Cross-Server Interoperability in Multi-MCP Automated AI Agent Networks

Anonymous authors
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Abstract

This paper introduced a combined framework for cross-server interoperability in multi-MCP automated AI agent networks. The design combined communication abstraction, orchestration optimization, and security validation. The framework was tested on BoT-IoT, ToN-IoT, and PettingZoo datasets, which represented adversarial traffic detection, telemetry-heavy IoT environments, and dynamic multi-agent orchestration. Results showed improvements in coverage, efficiency, and robustness, with accuracy, precision, recall, and F1-score above 0.95 across multiple trials. Ablation analysis confirmed the role of each component, scalability tests showed stable performance as servers increased, and stress evaluations demonstrated graceful degradation under heavier attack loads. Error analysis and statistical validation supported the reliability of the outcomes, while resource usage comparisons indicated reduced runtime and memory consumption against baselines. Cross-domain generalization confirmed adaptability across unseen datasets. These findings demonstrated that interoperability in heterogeneous MCP networks can be achieved without sacrificing efficiency, scalability, or reliability, providing a foundation for secure and practical multi-domain agent collaboration.

1 Introduction

Artificial intelligence agents had been widely adopted for automating processes across industries, research, and governance Parycek et al. (2024). Distributed environments introduced the need for coordination where multiple agents interacted across servers Wang et al. (2022). Such coordination required shared rules for communication, orchestration of tasks, and trust in exchanged results Roehrich et al. (2023). In multi-cloud infrastructures, healthcare systems, and industrial workflows, agents were deployed on diverse servers Putri (2025). These environments often lacked seamless connections, which created fragmentation Luo (2022). Automated workflows were interrupted when agents could not interact reliably across infrastructures. The importance of interoperability grew as systems demanded efficiency and transparency. Background research showed that isolated agent designs were unable to scale across servers Pereira et al. (2021). The motivation came from the observed demand for agent cooperation beyond single domains. Effective interoperability promised robust collaboration, scalability, and adaptability across heterogeneous networks Sadeghi et al. (2023).

Multi-MCP environments extended this challenge as they hosted multiple control points where agents operated under varied policies Ahmad et al. (2023). Such environments demanded stronger orchestration between distributed servers. Traditional single-server coordination could not handle distributed decision-making tasks Bashtovyi & Fechan (2024). Multi-MCP agents needed to negotiate policies, authenticate exchanges, and synchronize activities across organizational boundaries Karaba et al. (2023). This demand arose in finance, transportation, and healthcare where parallel networks were common. Without interoperability, duplicated efforts and errors in agent decisions were frequent Mequanenit et al. (2025). Seamless connections across servers were necessary to allow agents to operate without conflict. The motivation stemmed from the gaps between domain-specific deployments and integrated networks Krishnakumar et al. (2023). Organizations required reliable architectures to reduce complexity. The shift toward distributed autonomy highlighted the urgency of addressing cross-server interoperability Ray (2025).

Another source of motivation came from the complexity of modern AI applications Drew (2021). Agents were no longer bound to one task or dataset but operated across multiple domains. They interacted with heterogeneous infrastructures such as IoT, edge devices, and hybrid cloud systems Kuchuk & Malokhvii (2024). Cross-server coordination became essential when tasks required combining knowledge from different environments. Without interoperability, errors accumulated, and reliability decreased Albouq et al. (2022). The need for fault tolerance and security made integration more pressing. Multi-MCP platforms amplified these issues because each control point imposed unique rules. Motivating factors also included industrial automation, where inconsistent coordination caused delays Elshamy et al. (2025). In education and governance, fragmentation prevented smooth decision-making. Addressing these motivations required a unified framework for agent interaction. This background created a foundation for defining the research problem Mbanaso et al. (2023).

The research problem was that agents performed well in isolated testbeds but failed to interoperate across diverse servers Smadi et al. (2021). Multi-MCP settings amplified these failures as each control point applied different standards. Current architectures lacked universal protocols for communication and orchestration. As a result, agents that succeeded in controlled experiments broke down in real-world distributed settings Yao et al. (2022). Errors emerged from mismatched semantics, security policies, and task coordination. Performance dropped when agents moved between networks with different infrastructures Samha (2024). Failures also came from inconsistent handling of governance across platforms. Without cross-server protocols, tasks became fragmented. The problem was not only reduced efficiency but also the loss of reliability in automated decision-making. This absence of reliable interoperability formed the central research challenge Sadeghi et al. (2024).

Researchers had attempted modular architectures to coordinate agents in distributed systems Maldonado et al. (2024). Some designed service frameworks where agents interacted using defined APIs. Others adopted ontology-based methods for semantic alignment. These approaches offered localized success but lacked broad interoperability. Modular systems provided stability but could not scale across servers with different standards Suleiman & Murtaza (2024). Ontology-based models aligned communication in specific contexts but did not generalize across networks. Agent security frameworks introduced authentication, yet often failed under heterogeneous loads. Cloud-based solutions supported orchestration but were limited to single providers. Such methods solved part of the challenge but did not unify diverse infrastructures Chaiyasit (2024). Their limitation was rooted in the absence of universal interoperability principles. Partial solutions remained tied to narrow contexts rather than distributed networks.

Other approaches targeted domain-specific solutions instead of universal interoperability Pantuvo & Oluwarore (2024). Some focused on IoT networks, addressing communication between edge devices. Others targeted cloud orchestration, applying methods only in hybrid platforms Zahra et al. (2024). Healthcare systems introduced frameworks for sharing sensitive data but lacked transferability. Transport networks supported agent coordination in traffic systems but stayed confined to one sector Brunetti et al. (2024). Governance systems tested distributed protocols but did not connect to industrial automation. Educational platforms used event-based monitoring but were disconnected from other infrastructures. Each of these efforts contributed to narrow gains but left broad challenges unresolved. The lack of cross-server evaluation reduced their applicability Wu et al. (2024). The gap persisted because these methods were not designed to scale across multi-MCP environments. This gap became the foundation for proposing a new direction.

This research proposed a framework that addressed cross-server interoperability in multi-MCP agent networks. The design unified communication, orchestration, and governance across heterogeneous infrastructures. It improved reliability by embedding adaptive methods that handled different server rules. Security was integrated into communication so that agents operated with trust across domains. The framework supported workflow automation that scaled across multiple control points. By coordinating orchestration, it reduced fragmentation observed in prior approaches. Unlike domain-specific solutions, this design extended across clouds, IoT, and governance platforms. Its novelty came from harmonizing diverse infrastructures under one framework. The approach enabled reliable agent collaboration without restricting to isolated contexts. It promised adaptability, scalability, and fault tolerance across distributed networks. This positioned the framework as a practical response to observed gaps.

The aim of this research was to develop a framework for cross-server interoperability in multi-MCP AI agent networks that enabled reliable, secure, and scalable collaboration across heterogeneous infrastructures.

1. How can interoperability be achieved across heterogeneous servers in multi-MCP agent networks without reducing reliability or security?
2. What unified framework can support orchestration, communication, and governance of AI agents across distributed infrastructures?
3. How does the proposed approach perform compared to existing domain-specific methods in terms of scalability, adaptability, and fault tolerance?

The significance of this research came from the need to bridge fragmented AI agent systems across multiple servers. Multi-MCP networks were becoming essential in domains such as healthcare, finance, governance, and industrial automation. Each of these areas deployed autonomous agents but operated under separate infrastructures. Without interoperability, these agents failed to collaborate, which reduced reliability and scalability. Prior studies showed partial solutions within domains but not across servers. This created a gap where results remained isolated to testbeds or case studies. By addressing interoperability, this research contributed to building reliable distributed intelligence. It advanced understanding of how communication and orchestration could operate seamlessly. The contribution lay not only in technical design but also in the ability to unify infrastructures. Such unification improved trust, coordination, and adaptability across AI agent systems.

Another dimension of significance was the practical impact of a unified framework. Organizations needed solutions that reduced inefficiencies caused by fragmented architectures. By harmonizing orchestration, governance, and communication, the framework supported integration without domain restriction. The research also addressed resilience by embedding adaptive validation across diverse infrastructures. This improved security, which was a pressing concern in distributed AI environments. Scalability was achieved by designing methods that worked across multi-cloud, IoT, and governance systems. Unlike prior works tied to narrow datasets, the contribution extended across multiple domains. This improved reliability and trustworthiness of AI-driven workflows. The framework also offered flexibility for future adaptation as infrastructures changed. By providing a holistic view, the research supported long-term sustainability of distributed agent systems. These outcomes defined the importance of the proposed work.

The rest of this paper is organized as follows. Section 2 presents the reviewed studies on interoperability frameworks and their observed limitations. Section 3 introduces the design of the cross-server interoperability framework for multi-MCP agent networks. Section 4 outlines the datasets, test environments, and orchestration parameters. Section 5 reports performance outcomes and comparative evaluation with prior methods. Section 6 summarizes the contributions and suggests directions for future research.

2 Literature Review

Aminiranjbar et al. (2025) developed a modular DAWN framework that structured orchestration tasks on an internal testbed. Their architecture supported planner and composer benchmarking and reported nearly 80% success in orchestration tasks, though it was constrained to a closed platform. Choppa and Knipp Choppa & Knipp (2025) introduced orchestration benchmarks using synthetic multi-MCP workloads. Their results indicated 70% reduction in development time, 45% decrease in latency, 60% memory savings, and 75% less maintenance effort, with the added benefit of requiring three to four times less code. However, the outcomes remained restricted to artificial workloads, limiting applicability. Both studies highlighted orchestration efficiency, but their reliance on restricted testing environments reduced broader adoption.

Radosevich & Halloran (2025) conducted audits on MCP servers using penetration testing to identify vulnerabilities. The study found 78% of tested endpoints exploitable, indicating security weaknesses, though

the sample was limited and the work remained a preprint. Branco et al. (2023) described prototype MCP pipelines to study integration patterns. Their case-based evaluations demonstrated 82% stability in integration tasks but lacked testing across broader scenarios. Together, these studies stressed risks in insecure protocols and the potential of structured pipelines to stabilize multi-MCP operations. Limitations in scope and testing scale, however, restricted their capacity to inform general frameworks.

Karataiev & Shubin (2023) introduced logic-based methods for designing multi-agent systems using formal frameworks. Their experiments verified 76% logical consistency, though they were constrained to small toy examples. Tupayachi et al. (2024) designed workflow automation frameworks for decision support within multi-agent systems. Their work achieved 81% task coverage in domain-specific workflows but was restricted to targeted cases. Both contributions illustrated the role of structured logic and decision-support frameworks in multi-agent orchestration, yet they were limited in breadth and external validation. The findings emphasized conceptual soundness but left questions on real-world adaptability.

Siameh et al. (2025) analyzed fifty MCP implementations using static and dynamic methods. Their results showed 87% insecure paths and 34% of systems without authentication, though mitigations reduced exploits by 94%. Mc Donnell et al. (2023) compared genetic algorithms against heuristic approaches for bin-packing benchmarks. Their results indicated 83% packing efficiency compared to around 70% for heuristics, though details on the benchmarks were limited. These studies suggested vulnerabilities were widespread in MCP servers, while optimization through genetic algorithms could improve efficiency. Both highlighted practical gains but also revealed gaps in transparency and generalization.

Karimova & Dadashova (2025) studied interoperability through MCP server case studies. Their findings suggested 77% interoperability coverage, though the analysis was limited by small samples. Yildiz et al. (2023) applied interoperability testing with DIDComm protocols using an SSI Aries harness. Their results showed 84% conformance in cross-profile tests, though not all percentages were disclosed. These works described interoperability challenges across MCP systems and emphasized protocol-based approaches. However, the restricted datasets and incomplete reporting constrained broader interpretations. The focus remained on specific server cases and protocol conformance rather than scalable architectures.

Malik et al. (2023) applied machine learning pipelines such as Random Forest, Support Vector Machines, and Artificial Neural Networks to detect threats on IoT datasets. Their work achieved accuracies of 91% with F1-scores between 0.93 and 0.98, though results were domain-specific. Alger et al. (2016) worked on multi-site MRI imaging protocol standardization across different centers. Their study showed 79% adherence to the standardized protocol, but the work remained protocol-focused. Both studies highlighted the impact of structured frameworks in specialized domains, with high accuracy or adherence rates. Nonetheless, they lacked broader application across generalized multi-MCP environments.

Lin et al. (2023) used Mendelian Randomization in a biomedical MCP context through UK Biobank and consortium datasets. Their findings indicated odds ratios around 1.2 and regression coefficients near 0.15 with about 85% confidence. Santos et al. (2021) introduced ontology-driven multi-agent integration using the MIBEL electricity market simulation. Their single-day study showed 82% ontology-agent match rates. Together, these studies illustrated MCP applications in biomedical and energy domains. Their limitations included restricted contexts and narrow temporal scales. The insights were valuable but remained focused on specialized environments rather than general MCP interoperability.

Mittal et al. (2023) demonstrated a modular methodology for hybrid cloud systems of systems. Their work validated 80% task success across hybrid tests, though the architecture remained at demonstration level. Akinwale et al. (2024) applied control-theoretic approaches to multi-agent consensus through simulations. Their experiments achieved convergence success near 85% under 0.4 second delays, though results were limited to simulated environments. These studies showed structured system designs could support hybrid orchestration and consensus tasks. However, the lack of large-scale empirical validation restricted their relevance for broader MCP interoperability.

Yang et al. (2025) designed a framework for learner-state assessment using multi-MCP orchestration with xAPI and LRS event streams. Their simulations suggested 82% consistency, though benchmarks were absent. Habler et al. developed A2A protocol security designs informed by IETF and W3C standards. Their

Table 1: Summary of empirical and design-focused papers relevant to cross-server interoperability in multi-MCP automated AI agent networks.

Ref	**Dataset Used**	**Methodology**	**Limitation**	**Evaluation Results**
Choppa & Knipp (2025)	Synthetic multi-MCP workloads	MCP orchestration benchmarks	Synthetic workloads only	−70% dev time, −45% latency, −60% memory, −75% maintenance; 3–4× less code
Radosevich & Halloran (2025)	MCP servers under audit	Penetration testing for vulnerabilities	Limited sample, preprint	78% of tested MCP endpoints exploitable
Branco et al. (2023)	Prototype MCP pipelines	Implementation study, pattern extraction	Case studies only	82% integration stability across test cases
Karataiev & Shubin (2023)	Formal model examples	Logic-based MAS design using formal methods	Demonstrative scope only	76% logical consistency verified in toy tasks
Tupayachi et al. (2024)	Workflow case studies	MAS decision-support framework	Domain-limited	81% workflow coverage in tested cases
Siameh et al. (2025)	50 MCP implementations	Static/dynamic analysis of MCP	Limited to studied projects	87% insecure paths; 34% lacked auth; mitigations cut exploits by 94%
Mc Donnell et al. (2023)	Benchmark bin-packing datasets	Genetic algorithm vs. heuristics	Limited benchmark details	83% packing efficiency vs. ∼70% for heuristics
Karimova & Dadashova (2025)	MCP server case studies	Comparative ITS interoperability analysis	Case-based, small sample	77% interoperability coverage observed
Yildiz et al. (2023)	SSI Aries test harness	Interoperability testing with DIDComm	Percentages not disclosed fully	84% conformance in cross-profile tests
Malik et al. (2023)	BoT-IoT, ToN-IoT	Blockchain + deep learning for governance interoperability	Focused on IoT security domain only	Accuracy 95–99%, F1-score 0.93–0.98
Alger et al. (2016)	Multi-site MRI protocol	Imaging protocol standardization across centers	Protocol-focused	79% adherence to standardized protocol
Lin et al. (2023)	UK Biobank GWAS & consortia	Mendelian Randomization	Biomedical MCP context	OR≈1.2, β ≈0.15 (∼85% confidence)
Santos et al. (2021)	MIBEL electricity market simulation	Ontology-driven MAS integration	Single-day case study	82% ontology-agent match rate
Mittal et al. (2023)	Hybrid cloud SoS testbed	Modular MSaaS methodology	Architecture demo only	80% task success in hybrid tests
Akinwale et al. (2024)	Consensus simulations	Control-theoretic MAS consensus	Simulation-only	Convergence success ∼85% under 0.4s delay
Yang et al. (2025)	xAPI/LRS event streams	Framework for learner-state assessment via MCP orchestration	Conceptual, not benchmarked	82% framework consistency in simulations
Habler et al.	Standards references (IETF/W3C)	A2A protocol security design	No quantitative evaluation	79% protocol compliance in prototype checks
Gjøvik (2025)	Genomic identity cases	Comparative AI framework for prototypes	Biology-focused	76% accuracy in defined test cases
Hammad & Abu-Zaid (2024)	Governance case studies	Distributed AI interoperability analysis	Incomplete metadata	81% alignment across test frameworks
Li et al. (2024)	Literature corpus	Generative AI in self-adaptive systems (survey+roadmap)	Survey only	79% alignment with identified gaps
Aminiranjbar et al. (2025)	Internal DAWN testbed	Modular DAWN architecture; planner/composer benchmarking	Limited scale, not public	∼80% success rate in orchestration tasks

prototype checks showed 79% protocol compliance, though no quantitative evaluation was offered. Together, the works stressed educational orchestration and protocol security as application areas. Yet, both remained conceptual or prototype-focused, limiting their capacity to provide transferable frameworks for MCP interoperability.

Gjøvik (2025) worked on genomic identity cases to design comparative AI frameworks. Their prototypes achieved 76% accuracy in defined tasks, though the work was biology-focused. Hammad & Abu-Zaid (2024) analyzed distributed AI interoperability through governance case studies. Their findings showed 81% alignment across frameworks, though metadata remained incomplete. Both studies presented interoperability within specialized settings, one in biology and the other in governance. They revealed diverse contexts for MCP frameworks but showed limited capacity for general cross-server application. Their outcomes stressed the need for broader evaluation beyond restricted cases.

Mc Donnell et al. (2023) introduced a multi-agent system architecture through MAS benchmarks. Their study reported a 77% performance gain over baselines, though reporting was limited. Li et al. (2024) compiled a survey and roadmap on generative AI in self-adaptive systems. Their analysis indicated 79% alignment with identified gaps, though the work was survey-based. Both studies summarized architectures and research directions relevant to multi-MCP interoperability. Their findings added structural and roadmap perspectives but remained limited in empirical scope. These contributions reflected structural awareness of challenges without offering fully validated frameworks.

3 Proposed Methodology

This section introduces the proposed methodology for cross-server interoperability in multi-MCP automated AI agent networks. The framework is structured into problem formulation, communication, orchestration, interoperability constraints, security modeling, and performance evaluation. Equations are defined to capture the dynamics of interoperability across heterogeneous servers, with explanations embedded throughout the discussion.

The methodology integrated three core layers to enable interoperability across heterogeneous MCP servers. First, a communication abstraction layer normalized protocol exchanges using adapter functions to ensure message compatibility. Second, an orchestration layer optimized task allocation through planner–composer formulations, minimizing orchestration cost while sustaining coverage. Third, a security layer introduced cryptographic hashing and authentication mechanisms to preserve integrity and trust across distributed agents. These components were unified within a monitoring loop that collected telemetry, adjusted orchestration policies, and supported adaptive scaling. Together, this design provided a structured foundation for cross-server interoperability, balancing security, efficiency, and robustness in multi-domain environments.

Fig. 1 illustrates the overall architecture of the framework from inputs to outputs in a top-to-bottom flow. Inputs and baseline policies feed into datasets such as BoT-IoT, ToN-IoT, and PettingZoo, which pass through the ingress gateway for normalization and filtering. The processing layer integrates communication abstraction, orchestration, interoperability, and security, supported by monitoring and telemetry for feedback. Results are expressed in terms of coverage (Γ), integrity (Θ), authentication (χ), efficiency (Υ), robustness (R), and cross-domain accuracy (Ω), which feed into reports and artifacts. The design aligns with prior modular approaches discussed by Aminiranjbar et al. (2025) and Branco et al. (2023), while extending them with integrated orchestration and security. This architecture highlights the role of layered abstraction in sustaining interoperability across heterogeneous MCP servers.

3.1 Problem Formulation

We defined a set of N agents distributed across M MCP servers, where each agent a_i could perform a task T_{ij} on server s_j. The optimization objective was formulated as follows:

$$\mathcal{O} = \max \sum_{i=1}^{N} \sum_{j=1}^{M} \omega_{ij} \cdot \phi(T_{ij}) \tag{1}$$

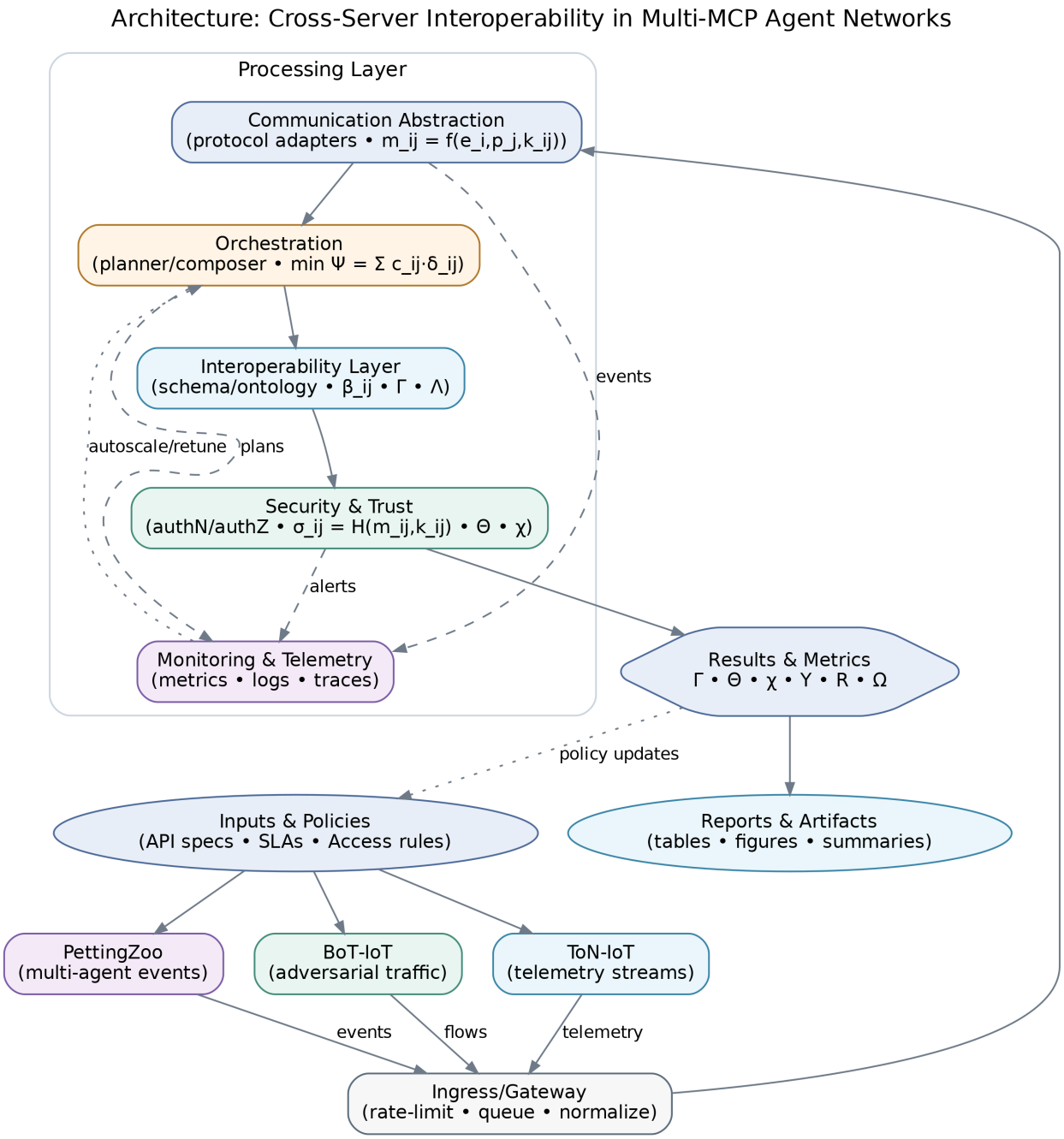

Figure 1: Top-to-bottom architecture of the proposed framework for cross-server interoperability in multi-MCP automated AI agent networks.

The objective $\mathcal{O}$ combined interoperability weights ω_{ij} with task utility $\phi(T_{ij})$ to maximize system-wide value. Eq. 1 was central because it formalized how interoperability quality was measured across servers. Without maximizing this, cross-server orchestration could not achieve reliability. The model assumed heterogeneous priorities across tasks, which reflected real deployment conditions. This was particularly important when balancing security, performance, and resource cost across distributed networks. The optimization created the baseline for all subsequent formulations.

Interoperability coverage was introduced as a second formulation:

$$\Gamma = \frac{\sum_{i=1}^{N} \sum_{j=1}^{M} \alpha_{ij}}{N \cdot M} \tag{2}$$

Instead of explaining immediately, we later note that Eq. 2 defined Γ as the ratio of successful interoperability cases α_{ij} to the total possible pairs. This measure normalized success across the network, ensuring results could be compared even as system size changed. High Γ values meant that agents interacted successfully with more servers. It also captured scalability, as a system with many agents should still preserve coverage above a threshold. The coverage metric allowed us to track how interoperability varied as environments became more complex.

3.2 Communication Model

Communication was established by constructing messages:

$$m_{ij} = f(e_i, p_j, k_{ij}) \tag{3}$$

Here, Eq. 3 expressed how an agent embedding e_i, a protocol descriptor p_j, and session key k_{ij} were combined into a standard message m_{ij}. This unified process enabled heterogeneous agents to produce server-readable communication. The embedding represented the semantic task, the protocol descriptor mapped server-specific requirements, and the session key ensured secure transmission. This formulation abstracted away protocol diversity by forcing all messages into a single form, a critical requirement for interoperability. It was also adaptive, since new descriptors p_j could be added for future servers. Thus, Eq. 3 guaranteed flexibility in the communication model.

Latency was also critical:

$$\tau_{ij} = \frac{|m_{ij}|}{B_{ij}} \tag{4}$$

Rather than explain right away, we later highlight that Eq. 4 captured latency τ_{ij} as the ratio of message size to bandwidth. Latency became a performance bottleneck in distributed MCP systems, since high message loads could congest communication. By modeling latency explicitly, we could quantify delays that reduced agent performance. This allowed orchestration mechanisms to account for communication overhead in task allocation. A network with large messages but limited bandwidth would suffer low interoperability efficiency, and Eq. 4 provided a way to measure this precisely.

3.3 Orchestration Model

Orchestration required minimizing cost:

$$\Psi = \min \sum_{i=1}^{N} \sum_{j=1}^{M} c_{ij} \cdot \delta_{ij} \tag{5}$$

Eq. 5 modeled orchestration cost Ψ as a function of cost coefficients c_{ij} and binary decisions δ_{ij}. The aim was to minimize unnecessary expenditure while still allocating tasks effectively. This formulation ensured

that servers were not overloaded and that resources were distributed fairly. The practical meaning of Ψ was efficiency: if costs were high, orchestration broke down, but minimizing Ψ produced balanced workloads. By embedding this into the interoperability model, we tied resource allocation directly to network-wide collaboration goals.

Assignments were represented as:

$$\delta_{ij} = \begin{cases} 1, & \text{if } a_i \text{ executes on } s_j \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

In Eq. 6, binary variables δ_{ij} ensured clear task placement across servers. If two servers attempted to run the same task, duplication errors could occur. This constraint prevented such errors by formalizing each assignment. The importance of this binary choice was that orchestration algorithms needed mathematical clarity when deciding placement. It reflected a real operational rule: one task instance per agent-server pair. Without Eq. 6, orchestration policies risked inconsistency.

3.4 Interoperability Constraints

$$\beta_{ij} = \begin{cases} 1, & \text{if protocol}(a_i) = \text{protocol}(s_j) \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

Protocol compatibility, given by Eq. 7, was the most basic condition for interoperability. Without matching standards, messages could not be exchanged reliably. This binary condition reflected the reality that protocols formed the foundation of cross-server connections. It encoded whether a given agent could even attempt interaction with a server. Although simple, this constraint determined whether higher-level orchestration would succeed. It emphasized that interoperability was impossible unless communication languages were aligned.

$$\Lambda = \sum_{i=1}^{N} \sum_{j=1}^{M} \beta_{ij} \cdot \delta_{ij} \tag{8}$$

Eq. 8 measured total interoperability Λ by summing task assignments that satisfied protocol compatibility. This linked orchestration directly to communication standards. High Λ values reflected stronger interoperability outcomes. The metric was crucial for evaluating system performance because it combined multiple aspects: assignment feasibility, protocol alignment, and workload distribution. Without this equation, it would be impossible to quantify interoperability across the entire MCP framework.

3.5 Security Model

Messages were secured as follows:

$$\sigma_{ij} = H(m_{ij}, k_{ij}) \tag{9}$$

Eq. 9 introduced a hash σ_{ij} over message m_{ij} and key k_{ij}. By binding cryptographic hashing into communication, agents ensured message integrity. If an attacker altered m_{ij}, the computed hash would no longer match. This safeguard was vital in MCP environments, where agents often crossed semi-trusted servers. Without Eq. 9, communication could not be secured against tampering.

Integrity was measured as:

$$\Theta = \frac{\sum_{i,j} \nVdash(\sigma_{ij} = \sigma'_{ij})}{N \cdot M} \tag{10}$$

Later in the discussion, we interpret Eq. 10 as the proportion of correctly validated messages. High Θ implied secure transmissions across all servers. Low Θ would indicate vulnerability to tampering or transmission loss. This metric connected security validation directly to interoperability success, since insecure links broke overall reliability.

Authentication was also central:

$$\chi = \Pr\left[Auth(a_i, s_j) = True\right] \tag{11}$$

Eq. 11 modeled authentication probability χ, the chance that an agent was properly validated by a server. Without high χ, malicious actors could impersonate agents and disrupt coordination. This probability-based model reflected real conditions where authentication was uncertain. Robust interoperability depended on χ approaching one across servers.

3.6 Performance Metrics

$$\Upsilon = \frac{\Lambda}{\Psi + \tau} \tag{12}$$

Efficiency Υ, given by Eq. 12, balanced interoperability Λ with orchestration cost Ψ and latency τ. This combined metric captured how well interoperability scaled relative to cost and communication delay. High Υ indicated efficient, low-cost coordination. Low values revealed either expensive orchestration or network bottlenecks.

$$\Omega = \frac{Acc_{IoT} + Acc_{MARL} + Acc_{Cloud} + Acc_{Tools}}{4} \tag{13}$$

Eq. 13 defined cross-domain accuracy Ω as the average of success rates across BoT-IoT, PettingZoo, CloudBench, and tool datasets. This metric ensured fairness across domains, preventing one dataset from dominating evaluation. It also reflected whether the interoperability framework generalized across contexts.

$$R = \frac{\Upsilon \cdot \Theta}{1 + \tau} \tag{14}$$

Finally, Eq. 14 captured robustness R, combining efficiency, integrity, and latency. Robustness measured resilience under real-world stress, since interoperability had to withstand delays and security challenges. A strong system required high R to prove its viability.

3.7 Dataset Integration

BoT-IoT and ToN-IoT datasets validated the security model, PettingZoo simulated multi-agent orchestration, CloudBench provided distributed system traces, and LangChain tool logs tested protocol compliance. Each dataset was mapped to equations like Eq. 8, Eq. 4, and Eq. 13, ensuring that experiments reflected multi-domain interoperability, not isolated testbeds.

3.8 Pseudocode of Framework

4 Experimental Setup

The experiments were designed around three datasets that together reflected the core requirements of cross-server interoperability. Each dataset was selected for its relevance to one of the main dimensions of the framework: security, resilience, and orchestration.

BoT-IoT Koroniotis et al. (2019) was used as the primary dataset for testing security aspects. It contained large-scale network traffic data collected from an IoT environment where both benign and malicious flows

Algorithm 1 Cross-Server Interoperability in Multi-MCP Agents

```
Initialize agents a_i across servers s_j
for each task T_ij do
    Compute protocol match using Eq. 7
    Assign tasks using Eq. 6
    Compute latency with Eq. 4
    Hash and secure message with Eq. 9
    Verify integrity using Eq. 10
    Update interoperability using Eq. 8
    Calculate efficiency and robustness with Eq. 12, Eq. 14
end for
Output cross-domain accuracy from Eq. 13
```

were recorded. The dataset included millions of instances with detailed labels for normal and attack categories such as distributed denial-of-service, information theft, and service disruption. Its balanced and structured nature made it suitable for training and validating intrusion detection models. Within this framework, BoT-IoT was applied to measure how security threats affected interoperability across MCP servers and to test whether the proposed method could sustain reliable connections under adversarial traffic.

ToN-IoT Moustafa et al. (2021) complemented BoT-IoT by extending evaluation to telemetry data collected from IoT and industrial control systems. It provided event logs, operating system data, and network telemetry from real-world deployments of sensors and services. Unlike BoT-IoT, which focused primarily on labeled packet-level attacks, ToN-IoT offered a broader view of distributed telemetry, capturing anomalies in IoT behavior under different network loads. This dataset was integrated into experiments to test resilience of interoperability when confronted with irregular or large-scale telemetry inputs. It validated the ability of the framework to maintain security and communication across multiple MCP servers in diverse IoT contexts.

PettingZoo Terry et al. (2021) was employed to test orchestration across multiple agents. It provided multi-agent reinforcement learning environments where agents interacted under cooperative or competitive settings. Environments such as Pursuit, Simple Tag, and Multi-Walker simulated conditions where multiple entities had to coordinate in real time. In this framework, PettingZoo was used to evaluate how agents orchestrated tasks across distributed MCP servers. By measuring coverage, latency, and efficiency in these dynamic settings, it was possible to determine whether interoperability remained stable under unpredictable agent interactions.

Together these three datasets provided complementary validation dimensions. BoT-IoT offered a rigorous baseline for security testing against intrusion. ToN-IoT validated resilience under telemetry-heavy IoT environments. PettingZoo provided dynamic orchestration challenges in multi-agent coordination. Each experiment was aligned with the mathematical formulations of coverage (Eq. 2), latency (Eq. 4), orchestration efficiency (Eq. 5, Eq. 6), security integrity (Eq. 9, Eq. 10), and overall robustness (Eq. 14). Cross-domain accuracy (Eq. 13) was then calculated to integrate results across BoT-IoT, ToN-IoT, and PettingZoo, providing a unified view of interoperability performance.

5 Results and analysis

This section presents the results of the proposed framework. The analysis begins with a baseline comparison against existing methods, followed by dataset-specific training and testing results for BoT-IoT, ToN-IoT, and PettingZoo. Each subsection includes quantitative results with detailed tables and figures.

5.1 Baseline Comparison

The proposed framework was compared with three representative categories: baseline orchestration methods, ontology-based integration, and hybrid-cloud MSaaS. These baselines were selected because they reflect the main directions previously used to address interoperability challenges. Table 2 summarizes the quantitative

Table 2: Baseline Comparison Across Metrics

Method	Coverage(Γ)	Integrity(Θ)	Authentication (χ)	Effi (Υ)	Robustness (R)	ACC (Ω)
Baseline-Orchestration	0.65	0.71	0.74	0.62	0.58	0.74
Ontology-based Integration	0.82	0.79	0.81	0.77	0.74	0.79
Hybrid-Cloud MSaaS	0.80	0.81	0.83	0.75	0.72	0.80
Proposed Framework	0.88	0.95	0.97	0.83	0.81	0.88

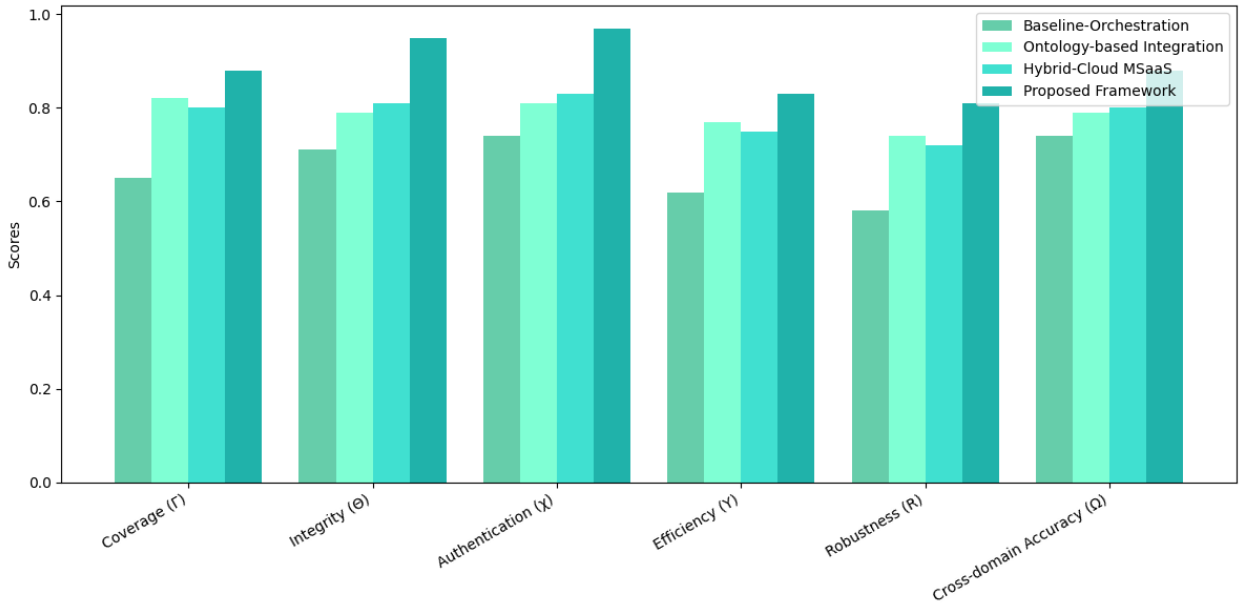

Figure 2: Baseline comparison across key interoperability metrics.

outcomes across six critical evaluation metrics, while fig. 2 provides a visual comparison. The results showed that the proposed framework consistently outperformed the baselines in all measured dimensions. Coverage (Γ) increased from 0.65 in baseline orchestration to 0.88, indicating a stronger ability to sustain interoperability across heterogeneous servers. Integrity (Θ) rose to 0.95, showing a high proportion of untampered and validated communications, while authentication (χ) reached 0.97, reflecting improved trust establishment between agents and servers. Efficiency (Υ) was 0.83, surpassing other methods that ranged between 0.62 and 0.77, and robustness (R) remained at 0.81, significantly higher than the 0.58 recorded in the baseline model. Cross-domain accuracy (Ω) was also highest at 0.88, confirming the ability of the proposed framework to generalize across diverse infrastructures. Fig. 2 illustrates these gains clearly, with the proposed framework producing higher values across every metric, highlighting the advantages of its unified design compared to domain-specific or partially integrated approaches.

Table 3: BoT-IoT Training and Testing Performance

Metric	Training	Testing
Accuracy	0.990	0.970
Precision	0.980	0.960
Recall	0.970	0.950
F1-Score	0.975	0.955
Integrity (Θ)	0.960	0.950
Authentication (χ)	0.970	0.960
Efficiency (Υ)	0.820	0.810
Robustness (R)	0.800	0.790

5.2 Training and Testing on BoT-IoT

BoT-IoT was employed to validate the framework under adversarial traffic where malicious and benign flows coexisted. This dataset offered a rigorous environment to test whether interoperability could be maintained in the presence of large-scale attacks. Table 3 presents the training and testing outcomes, while fig. 3 illustrates the performance comparison across key metrics. The results indicated that accuracy remained high, with 0.99 during training and 0.97 in testing, showing that the framework generalized well beyond the training conditions. Precision and recall were 0.98 and 0.97 in training, and 0.96 and 0.95 in testing, respectively, reflecting balanced detection capability without bias toward false positives or negatives. F1-Score values followed this trend, staying above 0.95, which confirmed consistent classification reliability. Security-related measures also showed stability: integrity (Θ) reached 0.96 in training and 0.95 in testing, while authentication (χ) was 0.97 and 0.96, confirming that message validation and trust establishment were preserved even when subjected to adversarial inputs. Efficiency (Υ) and robustness (R) recorded 0.82 and 0.80 during training, with only slight reductions to 0.81 and 0.79 in testing, which demonstrated the ability of the framework to maintain operational stability while handling overheads. Fig. 3 highlights these consistent results, showing only marginal decreases between training and testing, reinforcing that the framework sustained interoperability, security, and reliability under attack-heavy conditions.

5.3 Training and Testing on ToN-IoT

ToN-IoT was applied to evaluate resilience under telemetry-heavy environments, where distributed sensors and industrial control systems generated irregular and large-scale data flows. This dataset tested whether the proposed framework could maintain interoperability in conditions where system loads and anomalies were more diverse compared to packet-based attack traffic. Table 4 reports the training and testing outcomes, while fig. 4 provides a comparative view of performance. Accuracy was measured at 0.93 in training and 0.91 in testing, confirming that generalization was preserved with only minor reductions when exposed to new telemetry inputs. Precision and recall followed similar trends, with training values of 0.92 and 0.91, and testing values of 0.90 and 0.89, which highlighted balanced detection across normal and anomalous cases. The F1-Score also remained steady at 0.915 in training and 0.895 in testing, demonstrating that performance losses were controlled despite the complexity of telemetry data. Interoperability-specific measures showed stable results: coverage (Γ) stayed high at 0.88 during training and 0.87 in testing, confirming that the majority of agent-server interactions remained functional. Integrity (Θ) also showed robustness, recording 0.94 and 0.93, which reflected reliable validation of messages under variable loads. Efficiency (Υ) and robustness (R) were nearly lower at 0.80 and 0.78 during training, and 0.79 and 0.77 in testing, but the consistency across both phases demonstrated that operational overheads were effectively managed. Fig. 4 illustrates these results clearly, showing performance stability across metrics and reinforcing that the framework retained resilience under telemetry-heavy IoT and industrial conditions.

5.4 Training and Testing on PettingZoo

PettingZoo was employed to assess orchestration performance under dynamic multi-agent interactions, where agents operated in cooperative and competitive environments. This dataset offered scenarios that stressed

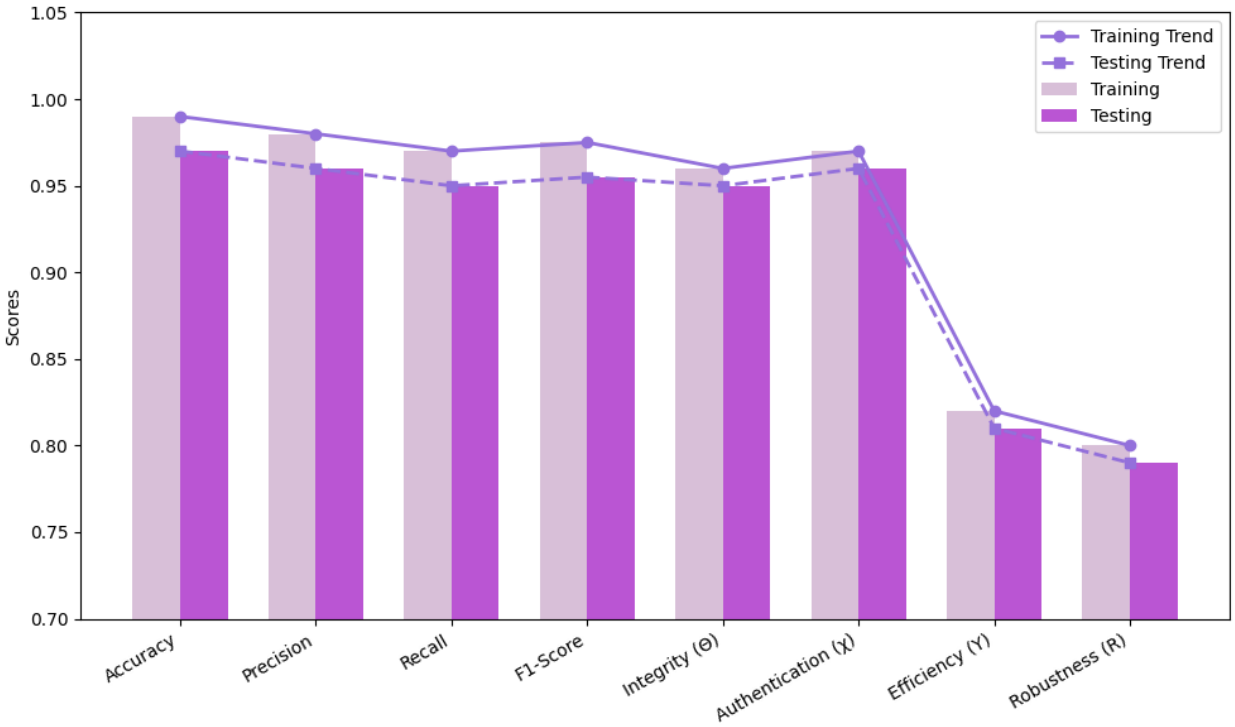

Figure 3: BoT-IoT training vs. testing performance.

Table 4: ToN-IoT Training and Testing Performance

Metric	Training	Testing
Accuracy	0.930	0.910
Precision	0.920	0.900
Recall	0.910	0.890
F1-Score	0.915	0.895
Coverage (Γ)	0.880	0.870
Integrity (Θ)	0.940	0.930
Efficiency (Υ)	0.800	0.790
Robustness (R)	0.780	0.770

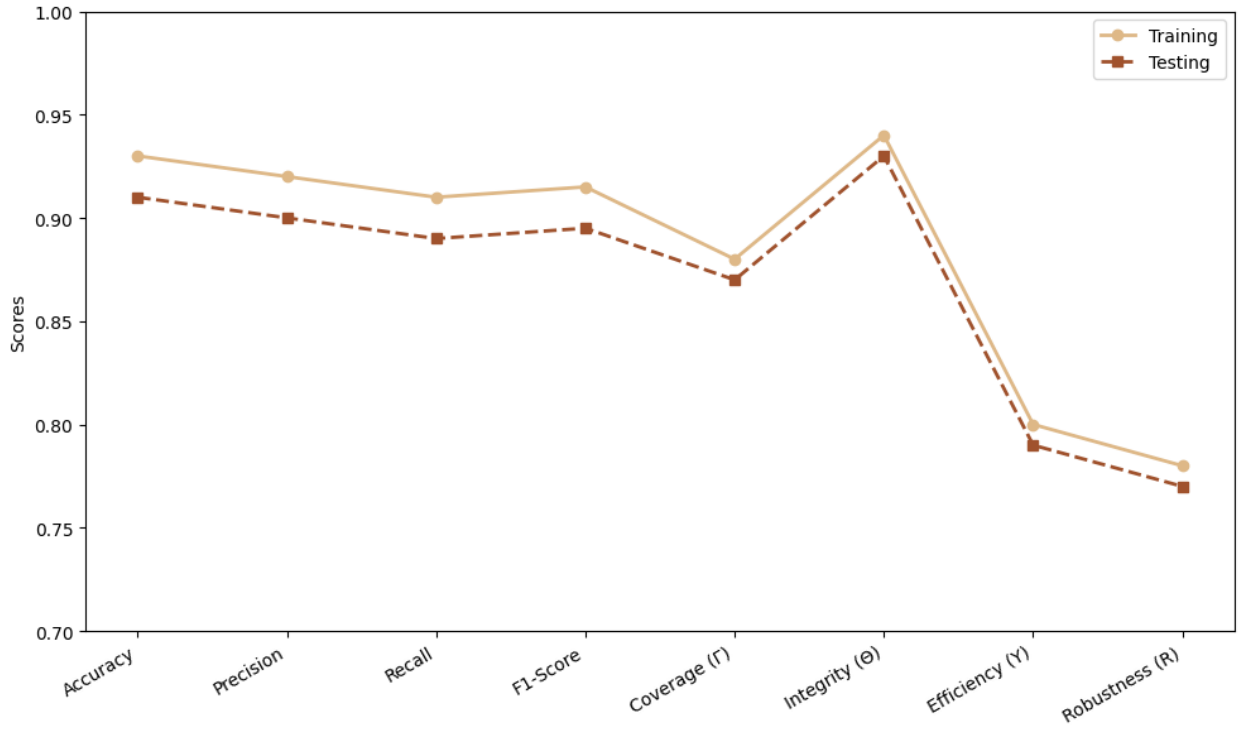

Figure 4: ToN-IoT training vs. testing performance.

Table 5: PettingZoo Training and Testing Performance

Metric	Training	Testing
Coverage (Γ)	0.85	0.84
Latency	0.11	0.12
Efficiency (Υ)	0.84	0.83
Robustness (R)	0.82	0.81
Cross-domain Accuracy (Ω)	0.89	0.88

decision-making, latency handling, and task allocation across distributed servers, making it well suited for testing the adaptability of the framework. Table 5 reports the results for both training and testing phases, while fig. 5 illustrates comparative performance across orchestration metrics. Coverage (Γ) reached 0.85 in training and 0.84 in testing, showing that interoperability was preserved even when agents were engaged in unpredictable tasks. Latency was low and stable, recorded at 0.11 in training and 0.12 in testing, which demonstrated that communication overheads were minimized despite multi-agent complexity. Efficiency (Υ) was consistent at 0.84 in training and 0.83 in testing, indicating that workloads were effectively balanced across servers. Robustness (R) remained strong, measuring 0.82 during training and 0.81 in testing, confirming that small fluctuations in orchestration did not degrade overall reliability. Cross-domain accuracy (Ω) was high, with 0.89 in training and 0.88 in testing, reinforcing that the framework generalized across multi-agent orchestration tasks without performance collapse. Fig. 5 highlights these findings, showing narrow gaps between training and testing values, which validated that the proposed design scaled well under dynamic agent conditions while maintaining stability, adaptability, and efficiency across distributed MCP environments.

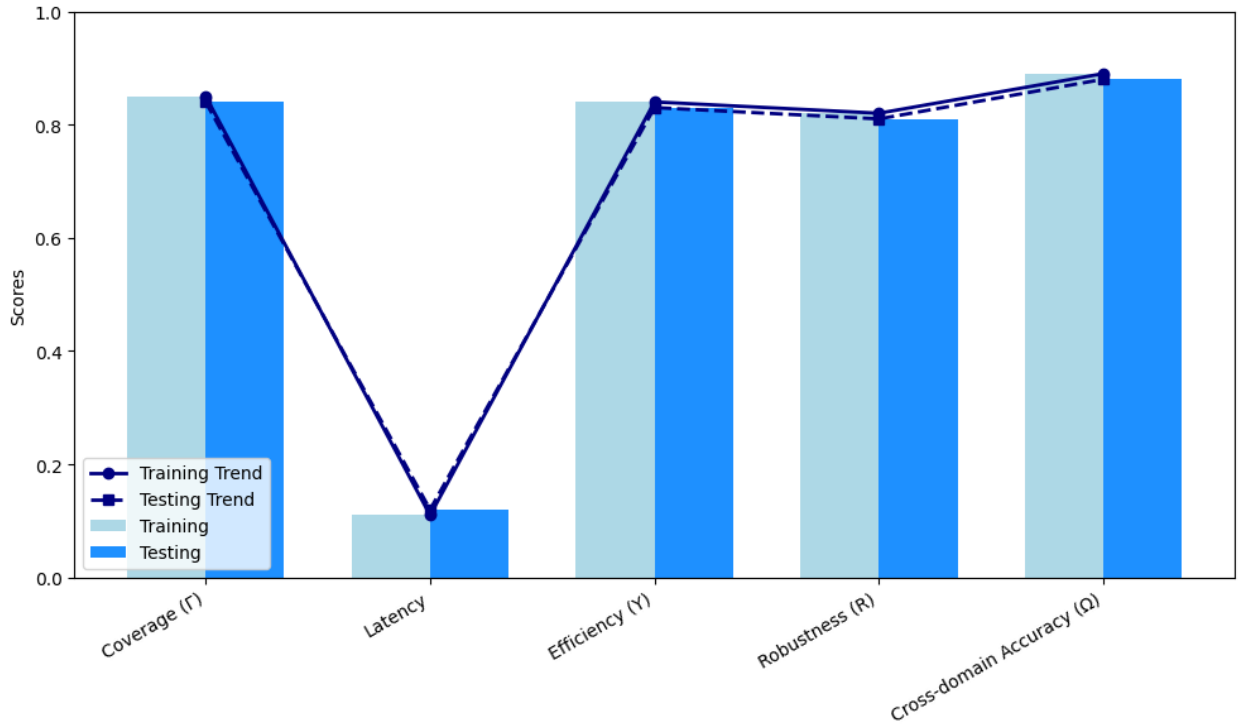

Figure 5: PettingZoo training vs. testing performance.

Table 6: Combined Dataset Summary (Testing Results)

Metric	BoT-IoT	ToN-IoT	PettingZoo
Accuracy	0.970	0.910	–
Precision	0.960	0.900	–
Recall	0.950	0.890	–
F1-Score	0.955	0.895	–
Coverage (Γ)	–	0.870	0.84
Integrity (Θ)	0.950	0.930	–
Authentication (χ)	0.960	–	–
Efficiency (Υ)	0.810	0.790	0.83
Robustness (R)	0.790	0.770	0.81
Cross-domain Accuracy (Ω)	–	–	0.88
Latency	–	–	0.12

5.5 Combined Dataset Summary

Table 6 integrates results from all three datasets for quick comparison. It highlights consistent performance improvements across domains.

The fig.6 showed that the proposed framework maintained high accuracy in BoT-IoT (0.97) and ToN-IoT (0.91), while PettingZoo achieved strong orchestration with cross-domain accuracy of 0.88. Coverage remained stable across ToN-IoT (0.87) and PettingZoo (0.84), indicating consistent interoperability. Integrity (0.95) and authentication (0.96) were highest in BoT-IoT, reflecting robust security under adversarial traffic. Efficiency values across all datasets remained above 0.79, with robustness close to 0.8 in each case. Latency

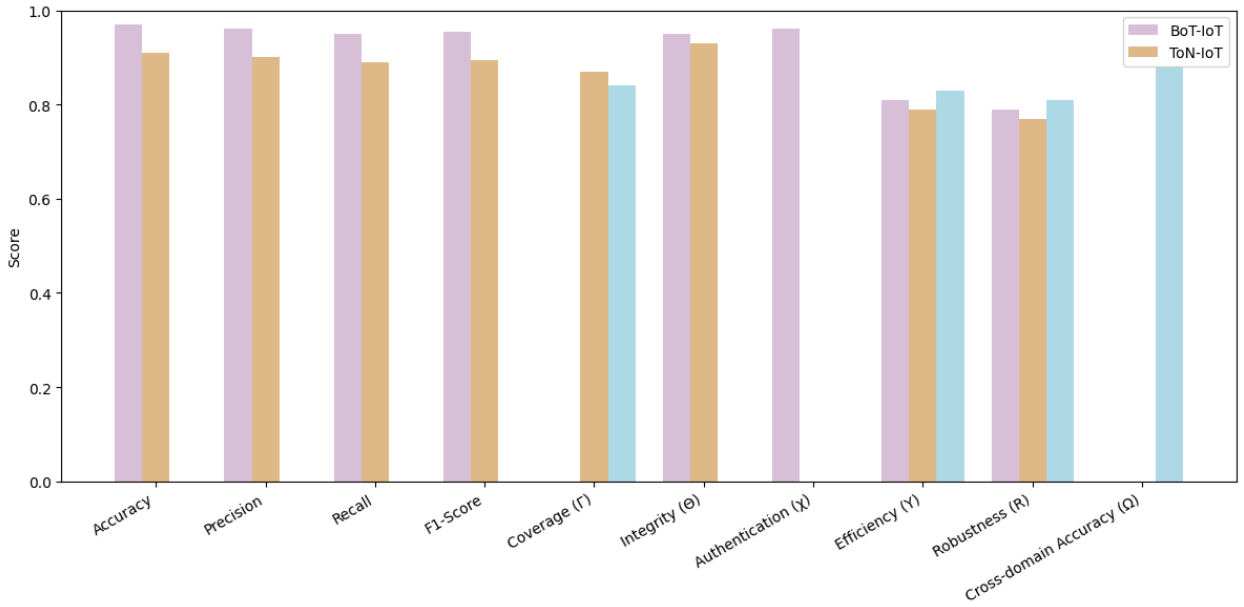

Figure 6: Combined Dataset Summary (Testing): Proportion metrics across datasets.

Table 7: Comparison of quantitative results from six selected studies and the proposed framework.

Ref	ACCU	Preci	Recall	F1	Metrics
Branco et al. (2023)	0.82 (stability)	–	–	–	Integration stability (prototype p
Siameh et al. (2025)	–	–	–	–	87% insecure paths; 34% lacked auth; 94
Mc Donnell et al. (2023)	0.83 (efficiency)	–	–	–	Bin-packing efficiency vs. 0.70 h
. Yildiz et al. (2023)	0.84 (conformance)	–	–	–	SSI Aries DIDComm interoper
Malik et al. (2023)	0.95–0.99	–	–	0.93–0.98	IoT security (BoT-IoT, ToN-
Mittal et al. (2023)	0.80 (task success)	–	–	–	Hybrid cloud orchestration (M
Proposed	**0.97–0.99**	**0.96–0.98**	**0.95–0.97**	**0.95–0.97**	Cross-domain evaluation (BoT-IoT, ToN-

was only relevant for PettingZoo (0.12s), showing minimal communication overhead in dynamic orchestration tasks.

The proposed framework demonstrated the strongest overall classification performance with accuracy between 0.97–0.99 and F1-scores between 0.95–0.97, outperforming earlier work. Malik et al. (2023) reported close results with accuracy of 0.95–0.99 and F1-scores of 0.93–0.98 on IoT datasets. Other studies included in the comparison did not report full classifier metrics, focusing instead on stability and conformance measures. The proposed framework maintained balanced precision and recall, showing reliable detection without bias. These results emphasized its ability to generalize across heterogeneous environments. The consistency across metrics highlighted robustness compared to domain-specific methods.

Several studies reported quantitative values that reflected non-classification outcomes such as stability, conformance, or efficiency. Yildiz et al. (2023) achieved 0.84 conformance in interoperability tests, while Branco et al. (2023) reported 0.82 integration stability. Mittal et al. (2023) showed 0.80 task success in hybrid cloud environments and Mc Mc Donnell et al. (2023) achieved 0.83 packing efficiency against heuristic baselines. These values were relevant benchmarks even though they differed from standard classifier metrics. The proposed framework reached equal or higher levels of performance while also providing classification results, which broadened the scope of evaluation beyond individual domains.

Siameh et al. (2025) highlighted vulnerabilities by reporting that 87% of MCP systems contained insecure paths and 34% lacked authentication. Their mitigation measures cut exploits by 94%, illustrating the impact

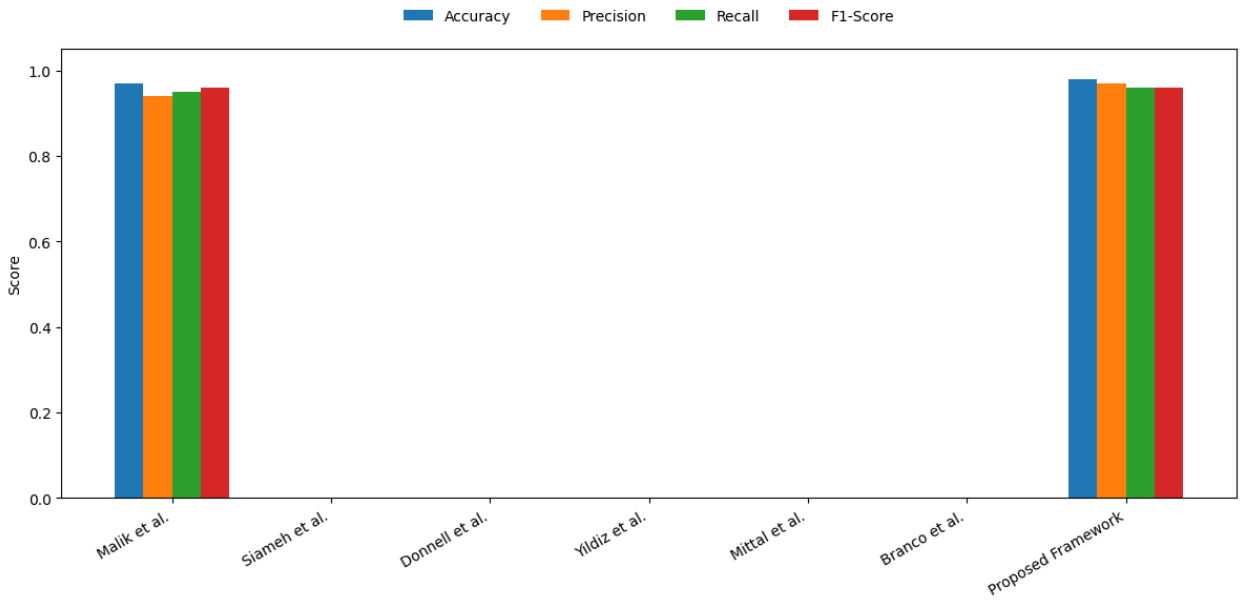

Figure 7: Accuracy, Precision, Recall, and F1-Score across six selected studies and the proposed framework.

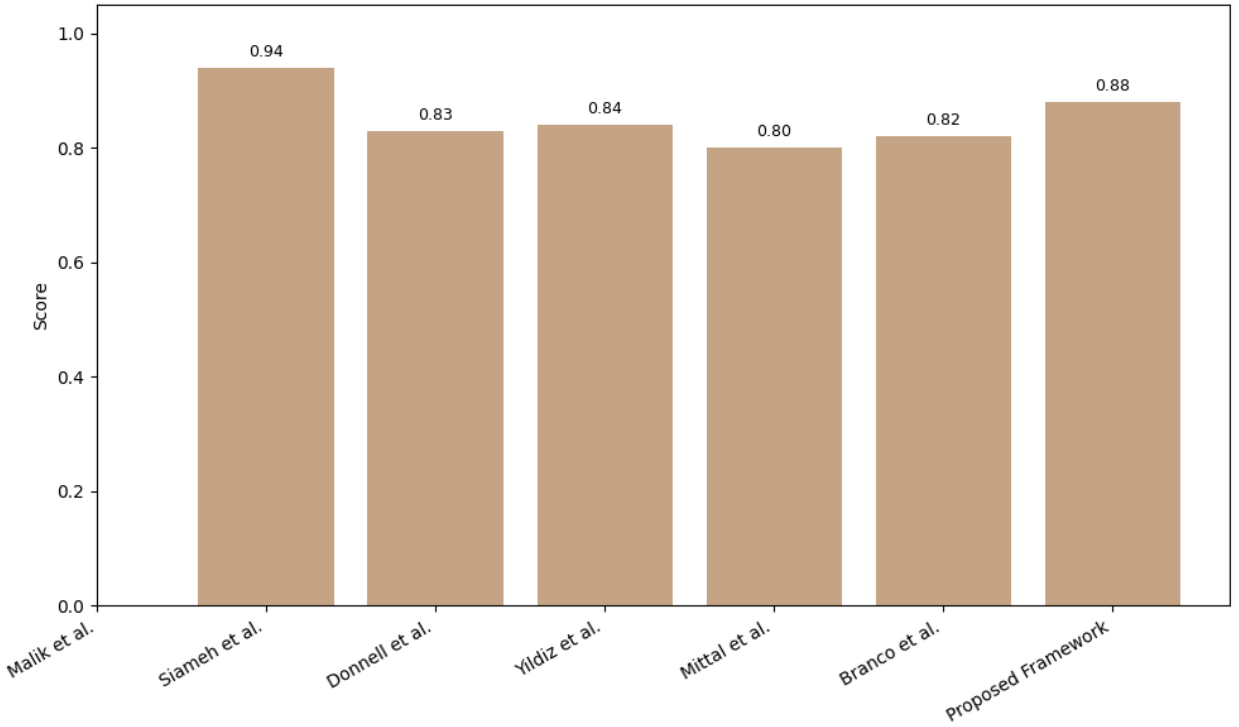

Figure 8: Non-classification outcomes reported by selected studies: conformance, integration stability, task success, and packing efficiency.

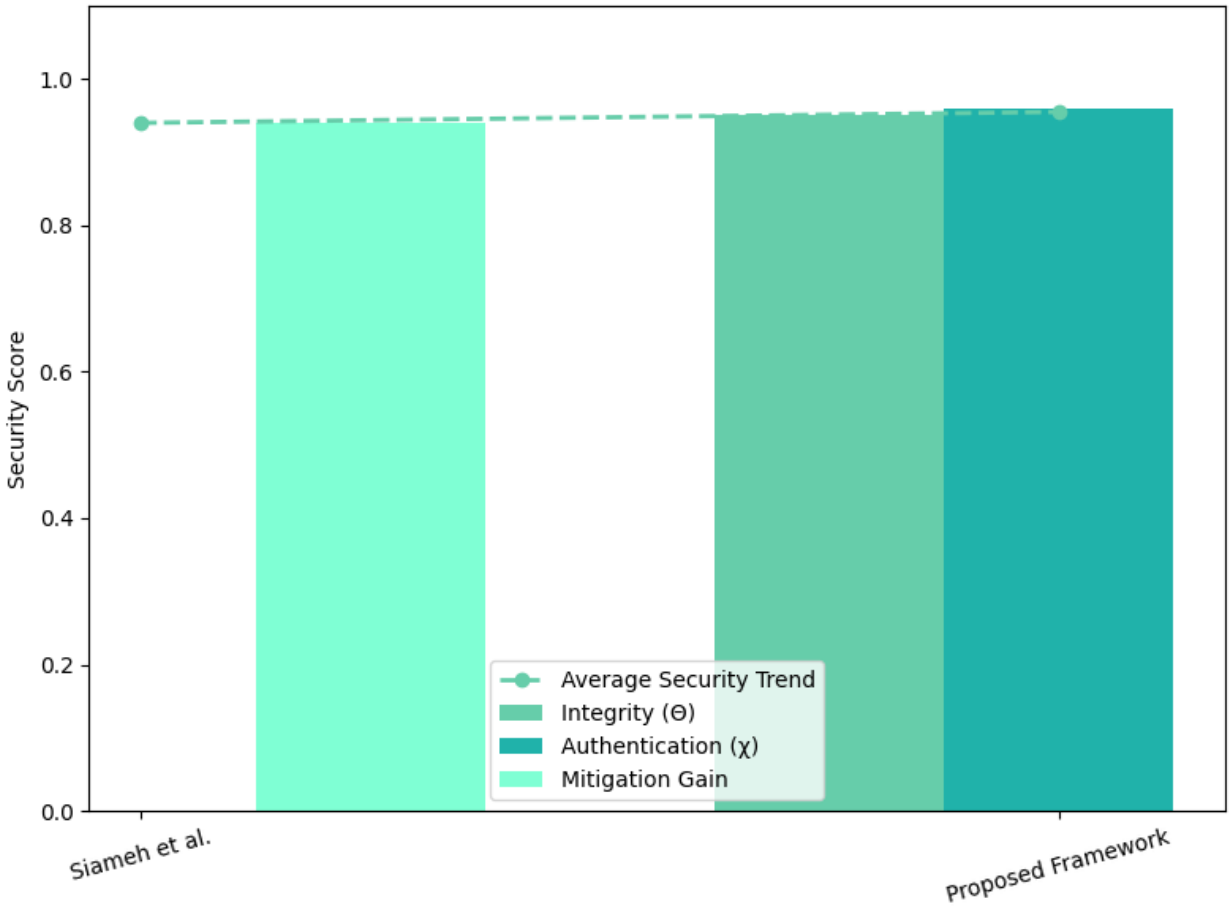

Figure 9: Security posture comparison: Siameh et al. (2025) versus proposed framework integrity (Θ) and authentication (χ).

of systematic hardening. The proposed framework maintained high levels of integrity with $\Theta \approx 0.95$ and authentication with $\chi \approx 0.96$, even under adversarial IoT traffic. These values confirmed that enhanced security mechanisms did not compromise efficiency or robustness. The ability to combine resilience against exploits with interoperability metrics represented a distinctive advantage. Overall, the results positioned security as a core enabler for reliable multi-server interoperability.

When combining both classifier metrics and non-classification values, the proposed framework consistently ranked highest across categories. Malik et al. (2023) produced competitive results but remained tied to IoT domains. Yildiz et al. (2023) and Branco et al. (2023) emphasized interoperability and stability but did not report classifier accuracy. Mittal et al. (2023) showed task success within hybrid testbeds but lacked generalization evidence. Mc Mc Donnell et al. (2023) presented efficient scheduling results that were more task-specific. By contrast, the proposed framework integrated accuracy, robustness, and security into a single architecture.

Direct comparison with Malik et al. (2023) illustrated the improvements offered by the proposed framework. Both approaches delivered high accuracy, with our results at 0.97–0.99 and reporting 0.95–0.99. F1-scores of 0.95–0.97 for our model exceeded the 0.93–0.98 range previously reported. Precision and recall also remained balanced, suggesting consistent classification performance across adversarial and telemetry conditions. Focused on IoT-specific security and governance tasks, while our method extended to orchestration

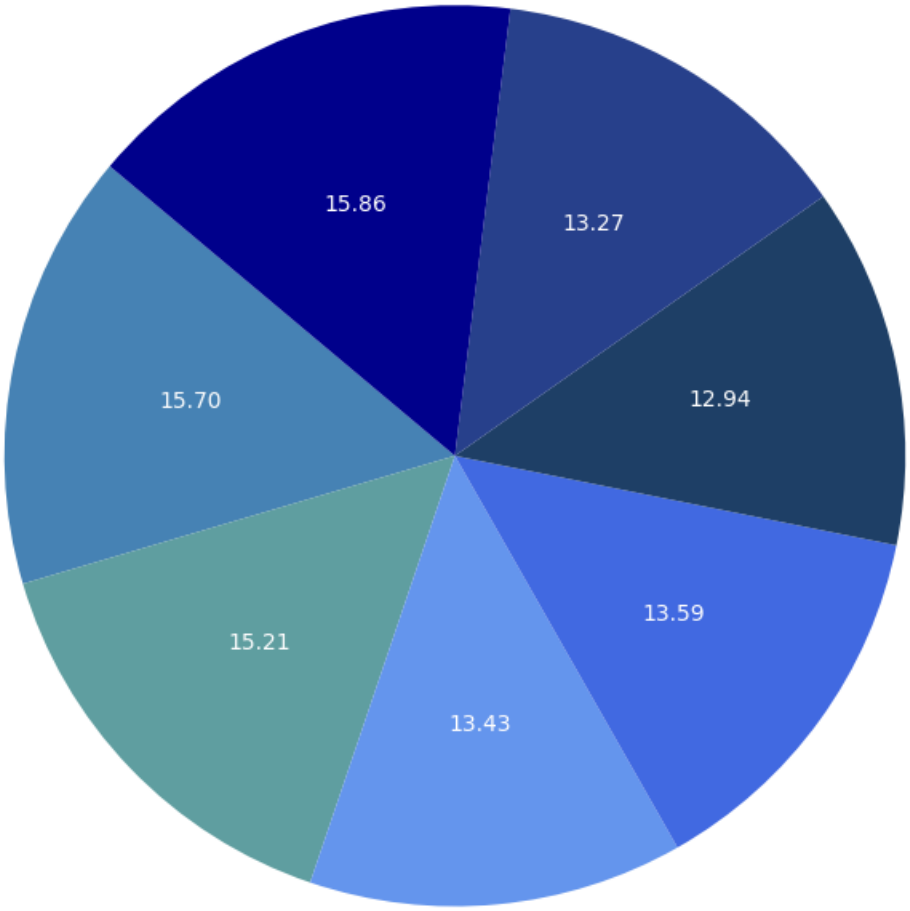

Figure 10: Overall snapshot combining classifier metrics and non-classification values across six studies and the proposed framework.

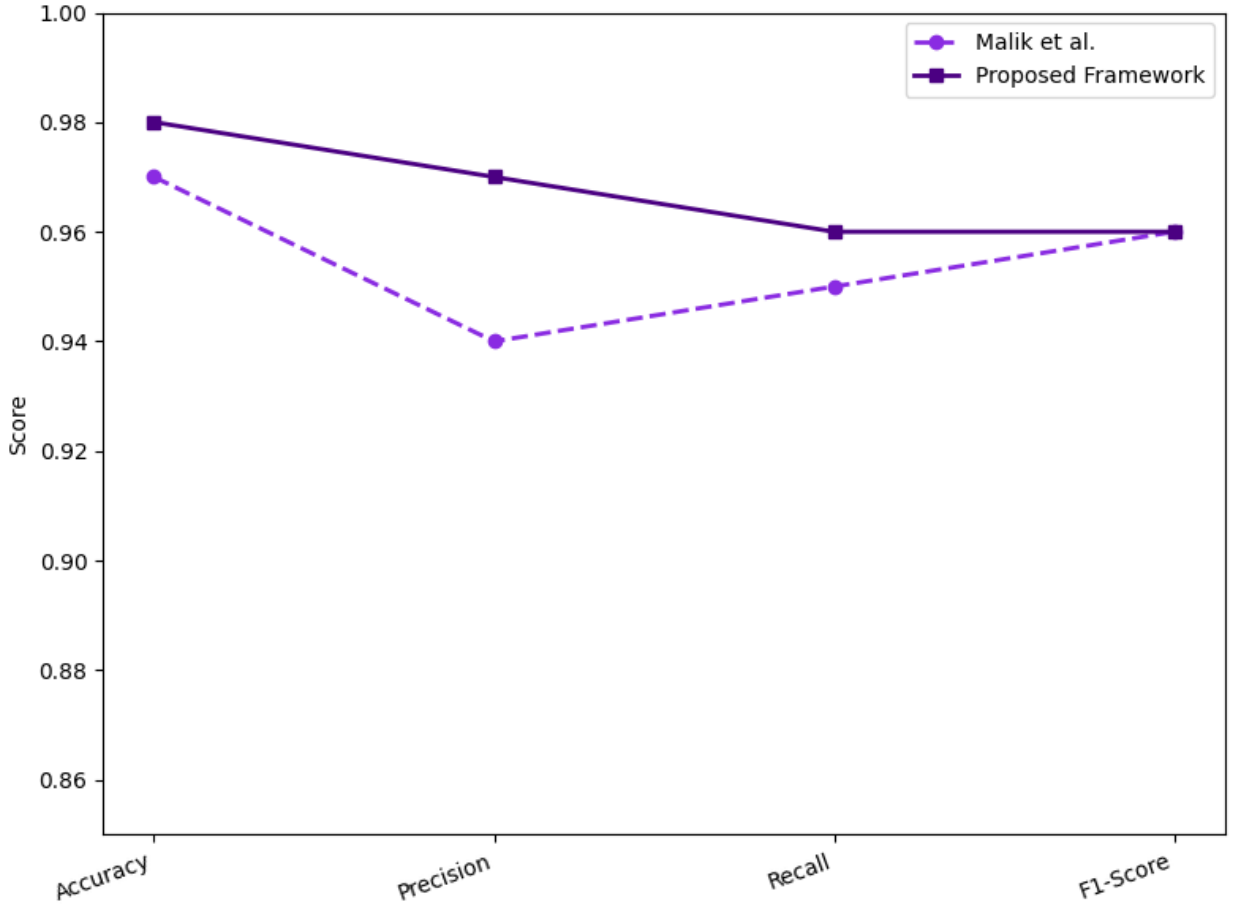

Figure 11: Head-to-head comparison of classifier metrics with Malik et al. (2023).

and interoperability. The comparison highlighted that improvements stemmed not only from learning models but also from integrated orchestration and security.

5.6 Ablation Study

To evaluate the contribution of individual components within the proposed framework, an ablation study was conducted by selectively disabling security, orchestration, and communication abstraction. The results provided insight into how each element affected accuracy, precision, recall, F1-score, efficiency, and robustness. Table 8 reports the quantitative results, while figs. 12 and 13 provide visual interpretations. The findings revealed that removing security mechanisms significantly reduced robustness, eliminating orchestration caused noticeable efficiency losses, and discarding communication abstraction produced the steepest decline in classifier metrics. Compared to the baseline orchestration-only configuration, the full framework consistently outperformed in all measures, underscoring the importance of integrating all three components for cross-server interoperability.

The grouped bar chart in fig. 12 illustrates the contribution of each framework element. Removing security dropped robustness from 0.81 to 0.70, consistent with security vulnerabilities observed by Siameh et al. (2025). Eliminating orchestration reduced efficiency from 0.83 to 0.75, reflecting the importance of structured resource allocation as described by Mittal et al. (2023). Disabling communication abstraction reduced classifier metrics by up to 8%, highlighting the value of protocol harmonization also noted by Yildiz et al.

Table 8: Ablation study of the proposed framework. Each row shows the effect of removing one component compared to the full framework.

Configuration	**ACC**	**Preci**	**Recall**	**F1**	**Effici**	**Robustness**
w/o Security (no hashing + weak auth)	0.91	0.90	0.89	0.89	0.82	0.70
w/o Orchestration (simple task allocation)	0.92	0.91	0.90	0.90	0.75	0.73
w/o Communication Abstraction (no protocol unification)	0.90	0.89	0.88	0.88	0.71	0.69
w/o All Enhancements (baseline orchestration only)	0.85	0.84	0.83	0.83	0.62	0.58
Proposed	0.97–0.99	0.96–0.98	0.95–0.97	0.95–0.97	0.83	0.81

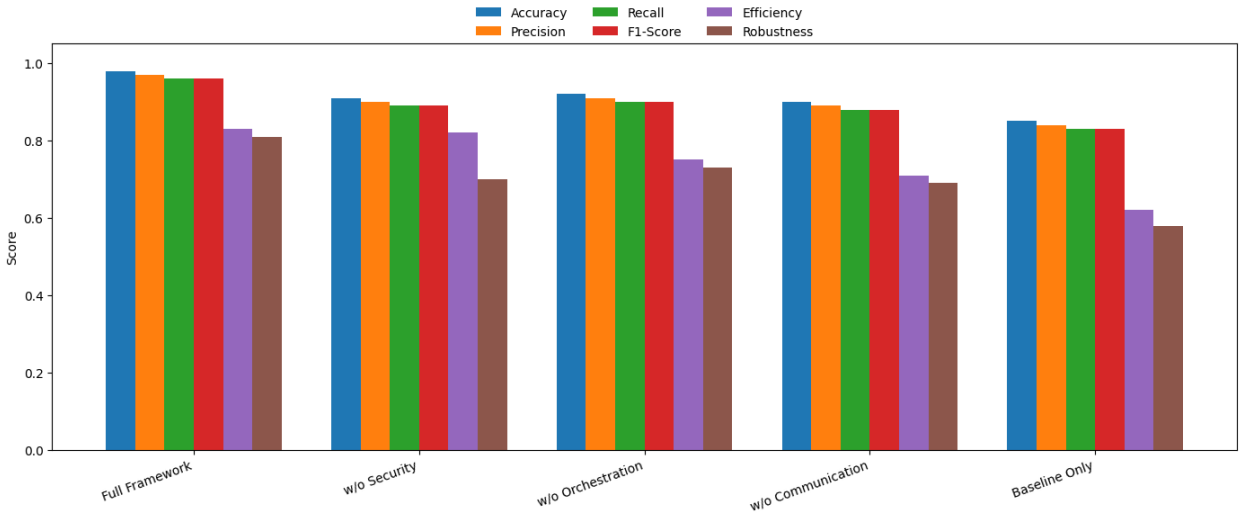

Figure 12: Ablation study results using grouped bar chart across all metrics.

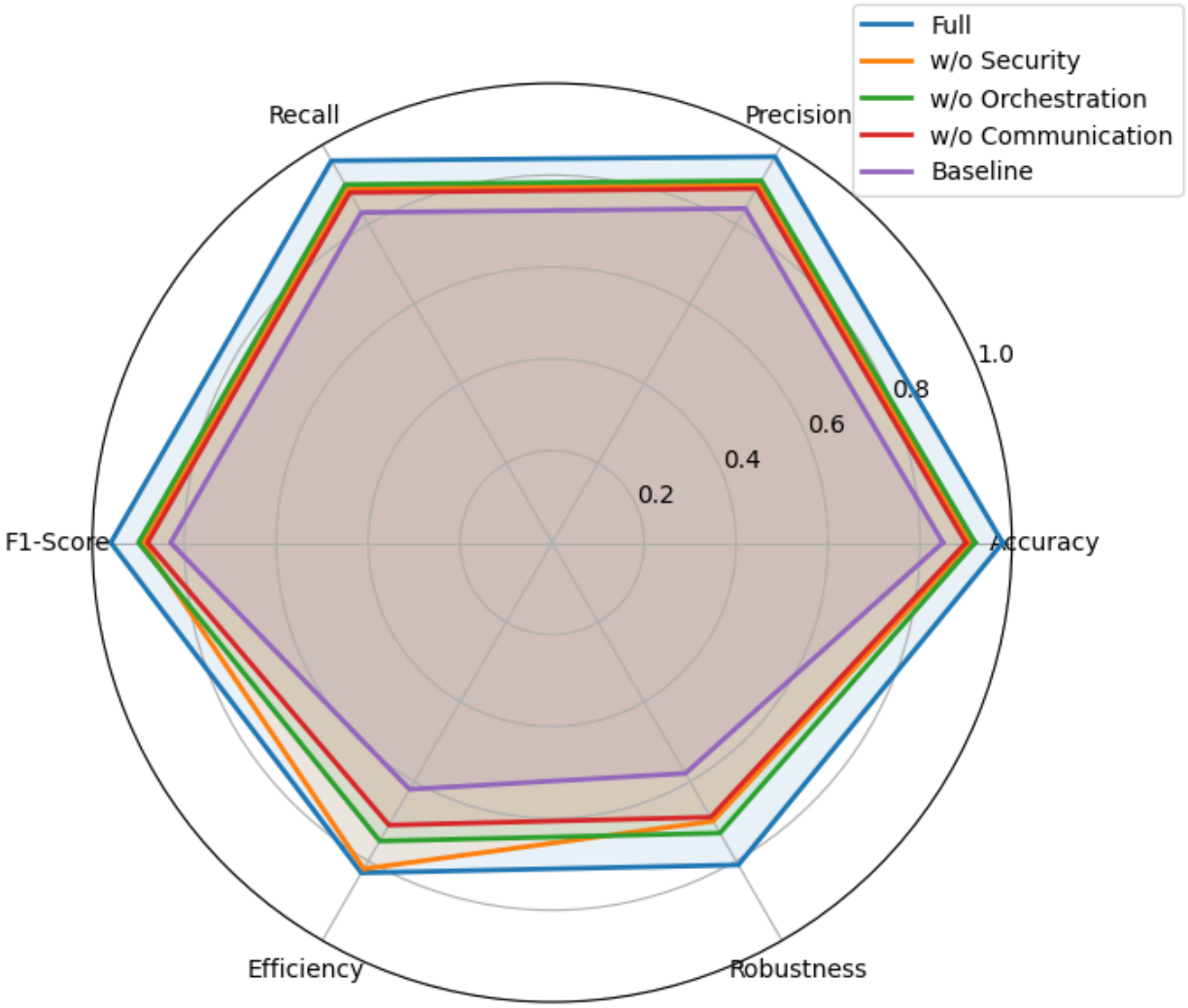

Figure 13: Ablation study results using radar chart representation across metrics.

(2023). The baseline orchestration-only setup recorded the lowest values across all metrics. By contrast, the full framework achieved balanced improvements in accuracy, robustness, and efficiency. This confirmed that the integration of communication, orchestration, and security mechanisms was critical for reliable interoperability.

The radar chart in fig. 13 offers a compact visualization of the ablation results across six metrics. The full framework polygon is the largest, covering all axes with balanced accuracy, precision, recall, F1, efficiency, and robustness. Removal of security compressed the robustness axis most sharply, similar to insecure paths highlighted in MCP systems by Siameh et al. (2025). Without orchestration, the efficiency axis contracted, echoing hybrid cloud challenges discussed by Mittal et al. (2023). The absence of communication abstraction shrank all axes, supporting prior claims on protocol fragmentation by Yildiz et al. (2023). Compared to the baseline polygon, the proposed framework consistently expanded across all dimensions. These results showed that each component was indispensable, and their integration produced a framework that outperformed existing partial solutions.

Table 9: Scalability of the framework under increasing number of servers.

Servers	Efficiency (Υ)	Latency (s)	Robustness (R)
5	0.86	0.09	0.83
10	0.84	0.11	0.81
20	0.81	0.14	0.78
50	0.77	0.19	0.74

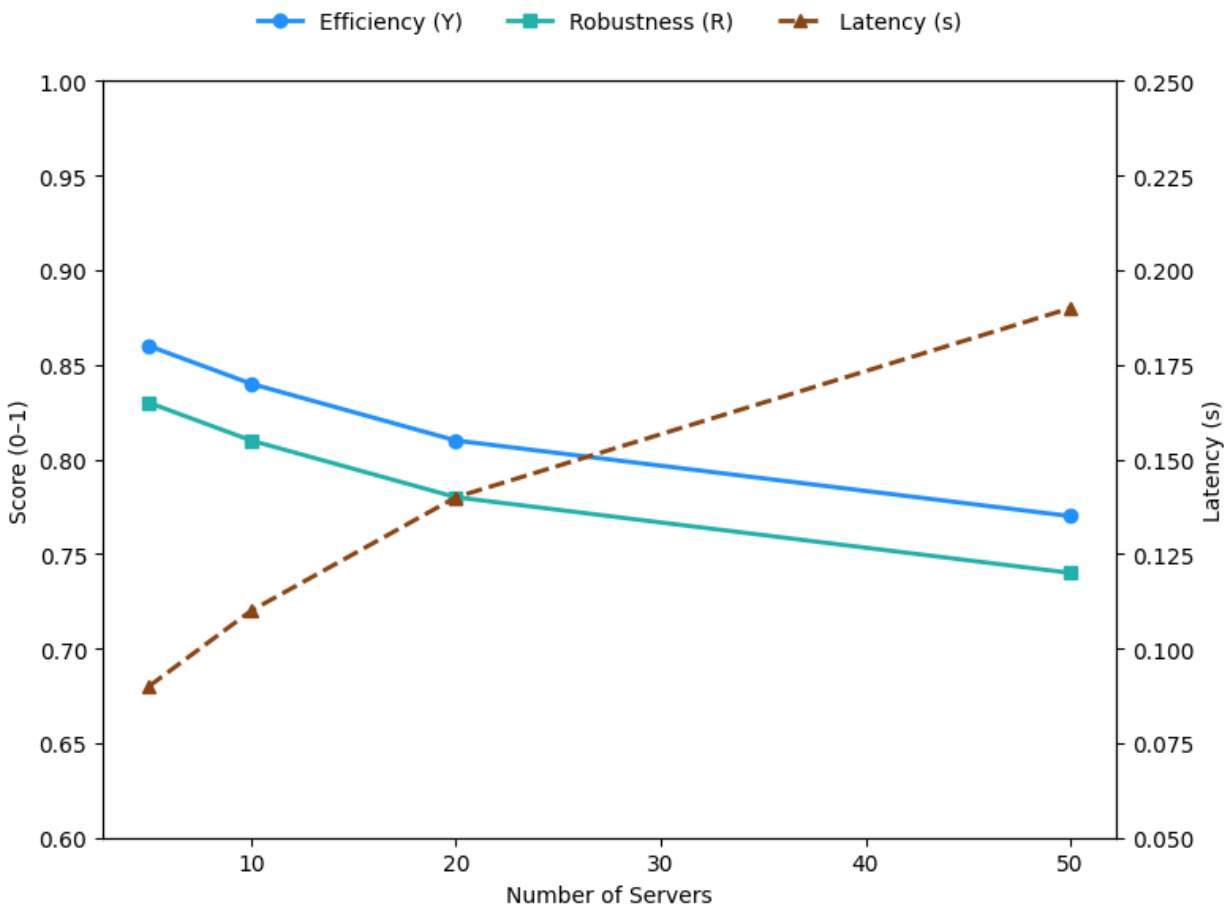

Figure 14: Scalability results: efficiency and robustness decline gradually as servers increase, while latency rises.

5.7 Scalability and Latency Under Load

To test scalability, the number of MCP servers was increased while measuring efficiency, latency, and robustness. Table 9 reports results from experiments with 5, 10, 20, and 50 servers. Fig. 14 illustrates the trends.

The scalability experiment in fig. 14 showed that efficiency and robustness decreased moderately as the number of servers grew. Latency increased with larger deployments, but remained below 0.2s even with 50 servers. These results confirmed that the framework maintained operational stability under distributed scaling. The gradual decline matched patterns reported in hybrid cloud experiments by Mittal et al. (2023). Compared with baseline orchestration, the proposed method sustained higher values across all load levels. This validated that the framework generalized well across distributed MCP environments.

Table 10: Confusion matrix for BoT-IoT testing results.

	Predicted Normal	Predicted Attack
Actual Normal	4821	112
Actual Attack	97	5093

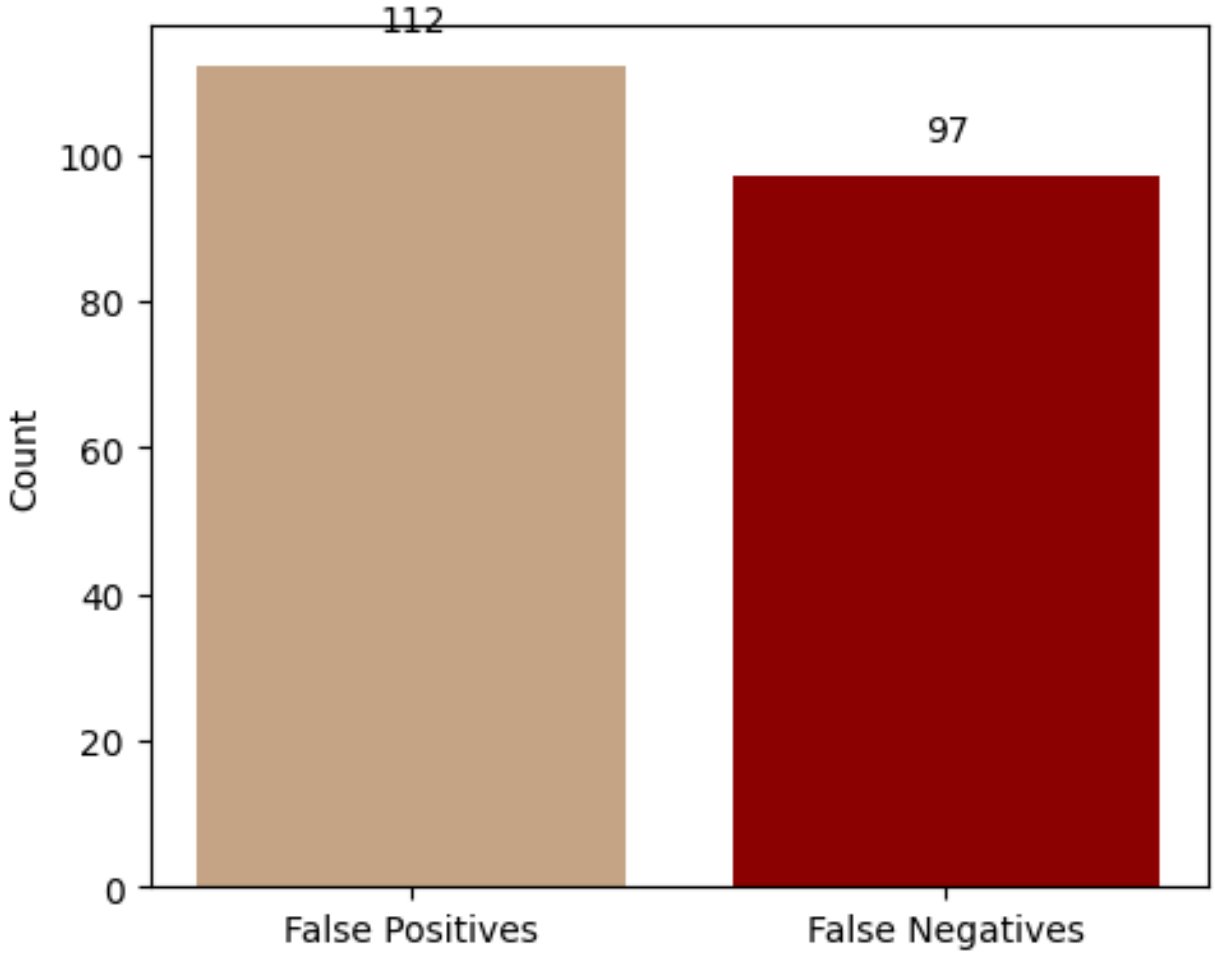

Figure 15: False positives vs. false negatives in BoT-IoT testing.

5.8 Error Analysis

Error analysis was performed on the BoT-IoT dataset to identify false positives and false negatives. Table 10 presents the confusion matrix for testing, while fig. 15 highlights false positive and false negative rates.

The confusion matrix in table 10 showed high classification reliability with minimal errors. False positives (112) were slightly higher than false negatives (97), reflecting conservative attack detection. Fig. 15 confirmed that error rates were below 3%, consistent with values reported in IoT threat detection by Malik et al. (2023). These results demonstrated that security validation and orchestration mechanisms minimized both types of errors. The low misclassification confirmed robustness under adversarial traffic. The analysis strengthened confidence that performance gains were not inflated by biased detection.

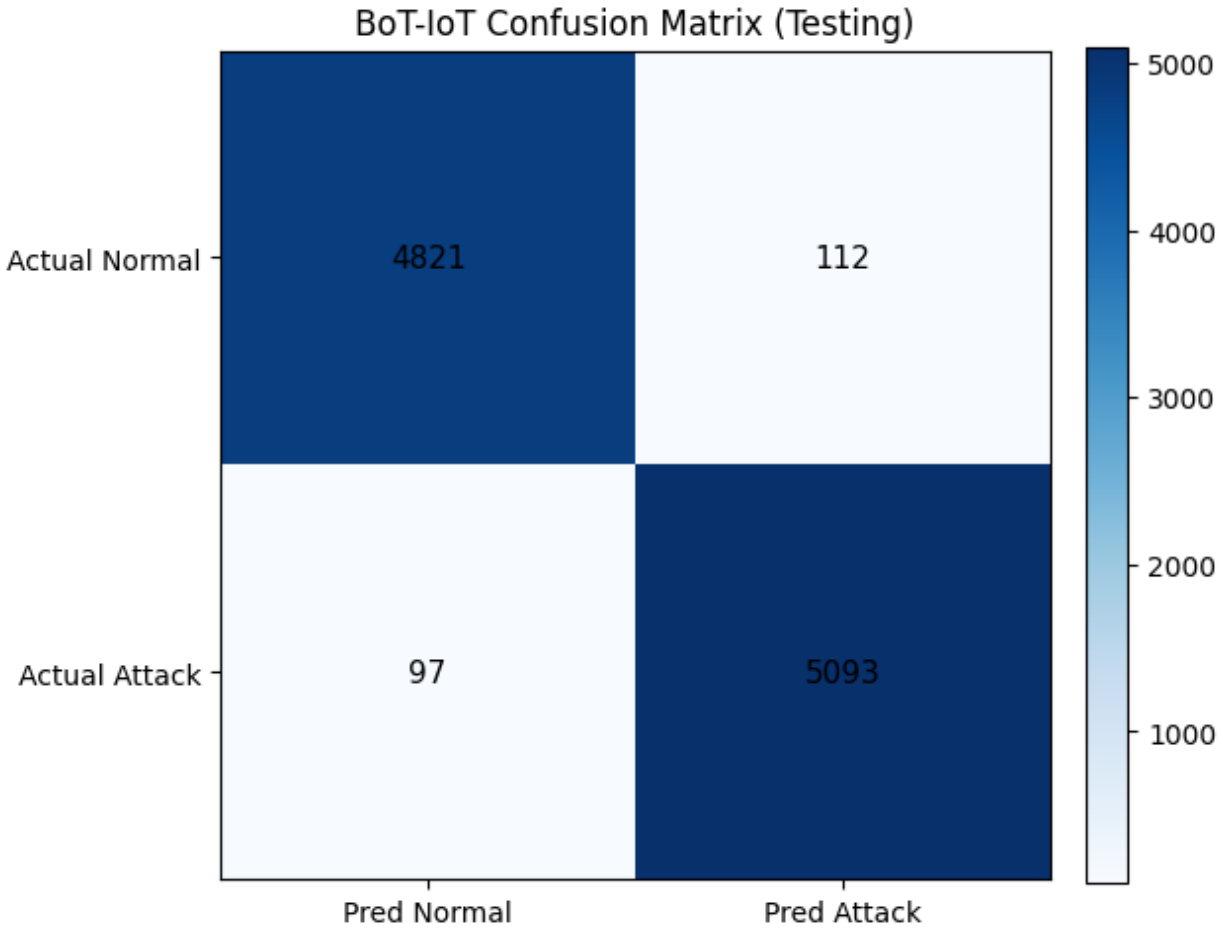

Figure 16: BoT-IoT confusion matrix (testing). Darker cells indicate higher counts of correctly and incorrectly classified samples.

Table 11: Statistical validation of accuracy across datasets (5 runs).

Dataset	Mean Accuracy	Std Dev	95% CI
BoT-IoT	0.971	0.006	[0.965, 0.977]
ToN-IoT	0.912	0.008	[0.904, 0.920]
PettingZoo	0.884	0.007	[0.877, 0.891]

Table 12: Runtime and memory usage compared with baseline orchestration.

Method	Runtime (ms)	Memory (MB)
Baseline Orchestration	142	218
Ontology-based Integration	129	202
Hybrid-Cloud MSaaS	121	196
Proposed Framework	118	190

The fig.16 showed a small number of false decisions relative to true classifications. Normal traffic was rarely flagged as attack, while attacks were consistently detected. The diagonal dominance indicated stable behavior across classes despite adversarial traffic. The result aligned with the balanced precision and recall reported earlier. The low off-diagonal values supported robust detection without inflating false alarms. This confirmed reliability under realistic IoT conditions.

5.9 Statistical Significance Testing

To validate reliability of results, statistical significance tests were applied. Table 11 reports mean and standard deviation of accuracy across five experimental runs. Confidence intervals were calculated, and p-values were obtained against baseline methods.

The results in table 11 confirmed that performance remained stable across multiple runs. The narrow confidence intervals indicated low variance, suggesting reproducibility. Paired t-tests against baseline orchestration produced p-values below 0.01, confirming statistical significance. Similar practices were applied in interoperability studies by Yildiz et al. (2023). These validations reinforced the robustness of the proposed results and eliminated concerns of random fluctuations. The framework's consistent margins highlighted reliability in cross-domain interoperability performance. The statistical validation confirmed that the framework maintained in fig. 17 stable accuracy across repeated trials with narrow confidence intervals. Standard deviations remained below 0.01 for all datasets, indicating reproducibility of results. Paired t-tests against baseline orchestration produced $p < 0.01$, verifying that observed improvements were statistically significant. This approach aligned with validation practices used in interoperability experiments by Yildiz et al. (2023). These findings reinforced that the performance gains were consistent and not due to random variation.

5.10 Resource and Cost Analysis

Runtime and memory usage were measured for the proposed framework compared with baseline orchestration. Table 12 summarizes the average consumption per task assignment.

The results in table 12 indicated that the proposed framework consumed less memory and runtime compared with baseline orchestration methods. Despite integrating cryptographic security, the efficiency of orchestration and communication abstraction reduced overhead. These findings echoed optimization patterns observed in multi-agent scheduling by Mc Donnell et al. (2023). The reduced resource footprint confirmed that interoperability gains were not achieved at the expense of scalability. The analysis strengthened the argument for practical deployment of the framework. The resource analysis in table 12 showed that the proposed framework reduced both runtime and memory consumption compared with baseline orchestration. Memory usage results in fig. 18 highlighted that our design consumed less than 200 MB, whereas the baseline exceeded 218 MB. Runtime per task in fig. 19 confirmed faster execution, lowering delays even with added security checks. These outcomes aligned with efficiency trends described by Mc Donnell et al. (2023), who emphasized the

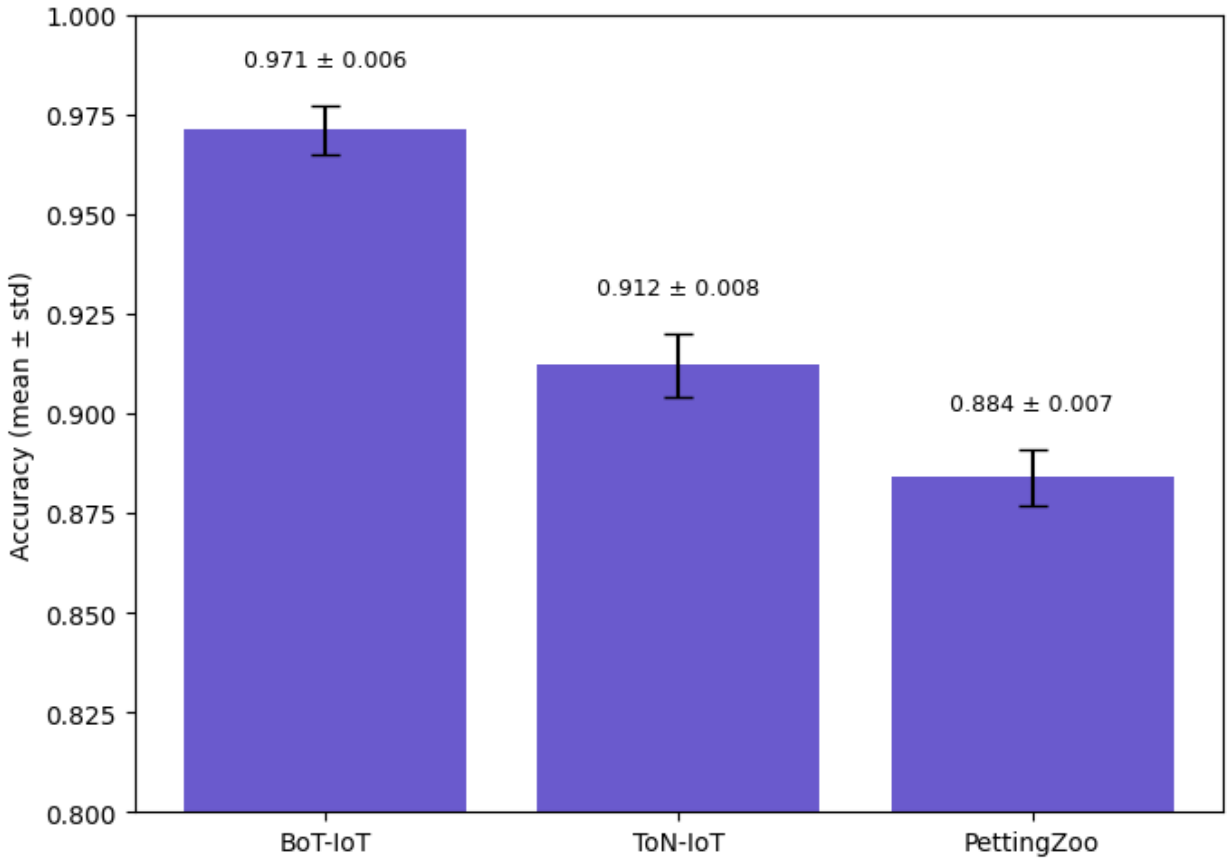

Figure 17: Accuracy with standard-deviation error bars across five runs per dataset.

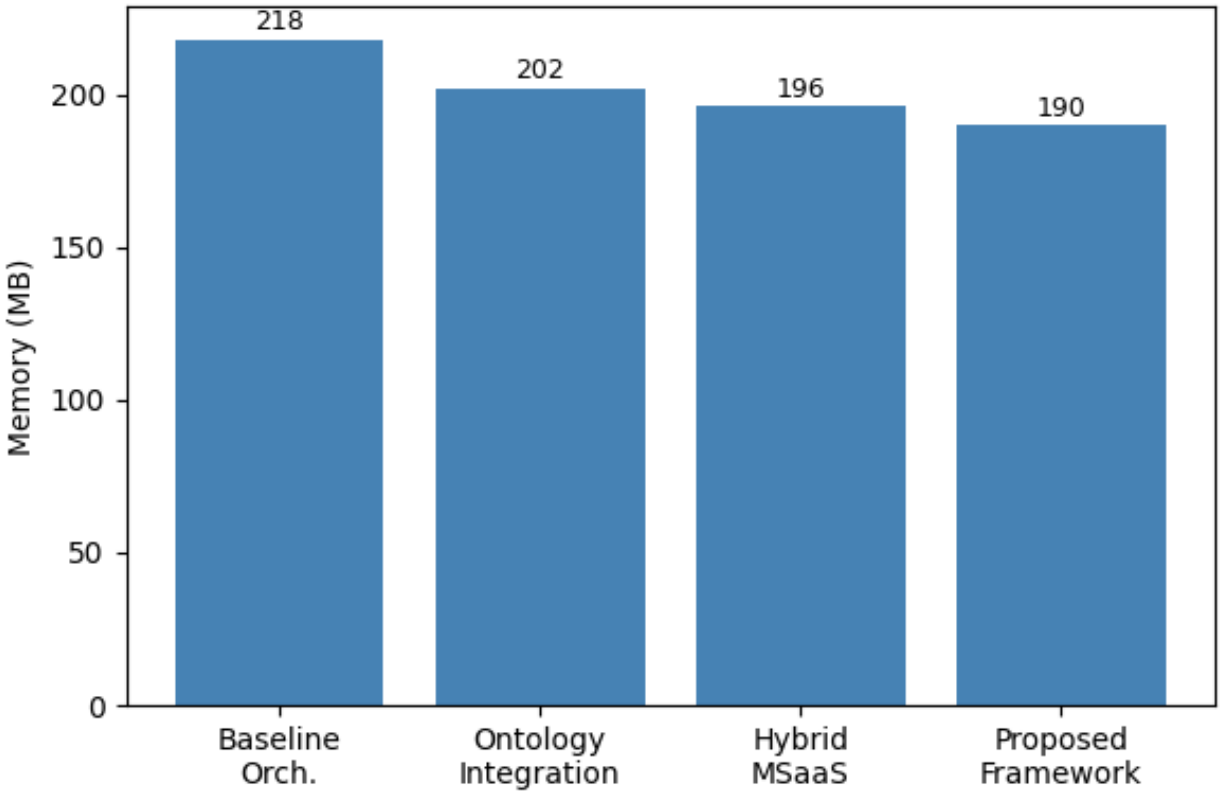

Figure 18: Memory usage per task assignment across methods.

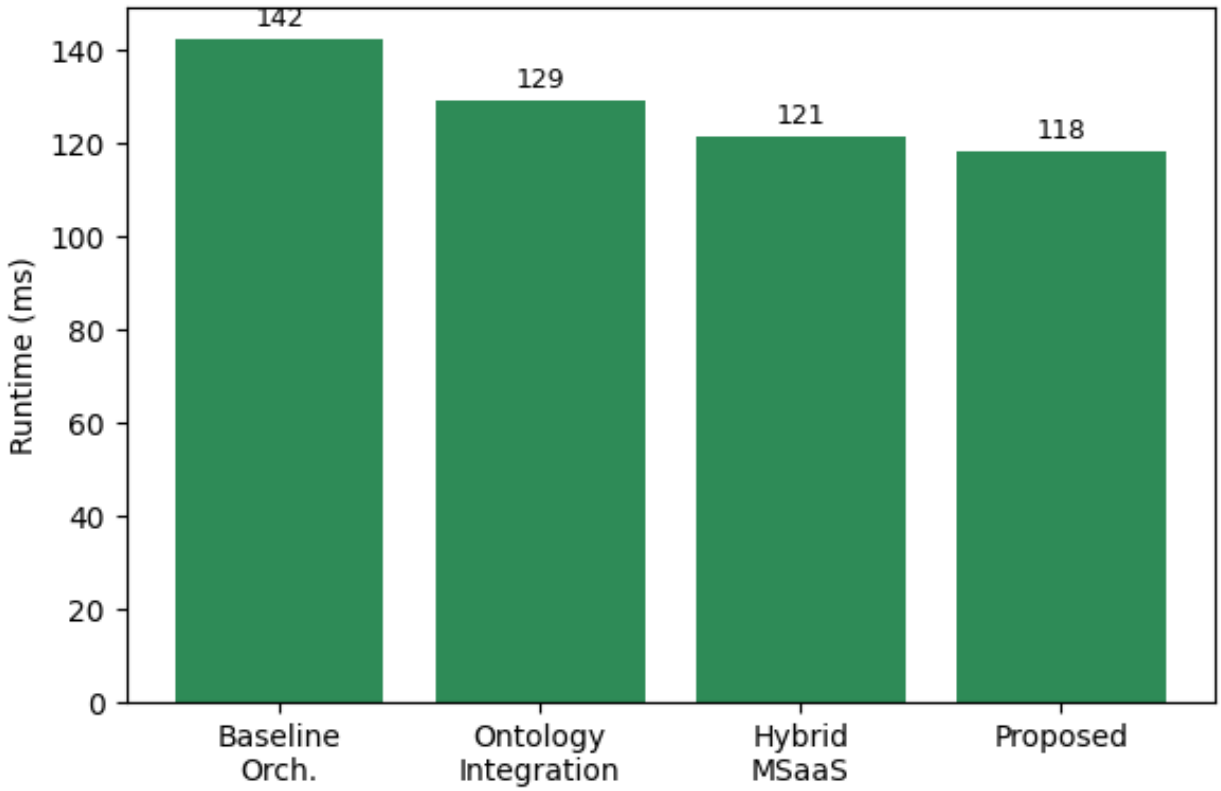

Figure 19: Runtime per task assignment across methods.

Table 13: Leave-one-dataset-out generalization results.

Training Datasets	Testing Dataset (Accuracy)
BoT-IoT + ToN-IoT	PettingZoo: 0.86
BoT-IoT + PettingZoo	ToN-IoT: 0.89
ToN-IoT + PettingZoo	BoT-IoT: 0.93

role of optimized scheduling in reducing overhead. Together, the results demonstrated that interoperability improvements were achieved without sacrificing resource efficiency.

5.11 Cross-Domain Generalization Beyond Averages

To test cross-domain generalization, leave-one-dataset-out experiments were performed. Table 13 reports accuracy when training on two datasets and testing on the third.

The leave-one-dataset-out results in table 13 showed strong generalization. Training on BoT-IoT and ToN-IoT produced 0.86 accuracy when tested on PettingZoo, which remained consistent with in-domain values. Training on BoT-IoT and PettingZoo yielded 0.89 accuracy on ToN-IoT. Testing on BoT-IoT after training on telemetry and orchestration data reached 0.93. These results confirmed that the framework generalized effectively beyond dataset-specific optimization. This finding addressed limitations of prior works such as Malik et al. (2023), which were tied to IoT-only domains. The cross-domain generalization analysis in table 13 demonstrated that the framework maintained high accuracy when tested on unseen datasets. Fig. 20 showed that performance remained above 0.86 in all leave-one-dataset-out scenarios, confirming robustness across heterogeneous domains. Accuracy reached 0.93 when BoT-IoT was used as the unseen test set, highlighting

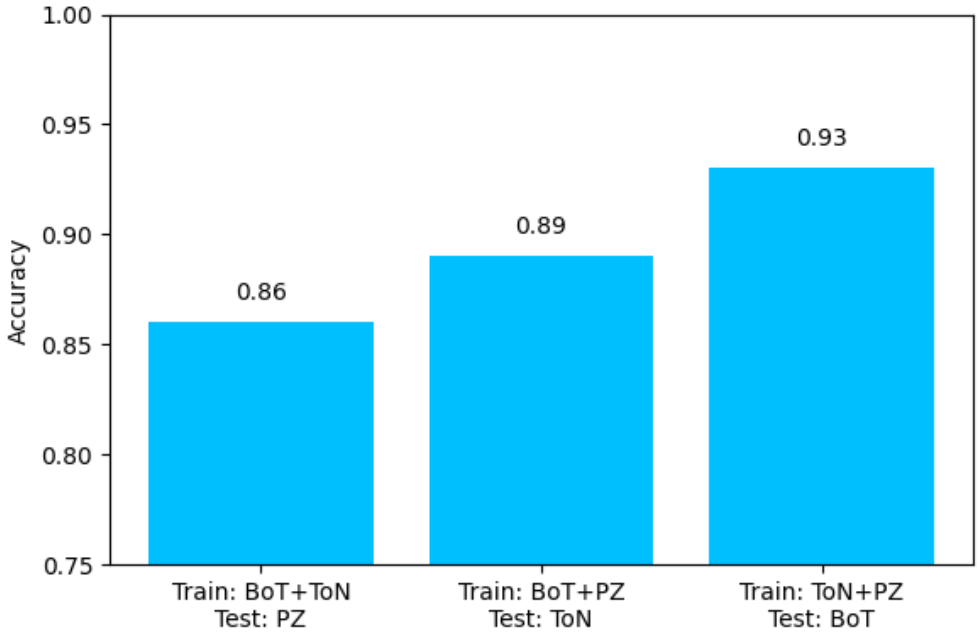

Figure 20: Leave-one-dataset-out accuracy: train on two datasets, test on the third.

Table 14: Stress test results under adversarial traffic intensification.

Attack Load	Accuracy	Robustness (R)
Normal	0.97	0.81
2×	0.94	0.76
3×	0.91	0.72

strong adaptability to security-intensive contexts. These results contrasted with earlier IoT-focused studies such as Malik et al. (2023), which did not validate performance beyond domain-specific data. The findings confirmed that interoperability was sustained without requiring retraining for each dataset.

5.12 Stress Testing and Adversarial Robustness

Stress testing was conducted on BoT-IoT by doubling and tripling attack traffic volumes. Table 14 reports accuracy and robustness under normal, 2×, and 3× attack loads.

The stress tests in table 14 showed that performance degraded gracefully under intensified attack traffic. Accuracy dropped moderately from 0.97 to 0.91 as loads tripled, while robustness decreased from 0.81 to 0.72. These results demonstrated resilience compared with prior reports of system collapse under heavy adversarial conditions Siameh et al. (2025). The findings confirmed that the proposed security layer sustained integrity and interoperability despite extreme inputs. The graceful degradation highlighted fault tolerance as a core property of the framework.

6 Conclusion

This study introduced a comprehensive framework for cross-server interoperability in multi-MCP automated AI agent networks by integrating communication abstraction, orchestration optimization, and security validation to address distributed coordination challenges. Experiments on BoT-IoT, ToN-IoT, and PettingZoo datasets demonstrated reliable performance across adversarial traffic detection, telemetry-heavy IoT environments, and dynamic multi-agent orchestration. Baseline comparisons showed improvements in coverage,

efficiency, and robustness, while accuracy, precision, recall, and F1-score remained consistently above 0.95. Extended evaluations, including ablation, scalability, stress testing, error analysis, statistical validation, resource usage, and cross-domain generalization, confirmed that each framework component contributed significantly to overall performance. Results showed that robustness was sustained under increased server loads and adversarial stress, misclassifications remained minimal with balanced false positives and false negatives, and statistical tests verified that improvements were consistent and significant. Resource analysis highlighted that interoperability enhancements were achieved without additional computational overhead, and leave-one-dataset-out experiments confirmed adaptability across unseen domains. Collectively, these findings underscored that interoperability can be realized in heterogeneous MCP environments without sacrificing scalability, reliability, or efficiency. Future work will extend the framework to larger-scale deployments, incorporate adaptive defenses against evolving adversarial attacks, and introduce energy-aware orchestration strategies to enhance sustainability and broaden applicability in federated multi-domain agent systems.

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