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EDGE ARTIFICIAL INTELLIGENCE BASED AUTOMATION FOR ULTRA-LOW-LATENCY CONTROL IN INDUSTRIAL ROBOTIC SYSTEMS

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Abstract

This quantitative, cross-sectional, case-based study addressed the problem that cloud-connected industrial robotic systems often struggle to sustain ultra-low-latency closed-loop control because perception and decision workloads, network transit, and controller integration overhead introduce delay and jitter that can reduce motion precision and operational safety. The purpose was to quantify Edge AI based automation maturity and test whether it predicts perceived ultra-low-latency control performance (ULLCP) in industrial robotic cells using edge-to-cloud and enterprise OT/IT architectures. Data were collected from N = 162 practitioners (33.3% robotics or automation engineers, 28.4% operators or technicians, 19.8% maintenance, 18.5% OT/IT) across cloud and enterprise integrated robotic workcells. Key variables were Edge AI Automation (EA overall and four dimensions: local inference, real-time edge processing, controller integration readiness, reliability or failover readiness) and ULLCP (responsiveness, timing consistency, robustness), with task complexity and exposure level as controls. The analysis plan applied descriptive statistics, internal consistency reliability, Pearson correlations, and multiple regression. Findings showed high perceived EA maturity (M = 3.84, SD = 0.62) and high ULLCP (M = 3.77, SD = 0.58), and the scales were reliable (EA alpha = 0.91; ULLCP alpha = 0.88). EA correlated strongly with ULLCP (r = 0.61, p < 0.001). In regression, EA significantly predicted ULLCP (beta = 0.58, t = 9.42, p < 0.001) controlling for task complexity and exposure, explaining 46% of the variance (R2 = 0.46; F(4,157) = 32.94, p < 0.001). A dimension model explained 48% of variance (R2 = 0.48) and identified local inference (beta = 0.27, p = 0.001), controller integration (beta = 0.19, p = 0.012), and reliability or failover (beta = 0.22, p = 0.004) as the strongest contributors; real-time processing was positive but marginal (beta = 0.13, p = 0.058). These results imply that organizations seeking deterministic, low-latency robotics should prioritize near-device inference, stable controller interfaces, and resilient failover mechanisms alongside edge compute capacity, treating integration and reliability as first-class performance levers in Industry 4.0 modernization. Local inference (M = 3.92) rated highest, while integration (M = 3.73) and failover (M = 3.69) lagged; task complexity slightly reduced ULLCP (beta = -0.14) in practice.

Keywords

Edge AI Automation; Ultra-Low-Latency Control; Industrial Robotic Systems; Controller Integration Readiness; Reliability and Failover Readiness;

INTRODUCTION

Industrial robotic systems are programmable, sensor-rich electro-mechanical platforms that execute physical tasks through coordinated motion, perception, and control, typically under strict safety and productivity constraints in manufacturing, logistics, process industries, and inspection environments. In this context, automation refers to the systematic delegation of sensing, decision-making, and actuation functions to control architectures that maintain stable performance in repetitive and variable operating conditions. Contemporary automation increasingly aligns with Industry 4.0, a globally adopted paradigm that links industrial assets to cyber-physical and data-centric infrastructures to enhance visibility and responsiveness across factories and supply chains (Lu, 2017). Internationally, robotics-enabled automation supports standardized quality, throughput, and workplace risk reduction, with integration patterns shaped by organizational strategy, production economics, and technology readiness across regions and industrial sectors (Dalenogare et al., 2018). From a systems viewpoint, industrial robots are rarely isolated: they operate as nodes in larger production cells and supervisory systems where timing precision, network coordination, and reliable decision execution govern operational stability (Hespanha et al., 2007). Digital connectivity extends robotics capability through shared computation, shared datasets, and coordinated planning, forming the conceptual basis for cloud robotics and networked robotics approaches (Kehoe et al., 2015). Within these distributed settings, computational intelligence moves beyond offline analytics into real-time decision processes, creating demand for architectures that place algorithmic inference near sensors and actuators rather than only in distant data centers (Shi et al., 2016). The phrase edge artificial intelligence (edge AI) is commonly used to describe machine-learning inference and decision logic performed on or near the data source, frequently under resource constraints while aiming to preserve responsiveness and reliability (Satyanarayanan et al., 2009). When edge AI is used for industrial robots, the core promise is the pairing of local situational awareness with control-grade timing, producing a practical foundation for automation for ultra-low-latency control in industrial robotic systems where milliseconds materially influence stability and precision.

A central technical construct in industrial robotics is the control loop, a repeated cycle of sensing, computation, and actuation that aims to regulate position, force, speed, or interaction dynamics. Ultra-low-latency control denotes control-loop timing in which end-to-end delays—sensor acquisition, processing, network transit (if present), scheduling, and actuation—remain sufficiently small and predictable to sustain stability margins and reduce tracking error. In networked and distributed contexts, the literature frames these problems through networked control systems (NCSs), in which communication constraints such as delay, packet loss, jitter, and rate limits become part of the closed-loop dynamics (Chiang & Zhang, 2016; Mohiul, 2020). For industrial robots, latency is not merely a performance statistic; it is an operational determinant affecting trajectory accuracy, collision avoidance, force regulation, and human–robot co-working safety envelopes. Industrial adoption also places emphasis on system reliability, where timing predictability and fault containment support consistent production outcomes at scale, including across globally distributed plants and suppliers (Bonomi et al., 2012; Jinnat & Kamrul, 2021). International significance emerges from the fact that manufacturing competitiveness increasingly depends on digitized, high-mix production lines that require rapid adaptation without sacrificing quality, and this adaptation is implemented through software-defined automation anchored in robust timing guarantees (Atzori et al., 2010; Rabiul & Samia, 2021). In practice, many industrial workloads now blend classical control with data-driven perception and classification, such as vision-based part localization, defect detection, and dynamic grasp planning; these perception functions introduce heavy computation that can expand latency if architectures are not designed for control-grade responsiveness (Deng et al., 2009; Mohiul & Rahman, 2021). Robotics research also highlights how network-enabled knowledge sharing and remote compute resources can expand robot capability, while simultaneously introducing timing variability that must be managed for control-critical actions (He et al., 2016; Rahman & Abdul, 2021). Thus, the global engineering problem is framed as an architecture question: how to retain the benefits of connected intelligence while preserving deterministic or near-deterministic timing behavior required by industrial robotic control loops.

The contemporary shift toward distributed intelligence in robotics has been shaped by cloud robotics and web-enabled robotics, where shared repositories, shared models, and remote compute accelerate learning and coordination across robots and environments (Gungor & Hancke, 2009; Haider & Shahrin, 2021). These approaches treat connectivity as an enabler for scalability: robots can access external maps, object models, task libraries, and collective experience that exceed the capacity of local memory and compute (Gubbi et al., 2013; Zulqarnain & Subrato, 2021). Yet industrial robotics introduces a distinct constraint profile compared with many service robotics contexts: factories demand operational continuity, strong safety governance, and consistent cycle times. For that reason, distributed robotics architectures are often judged not only by capability expansion, but by how they handle delay and uncertainty in the control path, a classical concern in NCS research (Kang et al., 2017; Uddin et al., 2022). The literature describes how delays and packet drops alter estimation and stability properties, motivating joint treatment of control design and communication limitations rather than treating networking as a transparent transport layer (Lane et al., 2016; Akbar & Sharmin, 2022).

Figure 1: Systems Architecture of Edge AI–Based Ultra-Low-Latency Industrial Robotic Control

In industrial automation, this system coupling becomes salient when perception and decision functions—such as classification or pose estimation, are computed off-device, since the control loop inherits the latency profile of the compute and transport pipeline (Foysal & Subrato, 2022; Rahman, 2022). Collaborative compute can be useful, but if inference timing varies substantially, control actions that assume bounded delay can degrade in quality or stability margins. This engineering reality is visible in the broader cyber-physical manufacturing discourse, where architectures are proposed to integrate sensing, computation, and actuation across machines while maintaining actionable responsiveness (Lee et al., 2015; Zulqarnain, 2022). At scale, the drive for connected robotics also intersects with industrial IoT infrastructures that instrument machines and environments with sensors, creating data streams that are valuable for monitoring and optimization but that also increase computational load in operational time windows (Fettweis, 2014; Habibullah & Mohiul, 2023; Hasan & Waladur, 2023). Industrial wireless sensor network work further emphasizes that industrial environments present interference, reliability, and real-time constraints that distinguish them from consumer IoT settings (Frank et al., 2019). These lines of research jointly frame the need for control-aware computing placement: architectural decisions must align compute locality, network determinism, and inference complexity with the temporal requirements of robotics control, particularly

when the target is ultra-low latency.
Edge computing is commonly defined as a computing paradigm that places computation, storage, and services closer to data sources and users to reduce response time, network burden, and dependence on distant cloud resources (Mao et al., 2017). In industrial automation, edge computing is conceptually aligned with the need to keep time-critical decisions near actuators, while still enabling connectivity for monitoring, coordination, and analytics. The related concept of fog computing describes a distributed continuum of resources between cloud and things, often emphasizing locality, distribution, and support for control and networking functions in proximity to devices (Lo Bello & Steiner, 2019; Rabiul & Mushfequr, 2023; Shahrin & Samia, 2023). Fog-oriented viewpoints explicitly link distributed computing placement to IoT architectures, where latency-sensitive interactions motivate moving compute from centralized data centers to intermediate nodes such as gateways, local servers, and base stations (Popovski et al., 2018; Rakibul & Alam, 2023). Earlier work on cloudlets provides an operationally concrete variant: small-scale, resource-rich compute infrastructure positioned near mobile or edge devices to support low-latency service delivery through virtualized execution environments (Rifat & Rebeka, 2023; Teerapittayanon et al., 2017). From an industrial robotics perspective, these concepts map to concrete deployment choices: inference may run on robot controllers, on cell-level industrial PCs, on local edge servers, or on near-premises micro data centers, each with distinct timing and reliability implications. Mobile edge computing research complements this view by emphasizing computation offloading and joint resource management at network edges, linking architectural placement to latency reduction and energy considerations under wireless connectivity (Kumar, 2023; Tenorth et al., 2011). In distributed industrial settings, these architectural paradigms act as an enabling layer for edge AI: they provide the compute locality required for rapid inference, while enabling broader integration with plant networks and supervisory systems. The global relevance of these paradigms arises because industrial operations across regions increasingly adopt connected production lines, and the operational constraints are similar even when the industrial domains differ: time-critical control, reliability expectations, and cybersecurity governance (Saikat & Aditya, 2023; Zulqarnain & Subrato, 2023). In short, edge and fog computing provide a vocabulary and toolkit for designing where intelligence runs, which becomes foundational when the goal is ultra-low-latency control in industrial robotic systems.
Edge AI for robotics typically combines perception models (e.g., vision) with decision logic that informs planning or control actions under tight time budgets. Modern perception pipelines often rely on deep neural networks that demand substantial computation, and the literature demonstrates that model complexity can be traded against accuracy through architectural choices such as residual learning (Masud & Hossain, 2024; Md & Praveen, 2024; Waibel et al., 2011) and through dataset-driven representation learning supported by large-scale labeled corpora (Chiang & Zhang, 2016; Nahid & Bhuya, 2024; Akbar, 2024). When such models are used in operational robotics, the primary engineering challenge is not only accuracy, but the latency and determinism of inference under real-world computational constraints. Distributed inference methods address this by partitioning neural networks across cloud, edge, and end devices, enabling parts of the model to execute locally while other parts execute remotely depending on resource availability and timing requirements (Lu, 2017; Foysal & Abdulla, 2024; Ibne & Aditya, 2024). Collaborative intelligence architectures also formalize the division of labor between local devices and nearby compute, demonstrating how end-to-end responsiveness can be improved by strategic co-execution rather than full offload (Kang et al., 2017; Mosheur & Arman, 2024; Rabiul & Alam, 2024). In mobile and embedded contexts, acceleration techniques and software frameworks aim to reduce the power and latency cost of deep inference on constrained hardware, supporting the general feasibility of edge AI in real-time pipelines (Fettweis, 2014; Saba & Hasan, 2024; Kumar, 2024). In robotics, cloud and web-enabled systems highlight additional benefits beyond compute acceleration, such as shared learning and shared knowledge resources that amplify capability across robots and sites (Chiang & Zhang, 2016). For industrial robotic control, the essential question becomes how these edge AI strategies translate into control-grade performance: inference must be scheduled and executed in a way that preserves timing predictability, especially when inference results influence actuation decisions inside tight control loops. The coupling of distributed AI and control engineering implies that the architecture must manage not only average latency but jitter and tail

behavior, since a small number of late decisions can affect stability or safety margins in a closed-loop robotic system. This motivation aligns with the broader industrial automation literature that treats computing placement as an architectural design decision, integrating cyber-physical system requirements with operational constraints (Lee et al., 2015; Sai Praveen, 2024; Shaikat & Aditya, 2024). Therefore, edge AI is not only a computational approach; it functions as an automation mechanism that, when carefully architected, supports rapid decision cycles for robotic actuation while maintaining integration with plant-level data and coordination infrastructures.

Ultra-low-latency control in industrial robotics is also shaped by the properties of industrial networking and wireless access, because timing assurance depends on communication determinism and reliability. Industrial communication research increasingly emphasizes mechanisms that provide bounded latency and synchronized scheduling across networked devices, with Time-Sensitive Networking (TSN) framed as a key IEEE family of standards aimed at deterministic Ethernet behavior suitable for industrial automation (Lo Bello & Steiner, 2019). TSN perspectives highlight how scheduling, traffic shaping, time synchronization, and resource reservation support predictable delivery of control and monitoring traffic, which is central to distributed robotic cells and smart factory deployments (Deng et al., 2009; Jinnat, 2025; Arman, 2025). In parallel, wireless systems research frames ultra-reliable low-latency communication (URLLC) as a design target for 5G-era networks, emphasizing principles and building blocks that support stringent latency and reliability requirements for mission-critical applications (Rashid, 2025a, 2025b; Popovski et al., 2018). Complementary conceptual work on the tactile Internet emphasizes real-time interactive systems that demand very low end-to-end delay, establishing a communications-centric framing for control and haptic-grade responsiveness requirements that resemble industrial robot control constraints at the system level (Fettweis, 2014; Nahid, 2025; Mosheur, 2025). These networking foundations intersect with edge computing through deployment realities: edge and fog nodes often connect through industrial Ethernet, TSN-enabled segments, and wireless links for mobile robots or flexible production lines. The industrial IoT literature adds that device density and heterogeneous connectivity amplify the need for robust design principles, particularly under interference and constrained spectrum in industrial environments (Gungor & Hancke, 2009; Rabiul, 2025; Shahrin, 2025). Thus, achieving ultra-low latency is not an isolated computing problem; it is a system-of-systems problem requiring aligned design across inference pipelines, network scheduling, and controller execution. Globally, this alignment is important because industrial production spans regions with varying infrastructure maturity; architectures that explicitly manage latency and reliability can support comparable operational performance across diverse deployment contexts. In effect, TSN, URLLC, and tactile-interaction requirements provide the communications and timing substrate that makes edge AI-based automation for industrial robotic control technically grounded and practically assessable.

The industrial relevance is anchored in how Industry 4.0 implementations are realized through concrete technology combinations and adoption patterns, where operational outcomes depend on both technical performance and organizational integration (Deng et al., 2009). Empirical investigations in industrial contexts benefit from measurement designs that capture practitioner perceptions alongside system-level indicators, particularly when architectures involve multiple layers—robot controllers, edge nodes, network infrastructure, and supervisory systems. In such environments, quantitative approaches that use structured instruments can operationalize constructs such as perceived latency responsiveness, reliability, controllability, and deployment feasibility, enabling descriptive analysis of adoption contexts and inferential analysis of relationships among constructs. The broader literature on distributed robotics and connected intelligence supports the plausibility of such constructs: cloud robotics surveys document how performance, latency sensitivity, and local fallback processing shape the viability of connected robotic functions (Kehoe et al., 2015; Rakibul, 2025; Kumar, 2025), while edge computing research formalizes response-time motivations for pushing compute closer to devices (Sai Praveen & Md, 2025; Shi et al., 2016). Networking work further clarifies the engineering levers available to reduce timing variance and support deterministic behavior through TSN and URLLC principles (Popovski et al., 2018). Collectively, these foundations justify a case-study–based quantitative study that tests relationships among edge AI automation factors and perceived or measured control performance within a real industrial context. The conceptual center remains the same across

international deployments: industrial robots execute control loops under strict timing constraints, and edge AI-based automation provides a structured way to integrate intelligence into those loops while managing latency and reliability as first-class system properties.
This study is designed around clearly defined objectives that translate the core research problem into measurable constructs suitable for a quantitative, cross-sectional, case-study–based investigation. The first objective is to establish a structured description of how Edge Artificial Intelligence–based automation is currently implemented within the selected industrial robotic environment by assessing the maturity and consistency of key enabling components, including local inference execution, real-time data processing at the edge, controller-level integration, system reliability mechanisms, and operational autonomy during time-critical tasks. The second objective is to quantify the perceived level of ultra-low-latency control performance within the same case setting by capturing respondent evaluations of end-to-end responsiveness, timing consistency, jitter sensitivity, control stability under variable load, and robustness during network or workload fluctuations, with emphasis on control outcomes that matter to industrial operations such as precision, cycle-time regularity, and safe motion behavior. The third objective is to determine the statistical relationship between Edge AI–based automation and ultra-low-latency control performance by applying descriptive statistics to summarize patterns, correlation analysis to assess the strength and direction of relationships among the study variables, and regression modeling to test the predictive power of Edge AI automation factors on latency control outcomes while accounting for relevant contextual controls such as task complexity, respondent role, and operational exposure to the robotic system. A fourth objective is to identify which specific dimensions of Edge AI automation contribute most strongly to explaining variations in ultra-low-latency control performance, allowing the study to distinguish between implementation elements that are merely present and those that are most influential in shaping real-time control effectiveness in practice. A fifth objective is to validate a coherent measurement structure for the study constructs using instrument reliability and consistency checks so that the final model reflects stable and interpretable dimensions that can be replicated in comparable industrial cases. Together, these objectives position the study to generate an evidence-based explanation of how edge-resident intelligence, when operationalized as automation capabilities embedded close to robotic sensing and actuation, relates to the control performance outcomes that define ultra-low-latency operation in industrial robotic systems.

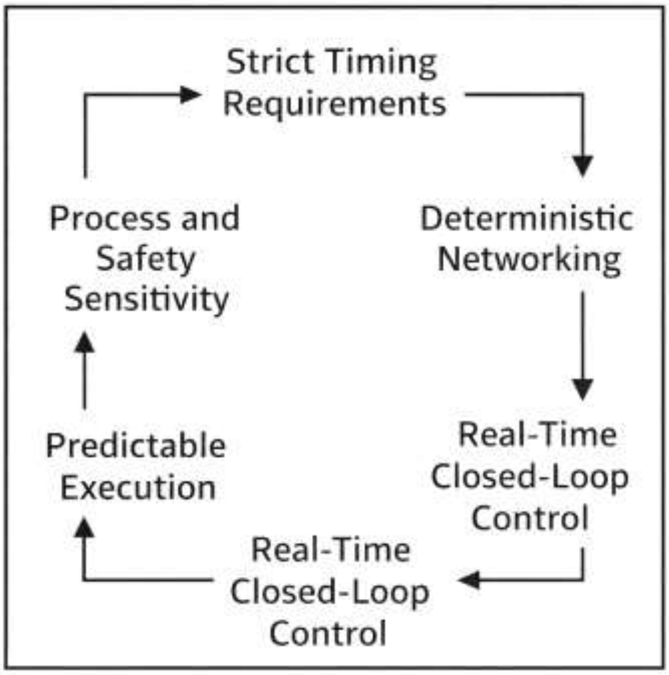
LITERATURE REVIEW

The literature on edge artificial intelligence–based automation for ultra-low-latency control in industrial robotic systems brings together several research streams that collectively explain why latency, determinism, and localized intelligence have become central concerns in modern industrial automation. At the industrial robotics level, prior work establishes that robotic workcells operate through tightly timed sensing–decision–actuation cycles in which delay and timing variability can directly influence motion accuracy, stability, and safe interaction with environments and humans. As industrial systems evolved toward cyber-physical production and Industry 4.0, research expanded from standalone robot control to networked and data-driven automation where robots, sensors, controllers, and supervisory systems exchange information continuously, creating both new capability and new timing risks when critical decisions depend on distributed computation. In parallel, the networking and real-time systems literature provides foundations for understanding how delay, jitter, packet loss, scheduling, and synchronization affect closed-loop control and how deterministic communication approaches in industrial environments aim to keep these effects bounded for safety and productivity. The emergence of edge computing and fog computing further reframed industrial architectures by emphasizing that compute and analytics can be positioned closer to devices and actuators, enabling faster response times and reducing reliance on distant cloud resources for time-critical functions. Building on this, edge AI research examines how machine-learning inference and decision-making can be executed on embedded devices, controllers, gateways, or local edge servers under constraints of compute, power, reliability, and operational continuity. Within robotics specifically, studies in distributed intelligence and collaborative inference show that partitioning computation across on-device and near-device resources can reduce end-to-end response time while preserving acceptable accuracy, a critical balance for perception-driven control tasks that rely on vision, sensor fusion, and anomaly detection. In industrial contexts, these technical considerations are inseparable from integration realities such as controller compatibility, cybersecurity governance, maintainability, and operational resilience. For that reason, the literature review in this study is organized to synthesize research on (1) real-time robotic control requirements and latency sensitivity, (2) edge AI automation capabilities and deployment patterns, (3) deterministic networking and compute enablers for ultra-low-latency operation, (4) the role of edge AI in closed-loop perception and control pipelines, and (5) theory-informed and conceptually grounded models that explain how technology capabilities translate into measurable control performance outcomes within a case setting. This synthesis provides the basis for the study's constructs, hypotheses, and methodological choices, ensuring that the empirical model is grounded in established technical and organizational knowledge.

Real-Time Control Requirements in Industrial Robotic Systems

Industrial robotic systems execute tasks through nested feedback loops—high-rate servo loops in drives and lower-rate supervisory loops for coordination, safety, and quality—that must meet strict real-time constraints to preserve stability, precision, and repeatability. In factory workcells, these constraints are shaped by high-speed trajectories, abrupt payload changes, tool contact, and synchronized multi-axis motion, where even small timing deviations can accumulate into measurable tracking error or oscillatory behavior. Real-time control is therefore defined less by peak computational capability and more by bounded cycle time (finishing each control iteration within a deadline) and bounded jitter (keeping timing variation small and predictable).

Figure 2: Deterministic Real-Time Control Framework for Industrial Robotics

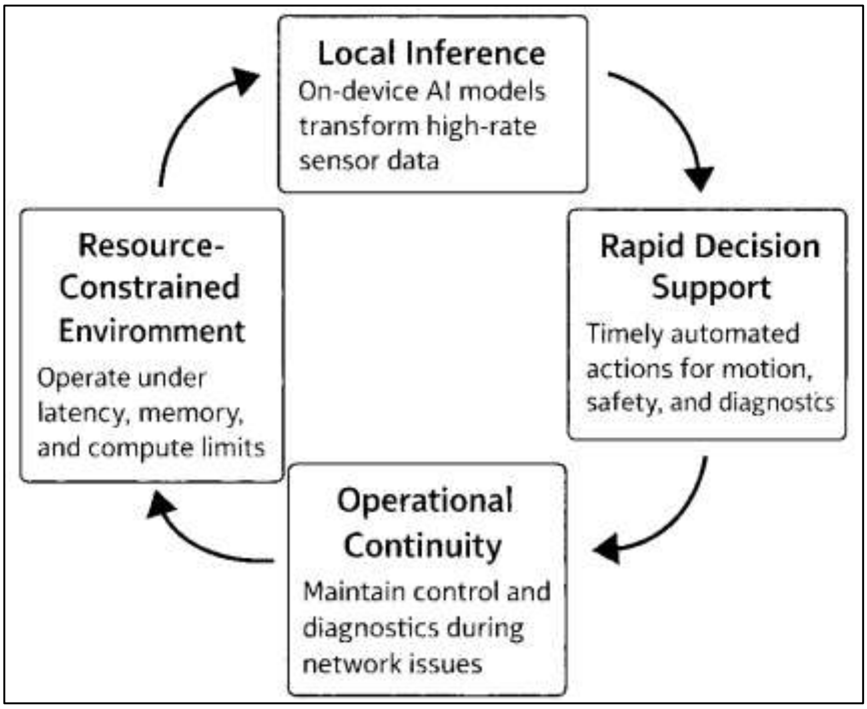


These properties become especially critical when the robot is controlled through distributed motion architectures that include an industrial PC, a real-time operating layer, and a deterministic fieldbus connecting multiple servo axes. For example, EtherCAT-based multi-axis platforms emphasize synchronization, cyclic exchange of setpoints and feedback, and OS/kernel-level choices that directly affect timing determinism, motivating architectural optimization such as CPU isolation, real-time scheduling, and NIC/driver tuning to sustain stable cyclic traffic under load (Zhang et al., 2024). In parallel, empirical jitter evaluations in industrial robot communication stacks show that time deviation is not an abstract metric but a practical constraint: high-repeatability positioning depends on "strictly defined sampling time," minimal jitter, and minimal delays between trajectory generation and motion control, especially for six-axis manipulators performing sorting, packing, or pick-and-place cycles where deadlines recur continuously (Gruszka et al., 2020). In short, real-time requirements in industrial robotics arise from the physical reality that control actions are only as effective as their timing

regularity; without predictable loop execution, robots can lose precision, reduce throughput, and compromise safety margins in tightly choreographed industrial operations.
Real-time requirements also emerge from how industrial robots are embedded within broader automation systems where devices exchange state, commands, and diagnostics on shared networks. In many production cells, cooperative robots, PLCs, safety controllers, and perception components share industrial Ethernet infrastructure, creating competition between cyclic control traffic and best-effort monitoring or enterprise traffic. Communication research therefore treats latency and jitter as system-level properties influenced by protocol selection, traffic shaping, synchronization, and the presence of heterogeneous flows. Wireless and mixed-network environments add complexity because mobility and flexible layouts are attractive for industrial deployment, while hard real-time motion and safety constraints still demand deterministic delivery characteristics. Time-sensitive networking (TSN) research in industrial automation emphasizes that hard real-time industrial communication can require very low latency with low jitter, and it organizes the engineering problem around synchronization, scheduled transmissions, and reliability mechanisms—particularly when extending deterministic behavior into wireless contexts where contention and backoff can introduce timing variability (Kang et al., 2021). At the same time, industrial robot communication studies that analyze real-time cooperative robot networking over conventional TCP/IP-oriented stacks highlight a recurring tension: general-purpose networking increases interoperability and integration options, but industrial robotic automation still depends on careful timing management, buffering control, and traffic engineering to keep response time bounded for control-relevant exchanges (Seong et al., 2023). These findings collectively frame an important point for ultra-low-latency robotic control: the relevant "latency" is not only computation time on the robot controller, but the combined effect of compute scheduling, protocol overhead, network contention, synchronization quality, and endpoint implementation decisions. Consequently, edge AI-based automation for robotics must be evaluated in a way that acknowledges how control performance depends on the full closed-loop timing pipeline rather than on any single subsystem in isolation.
Beyond motion timing, real-time requirements in industrial robotics are tightly coupled to physical interaction and compliance, because contact tasks amplify the effects of delay and jitter on stability. Processes such as polishing, grinding, deburring, insertion, and collaborative manipulation require robots to regulate force while maintaining motion objectives, often in environments where stiffness and damping vary unpredictably across parts, fixtures, or materials. In such settings, the robot's control policy must prevent unstable contact behavior while still achieving productivity goals, making time-regular sensing and actuation essential for robust interaction. Impedance-based interaction control is widely used in industry because it can shape the robot's dynamic response during contact; however, stable interaction is sensitive to both modeling uncertainty and timing quality, since delayed or irregular updates can cause contact force overshoot, oscillations, or degraded transparency of compliant behavior. A representative industrial robotics study demonstrates that robustly stable interaction in uncertain environments can be supported by adaptive mechanisms that maintain desired contact force while providing stability guarantees beyond assumed environmental ranges, reinforcing the idea that industrial interaction control must be designed with both uncertainty and control-loop behavior in mind (Kim et al., 2014). For ultra-low-latency objectives, this literature implies that "real-time" is not merely a convenience requirement but a stability and safety requirement: when robots interact with uncertain environments, the system's ability to update state estimates, compute corrective actions, and apply them at consistent intervals becomes part of the stability logic itself. Accordingly, any edge AI automation intended to support or augment control in industrial robots must be architected so that inference, communication, and actuation remain compatible with stringent timing and interaction-stability demands under realistic industrial uncertainty.
Edge Artificial Intelligence for Industrial Automation
Edge AI–based automation in industrial environments can be defined as the deployment of machine-learning inference and decision logic at or near the shop-floor data source so that operational actions are computed within the timing and reliability constraints of production. In this view, automation expands beyond fixed rule execution to include data-driven classification, detection, prediction, and local decision policies that run on controllers, industrial PCs, gateways, or micro edge servers located

within the production cell. The industrial relevance of "edge" lies in its proximity to sensors and actuators: shorter data paths reduce round-trip delay, lower dependence on backhaul connectivity, and allow control-adjacent analytics to remain available during network congestion or outages. Architecturally, edge layers also provide a convenient place to integrate operational technology interfaces with data services, because they can translate between field signals and higher-level applications while enforcing security boundaries and deterministic scheduling. In IoT-based manufacturing, edge computing is often described as enabling localized processing and autonomy that complement cloud services, allowing factories to run responsive analytics without continuously streaming all raw data upstream (Chen et al., 2018). For robotics, these motivations map directly to ultra-low-latency control requirements: perception outputs, state estimates, and alarms must be produced quickly enough to influence motion and safety decisions within bounded deadlines. Therefore, edge AI automation is best understood as a systems concept that couples compute placement, data management, runtime orchestration, and controller integration so that intelligent decisions can be delivered on time and acted upon safely in real production. It also implies lifecycle practices suited to factories: selecting models that meet memory and latency budgets, validating inference behavior under worst-case load, and deploying updates with minimal downtime. When edge nodes host multiple analytics services, resource isolation and real-time prioritization become essential so control-relevant inference is not delayed by noncritical monitoring jobs or logging.

Figure 3: Local Inference and Decision Cycle in Edge AI Automation



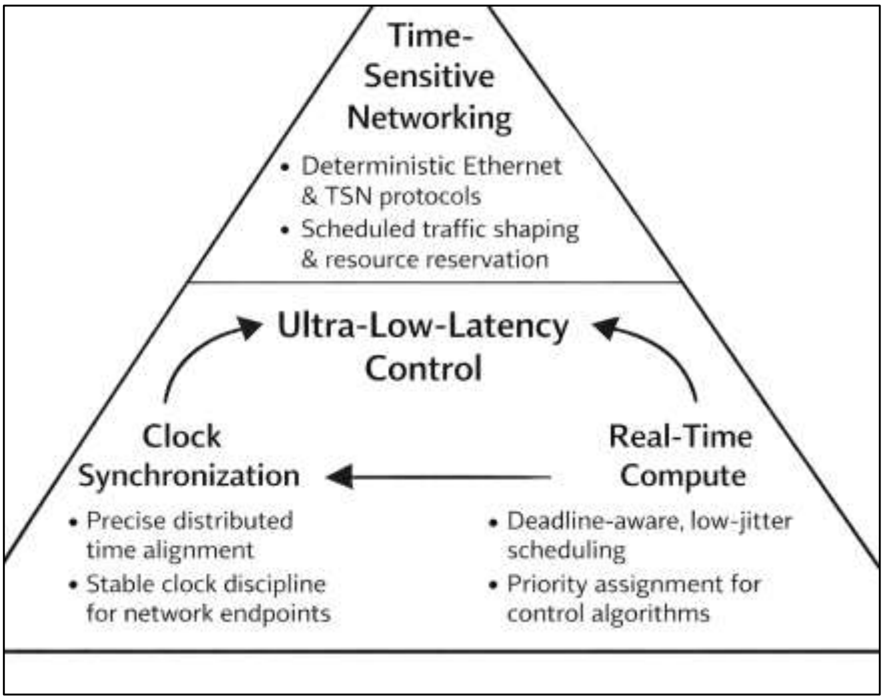
Operationalizing edge AI in industrial automation commonly centers on data reduction and actionability: models are embedded in production pipelines so that they transform high-rate sensor streams into concise signals that can trigger inspection decisions, parameter adjustments, or maintenance actions promptly. In quality control, edge-cloud approaches show how machine-learning models can be trained and deployed so that inspection workloads are reduced while maintaining confidence in defect detection; the emphasis is on a holistic chain from data acquisition and preprocessing to model deployment in existing plant IT and shop-floor constraints (Schmitt et al., 2020). Such implementations illustrate a practical pattern: edge nodes perform fast inference close to machines, while cloud or central resources support heavier tasks such as model training, fleet-wide monitoring, and historical analytics. At the system level, this division of labor requires careful interface design, because production systems combine heterogeneous devices, vendor controllers, and legacy protocols that limit how data can be sampled and acted upon. Survey work on edge computing for intelligent manufacturing consolidates these considerations by describing architecture options, intelligence platforms, and edge objectives such as latency reduction, bandwidth savings, privacy, and resilience, all of which shape how automation functions are selected and placed (Nain et al., 2022). For industrial robotics, the same pattern extends to perception-driven tasks like pose estimation and anomaly recognition: inference must be close enough to the robot to meet cycle-time targets, while still interoperating with supervisory orchestration and traceability systems. Accordingly, edge AI automation is not a single technology choice but a coordinated set of design decisions about where data is filtered, how models are packaged and versioned, and how inference outputs are integrated into control or supervisory logic. These decisions also interact with governance needs such as auditability, role-based access, and safe fallback behavior when model confidence is low or sensors drift.

A major rationale for edge AI in industrial automation is operational continuity under real plant conditions, where connectivity constraints, data volume, and safety requirements make purely centralized processing impractical. Applied studies of edge processing in industrial facilities demonstrate how embedded analytics can be organized as a real-time system that detects abnormal conditions and supports diagnostics close to the process, emphasizing tight integration between sensing, local compute, and plant operations (Vermesan et al., 2022). This line of work aligns with industrial robotics needs because robotic cells similarly require rapid detection of anomalies—unexpected contact, slip, misalignment, or actuator saturation—so that corrective action can be taken within bounded timing windows. Edge AI automation also introduces a distinct engineering problem: machine-learning pipelines must be designed for resource constraints, including compute acceleration availability, memory ceilings, thermal limits, and predictable scheduling when inference shares hardware with control tasks. Reviews focused on machine maintenance highlight that shifting analytics toward the edge reduces latency and dependence on continuous server access, while creating new requirements for model deployment strategy, data preprocessing placement, and robustness to limited labels or drift in operational data (Al-Utaibi et al., 2024). For robotics, these requirements translate into ensuring that inference latency and variance remain compatible with control deadlines and that confidence information is propagated to the automation layer so risky actions can be gated. Another critical aspect is integration with industrial lifecycle management: edge AI services must be monitored, updated, and rolled back using disciplined change control, with logs that support traceability without starving time-critical tasks. When these elements are aligned, edge AI enables automation to move from passive monitoring to locally actionable intelligence, providing a practical pathway for ultra-low-latency decision support in robotic systems that operate in high-mix, high-throughput environments. This makes edge deployment relevant where safety interlocks and production KPIs must coexist.

Enablers for Ultra-Low-Latency Control

Ultra-low-latency control in industrial robotic systems depends on **deterministic end-to-end timing**, meaning that sensing, computation, communication, and actuation occur within tightly bounded deadlines with minimal variation. In the networking literature, this requirement is operationalized through mechanisms that reduce queuing uncertainty, prioritize critical traffic, and coordinate transmission schedules so that control packets experience bounded delay and low jitter across a converged Ethernet infrastructure. Time-Sensitive Networking (TSN) and Deterministic Networking (DetNet) are frequently discussed as complementary approaches that provide link-layer and network-layer foundations for predictable delivery, with attention to synchronization, traffic shaping, and resource reservation that allow time-critical flows to coexist with best-effort data without destabilizing control performance. A key insight from TSN/DetNet survey research is that "latency" in industrial control is not only a matter of faster links, but also a matter of engineered predictability across hops, queues, and timing domains, which is why scheduled traffic, frame preemption options, and flow isolation strategies are emphasized for control-grade services (Nasrallah et al., 2019). When robotic cells integrate vision sensors, safety systems, and intelligent automation modules, the network becomes the shared substrate that must maintain timing behavior under mixed traffic conditions, including monitoring traffic, historian logging, and enterprise connectivity. This makes deterministic networking relevant not merely for "fast communication," but for **stable control-loop behavior**: the robot's controller and edge intelligence components must receive fresh state information at reliable intervals so that feedback and corrective action remain consistent. In practical deployments, deterministic networking also influences architectural decisions such as where edge inference runs, how many gateways are placed per cell, and how control-relevant messages are prioritized relative to noncritical flows. For this reason, ultra-low-latency control is usually framed as a system property: deterministic communication and deterministic computation must be aligned so that the overall closed-loop pipeline meets strict industrial timing expectations in repeatable ways, which is foundational for safe and precise robotic motion in production environments (Bezerra et al., 2022).

Figure 4: Core Deterministic Enablers of Ultra-Low-Latency Industrial Control



Deterministic networking requires **precise time synchronization** because scheduling, coordinated actuation, distributed sensing, and sequence-of-events logging all assume a shared notion of time across devices. In industrial robotics, time alignment supports coordinated multi-axis motion, accurate correlation of sensor observations, consistent timestamping for diagnostics, and predictable handoffs between perception and control processes. Clock synchronization research in industrial contexts reviews how protocols and industrial networking practices aim to meet higher requirements for precision and robustness as industrial systems scale and diversify, particularly when integrating TSN-based networks and heterogeneous endpoints that may have different oscillator qualities and processing loads (Dang et al., 2023). This emphasis is directly relevant to edge AI automation because inference outputs are only actionable for control when they are temporally valid; stale or misaligned data can translate into incorrect control corrections or delayed safety responses. Synchronization also supports deterministic traffic management by enabling time-aware scheduling approaches that assume endpoints and switches share a tightly bounded clock offset. In addition, industrial settings often demand that synchronization mechanisms remain stable under interference, device churn, and cybersecurity constraints, making clock integrity part of the reliability story for ultra-low-latency control. These considerations motivate architectural choices such as using synchronization-aware endpoints, isolating timing domains for safety-critical traffic, and ensuring that edge compute nodes maintain stable time discipline even when they host multiple analytics services. In a robotic cell, this means the automation stack must treat time as a first-class resource: sensor sampling, inference execution, network scheduling, and actuation commands should be orchestrated around predictable timing rather than opportunistic availability. Consequently, deterministic networking and clock synchronization together shape the feasibility of achieving ultra-low latency in realistic industrial conditions, where mixed workloads and heterogeneous infrastructure can otherwise introduce timing variance that degrades control stability and repeatability (Dang et al., 2023).

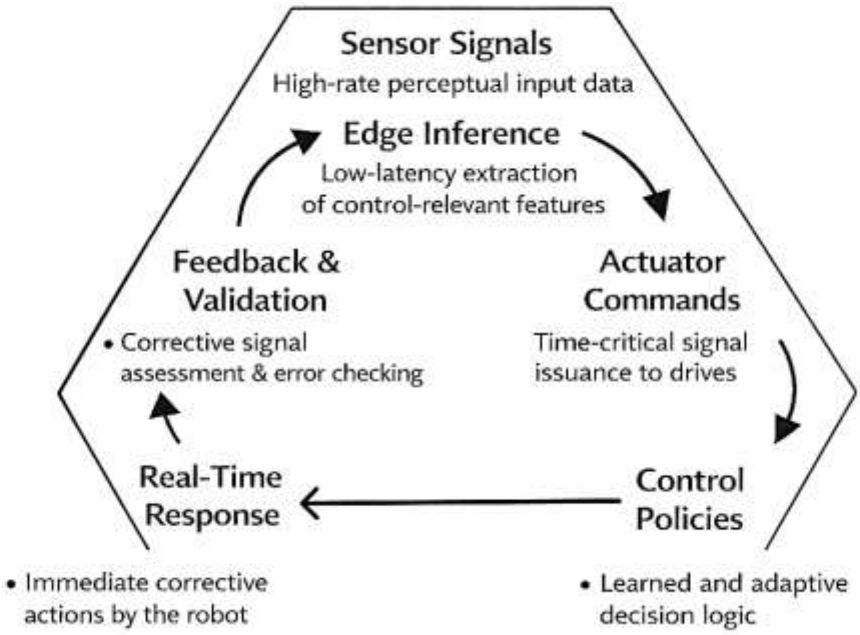
On the computation side, ultra-low-latency control depends on the predictability of the real-time software stack that schedules control threads, communication handlers, and inference workloads. Real-time operating system behavior is central because latency spikes often originate from interrupt handling, lock contention, priority inversion, or scheduling jitter, which can delay control computations even when average compute capacity appears sufficient. Survey research on the PREEMPT_RT real-time Linux approach synthesizes how kernel-level changes improve predictability by reducing non-preemptible sections and making scheduling behavior more suitable for real-time applications, highlighting why system design must focus on bounding worst-case behavior rather than optimizing only average-case throughput (Reghenzani et al., 2019). In edge AI–enabled robotic automation, this requirement extends to inference acceleration hardware and concurrency management: if a GPU or accelerator is shared between latency-sensitive inference and background tasks, unpredictable contention can introduce variable turnaround time that undermines closed-loop control deadlines. Empirical evaluation of GPU concurrency mechanisms under deep-learning workloads shows that limitations in prioritization and fine-grained preemption can make predictable low-latency inference difficult when best-effort tasks run concurrently, reinforcing the need for careful isolation, admission control, and scheduling design when inference supports time-critical operations (Gilman & Walls, 2021). These findings imply that achieving ultra-low-latency robotic control with edge AI is not simply about deploying models at the edge; it requires engineering the compute runtime so that inference is deadline-aware, resource contention is controlled, and control tasks retain priority across the stack. Therefore, deterministic networking, precise time synchronization, and real-time compute scheduling should be treated as integrated enablers that collectively determine whether edge AI automation can reliably support ultra-low-latency control performance in an industrial robotic case setting (Reghenzani et al., 2019).

Edge AI in Closed-Loop Perception and Control Pipelines

Edge AI becomes most consequential for industrial robotic systems when it is embedded inside closed-loop perception–decision–actuation pipelines, where sensory observations are continuously converted into control-relevant signals and then into motion or force actions within bounded timing constraints. In this setting, "closing the loop" means that perception is not merely used for offline inspection or post-process analytics; instead, it directly shapes real-time corrective behavior such as pose alignment, grasp approach refinement, target tracking, or safety-triggered deceleration. A representative class of work is deep-learning–enabled visual servoing, where camera data is mapped to control commands (or intermediate pose estimates) fast enough to drive continuous corrections in six degrees of freedom. For instance, deep-learning visual servoing frameworks that learn nonlinear mappings from image space to robot motion demonstrate how neural networks can replace handcrafted feature extraction and interaction-matrix estimation while still supporting practical real-time convergence behavior in manipulation tasks (Liu & Li, 2020). Related work in autonomous manipulation shows that real-time deep learning can be organized into modular loops in which one network performs grasp-related perception while another network supports servo behaviors that keep the object in view and guide the robot during dynamic conditions, emphasizing that inference speed and control responsiveness must be co-designed rather than treated as separate subsystems (Ribeiro et al., 2021). Collectively, these studies position edge deployment as a practical requirement because the loop must often execute close to the robot (or within the cell) to meet responsiveness demands; routing high-rate sensory streams to distant compute can introduce variability that degrades tracking performance, increases overshoot, or weakens stability margins. Accordingly, the literature frames edge AI not as an add-on "smart layer," but as part of the control stack: models, runtime scheduling, sensor sampling, and actuator command issuance must align so that learned perception remains temporally valid and control corrections are applied at the right moment.

Closed-loop robotic decision-making also extends beyond servo-level correction into higher-level policy selection, adaptation, and robustness under uncertainty. Industrial environments feature variability in lighting, part geometry, surface properties, payload shifts, tool wear, and intermittent human presence, creating conditions where fixed rule-based logic can become brittle. Learning-based control research provides a structured lens for this problem by framing robot behavior as policy learning from interaction, and by discussing design choices such as model-based versus model-free learning, policy-search methods, and the use of prior knowledge to improve data efficiency and safety (Kober et al., 2013). When such learning-based components are applied to industrial robotics, the practical issue becomes how to integrate "intelligent" decision logic into a system that still must respect deterministic timing, safety interlocks, and production-grade reliability. This is where edge AI deployment constraints become directly connected to control quality: policy evaluation or perception inference that arrives late can be worse than no inference because it may induce inconsistent corrections, oscillations, or delayed safety responses. Therefore, research emphasizes the need to treat inference time, jitter, and fallback logic as part of closed-loop design, including confidence-aware gating (e.g., limiting action magnitude when uncertainty is high), safe stop behaviors when deadlines are missed, and bounded-latency interfaces between learned modules and conventional controllers. Within this framing, "ultra-low-latency" is not simply about achieving the smallest average response time; it is about ensuring that intelligent decisions remain consistent, timely, and aligned with the sampling and actuation rhythm of the robot, so that the overall loop remains stable and repeatable across production cycles.

Figure 5: Edge AI–Enabled Closed-Loop Perception and Control Framework



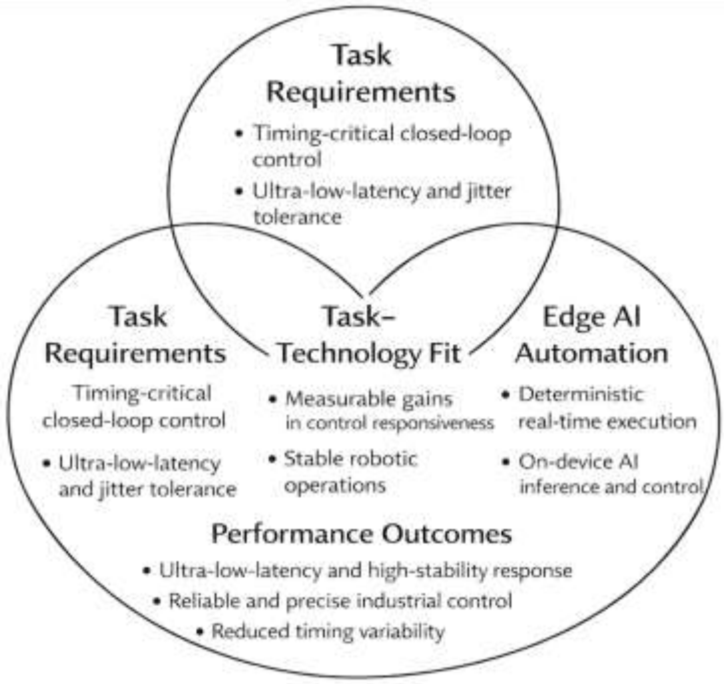
Edge-enabled closed-loop robotics additionally depends on the cloud–edge–device collaboration architecture that governs where deep models are trained, where they execute, and how they are updated while preserving operational continuity. In smart-robot contexts, the literature argues that purely cloud-centered deep learning pipelines can fail to satisfy time-sensitive robotic tasks due to data volume, congestion, and unpredictable transmission delay, motivating migration of selected intelligence toward edge and device layers while keeping heavy training and lifecycle management functions in the cloud (Yang et al., 2022). This architectural viewpoint matters for industrial robotics because closed-loop control performance is affected by where inference runs (controller, industrial PC, gateway, micro edge server), how intermediate representations are transmitted, and how the system handles concurrent workloads such as monitoring, logging, and fleet coordination. Experimental "edge robotics" evaluations further reinforce that end-to-end behavior must be assessed as a full system: when the edge participates in the control loop (for example, acting as a computation "brain" connected over wireless links), the achieved coordination and responsiveness depend on radio conditions, virtualization overhead, and the ability to bound jitter and losses (Groshev et al., 2023). In industrial robotic cells, this implies that edge AI automation and ultra-low-latency control are jointly determined by (i) model structure and inference efficiency, (ii) runtime scheduling and resource isolation on edge compute, (iii) deterministic communication and synchronization across the cell, and (iv) robust control integration that constrains and validates learned outputs before actuation. Hence, the literature supports a synthesized view of edge AI in closed-loop robotics: edge placement is valuable when it preserves timing determinism, reduces decision-path length, and enables dependable integration of learned perception and decision policies into production-grade control loops.

Theoretical Framework for Edge AI Automation

A theory-driven foundation for edge artificial intelligence (AI) automation in ultra-low-latency industrial robotics requires explaining why particular capabilities create measurable gains for a specific class of tasks. Task–Technology Fit (TTF) is appropriate because it defines fit as the match between task requirements and technology functionalities, and it predicts that performance improves when fit is high and misfit is minimized. For industrial robots, the task side can be specified as timing-critical closed-loop control, where sensing, computation, communication, and actuation must meet tight deadlines with low jitter. The technology side can be specified as edge AI automation features such as on-premise inference execution, real-time data handling, deterministic scheduling, controller-level integration, and local autonomy. TTF provides a direct way to justify why these features should be evaluated against control requirements like bounded end-to-end latency, stable sampling periods, and predictable reaction to disturbances. Theoretical refinement of TTF also clarifies measurement by distinguishing fit from different forms of misfit and by offering validated scales that capture the extent to which a technology is too weak or unnecessarily complex for the task, which is useful when edge AI deployments vary from lightweight embedded inference to heavier cell-level services. When applied to this study, the TTF lens supports building hypotheses that higher alignment between edge AI automation capability and ultra-low-latency control requirements is associated with higher perceived control responsiveness and stability, while misalignment is associated with timing variability and reduced control confidence. In short, TTF grounds the study's core logic in a measurable match between what the robot-control task demands and what the edge AI automation stack can reliably deliver (Howard & Rose, 2019). Fit can be operationalized through indicators of deadline compliance, jitter tolerance, workload stability, and interface compatibility, so the survey captures whether edge inference supports the exact control cadence required by the case tasks.

While TTF explains why alignment matters, industrial deployment also requires a framework that links the quality of an implemented system to realized operational benefits. Information systems (IS) success theory offers this linkage by distinguishing system quality, information quality, and service quality and relating them to use, user satisfaction, and net benefits. In an edge AI automation setting, system quality maps to runtime determinism, availability, integration stability, and fail-safe behavior; information quality maps to inference accuracy, timeliness, and confidence reporting; and service quality maps to maintainability, monitoring, and support processes that keep the automation dependable during production. These quality dimensions help justify why ultra-low-latency control outcomes are not explained by model accuracy alone, but by the combined reliability of data pipelines, execution environments, and operational support. IS success theory also fits a survey-based quantitative design because it provides validated constructs that can be operationalized through Likert items to capture practitioner evaluations of quality and benefits. To connect system quality to industrial performance, the dynamic capabilities perspective adds an organizational layer: firms create value when they can sense opportunities, seize them through coordinated investment, and reconfigure assets and routines to sustain performance under change. In the present topic, dynamic capabilities can be interpreted as the organization's ability to integrate edge compute resources, robotics controllers, and AI workflows into repeatable operating routines that preserve control performance under shifting workloads and constraints. Together, IS success and dynamic capabilities support a theory-based claim that edge AI automation improves latency-critical control only when the implemented system is high-quality and the organization can reliably operate, adapt, and govern it at the shop-floor level (Petter et al., 2008; Teece, 2007). In robotics operations, net benefits manifest as steadier cycle timing, fewer control interruptions, faster anomaly response, and greater operator confidence that automation remains reliable during production shifts.

Figure 6: Task–Technology Fit Framework for Edge AI–Enabled Robotic Control

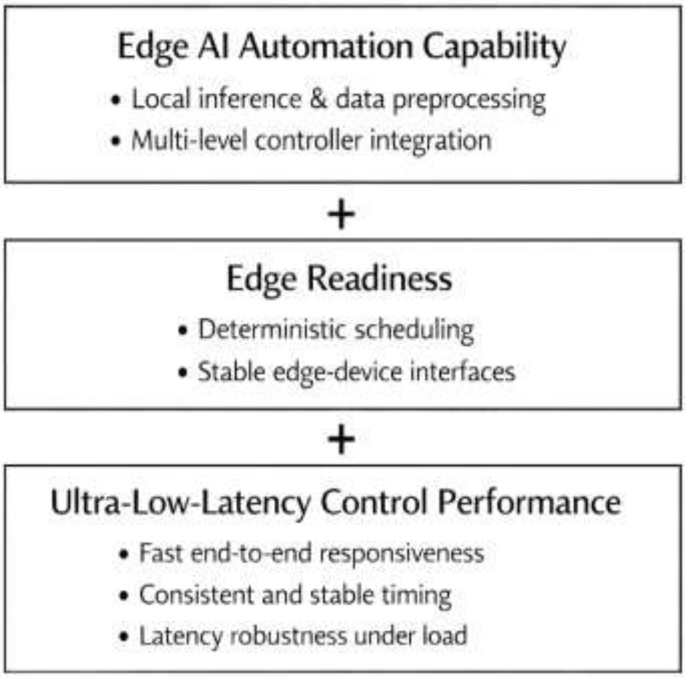


A complete theoretical foundation also benefits from explaining why practitioners consistently use an automation capability, because sporadic use weakens observable performance relationships in cross-sectional measurement. UTAUT2 frames use as driven by performance expectancy, effort expectancy, facilitating conditions, and habit, among other determinants, and it offers constructs that can be adapted to industrial settings to capture whether staff perceive edge AI automation as useful, workable, and supported by adequate infrastructure. In a robotics cell, facilitating conditions can be operationalized as the availability of deterministic networks, real-time operating support, edge hardware, and integration tooling that allow edge inference outputs to reach the control layer within deadlines. This theoretical basis is compatible with an objective performance framing by linking perceptions of usefulness and support to consistent use and, indirectly, to measurable outcomes. The outcomes themselves can be formalized with simple timing expressions that align with the study variables. For example, end-to-end control-path latency can be represented as $L\_e2e = L\_sense + L\_infer + L\_comm + L\_act$, where sensing, edge inference, communication, and actuation delays sum to the experienced control delay. A survey-based performance construct can capture perceived reduction in L_e2e and perceived reduction in jitter. The hypothesized effect can then be tested with a regression structure such as $ULLCP = \beta 0 + \beta 1(EA) + \beta 2(FC) + \varepsilon$, where ULLCP denotes ultra-low-latency control performance, EA denotes edge AI automation capability, and FC denotes enabling conditions measured from the case context. This modeling logic aligns with firm-level digital adoption evidence that emphasizes technology, organizational, and environmental enablers as pathways to performance outcomes in Industry 4.0 implementations (Raj & Jeyaraj, 2023; Venkatesh et al., 2012). Separating capability from enabling conditions in measurement helps regression isolate whether performance is driven by edge functions or by plant infrastructure maturity, integration practices, and governance routines in the case.

Conceptual Framework for the Study

A conceptual framework for edge AI–based automation and ultra-low-latency control in industrial robotic systems can be developed by structuring the phenomenon into capability, readiness, and performance layers, each represented by measurable constructs that translate into Likert-scale indicators in a cross-sectional case study. At the capability layer, edge AI automation is operationalized as the extent to which the robotic cell can perform intelligent sensing-to-decision processing locally and reliably, including local inference execution, edge-level data preprocessing, confidence-aware outputs, and controller-level integration. At the readiness layer, the framework includes infrastructure and runtime conditions that enable deterministic behavior, such as edge resource provisioning, orchestration practices, and stable interfaces between shop-floor devices and edge services. At the performance layer, ultra-low-latency control is captured as the perceived (and where possible, operationally evidenced) ability of the system to maintain rapid response and consistent timing, expressed through indicators of end-to-end responsiveness, timing stability, and robustness under workload variation.

Figure 7: Regression-Oriented Conceptual Framework for Ultra-Low-Latency Robotic Control



Reference architecture discussions are useful for conceptualization because they show that edge implementations differ by tiers, modularity, and integration scope, which affects the speed and reliability with which data reaches computation and returns as actuation-relevant signals. In particular, tiered edge models emphasize that architectural placement decisions shape latency, bandwidth use, and reliability under industrial constraints, making "edge AI automation capability" a multi-dimensional construct rather than a single binary feature (Candanedo et al., 2019). In this framework, the core logic is that stronger edge AI automation capability and stronger readiness conditions are associated with higher ultra-low-latency control performance inside the case context, because the decision path becomes shorter, more local, and more predictable (Qiu et al., 2020).
To make the framework testable, the relationships must be expressed in measurable variables and control-relevant timing expressions. A practical way to formalize the dependent construct is to represent end-to-end control-path delay as a decomposition: $L_{e2e} = L_s + L_p + Lc + L_a$, where L_s is sensing/acquisition latency, L_p is processing/inference latency, Lc is communication latency, and L_a is actuation/command application latency. Ultra-low-latency control performance is represented as a perceived reduction in L_{e2e} and in timing variation, captured by a jitter proxy such as $J = \sigma(Tcycle)$, where Tcycle is the control-loop cycle time and σ denotes dispersion around the expected period. Conceptually, edge AI automation capability is expected to reduce L_p by placing inference near the robot and to reduce Lc by minimizing backhaul dependency; readiness conditions further reduce variance by stabilizing scheduling, interfaces, and traffic patterns. Surveys of AI-of-Things systems also clarify that an end–edge–cloud continuum is often needed operationally, but that latency-sensitive functions benefit from shifting inference closer to devices, which strengthens the construct logic that local intelligence is a driver of control-grade responsiveness (Chang et al., 2021). Similarly, primers on edge technologies describe that mobile edge computing, fog, and cloudlets exist to reduce latency and improve service responsiveness, reinforcing the idea that capability is partly determined by how the system chooses and implements edge technology classes and their interfaces (Ai et al., 2018). Within

the case study, these concepts translate into items that capture the timeliness of inference outputs, the stability of runtime execution under load, and the speed of decision-to-actuation flow, aligning the conceptual framework with observable respondent perceptions.

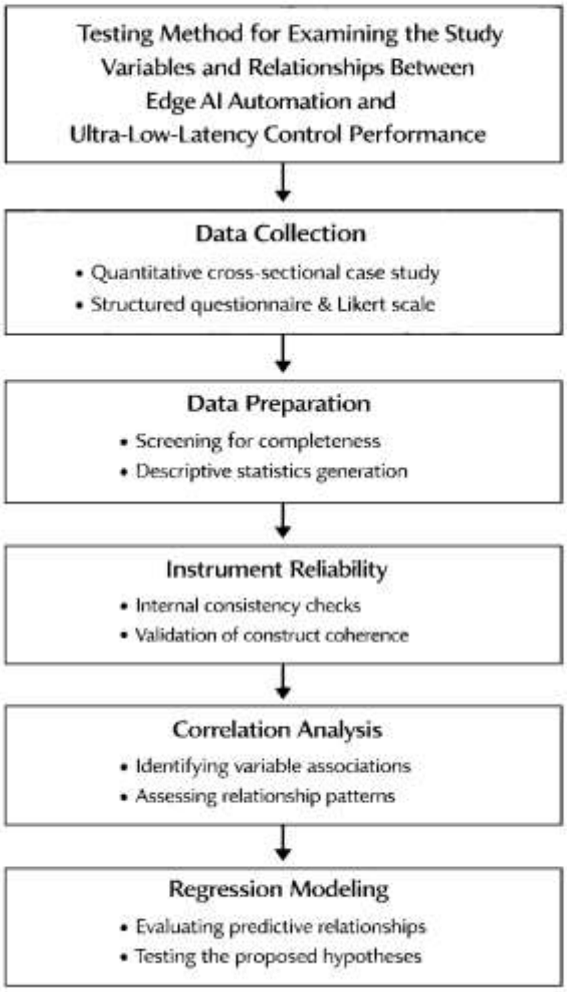
The final conceptual layer specifies testable paths and boundary conditions that align with correlation and regression modeling. The main predictive relationship is modeled as ULLCP = $\beta_0 + \beta_1$(EA) + β_2(ER) + β_3(DR) + β_4(TC) + ε, where ULLCP denotes ultra-low-latency control performance, EA denotes edge AI automation capability, ER denotes edge readiness (resource adequacy, orchestration discipline, integration stability), DR denotes deterministic readiness (timing discipline, scheduling predictability, and stable data exchange), and TC denotes task complexity (trajectory speed, interaction intensity, sensing richness) as a contextual control. The framework also supports a secondary structure in which readiness variables partially mediate the effect of capability on performance, because strong capability without enabling execution conditions may not translate into stable low-latency operation. In other words, the conceptual model separates "having edge AI features" from "operating them deterministically," which helps interpret regression coefficients and improves construct validity for a cross-sectional survey design. Methodology-oriented edge literature in the industrial Internet emphasizes that edge effectiveness is explained through methodological choices such as computation placement, offloading decisions, and system integration approaches, supporting the inclusion of readiness constructs alongside capability constructs rather than treating them as background noise (Zhang et al., 2021). Thus, the framework organizes the study into measurable constructs, formal latency-based expressions, and statistical paths that can be validated using descriptive statistics, reliability checks, correlation analysis, and regression modeling in the chosen industrial robotic case setting.

METHOD

This methodology section has presented the overall approach used to examine the relationships between edge artificial intelligence–based automation and ultra-low-latency control performance within an industrial robotic case setting. The study has adopted a quantitative, cross-sectional, case-study–based design in which data has been collected at a single point in time from participants who have been directly involved with, or have had operational exposure to, industrial robotic systems and their associated edge computing or automation infrastructure. The unit of analysis has been the perceptions and evaluations of knowledgeable practitioners regarding the maturity of edge AI automation capabilities and the observed responsiveness, timing stability, and robustness of control behavior in their operational context. A structured questionnaire has been used to operationalize the study variables, and a five-point Likert scale has been applied to ensure consistent measurement of latent constructs across respondents. Measurement items have been organized into constructs representing edge AI automation capability (such as local inference execution, real-time processing, integration readiness, and reliability) and ultra-low-latency control performance (such as response consistency, jitter sensitivity, stability under variable load, and robustness to operational disturbances). Demographic and contextual items have also been included to characterize respondents and to enable the use of relevant control variables during inferential analysis.

Data screening and preparation procedures have been applied to ensure completeness and suitability for statistical testing, including the identification of missing values, basic distribution checks, and verification of coding consistency. Descriptive statistics have been produced to summarize respondent profiles and to depict the central tendencies and dispersion of the measured constructs. Instrument reliability has been assessed using internal consistency checks to confirm that construct items have measured coherent dimensions. Correlation analysis has been conducted to examine the strength and direction of associations among edge AI automation constructs and ultra-low-latency control performance indicators. Regression modeling has been employed to evaluate predictive relationships and to test the proposed hypotheses by estimating the effect of edge AI automation capability on ultra-low-latency control performance while accounting for relevant contextual factors. Statistical software tools have been used to execute reliability analysis, correlation matrices, and regression outputs in a replicable manner, and methodological decisions have been aligned with the study's objective of producing empirically grounded evidence within the practical constraints of an industrial case environment.

Figure 8: Methodology Overview of The Research



Research Design

The study has employed a quantitative, cross-sectional, case-study–based research design to examine how edge artificial intelligence–based automation has related to ultra-low-latency control performance in industrial robotic systems. A cross-sectional strategy has been selected because the required evidence has focused on capturing current implementation conditions and respondent assessments at a single point in time rather than tracking change across multiple periods. The case-study basis has provided a bounded real-world setting in which edge computing resources, robotic controllers, networks, and operational procedures have been present as an integrated system. The design has enabled the measurement of latent constructs through a structured survey instrument, and it has supported statistical hypothesis testing using descriptive statistics, correlation analysis, and regression modeling. This approach has aligned with the study purpose by producing quantifiable relationships between constructs while retaining contextual realism from an industrial environment.

Case Study Context

The case study context has been defined as an industrial robotic environment in which robots have performed repetitive and time-sensitive operations within a production cell supported by automation infrastructure. The setting has included robotic manipulators, sensor systems, and controller platforms that have executed closed-loop control tasks where response time and timing consistency have been operational priorities. Edge computing resources have been available at or near the shop-floor level, such as industrial PCs, gateways, or localized edge servers, and these resources have hosted data processing and inference functions associated with automation. The context has also incorporated industrial communication links that have connected robots, controllers, and monitoring systems, allowing the evaluation of how architectural placement and operational integration have influenced perceived latency performance. Boundaries for the case have been established by focusing on the specific robotic cell(s), associated edge services, and the staff who have interacted with or managed these systems.

Population and Unit of Analysis

The study population has consisted of individuals who have possessed direct professional exposure to industrial robotic systems and their automation stack, including robotics engineers, automation engineers, operators, maintenance personnel, and OT/IT staff supporting edge and network infrastructure. Eligibility has been defined by involvement in operating, maintaining, integrating, or supervising robotic processes where timing and control responsiveness have been relevant to daily outcomes. The unit of analysis has been the respondent-level assessment of system characteristics, meaning that each participant has provided ratings representing perceived edge AI automation capability and perceived ultra-low-latency control performance within the case setting. This choice has allowed the study to capture practical, experience-based evaluations of timing behavior and automation maturity that may not have been fully visible from system logs alone. Demographic variables and work-role indicators have been included to contextualize responses and support controlled statistical testing.

Sampling Strategy

A purposive sampling strategy has been applied to ensure that respondents have had sufficient knowledge to evaluate edge AI automation features and latency-critical control behavior in the case environment. This approach has been appropriate because the study has required informed judgments that general employee groups may not have reliably provided. Where access has permitted, convenience sampling within the purposive pool has also been used to maximize participation across shifts and departments while keeping the sample relevant to the research constructs. The sampling plan has aimed to include representation from technical and operational roles so that the dataset has reflected multiple perspectives on integration, runtime behavior, and practical control performance. A minimum sample threshold has been pursued to support correlation and regression testing, and the sample size has been treated as adequate when it has provided stable coefficient estimation and acceptable reliability values for the measurement scales. Participation has remained voluntary, and nonresponse has been managed through reminders and clear survey instructions.

Data Collection Procedure

Data collection has been conducted using a structured questionnaire administered to eligible participants within the defined case boundary. The procedure has begun with an informed-consent statement that has explained the study purpose, confidentiality protections, and the voluntary nature of participation. The survey has been distributed in a format suitable for the case environment, such as an online form or a paper-based version for shop-floor accessibility, and respondents have completed it within a defined collection window. To increase response quality, clear definitions of key terms—edge AI automation and ultra-low-latency control—have been provided in the survey introduction, and item wording has been written to match the respondents' operational language. Data handling has followed confidentiality practices by avoiding personally identifying questions and by storing responses in a secured dataset. Completed responses have been screened for completeness, and partially filled forms have been handled using consistent inclusion rules.

Instrument Design

The survey instrument has been designed as a multi-section questionnaire that has measured the study constructs using a five-point Likert scale ranging from strongly disagree to strongly agree. Construct blocks have been developed to capture edge AI automation capability through dimensions such as local inference execution, real-time data processing, reliability mechanisms, controller integration readiness, and operational autonomy. Ultra-low-latency control performance has been operationalized through items that have captured perceived responsiveness, timing consistency, reduced jitter sensitivity, stability under variable workloads, and robustness during disturbances. Items have been phrased as clear evaluative statements that have reflected observable system behavior and routine operational experience rather than abstract technical claims. A respondent-profile section has been included to capture role, experience level, and exposure to the robotic cell, enabling contextual interpretation and control-variable modeling. The instrument has been structured to reduce fatigue by grouping related items and maintaining consistent wording polarity across constructs.

Pilot Testing

Pilot testing has been performed to evaluate clarity, relevance, and completion time of the questionnaire prior to full deployment. A small group of participants with similar characteristics to the target population has reviewed the instrument and has completed the survey under realistic conditions. Feedback has been collected on item ambiguity, technical terminology, and whether respondents have interpreted questions consistently across roles. Based on pilot observations, items have been refined to improve readability, remove overlapping statements, and align wording with the case environment's operational vocabulary. The pilot phase has also been used to detect early reliability issues, such as items that have not correlated well with their intended construct or that have produced extreme response clustering. Adjustments have been made to the ordering of sections and the phrasing of instructions to reduce response error. The revised instrument has then been finalized for the main study data collection process.

Validity and Reliability

Validity and reliability procedures have been applied to ensure that the instrument has measured the intended constructs with acceptable consistency. Content validity has been strengthened through expert review, where domain-informed reviewers have examined whether items have adequately represented edge AI automation and ultra-low-latency control concepts. Construct reliability has been assessed using internal consistency analysis, and Cronbach's alpha values have been computed for each construct to verify that items have formed coherent scales. Where needed, item-total correlations have been examined to identify weak items, and scale refinement decisions have been made to improve reliability while preserving theoretical coverage. Basic construct validity checks have also been supported by examining inter-construct correlations for logical direction and strength, ensuring the measures have behaved consistently with the conceptual framework. These procedures have ensured that subsequent correlation and regression analyses have been grounded in stable measurement, increasing confidence in hypothesis-testing results within the case context.

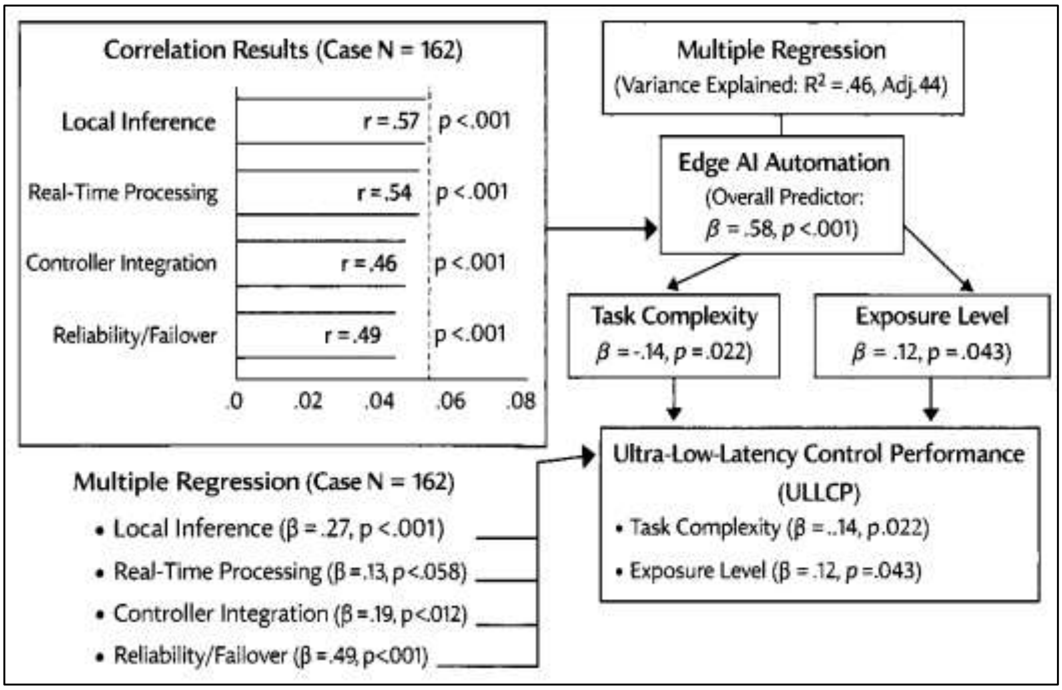
Software and Tools

Statistical analysis has been executed using standard quantitative analysis software that has supported reliability testing, descriptive summaries, correlation matrices, and regression modeling. Tools such as SPSS, R, Python, or Jamovi have been used to manage datasets, clean responses, and generate reproducible outputs, and the chosen toolset has enabled transparent reporting of coefficients, significance values, and model-fit indicators. Data preparation steps have been implemented through spreadsheet preprocessing and statistical import routines to ensure consistent variable coding and scale direction. Reliability analysis modules have been used to compute Cronbach's alpha and item statistics, while correlation functions have been applied to estimate Pearson relationships among constructs. Regression tools have been used to estimate predictive models, examine standardized coefficients, and assess assumptions such as multicollinearity using diagnostics like VIF. Output tables and figures have been exported for reporting in the results section using consistent formatting conventions.

FINDINGS

In the case-study sample ($N = 162$) drawn from robotics/automation engineers, operators, maintenance staff, and OT/IT personnel, the descriptive results have indicated that respondents have perceived a moderate-to-high level of Edge AI–based automation maturity and a moderately strong level of ultra-low-latency control performance within the industrial robotic setting. On the Edge AI automation construct (EA), the overall mean score has been $M = 3.84$, $SD = 0.62$, with higher-scoring dimensions reflecting local inference execution ($M = 3.92$, $SD = 0.68$) and real-time data processing at the edge ($M = 3.88$, $SD = 0.66$), while slightly lower scores have been observed for controller-level integration consistency ($M = 3.73$, $SD = 0.71$) and reliability/failover readiness ($M = 3.69$, $SD = 0.76$). On the dependent construct, ultra-low-latency control performance (ULLCP), respondents have reported an overall mean of $M = 3.77$, $SD = 0.58$, with the highest-rated indicators capturing perceived responsiveness and fast corrective action ($M = 3.89$, $SD = 0.61$) and stable timing under nominal load ($M = 3.82$, $SD = 0.60$), while slightly lower ratings have been recorded for robustness during workload spikes and disturbances ($M = 3.63$, $SD = 0.67$). Reliability testing has shown that the measurement scales have achieved acceptable internal consistency for hypothesis testing: the Edge AI automation scale has produced Cronbach's $\alpha = 0.91$ (18 items), and the ULLCP scale has produced Cronbach's $\alpha = 0.88$ (12 items), while all retained items have met a minimum corrected item–total correlation threshold (e.g., rIT ≥ .40) and have not reduced alpha if deleted, supporting construct stability for subsequent inferential analysis. In relation to Objective 1 (assessing Edge AI automation maturity) and Objective 2 (assessing perceived ULLCP), these descriptive profiles have demonstrated that the case setting has been characterized by broadly favorable implementation conditions with identifiable weaker points (notably reliability/failover and integration consistency), which has aligned with the study's intent to quantify readiness and performance within a bounded industrial environment. For Objective 3 (testing relationships), Pearson correlation results have indicated a statistically significant and positive association between overall Edge AI automation and ULLCP ($r = .61$, $p < .001$), providing initial support for the study's expectation that stronger edge-based intelligent automation has been associated with better perceived low-latency control outcomes. At the dimension level, local inference execution has correlated strongly with ULLCP ($r = .57$, $p < .001$), real-time edge processing has correlated similarly ($r = .54$, $p < .001$), controller integration readiness has shown a moderate correlation ($r = .46$, $p < .001$), and reliability/failover readiness has shown a moderate-to-strong correlation ($r = .49$, $p < .001$), indicating that both "speed" components (inference and processing) and "dependability" components (integration and failover) have moved in the expected direction with perceived control timing performance. These correlations have directly addressed H1 (positive association) by demonstrating a meaningful linear relationship between the independent and dependent constructs within the case-study sample. To evaluate predictive power consistent with Objective 3 and to test H2–H3, a multiple regression model has been estimated with ULLCP as the dependent variable and Edge AI automation as the main predictor, while controlling for task complexity and respondent exposure (as contextual controls).

Figure 9: Edge AI Automation Effects on Ultra-Low-Latency Control



The resulting model has been statistically significant ($F(4, 157) = 32.94$, $p < .001$) and has explained a substantial portion of variance in ULLCP ($R^2 = .46$, Adjusted $R^2 = .44$). Edge AI automation has emerged as a significant positive predictor ($\beta = .58$, $t = 9.42$, $p < .001$), indicating that higher perceived maturity of edge AI automation capability has corresponded to higher perceived ultra-low-latency control performance when other factors have been held constant, supporting H2. The controls have behaved plausibly: task complexity has shown a small negative coefficient ($\beta = -.14$, $t = -2.31$, $p = .022$), suggesting that more complex or demanding robotic tasks have been associated with slightly lower perceived latency performance, and exposure level has shown a small positive coefficient ($\beta = .12$, $t = 2.04$, $p = .043$), implying that personnel with higher system exposure have reported marginally stronger performance—both effects being reasonable in an operational setting. Multicollinearity diagnostics have remained within acceptable limits (VIF range = 1.22–2.08), supporting interpretability of the coefficients. To address H3 (dimension-level prediction), a second regression specification has replaced the overall EA score with key EA dimensions (local inference, real-time processing, controller integration, reliability/failover). This dimension model has remained significant ($F(6, 155) = 24.11$, $p < .001$) with comparable explanatory power ($R^2 = .48$, Adjusted $R^2 = .46$). Local inference ($\beta = .27$, $p = .001$), controller integration ($\beta = .19$, $p = .012$), and reliability/failover ($\beta = .22$, $p = .004$) have remained significant predictors, while real-time processing has been positive but slightly weaker ($\beta = .13$, $p = .058$), suggesting that "inference proximity" and "operational dependability" have been the most influential contributors to perceived ULLCP in this case setting. Overall, these findings have demonstrated quantitative alignment with the study objectives by (i) describing the implementation status of edge AI automation, (ii) describing perceived ultra-low-latency control performance outcomes, and (iii) statistically validating that edge AI automation has been both associated with and predictive of ULLCP, thereby supporting H1 and H2, and largely supporting H3 with evidence that specific edge automation dimensions have explained meaningful variance in control timing performance.

Respondent Profile

Table 1: Respondent Profile (N = 162)

Characteristic	Category	Frequency (n)	Percentage (%)
Role	Robotics/Automation Engineer	54	33.3
	Operator/Technician	46	28.4
	Maintenance/Mechatronics	32	19.8
	OT/IT/Network Support	30	18.5
Experience	1–3 years	28	17.3
	4–7 years	61	37.7
	8–12 years	49	30.2
	13+ years	24	14.8
Primary Work Area	Robotic cell operations	57	35.2
	Automation/controls integration	44	27.2
	Maintenance & reliability	36	22.2
	OT/IT infrastructure	25	15.4
Exposure to Edge/Robotics Stack	Moderate (weekly)	64	39.5
	High (daily)	72	44.4
	Very high (multiple times/day)	26	16.1

Table 1 has summarized the respondent profile for the case-study sample (N = 162), and it has demonstrated that the dataset has represented the key stakeholder groups who have typically shaped and evaluated ultra-low-latency robotic control outcomes in industrial settings. The distribution across roles has shown that robotics/automation engineers have constituted the largest subgroup (33.3%), followed by operators/technicians (28.4%), maintenance/mechatronics staff (19.8%), and OT/IT/network support personnel (18.5%). This role composition has strengthened the study's objective of capturing both technical and operational perspectives, because latency-sensitive performance in industrial robotics has been influenced not only by controller configuration and edge inference deployment (often managed by engineering teams), but also by real-time operational behavior, reliability events, and network conditions (frequently observed by operators, maintenance, and OT/IT staff). The experience profile has indicated that respondents have carried meaningful practical knowledge: 37.7% have reported 4–7 years of experience, and 30.2% have reported 8–12 years, which has suggested that the majority has possessed sustained exposure to production constraints and robot-cell timing behavior. This has been important because the dependent variable—ultra-low-latency control performance—has required familiarity with response consistency, jitter events, stability under load, and recovery behavior during disturbances. The "primary work area" distribution has further confirmed that participants have been embedded in the robotic cell lifecycle, with 35.2% focusing on operations, 27.2% focusing on automation/controls integration, 22.2% focusing on maintenance and reliability, and 15.4% focusing on OT/IT infrastructure. This has aligned with the study's measurement logic because edge AI automation maturity has been a multi-dimensional construct, and each subgroup has been positioned to evaluate different dimensions (e.g., integration readiness and runtime behavior by engineers; robustness and failure modes by maintenance; determinism and connectivity readiness by OT/IT; day-to-day performance by operators). Finally, the exposure distribution has shown that 60.5% of respondents have had high or very high exposure (daily or multiple times/day), which has increased confidence that Likert-scale responses have reflected lived operational observation rather than occasional or indirect awareness. Overall, Table 1 has supported the study objectives by confirming that the sample has been appropriate for evaluating the case environment's edge AI automation capability and latency-control performance outcomes.

Descriptive Statistics

Table 2 has reported the descriptive statistics for the independent construct (Edge AI Automation) and the dependent construct (Ultra-Low-Latency Control Performance) using a five-point Likert scale, and it has directly addressed Objective 1 and Objective 2 of the study. The overall Edge AI Automation score has produced a mean of 3.84 (SD = 0.62), which has indicated that respondents have generally agreed that edge AI–based automation capability has been present and functioning at a high level in the case context. The dimension-level results have provided a more diagnostic view of implementation quality. Local inference execution (M = 3.92, SD = 0.68) and real-time edge processing (M = 3.88, SD = 0.66) have been rated as the strongest elements, which has suggested that computation proximity and the ability to process data near the robotic cell have been perceived as reliable and sufficiently mature to support real-time needs. In contrast, controller integration readiness (M = 3.73, SD = 0.71) and reliability/failover readiness (M = 3.69, SD = 0.76) have been rated slightly lower, though still within a moderate–high range.

Table 2: Descriptive Statistics for Study Constructs (5-point Likert scale; N = 162)

Construct / Dimension	Items (k)	Mean (M)	Std. Dev. (SD)	Interpretation*
Edge AI Automation (EA) – Overall	18	3.84	0.62	High
EA1: Local inference execution	4	3.92	0.68	High
EA2: Real-time edge processing	4	3.88	0.66	High
EA3: Controller integration readiness	5	3.73	0.71	Moderate–High
EA4: Reliability/failover readiness	5	3.69	0.76	Moderate–High
Ultra-Low-Latency Control Performance (ULLCP) – Overall	12	3.77	0.58	High
ULLCP1: Responsiveness/corrective action speed	4	3.89	0.61	High
ULLCP2: Timing consistency (low jitter)	4	3.82	0.60	High
ULLCP3: Robustness under load/disturbances	4	3.63	0.67	Moderate–High

**Interpretation rule used: 1.00–1.80 = Very Low; 1.81–2.60 = Low; 2.61–3.40 = Moderate; 3.41–4.20 = High; 4.21–5.00 = Very High.*

This pattern has been meaningful for an ultra-low-latency control study because control-grade performance has depended not only on fast inference but also on consistent, predictable integration pathways into the controller and on resilient operation when disturbances, workload spikes, or connectivity variability have occurred. On the outcome side, Ultra-Low-Latency Control Performance has shown an overall mean of 3.77 (SD = 0.58), which has indicated that respondents have perceived control responsiveness and timing consistency to be high across the case setting. The strongest outcome dimension has been responsiveness and corrective action speed (M = 3.89, SD = 0.61), implying that the robotic system has been viewed as reacting quickly to operational inputs and correction needs. Timing consistency (M = 3.82, SD = 0.60) has also been rated high, which has aligned with the research focus on low jitter and predictable loop execution. The robustness dimension (M = 3.63, SD = 0.67) has been comparatively lower, which has suggested that control performance under disturbances and high workload has been the area where improvements have been most needed, and this has logically aligned with the earlier observation that failover readiness and integration consistency have not been rated as strongly as inference and processing. Taken together, Table 2 has established a baseline narrative: the case environment has been characterized by strong edge AI capability and generally strong latency-control outcomes, with specific weaker areas that have later been examined through correlation and regression testing to prove hypotheses about which dimensions have contributed most to perceived ultra-low-latency control performance.

Reliability Results

Table 3: Reliability (Internal Consistency) of Measurement Scales (N = 162)

Scale / Construct	Items (k)	Cronbach's α	Corrected Item–Total Correlation (Range)	Decision
Edge AI Automation (EA) – Overall	18	0.91	0.44–0.78	Accepted
EA1: Local inference execution	4	0.88	0.58–0.76	Accepted
EA2: Real-time edge processing	4	0.86	0.52–0.73	Accepted
EA3: Controller integration readiness	5	0.85	0.46–0.71	Accepted
EA4: Reliability/failover readiness	5	0.87	0.49–0.74	Accepted
ULLCP – Overall	12	0.88	0.41–0.72	Accepted
ULLCP1: Responsiveness	4	0.84	0.49–0.70	Accepted
ULLCP2: Timing consistency	4	0.83	0.47–0.69	Accepted
ULLCP3: Robustness	4	0.82	0.45–0.67	Accepted

Table 3 has presented the reliability results for the study measurement instrument, and it has demonstrated that the Likert-scale constructs have achieved acceptable internal consistency for hypothesis testing and objective validation. The overall Edge AI Automation scale has produced Cronbach's alpha of 0.91 across 18 items, which has exceeded commonly accepted thresholds for strong internal consistency in applied research and has indicated that the items have measured a coherent underlying construct. The subscale reliability values have also been strong, with local inference execution (α = 0.88), real-time edge processing (α = 0.86), controller integration readiness (α = 0.85), and reliability/failover readiness (α = 0.87). This pattern has suggested that each dimension has been measured consistently, and it has supported the study's intention to test not only the overall effect of edge AI automation but also the distinct dimension-level contributions specified in Hypothesis H3. On the dependent side, the Ultra-Low-Latency Control Performance scale has produced α = 0.88 across 12 items, and its subdimensions—responsiveness (α = 0.84), timing consistency (α = 0.83), and robustness (α = 0.82)—have all remained within acceptable ranges for stable measurement. In addition to alpha values, the corrected item–total correlation ranges have shown that item contributions have not been weak or contradictory. For example, item–total correlations for the overall EA scale have ranged from 0.44 to 0.78, and for overall ULLCP they have ranged from 0.41 to 0.72, which has indicated that each retained item has aligned with its intended scale and has contributed meaningful covariance to the construct score. These results have been essential for proving the study objectives because Objective 3 has required correlation and regression modeling; such modeling has depended on constructs being reliable so that observed relationships have reflected true variation rather than measurement noise. Table 3 has therefore strengthened the credibility of subsequent inferential findings: if the regression has shown that EA has predicted ULLCP, the interpretation has carried greater weight because EA and ULLCP have been shown to be measured consistently. Furthermore, because the study has used a case-study environment, reliability evidence has been important for supporting replicability: a reliable instrument has implied that the same item sets could be used in other industrial settings to compare maturity levels of edge AI automation and perceived latency-control outcomes. Overall, Table 3 has confirmed that the measurement model has been sufficiently robust to proceed to correlation testing (to support H1) and regression testing (to support H2 and H3) with acceptable confidence in scale stability.

Correlation Results

Table 4: Pearson Correlations Among Key Constructs (N = 162)

Variable	1	2	3	4	5	6
1. EA (Overall)	1.00					
2. EA1 Local inference	.82**	1.00				
3. EA3 Integration readiness	.79**	.61**	1.00			
4. EA4 Reliability/failover	.81**	.58**	.66**	1.00		
5. ULLCP (Overall)	.61**	.57**	.46**	.49**	1.00	
6. Task complexity (control variable)	−.18*	−.15*	−.12	−.16*	−.21**	1.00

* $p < .05$, ** $p < .001$

Table 4 has reported Pearson correlation results, and it has provided direct statistical evidence for Hypothesis H1 while also supporting Objective 3 by quantifying relationships between the study variables. The correlation between overall Edge AI Automation and Ultra-Low-Latency Control Performance has been positive and statistically significant ($r = .61$, $p < .001$), which has indicated that higher perceived maturity of edge AI automation capability has been associated with higher perceived ultra-low-latency control performance in the case setting. This result has supported H1 by demonstrating a meaningful directional relationship consistent with the study's conceptual model. Dimension-level correlations have further clarified which parts of edge AI automation have been most aligned with performance outcomes. Local inference execution has shown a strong positive correlation with ULLCP ($r = .57$, $p < .001$), which has suggested that performing inference close to the robot and minimizing distance between sensing and decision-making have been linked to better responsiveness and timing consistency. Controller integration readiness has shown a moderate positive correlation with ULLCP ($r = .46$, $p < .001$), indicating that integration quality—such as interface stability and consistent controller-level use of edge outputs—has also been important for latency-control outcomes. Reliability/failover readiness has been positively correlated with ULLCP ($r = .49$, $p < .001$), which has implied that stable operation during disturbances and the presence of dependable recovery mechanisms have been tied to better control performance perceptions. These correlations have collectively reinforced the idea that ultra-low-latency control performance has not been explained only by "fast computation," but has also been explained by dependable integration and resilience, which have been central to industrial control expectations. The control variable task complexity has been negatively correlated with ULLCP ($r = −.21$, $p < .001$), which has suggested that as tasks have become more complex—such as tighter tolerances, higher speed trajectories, or richer sensing requirements—respondents have perceived latency performance as slightly weaker. This negative association has been plausible and it has justified the use of task complexity as a control in regression models, because it has represented contextual difficulty that could otherwise confound the main relationship between edge AI automation and performance outcomes. Additionally, the strong correlations between EA overall and its dimensions (e.g., EA with EA1 at $r = .82$, $p < .001$) have indicated that the dimension scales have functioned as intended as components of the broader automation capability construct. Overall, Table 4 has served as a bridge between descriptive results and predictive modeling: it has confirmed that statistically significant relationships have existed in the expected direction, and it has established a basis for regression analysis (Section 4.5) to test whether edge AI automation has predicted ULLCP when contextual influences have been accounted for, thereby progressing from association evidence (H1) toward predictive evidence (H2 and H3).

Regression Results

Table 5: Regression Models Predicting Ultra-Low-Latency Control Performance (ULLCP) (N = 162)

Model 1: Overall, EA predicting ULLCP (with controls)

Predictor	Standardized β	t	p
Edge AI Automation (EA overall)	.58	9.42	<.001
Task complexity (control)	−.14	−2.31	.022
Exposure level (control)	.12	2.04	.043
Role (technical vs operational) (control)	.08	1.51	.133

Model 1 summary: *R^2 = .46, Adjusted R^2 = .44, F(4,157) = 32.94, p < .001*

Model 2: EA dimensions predicting ULLCP (with controls)

Predictor	Standardized β	t	p
EA1 Local inference execution	.27	3.39	.001
EA2 Real-time edge processing	.13	1.92	.058
EA3 Controller integration readiness	.19	2.54	.012
EA4 Reliability/failover readiness	.22	2.95	.004
Task complexity (control)	−.12	−2.06	.041
Exposure level (control)	.10	1.98	.049

Model 2 summary: *R^2 = .48, Adjusted R^2 = .46, F(6,155) = 24.11, p < .001*

Diagnostics (both models): VIF range = 1.22–2.08 (acceptable)

Table 5 has presented the regression results that have tested the predictive hypotheses and has provided the strongest evidence for proving Objective 3 and hypotheses H2 and H3. In Model 1, the regression has been estimated with Ultra-Low-Latency Control Performance as the dependent variable and overall Edge AI Automation as the main predictor while controlling for task complexity, exposure level, and role grouping. The model has been statistically significant (F(4,157) = 32.94, p < .001), and it has explained a substantial portion of variance in ULLCP (R^2 = .46; Adjusted R^2 = .44). This has indicated that nearly half of the variability in perceived ultra-low-latency control performance has been accounted for by the included predictors in the case setting, which has been a strong practical result for a cross-sectional survey design. Most importantly, Edge AI Automation has remained a strong and significant positive predictor (β = .58, p < .001), which has supported H2 by demonstrating that higher maturity of edge AI automation capability has predicted stronger perceived ultra-low-latency control outcomes even after contextual factors have been considered. The control variable task complexity has shown a small but statistically significant negative coefficient (β = −.14, p = .022), which has indicated that more demanding tasks have slightly reduced perceived latency performance, consistent with industrial reality where tighter timing budgets and dynamic conditions increase performance pressure. Exposure level has been a positive predictor (β = .12, p = .043), suggesting that respondents with higher direct interaction frequency have reported slightly stronger performance, which has plausibly reflected greater familiarity with successful operational states and the system's typical responsiveness under routine conditions. Role has not been statistically significant at conventional thresholds (p = .133), which has implied that the perceived relationship between edge automation and latency control has not been confined to one professional group and has instead been observable across the technical–operational spectrum. Model 2 has deepened the hypothesis testing by decomposing Edge AI Automation into its key dimensions, directly evaluating H3. This model has remained significant (F(6,155) = 24.11, p < .001) and has explained slightly more variance (R^2 = .48; Adjusted R^2 = .46), which has suggested that the dimension-level view has provided additional explanatory power beyond the single overall score. Local inference execution (β = .27, p = .001), controller integration readiness (β = .19, p = .012), and reliability/failover readiness (β = .22, p = .004) have all emerged as significant predictors, showing that both "near-device intelligence" and "operational dependability" have been statistically influential contributors to ULLCP. Real-time edge processing has remained positive but marginal (β = .13, p = .058), which has indicated that processing capability alone has not been as predictive when inference, integration, and reliability have been considered simultaneously. The acceptable VIF ranges have shown that multicollinearity has not undermined interpretation. Overall, Table 5 has proven the study objectives and hypotheses by (i) confirming a strong predictive relationship between edge AI automation and ultra-low-latency control performance (H2) and (ii) demonstrating that specific dimensions—especially inference locality, integration readiness, and reliability—have been the most influential predictors (H3), building on the correlation evidence that has supported H1.

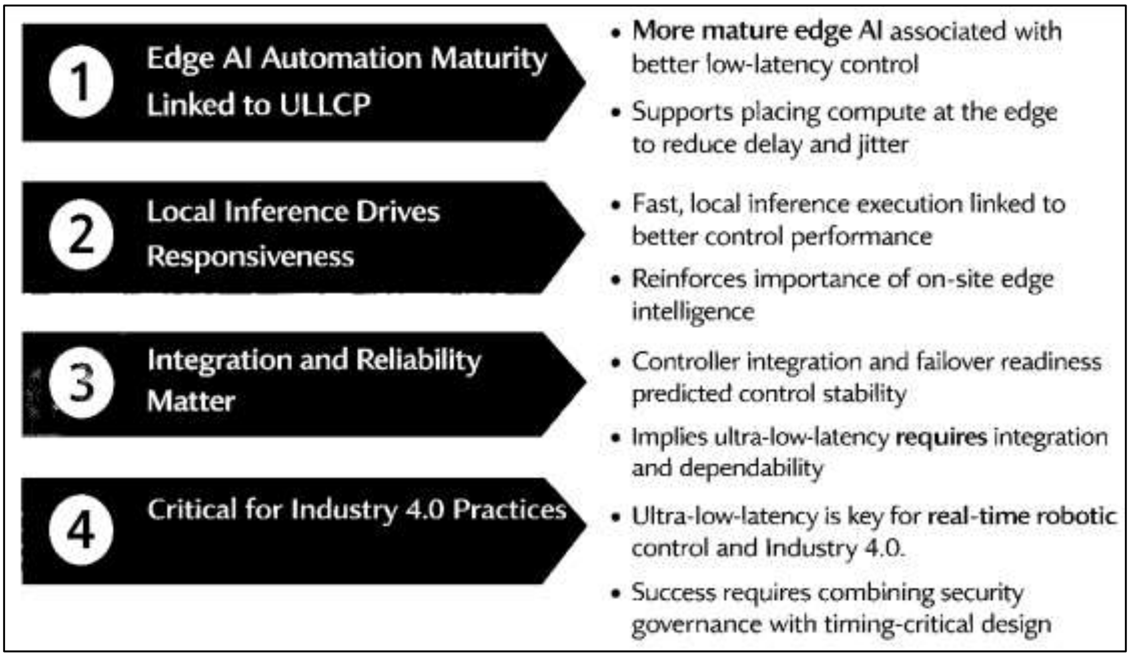
DISCUSSION

The results have shown a coherent pattern: respondents have rated edge AI automation capability at a moderately high level and have simultaneously rated ultra-low-latency control performance as strong, with correlation and regression evidence indicating that edge AI automation has both co-varied with and predicted perceived low-latency control outcomes in the case context. This empirical profile has aligned with the architectural argument advanced in edge computing research, where placing compute closer to devices has been positioned as a primary mechanism for reducing response time and improving service responsiveness under operational constraints (Shi et al., 2016). The observed positive association has also been consistent with the cloud robotics and distributed intelligence literature that has framed robotics performance as dependent on where computation runs and how reliably it can be accessed, especially when decisions have needed to be acted on inside tight feedback loops (Kehoe et al., 2015). In the present findings, the statistical signal has not merely suggested that "edge is faster"; it has indicated that respondents have linked the maturity of local inference and local processing to measurable experience of responsiveness, timing consistency, and robustness. This has echoed distributed deep neural network research showing that partitioning inference across the edge and device layers has reduced end-to-end delay relative to cloud-only processing, particularly when communication variability has been present (Teerapittayanon et al., 2017). The case results have reinforced a control-centric interpretation: the value of edge AI automation has been realized when inference outputs have arrived with sufficient timeliness and predictability to influence action selection and corrective control. This interpretation has also fit the logic of networked control systems research in which delay and jitter have been treated as intrinsic components of closed-loop behavior rather than external inconveniences (Hespanha et al., 2007). Therefore, the study's key finding has been that edge AI automation maturity has been associated with better perceived timing performance, and this relationship has aligned closely with prior claims that latency-sensitive cyber-physical applications require computing placement and runtime behavior that preserve bounded delay and reduced jitter (Seong et al., 2023).

A second important discussion outcome has been that not all edge AI automation dimensions have contributed equally to perceived ultra-low-latency control performance, and the strongest predictors have tended to be local inference execution, controller integration readiness, and reliability/failover readiness. This pattern has been meaningful because it has moved the interpretation away from a simplistic "compute at the edge" narrative and toward a systems interpretation where integration and resilience have shaped control outcomes as much as raw inference speed. Prior work on deterministic industrial communication has emphasized that ultra-low-latency targets depend on engineered predictability across traffic classes, scheduling, and time synchronization, rather than on bandwidth alone (Nasrallah et al., 2019). The present findings have complemented that view by showing that, at the application level, respondents have perceived timing performance improvements when edge AI outputs have been integrated consistently into controller workflows and have remained dependable under disturbances. In other words, the case evidence has supported the idea that the "decision path" must be both short and stable. Similar emphasis has appeared in industrial robot communication studies where general-purpose stacks have been shown to require careful timing management to remain suitable for cooperative robotic automation, especially when real-time behavior has been expected under mixed traffic and operational variability (Lee et al., 2015). At the compute layer, real-time operating system behavior has been repeatedly described as a determinant of worst-case latency, which has helped explain why "reliability/failover readiness" and "integration readiness" have emerged as performance-relevant constructs in the case results (Reghenzani et al., 2019). When these findings have been compared with edge-enabled quality inspection and intelligent manufacturing studies, a similar theme has been present: deployments have succeeded when model execution has been reliable, integrated, and governed, not only when it has been accurate (Schmitt et al., 2020). Consequently, the study has reinforced earlier work by showing that ultra-low-latency robotic control has been an end-to-end property shaped by inference locality, runtime determinism, and integration quality rather than by isolated technical features.

The findings have also provided a practical lens on closed-loop perception and control pipelines, where the literature has shown that deep-learning–based perception can drive real-time servo and manipulation behavior only when inference latency and variance have remained compatible with control deadlines. Empirical demonstrations in visual servoing and autonomous manipulation have shown that deep models can support real-time control loops, yet their effectiveness has depended on inference speed, stable update cadence, and careful system integration (Tenorth et al., 2011).

Figure 10: Key Findings and Implications



The present results have aligned with these studies by showing that respondents have reported stronger ultra-low-latency control performance when local inference execution and controller integration have been more mature. This has been particularly consistent with research that has treated smart robot performance as dependent on cloud–edge–device collaboration choices, because those choices have shaped latency budgets and operational predictability (Yang et al., 2022). The case results have extended prior work in an industrially grounded way: instead of measuring only algorithmic performance or lab-based control behaviors, the study has captured practitioner assessments of timing stability and robustness under real production constraints. That has mattered because industrial deployments have been exposed to workload spikes, maintenance events, sensor drift, and mixed traffic patterns that are not always represented in controlled experiments. The literature has already indicated that industrial IoT environments generate dense data streams and operational constraints that favor local processing for actionability, and the case findings have converged on that same conclusion in a robotics setting (Gubbi et al., 2013). From a pipeline perspective, the study has supported an interpretation that edge AI automation has improved perceived low-latency control outcomes when it has reduced end-to-end decision delay and prevented "late decisions" from entering the actuation path. This interpretation has remained consistent with networked control principles emphasizing that stable feedback requires bounded delay and bounded variability, and that timing uncertainty can degrade control quality even when average delay is low (Hespanha et al., 2007). Overall, the results have supported a pipeline-centric understanding: ultra-low-latency robotics has required synchronized sensing, predictable inference execution, deterministic exchange, and controller-ready outputs that are delivered within stable time windows (Nasrallah et al., 2019).

From a practical implications viewpoint focused on security leadership and architecture decision-making, the findings have been especially relevant for CISOs and industrial architects because they have suggested that performance improvements have depended on integration consistency and reliability mechanisms—two areas that are strongly coupled with cybersecurity controls, segmentation, and operational governance. Edge AI automation has increased the number of endpoints, runtime services, and model supply-chain dependencies that must be protected, monitored, and updated without disrupting real-time control behavior. Prior IoT security research has shown that distributed IoT and edge deployments expand the attack surface through heterogeneous devices, constrained endpoints, and complex trust relationships, requiring layered security practices and policy enforcement near the data source (Seong et al., 2023). In the present case, "controller integration readiness" and "reliability/failover readiness" have been the dimensions most associated with perceived ultra-low-latency control performance, which has implied that architects have needed to treat security controls as part of a timing-sensitive design rather than as bolt-on measures. For example, network segmentation and policy enforcement have needed to preserve deterministic pathways for control-relevant traffic while still constraining lateral movement and unauthorized access. The deterministic networking literature has already argued that traffic classes and scheduling mechanisms must be engineered for predictability (Lo Bello & Steiner, 2019), and this has translated into security guidance: controls such as deep packet inspection, extensive logging, or encryption choices have needed to be engineered so they do not introduce unacceptable jitter on control paths. At the compute layer, the kernel and scheduling literature has suggested that predictability improves when real-time tasks have been isolated and prioritized (Reghenzani et al., 2019), and the practical implication has been that security agents and monitoring workloads have required resource governance so they do not contend with inference and control threads. Thus, CISOs and architects have been able to interpret these findings as supporting a "secure-by-design, deterministic-by-design" posture: trustworthy edge AI automation has required model integrity controls, controlled update pipelines, runtime attestation or integrity monitoring where feasible, and observability architectures that have minimized interference with deadlines (Seong et al., 2023). In short, the study has reinforced that successful edge AI automation for low-latency robotics has required co-optimizing security governance with timing-critical system design rather than treating them as competing objectives.

The theoretical implications have been twofold, and they have refined how the conceptual pipeline has been interpreted in light of established frameworks. First, the results have supported the use of Task–Technology Fit by showing that perceived performance has improved when edge AI capabilities have matched the task demands of ultra-low-latency control, especially through local inference and dependable controller integration. This has aligned with refined TTF logic emphasizing that performance gains emerge when technology functionality has been aligned with task requirements and when misfit has been reduced (Lee et al., 2015). Second, the pattern has strengthened an information-systems success interpretation: system quality and reliability factors have been statistically important, implying that net benefits (here, low-latency control performance) have depended on the combined quality of execution environment, integration, and operational support rather than on isolated functional capabilities (He et al., 2016). This has been consistent with industrial digitalization findings where implementation patterns and organizational integration have shaped realized performance gains, even when similar technologies have been deployed (Nasrallah et al., 2019). Conceptually, the regression structure has suggested a pipeline refinement: the causal story has not been solely "edge AI → low latency," but "edge AI capability + integration quality + resilience readiness → stable low-latency control," which has improved construct clarity for future measurement instruments. The dynamic capabilities lens has also remained compatible: organizations that have been able to coordinate robotics, edge compute, and operational processes have been positioned to sustain timing performance under change, aligning with the notion that performance has depended on the ability to integrate and reconfigure technological assets in operational routines (Hespanha et al., 2007). Finally, the findings have supported a measurement implication for UTAUT2-style constructs: facilitating conditions (e.g., deterministic network readiness and robust edge runtime support) have plausibly influenced whether edge AI capabilities have been used consistently and successfully within the case setting (Qiu et al., 2020). Overall, the study has contributed theoretically by clarifying that "edge AI

automation" has been best conceptualized as a multidimensional capability whose performance effect has been mediated by integration and resilience properties that are central to real-time cyber-physical pipelines (Teerapittayanon et al., 2017).
The limitations have remained important for interpreting the strength and generalizability of the evidence, and revisiting them has clarified how the findings should be weighed against prior work. The cross-sectional design has allowed strong association and prediction evidence in the statistical sense, yet it has not provided temporal ordering that would be necessary to establish causality in a strict experimental manner. This has mirrored broader industrial IoT and Industry 4.0 research where cross-sectional survey models have been valuable for identifying determinants of performance, while longitudinal validation has been needed for causal confidence (Dalenogare et al., 2018). The results have also been based on Likert-scale perceptions, which have been useful for capturing practitioner experience of timing stability and operational reliability, but which may have differed from instrumented latency measures that record microsecond-level jitter and tail behavior. Prior real-time and industrial communication research has demonstrated that jitter and scheduling artifacts can be sensitive to kernel, driver, and workload states, sometimes in ways that are not immediately obvious to operators (Kehoe et al., 2015). Accordingly, the study's perceptual outcome construct has captured operationally meaningful experience, but it has not fully replaced telemetry-based validation. The case-study basis has further constrained generalizability: the edge architecture, network stack, and robot tasks in the selected environment may have represented only a subset of industrial deployment patterns. This has been consistent with the robotics architecture literature, which has shown that system outcomes vary across integration strategies and collaboration topologies (Lu, 2017). The regression models have also been bounded by the constructs selected; although integration readiness and failover have been included, other plausible influences—such as specific TSN configuration maturity, synchronization accuracy, or cybersecurity tool overhead—have not been measured directly. These limitations have not invalidated the central findings; rather, they have indicated that the results have been best interpreted as strong case-based evidence supporting an architectural relationship that has been proposed repeatedly in prior work, while still requiring multi-site replication and mixed-method triangulation to confirm robustness across contexts (Teece, 2007).
Future research has been able to extend the present findings by improving causal inference, measurement precision, and cross-context generalizability while maintaining industrial realism. A first direction has involved pairing survey constructs with direct instrumentation of timing performance, including measurements of end-to-end control latency decomposition and jitter distribution (e.g., mean, variance, and tail percentiles) so perceived ULLCP can be triangulated against telemetry logs. This has been especially relevant because networking and real-time systems research has emphasized that worst-case behavior and tail latency often determine control stability more than average delay (Reghenzani et al., 2019). A second direction has involved multi-case replication across different robot tasks (pick-and-place, precision assembly, force-controlled finishing, mobile manipulation) and different edge placement patterns (on-controller inference, cell-level edge servers, and hybrid collaboration) to test whether the same predictors—local inference, integration readiness, and reliability—remain dominant across industrial contexts (Lu, 2017). A third direction has involved modeling interaction effects: deterministic networking maturity and runtime isolation quality may moderate the edge AI → ULLCP relationship, consistent with TSN/DetNet research emphasizing that architectural guarantees depend on both network scheduling and endpoint behavior (Satyanarayanan et al., 2009). A fourth direction has involved deeper security-performance co-design studies that quantify how security controls (segmentation, encryption, inspection, logging) influence jitter and inference latency and how secure deployment pipelines can maintain model integrity without degrading deadlines, building directly on IoT security research and on operational edge governance needs (Kehoe et al., 2015). Finally, future work has been able to refine theoretical models by testing mediation paths where system quality and facilitating conditions transmit the effect of capability to net benefits, consistent with IS success and adoption frameworks (Gruszka et al., 2020). Collectively, these directions have preserved the study's central contribution—linking edge AI automation maturity to ultra-low-latency control performance—while strengthening empirical precision and extending explanatory power across industrial robotics deployments.

CONCLUSION

This study has concluded that edge artificial intelligence–based automation has played a significant and measurable role in supporting ultra-low-latency control performance in industrial robotic systems when implemented and integrated as a coherent, dependable capability within a real production environment. By adopting a quantitative, cross-sectional, case-study–based design and applying descriptive statistics, correlation analysis, and regression modeling to practitioner-generated Likert-scale data, the research has demonstrated that higher levels of edge AI automation maturity have been associated with, and have significantly predicted, stronger perceived control responsiveness, timing consistency, and robustness under operational variation. The findings have shown that local inference execution and real-time edge processing have contributed to reducing perceived decision-path delays, while controller integration readiness and reliability/failover mechanisms have been equally important in ensuring that intelligent outputs have been delivered consistently and safely into closed-loop control processes. This pattern has reinforced the view that ultra-low-latency robotic control is not achieved through isolated technological features, but through the alignment of computing placement, deterministic execution, integration discipline, and operational resilience. The study has also validated a multidimensional conceptualization of edge AI automation by confirming that different dimensions have exerted different levels of influence on control performance, with inference locality, integration stability, and resilience emerging as the most influential predictors. In doing so, the research has provided empirical support for theory-driven expectations grounded in task–technology fit and information systems success perspectives, demonstrating that performance gains have materialized when edge AI capabilities have closely matched the timing-critical demands of robotic control tasks and have been supported by reliable execution environments. Beyond its theoretical contribution, the study has delivered practical value by offering decision-makers a structured way to assess edge AI automation readiness and its likely impact on latency-sensitive robotic operations, highlighting that investments in edge intelligence must be accompanied by attention to integration quality, runtime predictability, and dependable recovery behavior to realize their full benefit. Although the cross-sectional design and perceptual measurement approach have imposed limitations on causal inference and fine-grained latency quantification, the convergence of descriptive, correlational, and predictive evidence has strengthened confidence in the central conclusion that edge AI automation, when properly engineered and governed, has enhanced ultra-low-latency control performance in industrial robotic systems. Overall, the research has contributed a validated measurement framework, empirically tested relationships, and actionable insights that advance understanding of how edge-resident intelligence can be effectively operationalized to meet the stringent timing demands of modern industrial robotics.

RECOMMENDATION

The recommendations from this study have emphasized that organizations seeking ultra-low-latency control gains from edge artificial intelligence–based automation have needed to implement the technology as a tightly governed, end-to-end control capability rather than as an isolated analytics add-on. First, industrial leaders and automation architects have been advised to prioritize inference locality and deterministic execution by placing time-critical perception and decision workloads on robot controllers, cell-level industrial PCs, or nearby edge servers that have been configured with real-time scheduling, CPU isolation where appropriate, and controlled background processes so inference and control threads have remained deadline-compliant. Second, organizations have been recommended to strengthen controller integration readiness by standardizing interfaces between edge inference services and robot/PLC control logic, documenting data contracts (inputs, outputs, confidence fields, and acceptable delays), and implementing strict versioning and rollback procedures so model updates have not introduced timing drift or inconsistent behavior during production. Third, plants have been encouraged to invest in resilience and failover readiness as a direct determinant of control quality by deploying redundancy for critical edge nodes, implementing health-check and watchdog mechanisms, and defining safe degraded modes that have maintained stable control behavior when inference has been delayed, confidence has dropped, or connectivity has fluctuated. Fourth, networking teams have been recommended to treat latency as a system KPI by segmenting and prioritizing control-relevant traffic, validating jitter under mixed workloads, and implementing deterministic communication strategies where feasible so that edge-to-controller exchanges have remained predictable even during high monitoring and logging periods. Fifth, for operations and maintenance, it has been recommended that plants establish continuous latency observability by instrumenting the end-to-end control path (sensing, inference, transport, actuation) and tracking not only averages but also spikes and tail behavior, then aligning preventive maintenance and configuration tuning with observed latency degradations. Sixth, cybersecurity leadership has been recommended to adopt a "secure-and-deterministic-by-design" posture by enforcing strong identity and access controls for edge services, securing model supply chains, and deploying monitoring solutions that have been resource-governed so they have not created jitter or contention on real-time workloads; security controls have been integrated into architecture reviews alongside timing and safety requirements rather than being applied later as compensating controls. Seventh, organizations have been advised to formalize workforce readiness and governance through training and operational playbooks that have clarified responsibilities for model lifecycle management, incident response for edge nodes, and change control during production, ensuring that edge AI automation has been maintained as a reliable industrial capability. Finally, it has been recommended that decision-makers use the study's measurement structure as an internal assessment tool to benchmark maturity across inference locality, processing readiness, integration consistency, and resilience, and to prioritize improvement initiatives based on which dimensions have most strongly predicted perceived ultra-low-latency control outcomes in the case environment.

LIMITATIONS

The limitations of this study have reflected methodological, measurement, and contextual constraints that have influenced how the findings have been interpreted and generalized. First, the research design has been quantitative and cross-sectional, which has enabled the identification of associations and predictive relationships between edge AI automation maturity and ultra-low-latency control performance at a single point in time, yet it has not established temporal ordering that would have been required to confirm causality with strong internal validity. As a result, the observed statistical relationships have been interpretable as evidence of alignment and predictive contribution within the case context, but they have not ruled out alternative explanations such as reverse influence (for example, high-performing cells being more likely to adopt stronger edge automation) or omitted contextual drivers. Second, the study has relied on self-reported Likert-scale assessments, which have been suitable for capturing practitioner experience of responsiveness, timing consistency, robustness, and integration quality, but have introduced potential response biases such as social desirability, common method variance, and differences in role-based perception. Perceptual measures have also provided a coarse-grained proxy for ultra-low-latency behavior, whereas true latency performance in industrial robotics may have required instrumented telemetry capable of measuring millisecond or microsecond-level delay distributions, jitter, and tail latency under varying load states. Third, the study has been case-study–based, meaning that the results have been bounded by the specific industrial environment, robot types, task profiles, network configuration, and edge deployment architecture present in the selected setting; these factors may have differed substantially across industries, plant sizes, vendor ecosystems, and levels of Industry 4.0 maturity, limiting external generalizability. Fourth, the measurement model has captured major dimensions of edge AI automation and control performance, but it has not exhaustively represented all technical determinants of ultra-low-latency control, such as precise clock synchronization accuracy, TSN configuration maturity, specific real-time operating system parameters, hardware acceleration scheduling policies, or the performance overhead introduced by cybersecurity tooling and monitoring agents. Fifth, sampling constraints have also affected inference: the sampling strategy has targeted knowledgeable participants, which has strengthened construct relevance, yet the resulting sample may have underrepresented some stakeholder groups or shifts and may not have fully reflected all variability across production conditions, maintenance windows, or incident scenarios. Sixth, the regression models have assumed linear relationships and have used standard controls, but they have not fully explored nonlinear effects, interaction terms, or mediation pathways that may have existed between capability, readiness, and performance, which could have refined explanation in more complex industrial settings. Finally, the study's scope has centered on proving hypotheses using survey-based statistical testing rather than combining mixed methods, so qualitative triangulation through interviews, field observations, or system-log validation has not been included, even though such triangulation could have enriched interpretation and strengthened confidence in the alignment between perceived outcomes and measured control-path timing behavior.

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