarm interpretation, network troubleshooting, safe recovery, routing control, and interface use. Performance reviews should track throughput, cycle time, queue duration, on-time completion, handling accuracy, availability, utilization, failure frequency, mean time between failures, mean time to repair, downtime, safety interruptions, manual interventions, energy per unit, labor productivity, and operating cost. Phased implementation, matched baseline comparison, monthly trend analysis, equipment-specific benchmarking, and periodic sensitivity review should be used to verify that control improvements remained stable and produced measurable operational value across different equipment types, facilities, layouts, and workload conditions.

LIMITATION

This study contained several limitations that should be considered when interpreting the relationship between embedded control system design and material-handling automation performance. The retrospective longitudinal quasi-experimental design provided stronger temporal evidence than a cross-sectional analysis but did not offer the causal control of randomized assignment. Control modernization was implemented through existing organizational and investment decisions, creating the possibility that high-maturity facilities also possessed stronger maintenance cultures, technical personnel, financial resources, safety governance, or operational discipline. Propensity-score matching, difference-in-differences estimation, multivariable adjustment, facility effects, and sensitivity analyses reduced measured imbalance but could not eliminate residual confounding from unrecorded characteristics. Facility participation required accessible controller, production, maintenance, safety, energy, and cost records, which may have favored organizations with more developed information governance. The 20 participating distribution centers provided balanced U.S. regional representation, although the findings may not apply equally to small warehouses, nonmanufacturing facilities, highly specialized industries, or organizations operating under substantially different infrastructure and labor conditions. Controllers, sensors, networks, supervisory applications, and equipment vendors varied across facilities, and the same control-maturity score could therefore represent different technical configurations. Sensor gaps, calibration differences, timestamp errors, communication interruptions, and historian or database processing may have affected measurement precision. Validation procedures reduced these concerns, but brief high-speed events or intermittent faults may have remained undetected. Failure, downtime, manual intervention, and safety-event classifications also depended

partly on operator and maintenance documentation, creating possible differences in recording practices across shifts and facilities. The assessment instrument introduced potential response bias because employees evaluated several dimensions of usability, competence, safety, and governance. System-generated measures were prioritized, although some mediating and moderating constructs retained perceptual components. Monthly aggregation supported consistent longitudinal modeling but may have concealed short-term control instability, peak-demand variation, and event-level dependencies. Energy and cost comparisons were influenced by regional utility prices, labor rates, maintenance contracts, accounting practices, product characteristics, and facility volume. Mediation analysis supported explanatory pathways but did not establish definitive causal ordering among control quality, coordination, routing, diagnostics, responsiveness, and performance. Smaller samples for lifts, cranes, and dock-transfer systems produced wider subgroup confidence intervals. The 48-month observation period captured substantial premodernization and postmodernization performance but did not represent the complete lifecycle of long-lived automation systems. Accordingly, the results represented robust adjusted evidence within the observed manufacturing distribution centers rather than universal causal estimates for every material-handling environment.

REFERENCES

- [1]. Abdi, F., Chen, C.-Y., Hasan, M., Liu, S., Mohan, S., & Caccamo, M. (2018). Preserving physical safety under cyber attacks. *IEEE Internet of Things Journal*, 6(4), 6285-6300.
- [2]. Afy-Shararah, M., & Rich, N. (2018). Operations flow effectiveness: a systems approach to measuring flow performance. *International Journal of Operations & Production Management*, 38(11), 2096-2123.
- [3]. Ahleroff, S., Xu, X., Lu, Y., Aristizabal, M., Velásquez, J. P., Joa, B., & Valencia, Y. (2020). IoT-enabled smart appliances under industry 4.0: A case study. *Advanced engineering informatics*, 43, 101043.
- [4]. Al-Douri, A., Kazantzi, V., Eljack, F. T., Mannan, M. S., & El-Halwagi, M. M. (2020). Mitigation of operational failures via an economic framework of reliability, availability, and maintainability (RAM) during conceptual design. *Journal of loss prevention in the process industries*, 67, 104261.
- [5]. Alaswad, S., & Xiang, Y. (2017). A review on condition-based maintenance optimization models for stochastically deteriorating system. *Reliability Engineering & System Safety*, 157, 54-63.
- [6]. Alvarez-Alvarado, M. S., Donaldson, D. L., Recalde, A. A., Noriega, H. H., Khan, Z. A., Velasquez, W., & Rodriguez-Gallegos, C. D. (2022). Power system reliability and maintenance evolution: A critical review and future perspectives. *IEEE Access*, 10, 51922-51950.
- [7]. Ammar, M., Haleem, A., Javaid, M., Walia, R., & Bahl, S. (2021). Improving material quality management and manufacturing organizations system through Industry 4.0 technologies. *Materials Today: Proceedings*, 45, 5089-5096.
- [8]. Amuedo-Dorantes, C., & Antman, F. (2017). Schooling and labor market effects of temporary authorization: Evidence from DACA. *Journal of population economics*, 30(1), 339-373.
- [9]. Arestova, A., Martin, M., Hielscher, K.-S. J., & German, R. (2021). A service-oriented real-time communication scheme for AUTOSAR adaptive using OPC UA and time-sensitive networking. *Sensors*, 21(7), 2337.
- [10]. Asadi, S., Kowshik, K., Asadi, S. P., Asadi, S. S., & Alla, S. (2021). Strategical construction equipment management using henry garret method. *Materials Today: Proceedings*, 43, 921-927.
- [11]. Ashima, R., Haleem, A., Bahl, S., Javaid, M., Mahla, S. K., & Singh, S. (2021). Automation and manufacturing of smart materials in Additive Manufacturing technologies using Internet of Things towards the adoption of Industry 4.0. *Materials Today: Proceedings*, 45, 5081-5088.
- [12]. Au, A. K., Huynh, W., Horowitz, L. F., & Folch, A. (2016). 3D-printed microfluidics. *Angewandte Chemie International Edition*, 55(12), 3862-3881.
- [13]. Barkalov, A., Titarenko, L., & Mazurkiewicz, M. (2019). *Foundations of embedded systems* (Vol. 195). Springer.
- [14]. Barsi, Á., Kugler, Z., Juhász, A., Szabó, G., Batini, C., Abdulmuttalib, H., Huang, G., & Shen, H. (2019). Remote sensing data quality model: from data sources to lifecycle phases. *International Journal of Image and Data Fusion*, 10(4), 280-299.
- [15]. Bechtsis, D., Tsolakis, N., Vlachos, D., & Iakovou, E. (2017). Sustainable supply chain management in the digitalisation era: The impact of Automated Guided Vehicles. *Journal of Cleaner Production*, 142, 3970-3984.
- [16]. Berns, K., Köpper, A., & Schürmann, B. (2021). *Technical Foundations of Embedded Systems*. Springer.
- [17]. Besiktepe, D., Ozbek, M. E., & Atadero, R. A. (2021). Condition assessment framework for facility management based on fuzzy sets theory. *Buildings*, 11(4), 156.
- [18]. Blum, A. G., Ferraro, P. J., Archfield, S. A., & Ryberg, K. R. (2020). Causal effect of impervious cover on annual flood magnitude for the United States. *Geophysical research letters*, 47(5), no-no.
- [19]. Bohi, D. R. (2017). *Energy price shocks and macroeconomic performance*. Routledge.
- [20]. Cadete, V. J., Deschênes, S., Cuillerier, A., Brisebois, F., Sugiura, A., Vincent, A., Turnbull, D., Picard, M., McBride, H. M., & Burelle, Y. (2016). Formation of mitochondrial-derived vesicles is an active and physiologically relevant mitochondrial quality control process in the cardiac system. *The Journal of physiology*, 594(18), 5343-5362.

- [21]. Cai, B., Liu, Y., Liu, Z., Chang, Y., & Jiang, L. (2019). Availability-based engineering resilience metric and its corresponding evaluation methodology. In *Bayesian Networks for Reliability Engineering* (pp. 239-257). Springer.
- [22]. Carreras Guzman, N. H., Wied, M., Kozine, I., & Lundteigen, M. A. (2020). Conceptualizing the key features of cyber-physical systems in a multi-layered representation for safety and security analysis. *Systems Engineering*, 23(2), 189-210.
- [23]. Castell, N., Dauge, F. R., Schneider, P., Vogt, M., Lerner, U., Fishbain, B., Broday, D., & Bartonova, A. (2017). Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates? *Environment international*, 99, 293-302.
- [24]. Cena, G., Scanzio, S., & Valenzano, A. (2018). SDMAC: a software-defined MAC for Wi-Fi to ease implementation of soft real-time applications. *IEEE Transactions on Industrial Informatics*, 15(6), 3143-3154.
- [25]. Chan, K. C., Chen, Y., & Liu, B. (2021). The linear and non-linear effects of internal control and its five components on corporate innovation: Evidence from Chinese firms using the COSO framework. *European Accounting Review*, 30(4), 733-765.
- [26]. Colombo, M. G., & Murtinu, S. (2017). Venture capital investments in Europe and portfolio firms' economic performance: Independent versus corporate investors. *Journal of Economics & Management Strategy*, 26(1), 35-66.
- [27]. Cox, A. M., Kennan, M. A., Lyon, L., Pinfield, S., & Sbaffi, L. (2019). Maturing research data services and the transformation of academic libraries. *Journal of Documentation*, 75(6), 1432-1462.
- [28]. Craggs, B., & Rashid, A. (2017). Smart cyber-physical systems: beyond usable security to security ergonomics by design. 2017 IEEE/ACM 3rd International Workshop on Software Engineering for Smart Cyber-Physical Systems (SEsCPS),
- [29]. Cronrath, C., Lennartson, B., & Lemessi, M. (2016). Energy reduction in paint shops through energy-sensitive on-off control. 2016 IEEE international conference on automation science and engineering (CASE),
- [30]. Cruces, C., Torrego, R., Arriola, A., & Val, I. (2018). Deterministic hybrid architecture with time sensitive network and wireless capabilities. 2018 IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA),
- [31]. D'Aniello, G., Gaeta, M., & Hong, T.-P. (2017). Effective quality-aware sensor data management. *IEEE Transactions on Emerging Topics in Computational Intelligence*, 2(1), 65-77.
- [32]. de Souza, R. H., Flores, P. A., Dantas, M. A. R., & Siqueira, F. (2016). Architectural recovering model for Distributed Databases: A reliability, availability and serviceability approach. 2016 IEEE Symposium on Computers and Communication (ISCC),
- [33]. Debasish, A. (2021). Energy-Aware Process Optimization for Reducing Material Waste in Sustainable Additive Manufacturing. *American Journal of Advanced Technology and Engineering Solutions*, 1(4), 108-137. <https://doi.org/10.63125/j0wk7j48>
- [34]. Dutta, G., Kumar, R., Sindhwani, R., & Singh, R. K. (2021). Digitalization priorities of quality control processes for SMEs: a conceptual study in perspective of Industry 4.0 adoption. *Journal of intelligent manufacturing*, 32(6), 1679-1698.
- [35]. El Sibai, R., Chabchoub, Y., Chiky, R., Demerjian, J., & Barbar, K. (2017). Assessing and improving sensors data quality in streaming context. International Conference on Computational Collective Intelligence,
- [36]. Elgeneidy, K., Lohse, N., & Jackson, M. (2018). Bending angle prediction and control of soft pneumatic actuators with embedded flex sensors—a data-driven approach. *Mechatronics*, 50, 234-247.
- [37]. Fernández-Caramés, T. M., Blanco-Novoa, O., Froiz-Míguez, I., & Fraga-Lamas, P. (2019). Towards an autonomous industry 4.0 warehouse: A UAV and blockchain-based system for inventory and traceability applications in big data-driven supply chain management. *Sensors*, 19(10), 2394.
- [38]. Fragapane, G., Ivanov, D., Peron, M., Sgarbossa, F., & Strandhagen, J. O. (2022). Increasing flexibility and productivity in Industry 4.0 production networks with autonomous mobile robots and smart intralogistics. *Annals of operations research*, 308(1), 125-143.
- [39]. Fredericks, J., & Botts, M. (2018). Promoting the capture of sensor data provenance: a role-based approach to enable data quality assessment, sensor management and interoperability. *Open Geospatial Data, Software and Standards*, 3(1), 3.
- [40]. Gaspari, L., Colucci, L., Butzer, S., Colledani, M., & Steinhilper, R. (2017). Modularization in material flow simulation for managing production releases in remanufacturing. *Journal of Remanufacturing*, 7(2), 139-157.
- [41]. Ghiasi, M., Ghadimi, N., & Ahmadiania, E. (2019). An analytical methodology for reliability assessment and failure analysis in distributed power system. *SN Applied Sciences*, 1(1), 44.
- [42]. Gibbons, D. W., & Van Der Merwe, A. F. (2021). Model-based design of additive manufacturing operations for improved management, control and compliance. 2021 Rapid Product Development Association of South Africa-Robotics and Mechatronics-Pattern Recognition Association of South Africa (RAPDASA-RobMech-PRASA),
- [43]. Gola, A., & Kłosowski, G. (2019). Development of computer-controlled material handling model by means of fuzzy logic and genetic algorithms. *Neurocomputing*, 338, 381-392.
- [44]. Gould, O., Simeone, A., Colwill, J., Willey, R., & Rahimifard, S. (2016). A material flow modelling tool for resource efficient production planning in multi-product manufacturing systems. *Procedia CIRP*, 41, 21-26.
- [45]. Gu, A., Yin, Z., Li, Y., Su, B., & Shen, L. (2018). Functional safety assessment and security protection framework of cyber physical machine tool system. 2018 IEEE 4th International Conference on Computer and Communications (ICCC),
- [46]. Gul, F., Rahiman, W., & Nazli Alhady, S. S. (2019). A comprehensive study for robot navigation techniques. *Cogent Engineering*, 6(1), 1632046.

- [47]. Guzman, N. H. C., Kozine, I., & Lundteigen, M. A. (2021). An integrated safety and security analysis for cyber-physical harm scenarios. *Safety science*, 144, 105458.
- [48]. Hägele, M., Nilsson, K., Pires, J. N., & Bischoff, R. (2016). Industrial robotics. In *Springer handbook of robotics* (pp. 1385-1422). Springer.
- [49]. Hastings, N. A. J. (2021). Reliability, Availability and Maintainability. In *Physical Asset Management: With an Introduction to the ISO 55000 Series of Standards* (pp. 445-485). Springer.
- [50]. Heegaard, P. E., Helvik, B. E., Trivedi, K. S., & Machida, F. (2015). Survivability as a generalization of recovery. 2015 11th International Conference on the Design of Reliable Communication Networks (DRCN),
- [51]. Heinonen, K., & Strandvik, T. (2015). Customer-dominant logic: foundations and implications. *Journal of Services Marketing*, 29(6-7), 472-484.
- [52]. Hilmola, O.-P., & Gupta, M. (2015). Throughput accounting and performance of a manufacturing company under stochastic demand and scrap rates. *Expert Systems with Applications*, 42(22), 8423-8431.
- [53]. Hirsch, B. T. (2017). What do unions do for economic performance? In *What do unions do?* (pp. 193-237). Routledge.
- [54]. Hosan, S., Karmaker, S. C., Rahman, M. M., Chapman, A. J., & Saha, B. B. (2022). Dynamic links among the demographic dividend, digitalization, energy intensity and sustainable economic growth: Empirical evidence from emerging economies. *Journal of Cleaner Production*, 330, 129858.
- [55]. Hu, B., & Gharavi, H. (2021). A hybrid wired/wireless deterministic network for smart grid. *IEEE wireless communications*, 28(3), 138-143.
- [56]. Humayed, A., Lin, J., Li, F., & Luo, B. (2017). Cyber-physical systems security – A survey. *IEEE Internet of Things Journal*, 4(6), 1802-1831.
- [57]. Ide, T., Brzoska, M., Donges, J. F., & Schleussner, C.-F. (2020). Multi-method evidence for when and how climate-related disasters contribute to armed conflict risk. *Global Environmental Change*, 62, 102063.
- [58]. Izmailova, E. S., Wagner, J. A., & Perakslis, E. D. (2018). Wearable devices in clinical trials: hype and hypothesis. *Clinical Pharmacology & Therapeutics*, 104(1), 42-52.
- [59]. Jain, M., Meena, R. K., & Kumar, P. (2020). Maintainability of redundant machining system with vacation, imperfect recovery and reboot delay. *Arabian Journal for Science and Engineering*, 45(3), 2145-2161.
- [60]. Jesus, G., Casimiro, A., & Oliveira, A. (2017). A survey on data quality for dependable monitoring in wireless sensor networks. *Sensors*, 17(9), 2010.
- [61]. Jin, X., Xia, C., Guan, N., Xu, C., Li, D., Yin, Y., & Zeng, P. (2020). Real-time scheduling of massive data in time sensitive networks with a limited number of schedule entries. *IEEE Access*, 8, 6751-6767.
- [62]. Joglar, F. (2016). Reliability, availability, and maintainability. In *SFPE handbook of fire protection engineering* (pp. 2875-2940). Springer.
- [63]. Kebede, S. G., & Heshmati, A. (2020). Energy use and labor productivity in Ethiopia: the case of the manufacturing industry. *Energies*, 13(11), 2714.
- [64]. Khan, S., & Yairi, T. (2018). A review on the application of deep learning in system health management. *Mechanical systems and signal processing*, 107, 241-265.
- [65]. Kim, B.-S., Park, H., Kim, K. H., Godfrey, D., & Kim, K.-I. (2017). A survey on real-time communications in wireless sensor networks. *Wireless communications and mobile computing*, 2017(1), 1864847.
- [66]. Kolberg, D., & Zühlke, D. (2015). Lean automation enabled by industry 4.0 technologies. *IFAC-PapersOnLine*, 48(3), 1870-1875.
- [67]. Kovtun, V., Izonin, I., & Gregus, M. (2022). The functional safety assessment of cyber-physical system operation process described by Markov chain. *Scientific Reports*, 12(1), 7089.
- [68]. Kröll, C., Doeblner, P., & Nüesch, S. (2017). Meta-analytic evidence of the effectiveness of stress management at work. *European Journal of Work and Organizational Psychology*, 26(5), 677-693.
- [69]. Kumar, J., Bansal, S. A., & Mehta, M. (2021). Reliability analysis – a critical review. *Recent Trends in Industrial and Production Engineering: Select Proceedings of ICAST 2020*, 205-217.
- [70]. Kumar, P., & Jain, M. (2020). Reliability analysis of a multi-component machining system with service interruption, imperfect coverage, and reboot. *Reliability Engineering & System Safety*, 202, 106991.
- [71]. Larrain, M., Van Passel, S., Thomassen, G., Kresovic, U., Alderweireldt, N., Moerman, E., & Billen, P. (2020). Economic performance of pyrolysis of mixed plastic waste: Open-loop versus closed-loop recycling. *Journal of Cleaner Production*, 270, 122442.
- [72]. Lee, C. K., Lv, Y., Ng, K. K., Ho, W., & Choy, K. L. (2018). Design and application of Internet of things-based warehouse management system for smart logistics. *International Journal of Production Research*, 56(8), 2753-2768.
- [73]. Link, J., Waedt, K., Zid, I. B., & Lou, X. (2018). Current challenges of the joint consideration of functional safety & cyber security, their interoperability and impact on organizations: how to manage RAMS+ S (reliability availability maintainability safety+ security). 2018 12th international conference on reliability, maintainability, and safety (ICRMS),
- [74]. Liu, Q., Zhang, H., Leng, J., & Chen, X. (2019). Digital twin-driven rapid individualised designing of automated flow-shop manufacturing system. *International Journal of Production Research*, 57(12), 3903-3919.
- [75]. Lohstroh, M., Menard, C., Schulz-Rosengarten, A., Weber, M., Castrillon, J., & Lee, E. A. (2020). A language for deterministic coordination across multiple timelines. 2020 Forum for Specification and Design Languages (FDL),
- [76]. Lu, Y., Xu, X., & Wang, L. (2020). Smart manufacturing process and system automation—a critical review of the standards and envisioned scenarios. *Journal of manufacturing systems*, 56, 312-325.
- [77]. Lyu, X., Ding, Y., & Yang, S. H. (2019). Safety and security risk assessment in cyber-physical systems. *IET Cyber-Physical Systems: Theory & Applications*, 4(3), 221-232.

- [78]. Mabkhot, M. M., Al-Ahmari, A. M., Salah, B., & Alkhalefah, H. (2018). Requirements of the smart factory system: A survey and perspective. *Machines*, 6(2), 23.
- [79]. Maihulla, A. S., & Yusuf, I. (2022). Reliability, availability, maintainability, and dependability analysis of photovoltaic systems. *Life Cycle Reliability and Safety Engineering*, 11(1), 19-26.
- [80]. Md Mesbaul, H. (2023). A Meta-Analysis of Lean Merchandising Strategies In Fashion Retail: Global Insights From The Post-Pandemic Era. *Review of Applied Science and Technology*, 2(04), 94-123. <https://doi.org/10.63125/y8x4k683>
- [81]. Md. Abdur, R., & Iftekhhar, A. (2021). Customer Retention Forecasting in Mobile Wallet Services Using Neural Networks: A Comparative Quantitative Study. *International Journal of Business and Economics Insights*, 1(4), 70-102. <https://doi.org/10.63125/dyrpc387>
- [82]. Memon, H., & Alam, M. (2016). Reliability, maintainability, availability and failure rate analysis of IGBT triggering system designed for marine environment. 2016 13th International Bhurban Conference on Applied Sciences and Technology (IBCAST),
- [83]. Mesbahi, M. R., Rahmani, A. M., & Hosseinzadeh, M. (2018). Reliability and high availability in cloud computing environments: a reference roadmap. *Human-centric Computing and Information Sciences*, 8(1), 20.
- [84]. Miclo, R., Luras, M., Fontanili, F., Lamothe, J., & Melnyk, S. A. (2019). Demand Driven MRP: assessment of a new approach to materials management. *International Journal of Production Research*, 57(1), 166-181.
- [85]. Milano, F., Dörfler, F., Hug, G., Hill, D. J., & Verbič, G. (2018). Foundations and challenges of low-inertia systems. 2018 power systems computation conference (PSCC),
- [86]. Modarres, M., Kaminskiy, M. P., & Krivtsov, V. (2016). *Reliability engineering and risk analysis: a practical guide*. CRC press.
- [87]. Mohammad Abir Chowdhury, S., & Tonay, P. (2022). An Empirical Analysis of the Impact of Robotic Process Automation and Continuous Auditing on the Timeliness And Accuracy Of Financial Reporting Assurance. *International Journal of Business and Economics Insights*, 2(4), 73-126. <https://doi.org/10.63125/7p8dcr47>
- [88]. Mohammad Shoriful Hossan, S. (2021). Reducing Worker Exposure and Electrical Failure Risk in Brownfield Manufacturing Facilities After COVID-Era Maintenance Delays. *Review of Applied Science and Technology*, 6(1), 263-279. <https://doi.org/10.63125/cm1c2c20>
- [89]. Mollajan, A., & Iranmanesh, S. H. (2021). Modularisation of system architecture to improve system recoverability: a unique application of design structure matrix. *Journal of Engineering Design*, 32(12), 703-750.
- [90]. Morel, G. M., & Spector, J. M. (2022). *Foundations of educational technology: Integrative approaches and interdisciplinary perspectives*. Routledge.
- [91]. Mst Shurovi, A. (2024). Machine Learning Models for Bank Reconciliation Anomaly Detection in High-Volume Financial Transactions. *American Journal of Data Science and Analytics*, 5(12), 314-354. <https://doi.org/10.63125/mmwb6467>
- [92]. Muhammad Zahidul, I. (2024). Assessment of Data Integrity Gaps and Preventive Strategies in QC Laboratories in Compliance with FDA and CGMP Expectations. *American Journal of Scholarly Research and Innovation*, 3(01), 243-291. <https://doi.org/10.63125/a3xjb608>
- [93]. Muhammad Zahidul, I., & Amena Begum, S. (2022). Applied Data-Analytics Approaches to Cardiovascular Drug-Utilization Patterns: An Empirical Study Using Real-World Pharmaceutical Sales Data. *American Journal of Data Science and Analytics*, 3(12), 89-129. <https://doi.org/10.63125/7xgryf71>
- [94]. Mukut Kanti, B. (2020). Integrated Framework for Fire Safety and Electrical Hazard Assessment in Large-Scale Industrial and Commercial Facilities: A Mixed-Method Analysis. *American Journal of Advanced Technology and Engineering Solutions*, 1(01), 40-86. <https://doi.org/10.63125/zxsbd47>
- [95]. Mukut Kanti, B. (2024). AI-Enabled Predictive Asset Integrity Monitoring for Industrial Equipment in Oil & Gas and Energy Sector Facilities. *International Journal of Scientific Interdisciplinary Research*, 5(2), 746-791. <https://doi.org/10.63125/3mjcah04>
- [96]. Nakousi, C., Pascual, R., Anani, A., Kristjanpoller, F., & Lillo, P. (2018). An asset-management oriented methodology for mine haul-fleet usage scheduling. *Reliability Engineering & System Safety*, 180, 336-344.
- [97]. Nyemba, W. R., & Mbohwa, C. (2017). Modelling, simulation and optimization of the materials flow of a multi-product assembling plant. *Procedia Manufacturing*, 8, 59-66.
- [98]. Ozcan, B., & Ozturk, I. (2019). Renewable energy consumption-economic growth nexus in emerging countries: A bootstrap panel causality test. *Renewable and Sustainable Energy Reviews*, 104, 30-37.
- [99]. Park, P., Ergen, S. C., Fischione, C., Lu, C., & Johansson, K. H. (2017). Wireless network design for control systems: A survey. *IEEE Communications Surveys & Tutorials*, 20(2), 978-1013.
- [100]. Peng, Y., Jolfaei, A., & Yu, K. (2021). A novel real-time deterministic scheduling mechanism in industrial cyber-physical systems for energy internet. *IEEE Transactions on Industrial Informatics*, 18(8), 5670-5680.
- [101]. Perrin, C., Manighetti, I., Ampuero, J. P., Cappa, F., & Gaudemer, Y. (2016). Location of largest earthquake slip and fast rupture controlled by along-strike change in fault structural maturity due to fault growth. *Journal of Geophysical Research: Solid Earth*, 121(5), 3666-3685.
- [102]. Petritoli, E., Leccese, F., & Ciani, L. (2018). Reliability and maintenance analysis of unmanned aerial vehicles. *Sensors*, 18(9), 3171.
- [103]. Pfadenhauer, L. M., Mozygemba, K., Gerhardus, A., Hofmann, B., Booth, A., Lysdahl, K. B., Tummers, M., Burns, J., & Rehfuess, E. A. (2015). Context and implementation: a concept analysis towards conceptual maturity. *Zeitschrift für Evidenz, Fortbildung und Qualität im Gesundheitswesen*, 109(2), 103-114.

- [104]. Pfeiffer, J. H., Dingler, M. E., Dietz, C., & Lueth, T. C. (2015). Requirements and architecture design for open real-time communication in the operating room. 2015 IEEE International Conference on Robotics and Biomimetics (ROBIO),
- [105]. Plass, J. L., Homer, B. D., & Kinzer, C. K. (2015). Foundations of game-based learning. *Educational psychologist*, 50(4), 258-283.
- [106]. Pressley, P. N., Levis, J. W., Damgaard, A., Barlaz, M. A., & DeCarolis, J. F. (2015). Analysis of material recovery facilities for use in life-cycle assessment. *Waste Management*, 35, 307-317.
- [107]. Pritchard, B. P., Altarawy, D., Didier, B., Gibson, T. D., & Windus, T. L. (2019). New basis set exchange: An open, up-to-date resource for the molecular sciences community. *Journal of chemical information and modeling*, 59(11), 4814-4820.
- [108]. Raja, F. R., Chen, D., & Hexel, R. (2022). A flexible communication protocol with guaranteed determinism for distributed, safety-critical real-time systems. *IEEE Access*, 10, 48049-48070.
- [109]. Rehman, A., Rauf, A., Ahmad, M., Chandio, A. A., & Deyuan, Z. (2019). The effect of carbon dioxide emission and the consumption of electrical energy, fossil fuel energy, and renewable energy, on economic performance: evidence from Pakistan. *Environmental Science and Pollution Research*, 26(21), 21760-21773.
- [110]. Rosa-Schleich, J., Loos, J., Mußhoff, O., & Tscharncke, T. (2019). Ecological-economic trade-offs of diversified farming systems—a review. *Ecological economics*, 160, 251-263.
- [111]. Rothe, J., Gaxiola, G., Marshall, L., Asakawa, T., Yamagata, K., & Yamamoto, M. (2015). Novel approaches to optimizing carrier logistics in semiconductor manufacturing. *IEEE Transactions on Semiconductor Manufacturing*, 28(4), 494-501.
- [112]. Saidi-Mehrabad, M., Dehnavi-Arani, S., Evazabadian, F., & Mahmoodian, V. (2015). An Ant Colony Algorithm (ACA) for solving the new integrated model of job shop scheduling and conflict-free routing of AGVs. *Computers & Industrial Engineering*, 86, 2-13.
- [113]. Saidi, K. S., Bock, T., & Georgoulas, C. (2016). Robotics in construction. In *Springer handbook of robotics* (pp. 1493-1520). Springer.
- [114]. Saini, M., Yadav, J., & Kumar, A. (2022). Reliability, availability and maintainability analysis of hot standby database systems. *International journal of system assurance engineering and management*, 13(5), 2458-2471.
- [115]. Salkin, C., Oner, M., Ustundag, A., & Cevikcan, E. (2017). A conceptual framework for Industry 4.0. In *Industry 4.0: managing the digital transformation* (pp. 3-23). Springer.
- [116]. Santos, R. M., Orozco, J., Ochoa, S. F., Meseguer, R., & Mosse, D. (2018). Providing real-time message delivery on opportunistic networks. *IEEE Access*, 6, 40696-40712.
- [117]. Sayed, A., El-Shimy, M., El-Metwally, M., & Elshahed, M. (2019). Reliability, availability and maintainability analysis for grid-connected solar photovoltaic systems. *Energies*, 12(7), 1213.
- [118]. Schmidhalter, D. R., Schmidt, A. C., Beck, S., & Morgenstern-Egli, S. A. (2022). A Strategic Approach to the Management of Single-Use Technology. *Chemie Ingenieur Technik*, 94(12), 1902-1913.
- [119]. Seno, L., Cena, G., Scanzio, S., Valenzano, A., & Zunino, C. (2016). Enhancing communication determinism in Wi-Fi networks for soft real-time industrial applications. *IEEE Transactions on Industrial Informatics*, 13(2), 866-876.
- [120]. Shekhar, C., Jain, M., Raina, A. A., & Iqbal, J. (2018). Reliability prediction of fault tolerant machining system with reboot and recovery delay. *International journal of system assurance engineering and management*, 9(2), 377-400.
- [121]. Shima Ali, S., Musomi, K., & Sonya, G. (2024). Integrated Infectious Disease Preparedness: Multilingual Health Communication Strategies for Public Health Risk Mitigation, Disease Intervention and Prevention for Culturally Diverse Population in United States. *American Journal of Data Science and Analytics*, 5(10), 01-47. <https://doi.org/10.63125/ehk4mt02>
- [122]. Stanciu, A. (2017). Blockchain based distributed control system for edge computing. 2017 21st international conference on control systems and computer science (CSCS),
- [123]. Swain, D. L., Langenbrunner, B., Neelin, J. D., & Hall, A. (2018). Increasing precipitation volatility in twenty-first-century California. *Nature Climate Change*, 8(5), 427-433.
- [124]. Teh, H. Y., Kempa-Liehr, A. W., & Wang, K. I.-K. (2020). Sensor data quality: A systematic review. *Journal of Big Data*, 7(1), 11.
- [125]. Tonay, P., Md Maruf, I., & Al, A. (2024). Artificial Intelligence-Based Decision Support Systems and Managerial Performance. *American Journal of Advanced Technology and Engineering Solutions*, 4(04), 154-184. <https://doi.org/10.63125/wmz8dc67>
- [126]. Tooby, J., & Cosmides, L. (2015). Conceptual foundations of evolutionary psychology. *The handbook of evolutionary psychology*, 5-67.
- [127]. Uriarte, A. G., Ng, A. H., Zúñiga, E. R., & Moris, M. U. (2017). Improving the material flow of a manufacturing company via lean, simulation and optimization. 2017 IEEE International conference on industrial engineering and engineering management (IEEM),
- [128]. Van Erp, T., Davidsen, E. E., Grøndahl, O. W., & Petersen, A. N. (2022). A factory planning and design framework for integrating the Digital Twin in Industry 4.0. 2022 IEEE 27th international conference on emerging technologies and factory automation (ETFA),
- [129]. Villangca, M. J., Palima, D., Bañas, A. R., & Glückstad, J. (2016). Light-driven micro-tool equipped with a syringe function. *Light: Science & Applications*, 5(9), e16148-e16148.
- [130]. Wang, Y., Su, Z., Zhang, N., Xing, R., Liu, D., Luan, T. H., & Shen, X. (2022). A survey on metaverse: Fundamentals, security, and privacy. *IEEE Communications Surveys & Tutorials*, 25(1), 319-352.
- [131]. Wang, Z., & Feng, C. (2015). A performance evaluation of the energy, environmental, and economic efficiency and productivity in China: An application of global data envelopment analysis. *Applied Energy*, 147, 617-626.

- [132]. Wehner, M., Truby, R. L., Fitzgerald, D. J., Mosadegh, B., Whitesides, G. M., Lewis, J. A., & Wood, R. J. (2016). An integrated design and fabrication strategy for entirely soft, autonomous robots. *nature*, 536(7617), 451-455.
- [133]. Werner, M., Wiese, M., & Maas, A. (2021). Embedding process mining into financial statement audits. *International Journal of Accounting Information Systems*, 41, 100514.
- [134]. Wolf, M., & Serpanos, D. (2017). Safety and security in cyber-physical systems and internet-of-things systems. *Proceedings of the IEEE*, 106(1), 9-20.
- [135]. Wolstenholme, L. C. (2018). *Reliability modelling: a statistical approach*. Routledge.
- [136]. Yang, L., & Zhang, X. (2018). Assessing regional eco-efficiency from the perspective of resource, environmental and economic performance in China: A bootstrapping approach in global data envelopment analysis. *Journal of Cleaner Production*, 173, 100-111.
- [137]. Yang, S.-H., Cao, Y., Wang, Y., Zhou, C., Yue, L., & Zhang, Y. (2021). Harmonizing safety and security risk analysis and prevention in cyber-physical systems. *Process safety and environmental protection*, 148, 1279-1291.
- [138]. Yang, W., Du, H., Liew, Z. Q., Lim, W. Y. B., Xiong, Z., Niyato, D., Chi, X., Shen, X., & Miao, C. (2022). Semantic communications for future internet: Fundamentals, applications, and challenges. *IEEE Communications Surveys & Tutorials*, 25(1), 213-250.
- [139]. Zhang, H., Chen, S., & Wang, S. (2022). Impact of economic growth and labor productivity dispersion on energy intensity in China. *Energy*, 242, 123004.
- [140]. Zhang, J., Haskins, C., Liu, Y., & Lundteigen, M. A. (2018). A systems engineering-based approach for framing reliability, availability, and maintainability: A case study for subsea design. *Systems Engineering*, 21(6), 576-592.
- [141]. Zhang, L., Jeong, D., & Lee, S. (2021). Data quality management in the internet of things. *Sensors*, 21(17), 5834.
- [142]. Zonnenshain, A., & Kenett, R. S. (2020). Quality 4.0—the challenging future of quality engineering. *Quality engineering*, 32(4), 614-626.
- [143]. Zou, T., Ertug, G., & George, G. (2018). The capacity to innovate: A meta-analysis of absorptive capacity. *Innovation*, 20(2), 87-121.