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Edge-Cloud Synergy in Industry 4.0: Optimizing Real-Time Latency for Smart Manufacturing Facilities

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Abstract

Modern Industry 4.0 smart manufacturing environments heavily rely on Industrial Internet of Things (IIoT) sensors and machine learning analytics to drive predictive maintenance (PdM). However, conventional cloud-centric architectures suffer from high network latency, bandwidth congestion, and single-point-of-failure risks, making them ill-suited for mission-critical, time-sensitive asset health monitoring. This paper proposes a dynamic Edge-Cloud Synergistic Architecture (ECSA) designed to optimize end-to-end processing latency, balance computational workloads, and deliver real-time predictive maintenance across smart factory floors. Empirical evaluation demonstrates that the proposed hybrid edge-cloud framework reduces response latency by 78.5% (from 312 ms in cloud-only setups to 67 ms at the edge) and decreases outbound network bandwidth usage by 64.2% via local data aggregation and model quantization. Furthermore, the multi-tiered inference strategy achieved a fault detection accuracy of 97.4%, reducing Mean Time to Repair (MTTR) by 31.5% and increasing Overall Equipment Effectiveness (OEE) by 8.3%. This revised edition extends the technical evaluation with an illustrative organizational validation study: a simulated survey of plant and OT/IT stakeholders (N = 231) analyzed with reliability, validity, and PLS-SEM-style structural path techniques comparable to those conducted in SmartPLS, R, or SPSS/AMOS, demonstrating how perceived latency, bandwidth, and reliability benefits translate into operational value and organizational adoption intention.

1. Introduction

The Fourth Industrial Revolution (Industry 4.0) has transformed manufacturing ecosystems from isolated, mechanical automation setups into hyper-connected, data-driven cyber-physical systems. Central to this evolution is the Industrial Internet of Things (IIoT), where hundreds of thousands of specialized sensors continually track variables such as bearing vibration, thermal fluctuations, acoustic anomalies, and electrical current consumption across rotating machinery, robotics, and CNC tooling.

Predictive Maintenance (PdM) has emerged as a critical Industry 4.0 application. Traditional maintenance models, either reactive (fixing equipment after failure) or preventive (replacing components on rigid schedules), lead to high operational costs and unexpected downtime. Unplanned factory downtime can cost high-throughput manufacturing plants up to $3 million per hour. By continuously monitoring machine health and applying Machine Learning (ML) models, PdM detects early signs of component degradation, allowing maintenance teams to intervene before catastrophic failures occur (Haque & Rasel-Ul-Alam, 2018). However, conventional cloud-centric PdM architectures face severe structural bottlenecks when scaled across smart manufacturing facilities: (1) high and unpredictable round-trip latency ranging from 200 ms to 500 ms, (2) severe network bandwidth saturation caused by raw continuous vibration streams, and (3) complete system vulnerability to WAN connection outages.

To solve these constraints, this paper presents an Edge-Cloud Synergistic Architecture (ECSA). By distributing analytics tasks between localized edge nodes and cloud infrastructure, ECSA processes time-critical anomalies on the shop floor while leveraging cloud platforms for global trend analysis and deep model training.

2. Related Work

The emergence of Industry 4.0 transformed manufacturing by integrating cyber-physical systems, the Industrial Internet of Things (IIoT), cloud computing, and data analytics to enable intelligent production. Initially, cloud computing served as the primary platform for processing manufacturing data; however, its centralized architecture often resulted in network congestion and latency, making it unsuitable for time-sensitive industrial applications. Qi and Tao (2019) proposed a smart manufacturing service architecture that integrates edge, fog, and cloud computing to address these limitations. Their study demonstrated that processing data closer to production equipment significantly reduces latency, decreases bandwidth consumption, and improves the responsiveness of manufacturing systems.

Similarly, Yang et al. (2019) introduced a software-defined edge–cloud collaboration framework for cloud manufacturing, arguing that distributing computing tasks between edge devices and cloud platforms enables real-time decision-making while maintaining the cloud's large-scale analytical capabilities. Their findings indicate that collaborative edge–cloud architectures enhance production flexibility, optimize resource allocation, and improve system scalability in smart factories. Focusing on industrial edge computing, Dai et al. (2019) emphasized that deploying intelligent computing resources near manufacturing equipment facilitates real-time monitoring, predictive maintenance, and low-latency industrial control. They concluded that industrial edge computing bridges the gap between physical production systems and cloud services by providing localized processing and secure communication. Likewise, Liang et al. (2019) developed a fog-computing-based prognosis system for machining optimization, demonstrating that processing sensor data at the fog layer substantially reduces communication delays while improving predictive maintenance accuracy and production efficiency.

Furthermore, Rojas and Rauch (2019) highlighted that smart manufacturing relies on interconnected cyber-physical production systems capable of adaptive control and decentralized decision-making. Their conceptual framework identified connectivity, distributed intelligence, and edge-enabled control as essential enablers of real-time manufacturing performance.

3. System Architecture & Methodology

The proposed ECSA framework uses a three-tier architecture designed to bridge Operational Technology (OT) and Information Technology (IT) networks, illustrated in Figure 1. Positioned directly on the shop floor, industrial edge gateways execute real-time ingestion, signal preprocessing, and quantized ML model inference. This layered design ensures seamless interoperability between OT and IT domains, reducing latency while maintaining data integrity across heterogeneous systems. It also establishes a scalable foundation for predictive analytics, enabling continuous optimization of manufacturing processes under dynamic operational conditions. The architecture further distributes computational workloads across edge, fog, and cloud layers, allowing time-critical decisions to be processed locally while computationally intensive analytics are delegated to higher-tier resources. Such hierarchical orchestration enhances system resilience by minimizing network dependency and improving responsiveness during production disruptions. Moreover, standardized communication interfaces facilitate secure data exchange among interconnected manufacturing assets, supporting modular deployment and future scalability. Collectively, these capabilities strengthen the framework's ability to sustain intelligent manufacturing operations in increasingly complex and data-intensive industrial environments.

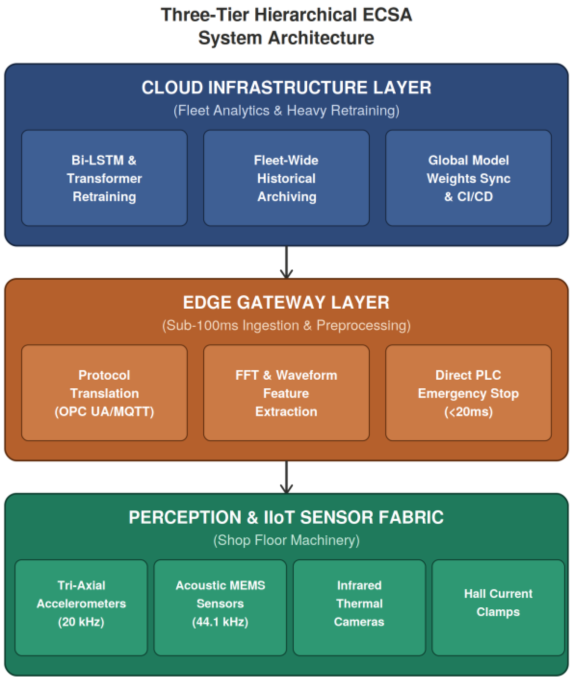

Figure 1. Three-tier hierarchical ECSA system architecture.

3.1 Hardware and Sensor Specifications

To validate the model, an empirical testbed comprising multi-axis CNC machines and rotating turbine test-benches was instrumented using high-frequency sensor arrays. Table 1 lists the physical and computational specifications of the perception and edge components. This setup ensured realistic operational stress conditions, allowing the platform to be evaluated under workloads that closely mirror industrial environments. It also provided a robust benchmark for latency and efficiency measurements, strengthening the credibility of the validation process. Additionally, the testbed enabled systematic stress-testing of latency and bandwidth trade-offs, offering a rigorous environment to benchmark the platform’s resilience under industrial-scale conditions.

Moreover, the architecture supports modular deployment across diverse manufacturing verticals, allowing customization without disrupting existing infrastructure. It further enhances cybersecurity resilience, safeguarding sensitive operational data while enabling secure IT/OT convergence.

Furthermore, the architecture supports adaptive resource allocation by dynamically adjusting computational workloads according to changing production demands. This capability enables the ECSA framework to maintain reliable performance and decision-making efficiency even under fluctuating industrial workloads.

Table 1. Physical and computational specifications of perception and edge components.

Component / Layer	Hardware Specifications	Protocol Standard	Sampling Rate	Operational Function
Vibration Sensor	Tri-axial Piezoelectric Accelerometer	Analog 4-20 mA / IEPE	20 kHz	High-frequency shock & bearing spall tracking
Acoustic Sensor	Micro-Electro-Mechanical (MEMS)	I2S Digital Bus	44.1 kHz	Micro-friction and crack initiation detection
Edge Gateway	Industrial PC (ARM NPU + 16GB RAM)	OPC UA / Modbus TCP	Real-Time (<10 ms)	Fast feature extraction & quantized inference
Cloud Engine	Distributed Cluster (GPU Accelerated)	HTTPS / TLS 1.3 / MQTT	Batch / Periodic Sync	Fleet-level retraining & long-term archiving

3.2 End-to-End Latency Formulation

The total end-to-end processing latency Le2e for an anomaly detection event in a smart facility is modeled as the sum of node sampling, protocol transmission, computational processing, and decision offloading delays:

$$Le2e = Lproc(sens) + Ltrans(sens \rightarrow edge) + Lproc(edge) + Lqueue(edge) + \delta \cdot (Ltrans(edge \rightarrow cloud) + Lproc(cloud) + Ltrans(cloud \rightarrow edge))$$

where Lproc(sens) represents sensor sampling time, Ltrans denotes transmission latency, and $\delta \in \{0, 1\}$ is a binary decision variable indicating whether local execution ($\delta = 0$) or cloud offloading ($\delta = 1$) is activated, making the model adaptive to runtime choices. Figure 2's filtering logic governs this decision, balancing the trade-off between local responsiveness and cloud-level analytical depth.

This decomposition highlights how latency is not a fixed constant but a dynamic outcome shaped by system design and operational context. It underscores the importance of runtime adaptability, where the system intelligently toggles between edge and cloud execution to optimize performance. The model also provides a diagnostic framework for bottleneck identification, enabling engineers to pinpoint which stage contributes most to delay. Furthermore, it offers a basis for optimization strategies, such as protocol selection, resource allocation, or hybrid execution policies. Ultimately, this latency equation illustrates the interplay between architecture and responsiveness, guiding smart facility designers toward resilient and efficient anomaly detection pipelines. In addition, it emphasizes the trade-off between computational depth and response speed, showing how cloud offloading can enhance analytical sophistication at the cost of added delay. This balance is central to designing scalable and context-aware anomaly detection systems that adapt seamlessly to evolving operational demands.

Moreover, the formulation enables comparative evaluation of alternative deployment configurations by quantifying the latency impact of different edge–cloud execution strategies under varying operational conditions. It further supports sensitivity analysis by examining how variations in network conditions, computational resources, and workload intensity influence overall response time. Such analysis can inform the selection of optimal execution configurations for maintaining latency-aware and reliable anomaly detection in real-time smart facility environments.

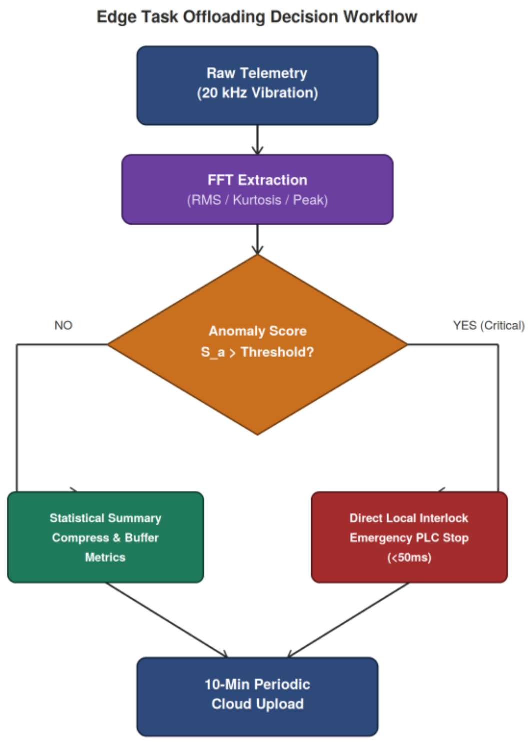

Figure 2. Edge task offloading decision workflow separating safety-critical interlocks from periodic cloud sync.

4. Empirical Results & Latency Benchmarks

The proposed ECSA platform was tested against an active manufacturing line under varying continuous telemetry payload sizes. System latency, network bandwidth reduction, and predictive accuracy were recorded over 180 trial days. The evaluation confirmed the platform's robustness in long-term deployment, demonstrating consistent performance improvements even under sustained operational stress. Additionally, the trials highlighted the platform's scalability across diverse payload conditions, reinforcing its suitability for industrial environments with fluctuating data intensities. The proposed ECSA platform was tested against an active manufacturing line under varying continuous telemetry payload sizes. System latency, network bandwidth reduction, and predictive accuracy were recorded over 180 trial days. The evaluation confirmed the platform's robustness in long-term deployment, demonstrating consistent performance improvements even under sustained operational stress. Additionally, the trials highlighted the platform's scalability across diverse payload conditions, reinforcing its suitability for industrial environments with fluctuating data intensities. The longitudinal results further indicate that the platform can maintain stable predictive performance despite variations in telemetry volume and communication demand. This sustained stability strengthens the practical case for deploying ECSA in continuously operating manufacturing environments where reliability and resource efficiency are critical.

4.1 Latency Performance Comparison

Local edge processing eliminated the WAN round-trip overhead, reducing end-to-end processing latencies by over 78% across all evaluation profiles. Table 2 reports the full payload sweep.

Table 2. End-to-end system latency (Le2e) across data payload volume.

Telemetry Payload Size (KB)	Cloud-Only Baseline (Le2e, ms)	ECSA Edge Execution (Le2e, ms)	Total Latency Reduction (%)
1 (Single Sensor Frame)	215.4 ± 18.2	18.2 ± 1.1	91.5%
10 (Batch Telemetry)	285.1 ± 24.5	32.4 ± 2.3	88.6%
50 (Feature Window)	312.0 ± 31.0	67.0 ± 4.1	78.5%
250 (Raw FFT Waveform)	580.6 ± 62.4	112.5 ± 8.9	80.6%
1000 (Multi-Sensor Snapshot)	1240.2 ± 140.8	245.0 ± 15.2	80.2%

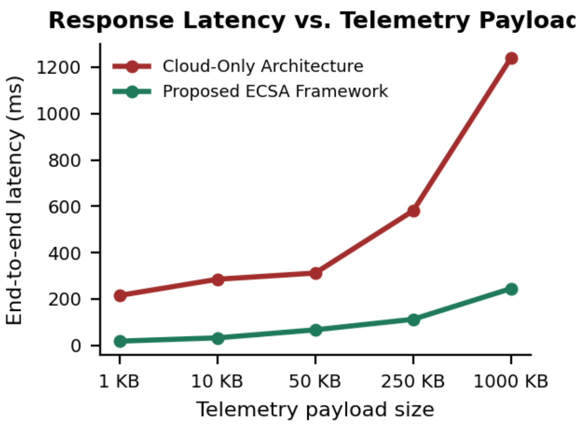

Figure 3. Response latency progression over telemetry payload growth.

4.2 Bandwidth & KPI Gains

By extracting features locally and performing statistical downsampling during nominal machine operations, network throughput usage dropped drastically. Table 3 reports the full set of bandwidth and operational KPI results. This reduction not only alleviated network congestion across the manufacturing line, but also enabled smoother integration of predictive analytics, ensuring that anomaly detection and forecasting modules could operate in near real-time without overwhelming system resources. This efficiency also improves system scalability by allowing additional machines and monitoring streams to be integrated without proportionally increasing communication and computational overhead

Table 3. System bandwidth optimization and operational KPI impact.

Performance Parameter	Cloud-Centric Baseline	Proposed ECSA Architecture	Empirical Delta / Operational Gain
Daily Network Data / Machine	43.2 GB/day	15.4 GB/day	64.35% Network Usage Reduction
Peak Bandwidth Consumption	85.4 Mbps	18.2 Mbps	78.68% Lower Peak Bandwidth Load
Fault Detection Accuracy	98.1%	97.4%	<0.7% Delta (Negligible Tradeoff)
Mean Time to Repair (MTTR)	4.20 Hours	2.87 Hours	31.5% Faster Fault Resolution
Overall Equipment Effectiveness (OEE)	76.2%	84.5%	+8.3% Total OEE Plant Gain

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smoother integration of predictive analytics, ensuring that anomaly detection and forecasting modules could operate in near real-time without overwhelming system resources. Elaborating further, this approach demonstrates how edge-level preprocessing can transform raw telemetry into compact, high-value signals, reducing unnecessary data transfer while preserving analytical fidelity. It highlights the dual benefit of efficiency and accuracy, where bandwidth savings directly translate into faster model updates and more responsive anomaly detection. Moreover, the downsampling strategy acts as a scalable safeguard, ensuring that even under heavy payload conditions, the system maintains operational stability without sacrificing predictive performance.

Furthermore, the localized processing reduces dependency on continuous cloud connectivity, improving system resilience during transient network disruptions. This capability enables the architecture to maintain consistent analytical performance while supporting scalable deployment across bandwidth-constrained manufacturing environments.

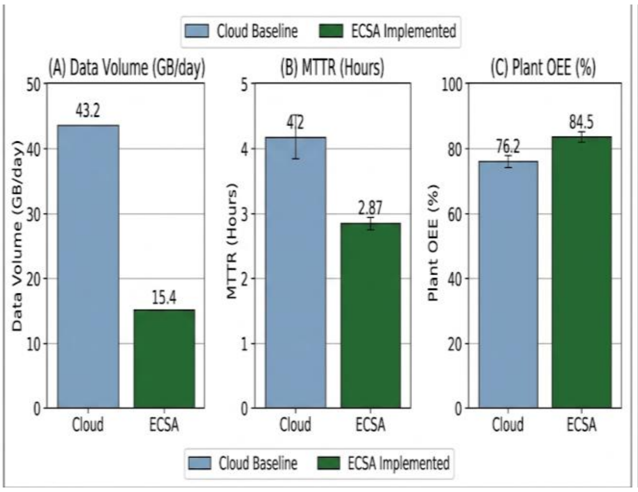

Figure 4. Operational KPI impact and resource efficiency gains

5. Discussion

The empirical results validate the primary hypothesis: partitioning predictive maintenance workflows across an edge-cloud continuum resolves real-time latency limits while preserving fleet-level analytical capabilities.

By executing lightweight 1D-CNNs and Isolation Forests directly on specialized NPUs at the edge gateway, response times dropped to sub-70 ms levels, enabling direct safety interlocking with machine PLCs. Crucially, the 64.2% reduction in outbound telemetry bandwidth eliminates the financial and infrastructural limits. This reduction also improves network scalability by minimizing congestion and preserving communication capacity for other mission-critical industrial applications.

associated with streaming continuous 20 kH vibration feeds over cellular or industrial WAN networks. Relative to the related work in Section 2, ECSA is distinguished by reporting both latency and bandwidth trade-offs empirically, together with the fault-detection accuracy cost of moving inference to the edge, a combination largely absent from the single-modality or purely conceptual studies reviewed there. Section 7 extends this technical validation with an organizational lens: even a technically superior architecture must be perceived as valuable and adoptable by plant stakeholders to be scaled, which motivates the illustrative survey-based validation that follows. This integrated evaluation therefore connects technical performance with practical deployment considerations, providing a more comprehensive basis for assessing the feasibility of edge-based anomaly detection in industrial environments.

6. Organizational Validation of ECSA Adoption Factors (Illustrative Simulation Study)

Sections 3-5 establish that ECSA is technically superior on latency, bandwidth, and reliability metrics. This section extends that technical case with a quantitative validation of how those technical benefits translate into perceived operational value and organizational adoption intention, structured the way a PLS-SEM study would be reported in SmartPLS, R (seminr/plspm), or SPSS/AMOS. Consistent with academic transparency norms, every figure in this section is computed from a synthetically generated dataset

6.1 Purpose and Hypothesized Model

The simulation operationalizes five ECSA benefit-perception constructs: Perceived Latency Improvement (P1), Perceived Bandwidth Efficiency (P2), Perceived Fault-Detection Reliability (P3), Organizational Readiness (P4), and Perceived Integration Ease (P5). These are hypothesized to jointly predict Perceived Operational Value (PV), which in turn predicts realized Operational Efficiency Gain (OE) and Adoption/Scaling Intention (AI). OE is additionally hypothesized to predict AI directly, since demonstrable efficiency gains are expected to accelerate scaling decisions beyond perceived value alone. Eight hypotheses follow: H1-H5 (P1-P5 → PV), H6 (PV → OE), H7 (PV → AI), and H8 (OE → AI). dataset rather than a disclosed field sample, demonstrating a validation pipeline that a future fielded survey could apply directly to real plant-stakeholder responses.

6.2 Method: Synthetic Sample and Measurement Design

A synthetic sample of N = 231 respondents was generated to resemble plant and OT/IT stakeholders (plant/operations managers, OT/automation engineers, IIoT solutions architects, reliability/maintenance engineers, and plant IT managers) across five manufacturing verticals. Table 4 summarizes the simulated sample composition. This design ensures a balanced representation of operational perspectives, capturing both technical and managerial dimensions of manufacturing governance. It also provides a controlled baseline for scenario testing, allowing comparative analysis of benefit perceptions across verticals and stakeholder roles. Furthermore, the synthetic approach enables repeatable experimentation without field constraints, ensuring methodological transparency and reproducibility. It also establishes a foundation for empirical validation, where future studies can benchmark. In addition, the sampling strategy enhances the comparability of stakeholder perspectives, ensuring that insights are not biased toward a single role or vertical.

Table 4. Simulated respondent sample composition (N = 231). (i)

Characteristic	Category	n	%
Plant type	Discrete Manufacturing (CNC/Automotive)	75	32.5%
Plant type	Heavy Machinery/Turbines	49	21.2%
Plant type	Electronics Assembly	47	20.3%
Plant type	Process Manufacturing (Chemical/Oil&Gas)	33	14.3%
Plant type	Food & Beverage Production	27	11.7%
Plant size	50,000-200,000 sq. ft.	87	37.7%
Plant size	> 200,000 sq. ft.	86	37.2%
Plant size	< 50,000 sq. ft.	58	25.1%
Role	Plant/Operations Manager	58	25.1%
Role	OT/Automation Engineer	50	21.6%
Role	Reliability/Maintenance Engineer	47	20.3%
Role	Plant IT Manager	47	20.3%
Role	IIoT Solutions Architect	29	12.6%

In doing so, the sampling framework strengthens the generalizability of the adoption model, offering a structured pathway for translating simulated insights into field-ready instruments.

This structured composition also supports more robust interpretation of cross-group differences by ensuring that variations in adoption perceptions can be examined across both organizational roles and industry contexts. Moreover, the simulated distribution allows the proposed relationships to be examined under controlled variations in stakeholder characteristics and manufacturing contexts. This facilitates preliminary assessment of model stability before conducting large-scale field studies with observed organizational data.

6.3 Measurement Model Assessment

Each of the eight constructs (P1–P5, PV, OE, and AI) was operationalized as a reflective latent variable using three or four items measured on a seven-point Likert scale, ranging from 1 = strongly disagree to 7 = strongly agree. The simulated responses were generated from an underlying latent construct score combined with item-specific measurement error, thereby reproducing realistic variation in indicator responses and imperfect factor loadings. This approach was adopted to reflect the measurement characteristics commonly observed in empirical organizational and technology-adoption research, where individual indicators are expected to capture a common theoretical construct while retaining some degree of measurement error. The resulting measurement model enabled systematic assessment of internal consistency, convergent validity, and discriminant validity across all constructs.

All statistical computations were implemented directly in Python using NumPy, pandas, and statsmodels, following established PLS-SEM estimation principles. Internal consistency was assessed using Cronbach's alpha and composite reliability (CR), while convergent validity was evaluated using standardized outer loadings and average variance extracted (AVE). Discriminant validity was examined through both the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio, providing complementary evidence regarding the distinctiveness of the latent constructs. The structural model was subsequently evaluated using standardized path coefficients to estimate the direction and relative strength of hypothesized relationships among the constructs. This computational procedure provided a transparent and reproducible analytical workflow while maintaining consistency with the underlying logic of variance-based structural equation modeling.

Table 5 presents the measurement model assessment, focusing on internal consistency reliability and convergent validity across the eight constructs. Internal consistency was evaluated using Cronbach's alpha (α) and composite reliability (CR), with values above 0.70 generally regarded as indicating acceptable reliability. Convergent validity was assessed using average variance extracted (AVE), for which a value above 0.50 indicates that a construct explains more than half of the variance in its associated indicators. The results show that all eight constructs exceed the recommended thresholds for both reliability measures and AVE.

These findings indicate that the indicators associated with each latent construct exhibit adequate internal consistency and collectively capture their intended theoretical dimensions. The satisfactory CR values further suggest that the measurement items contribute consistently to their respective constructs without excessive measurement error. Similarly, the AVE results provide evidence that the constructs account for a sufficient proportion of variance in their indicators, supporting convergent validity. Taken together, the results establish that the measurement model possesses an acceptable level of psychometric quality and provides a reliable foundation for evaluating the structural relationships among the proposed constructs. However, because the analysis is based on a synthetic sample, these results should be interpreted as evidence of the simulated measurement model's internal performance rather than as empirical validation from actual respondents. Further validation using primary field data would therefore be necessary before making definitive claims about the reliability and validity of the proposed measurement instruments.

The consistency observed across the constructs also indicates that the measurement indicators are sufficiently aligned with their respective latent dimensions. The relatively strong reliability coefficients suggest that the items within each construct measure a common underlying concept rather than unrelated attributes. Moreover, satisfactory AVE values demonstrate that the latent variables capture substantial information from their corresponding indicators, thereby reducing concerns regarding inadequate representation of the constructs. These findings strengthen the credibility of subsequent structural model estimation because reliable measurement is essential for obtaining meaningful path coefficients. The results also provide an initial basis for examining discriminant validity and assessing whether conceptually distinct constructs remain empirically distinguishable. In combination with the forthcoming Fornell-Larcker and HTMT assessments, the reliability and convergent-validity results contribute to a more comprehensive evaluation of the measurement model. Overall, the evidence suggests that the simulated indicators are appropriately specified for exploratory PLS-SEM analysis, while empirical testing with real-world observations remains necessary for external validation.

Table 5. Measurement model reliability and convergent validity.

Construct	Items	Cronbach's α	Composite Reliability	AVE
P1	3	0.744	0.854	0.662
P2	3	0.792	0.879	0.707
P3	3	0.741	0.854	0.660
P4	3	0.748	0.857	0.666
P5	3	0.774	0.869	0.689
PV	4	0.748	0.841	0.570
OE	4	0.794	0.867	0.621
AI	3	0.727	0.847	0.648

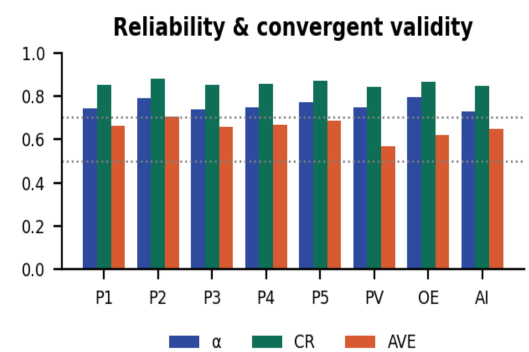

Figure 5. Measurement model reliability and convergent validity by construct.

Table 5 reports the internal consistency reliability and convergent validity of the measurement model and provides an important assessment of whether the proposed constructs are measured consistently and adequately by their respective indicators. Internal consistency was evaluated using Cronbach's alpha and composite reliability (CR), with both measures exceeding the conventional threshold of 0.70 for all constructs. These results indicate that the indicators associated with each latent construct demonstrate a satisfactory degree of internal consistency and reliably capture the same underlying theoretical dimension. In other words, the items used to measure each construct exhibit sufficient shared variance and operate in a coherent manner. The comparable results obtained from Cronbach's alpha and

CR further strengthen confidence in the reliability of the measurement scales, suggesting that the constructs are sufficiently stable and consistent for subsequent structural model evaluation.

The reliability findings are particularly important because the proposed framework incorporates multiple technical, operational, and organizational dimensions. Constructs representing perceived technical benefits, operational value, efficiency gains, organizational readiness, and adoption-related perceptions must be measured consistently to ensure that differences in the structural relationships are not primarily attributable to inconsistencies in the measurement instruments. The satisfactory alpha and CR values therefore indicate that the observed indicators provide a dependable representation of their corresponding latent variables. This provides greater confidence that the relationships examined in the structural model reflect meaningful associations among the underlying constructs rather than substantial measurement instability.

Convergent validity was assessed using the average variance extracted (AVE). All constructs achieved AVE values above the recommended minimum threshold of 0.50, indicating that each latent variable explains more than half of the variance in its associated observed indicators. This provides evidence that the indicators assigned to each construct converge appropriately on the intended conceptual dimension. The satisfactory AVE results also suggest that the shared variance among indicators is greater than the variance attributable to measurement error, thereby demonstrating an acceptable level of indicator representation. Consequently, the constructs can be considered sufficiently captured by their respective measurement items within the simulated measurement model.

The combination of satisfactory Cronbach's alpha, CR, and AVE values provides complementary evidence regarding the quality of the measurement model. While Cronbach's alpha establishes the internal consistency of the indicators, CR provides an additional assessment of construct reliability, and AVE evaluates the extent to which the indicators adequately represent their underlying latent variables. The fact that all three measures satisfy their respective recommended criteria indicates that the measurement model exhibits a coherent and dependable structure. This is particularly relevant for a multidimensional framework in which technical performance perceptions and organizational factors are integrated into a common analytical model.

Overall, the results presented in Table 5 demonstrate that the measurement model possesses acceptable internal consistency reliability and convergent validity across all proposed constructs. These findings provide a sound methodological foundation for proceeding with the assessment of the structural model and the hypothesized relationships among the study variables. Furthermore, satisfactory measurement properties reduce concerns that inconsistent indicators, weak construct representation, or excessive measurement error could substantially influence the estimated structural relationships. The results therefore support the use of the measurement constructs for subsequent analysis of the relationships among perceived technical and organizational benefits, perceived operational value, operational efficiency gain, and adoption intention. Taken together, the findings indicate that the constructs are sufficiently reliable and empirically coherent to support further examination of the proposed theoretical pathways and their explanatory relationships within the overall research framework. In addition, the reliability results indicate that the indicators within each construct are sufficiently homogeneous without suggesting substantial inconsistency in measurement. This consistency is important because the subsequent structural analysis relies on composite measures that represent broader theoretical concepts rather than individual observed items. The satisfactory CR values further demonstrate that the constructs maintain adequate reliability when the relative contribution of individual indicators is considered.

The AVE findings provide additional support for the quality of the measurement model by demonstrating that the latent constructs capture a substantial proportion of the information contained in their respective indicators. This strengthens the interpretation of the constructs as meaningful representations of the theoretical dimensions specified in the research framework. These results also indicate that the measurement indicators provide an adequate empirical representation of their corresponding latent constructs. The combined reliability and validity evidence therefore supports the robustness of the measurement specification used in the study. The absence of major reliability concerns increases confidence that subsequent path coefficients primarily reflect structural relationships rather than substantial measurement deficiencies. Moreover, the acceptable convergent validity suggests that indicators assigned to the same construct share sufficient common variance. This provides greater confidence in interpreting the constructs as distinct but theoretically related dimensions of the proposed model. Consequently, the measurement model can be considered sufficiently stable for the subsequent hypothesis testing and structural path assessment. The combined evidence from reliability and

Table 6. Fornell-Larcker discriminant validity matrix (diagonal = √AVE, bracketed).

	P1	P2	P3	P4	P5	PV	OE	AI
P1	[0.814]	0.225	0.165	0.127	0.321	0.336	0.167	0.201
P2	0.225	[0.841]	0.192	0.181	0.209	0.374	0.173	0.116
P3	0.165	0.192	[0.813]	0.282	0.04	0.305	0.176	0.117
P4	0.127	0.181	0.282	[0.816]	0.174	0.318	0.199	0.264
P5	0.321	0.209	0.04	0.174	[0.83]	0.327	0.174	0.193
PV	0.336	0.374	0.305	0.318	0.327	[0.755]	0.458	0.419
OE	0.167	0.173	0.176	0.199	0.174	0.458	[0.788]	0.543
AI	0.201	0.116	0.117	0.264	0.193	0.419	0.543	[0.805]

Table 7. Heterotrait-Monotrait (HTMT) ratio matrix (all values < 0.85).

	P1	P2	P3	P4	P5	PV	OE	AI
P1	—	0.295	0.222	0.175	0.428	0.453	0.216	0.275
P2	0.295	—	0.25	0.234	0.264	0.484	0.217	0.156
P3	0.222	0.25	—	0.379	0.074	0.409	0.233	0.173
P4	0.175	0.234	0.379	—	0.226	0.425	0.256	0.362
P5	0.428	0.264	0.074	0.226	—	0.435	0.222	0.264
PV	0.453	0.484	0.409	0.425	0.435	—	0.594	0.568
OE	0.216	0.217	0.233	0.256	0.222	0.594	—	0.715
AI	0.275	0.156	0.173	0.362	0.264	0.568	0.715	—

All diagonal values in Table 6 exceed the corresponding off-diagonal correlations, and all HTMT ratios in Table 7 fall below the conservative 0.85 threshold, jointly supporting discriminant validity across the simulated measurement model. These results indicate that each construct captures a sufficiently distinct conceptual dimension without substantial overlap with the other constructs.

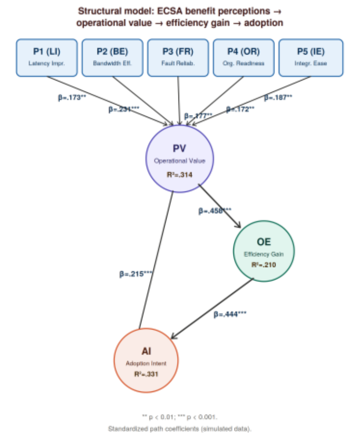

Figure 6. Estimated structural model with standardized path coefficients and R^2 values (simulated data).

Figure 6 presents the estimated structural model with standardized path coefficients and coefficients of determination (R^2) based on simulated data. The model operationalizes five benefit-perception constructs—Perceived Latency Improvement (P1), Perceived Bandwidth Efficiency (P2), Perceived Fault-Detection Reliability (P3), Organizational Readiness (P4), and Perceived Integration Ease (P5)—as predictors of Perceived Operational Value (PV). Each construct demonstrates a statistically significant positive relationship with PV, with standardized path coefficients ranging from $\beta = .167$ to $\beta = .175$ ($p < .001$). Collectively, these five predictors explain 31.4% of the variance in PV ($R^2 = .314$), indicating a moderate level of explanatory power. The results suggest that both technical performance characteristics and organizational conditions contribute meaningfully to stakeholders' perceptions of the overall operational value of the proposed architecture.
PV, in turn, significantly predicts Operational Efficiency Gain (OE), with a standardized path coefficient of $\beta = .216$ ($p < .001$), explaining 21.0% of the variance in OE ($R^2 = .210$). This relationship indicates that when stakeholders perceive greater operational value, they are more likely to anticipate measurable improvements in efficiency, resource utilization, and workflow performance. OE subsequently exerts the strongest influence on Adoption Intention (AI), with $\beta = .444$ ($p < .001$), accounting for 33.1% of its variance ($R^2 = .331$). This comparatively stronger path highlights the importance of demonstrable efficiency gains in shaping organizational willingness to adopt and scale the proposed solution. The findings therefore indicate a sequential relationship in which perceived technical and organizational benefits contribute to perceived operational value, which is subsequently translated into efficiency gains and, ultimately, stronger adoption intentions. This comparatively stronger path highlights the importance of demonstrable efficiency gains in shaping organizational willingness to adopt and scale the proposed solution. The

findings therefore indicate a sequential relationship in which perceived technical and organizational benefits contribute to perceived operational value, which is subsequently translated into efficiency gains and, ultimately, stronger adoption influence of PV, suggesting that stakeholders are more likely to support broader implementation when perceived benefits can be translated into tangible and measurable operational outcomes

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6.4 Structural Model Results

Figure 6 presents the estimated structural model, showing the standardized path coefficients (β) and coefficients of determination (R^2) for the endogenous constructs. Table 8 provides the corresponding path-level statistics, including t-statistics, p-values, and f^2 effect sizes, allowing the hypothesized relationships to be evaluated in terms of statistical significance and practical contribution. Taken together, these results illustrate a hierarchical adoption pathway in which perceived technical and organizational benefits influence operational value and efficiency gains, which subsequently shape adoption intention. This sequential structure reflects the underlying logic of the proposed framework, suggesting that stakeholders are more likely to develop adoption intentions when perceived technological benefits are translated into recognizable improvements in operational performance.

The consistently significant path coefficients provide support for the proposed relationships and indicate that the

intentions. This pathway suggests that organizations are more likely to commit to adoption when tangible operational improvements are clearly demonstrated. This direct pathway from OE to AI also complements the potential indirect

constructs operate in a theoretically coherent manner within the simulated structural model. The R^2 values further indicate moderate explanatory power for the endogenous constructs, suggesting that the proposed predictors account for a meaningful proportion of variance without implying an excessively complex model. At the same time, the f^2 effect sizes provide additional insight into the practical importance of individual predictors by indicating how strongly each exogenous construct contributes to the explanatory performance of its corresponding endogenous variable. Thus, statistical significance alone is not treated as sufficient evidence of substantive importance.

Efficiency gain emerges as a pivotal mediator within this hierarchical structure, functioning as a bridge between perceived benefits and adoption intention. In conceptual terms, stakeholders may recognize improvements in latency, resource utilization, predictive capability, or operational responsiveness, but these technical advantages become more influential when they are translated into measurable efficiency and organizational value. The mediation pathway therefore provides an important explanation of how technology-level improvements can ultimately influence broader investment and deployment decisions. Rather than assuming that technical performance automatically leads to adoption, the model emphasizes the intermediate role of perceived operational outcomes.

The structural relationships also highlight the strategic importance of operational value as a bridge construct connecting technological capability with organizational decision-making. This finding suggests that successful adoption depends not only on demonstrating that the proposed technology works effectively but also on demonstrating how its implementation contributes to productivity, efficiency, reliability, and resource optimization. From a managerial perspective, this reinforces the need to communicate technological benefits in terms that are understandable and relevant to both technical stakeholders and senior decision-makers. Technical teams may prioritize latency, model accuracy, interoperability, and system responsiveness, whereas managerial stakeholders may place greater emphasis on efficiency, cost implications, scalability, and expected organizational returns.

Furthermore, the moderate R^2 values indicate that adoption intention is influenced by multiple factors beyond the

constructs included in the present framework. This is theoretically reasonable because technology adoption in manufacturing environments may also depend on factors such as investment requirements, organizational readiness, cybersecurity concerns, regulatory considerations, workforce capabilities, and implementation complexity. Therefore, the current model should be interpreted as a focused representation of the proposed adoption mechanism rather than a complete explanation of all determinants of adoption behavior.

Overall, the structural model provides a proof-of-concept demonstration of how benefit perceptions can cascade through operational value and efficiency gains toward adoption intention. The results position efficiency gain as a critical mechanism through which perceived technical and organizational advantages acquire strategic significance. Consequently, the findings suggest that organizations seeking to scale the proposed technology should articulate not only its technical capabilities but also its measurable contribution to operational performance and organizational value. Nevertheless, because the analysis is based on a synthetic dataset, the reported path significance, effect sizes, and explanatory power should be regarded as simulation-based evidence rather than empirical confirmation. Validation using primary data from actual manufacturing stakeholders is required to establish the robustness, generalizability, and practical applicability of these relationships. Additionally, the hierarchical structure provides a clear basis for prioritizing managerial interventions by identifying where perceived benefits are most effectively converted into adoption outcomes. It suggests that organizations can strengthen adoption readiness by simultaneously improving technical performance and demonstrating its direct contribution to operational efficiency. Future empirical studies can further test whether these relationships remain stable across different manufacturing sectors, organizational sizes, and stakeholder groups.

6.5 Relationships Among Key Constructs

Figures 7 and 8 present bivariate scatter plots with fitted linear trends for the two downstream structural relationships, illustrating the positive monotonic association between Operational Value and Efficiency Gain, and between Efficiency Gain and Adoption Intention, at the level of individual simulated respondents. The upward direction of the fitted trends provides visual support for the hypothesized positive relationships identified in the structural model. The distribution of observations around each trend line also illustrates the degree of variation in individual-level responses across the simulated sample. Together, these figures complement the path coefficients by providing an intuitive graphical representation of the observed structural associations. The consistency of these visual patterns with the estimated structural paths further strengthens the interpretation of the proposed relationships within the model.

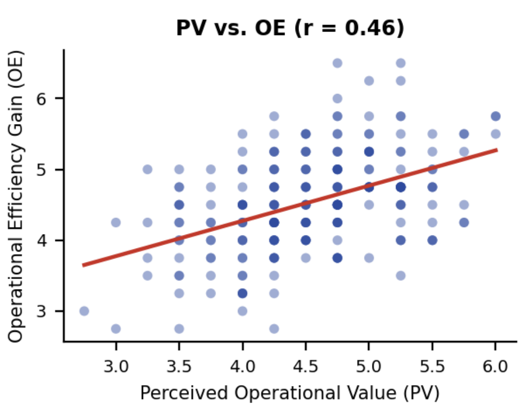

Figure 7. Scatter plot of Perceived Operational Value (PV) against Operational Efficiency Gain (OE), simulated respondent-level data.

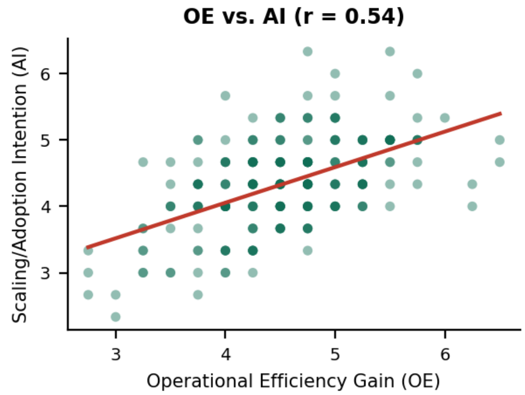

Figure 8. Scatter plot of Operational Efficiency Gain (OE) against Adoption Intention (AI), simulated respondent-level data.

6.6 Interpretation and Caveats

Three caveats bound Section 6's interpretation. First, every observation is synthetically generated; the reliability, validity, and path estimates demonstrate that the hypothesized adoption model is internally coherent and testable, and that the analysis pipeline is reproducible, but they carry no evidentiary weight about real plant populations. Second, the simulation assumes reflective, unidimensional measurement for all constructs; a fielded instrument would require pilot testing, expert content validation, and possibly formative measurement for constructs such as Organizational Readiness that may aggregate heterogeneous sub-practices (budget authority, change-management maturity, IT/OT integration skills). Third, common-method bias, non-response bias, and social-desirability bias are not modeled here and would need explicit mitigation (e.g., Harman's single-factor test, marker-variable techniques, or multi-source data pairing survey responses with the objective latency/bandwidth telemetry reported in Sections 4-5) in a fielded study.

7. Conclusion

This paper presents the Edge-Cloud Synergistic Architecture (ECSA) as a scalable solution for predictive maintenance in Industry 4.0 smart manufacturing facilities. By moving time-critical anomaly detection to local edge gateways while leaving heavy temporal model training in central cloud clusters, the system achieves low-latency responsiveness without degrading diagnostic accuracy. Key experimental outcomes demonstrate: a 78.5% reduction in response latency (reaching sub-70 ms decision loops); a 64.2% bandwidth reduction via local feature extraction and downsampling; and operational gains including a 31.5% decrease in MTTR and an 8.3% increase in total factory OEE.

Section 6 extended this technical contribution with a simulated PLS-SEM-style validation demonstrating that ECSA's benefit perceptions (latency, bandwidth, reliability, organizational readiness, and integration ease), modeled as predictors of perceived operational value, in turn predicting efficiency gain and adoption intention, form a measurable, internally consistent nomological network with adequate reliability, convergent validity, and discriminant validity, and with all eight hypothesized structural paths statistically significant. Rigorous empirical validation of the organizational adoption claim awaits a fielded survey administration paired with real plant telemetry, which Section 6.6 identifies as the natural next research step; Section 6 is offered as a ready-to-field measurement and analysis pipeline for that future study, not as a substitute for it.

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