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BRIDGING THE DIGITAL-PHYSICAL DIVIDE: TRANSFER LEARNING FOR UNIFIED THREAT CORRELATION IN CONVERGED IT/OT/IOT ECOSYSTEMS

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Abstract

The increased integration of operational technology (OT), Internet of Things (IoT), and business IT systems has allowed sophisticated attackers to circumvent isolated security features and launch cross-platform assaults. Current fragmented techniques, with discrete detectors monitoring Modbus, Kubernetes, MQTT, or other domain-specific protocols, cannot handle cross-system risks. These methodologies overlook 68% of multi-vector marketing that uses both physical and digital channels. This study introduces a transfer learning architecture to integrate detection capabilities by correlating threats across protocols, devices, and settings. The architecture generates a unified feature space that extracts behavioral semantics from industrial control system logs, cloud telemetry, network traffic, and device-level signals to produce protocol-agnostic threat representations. Adversarial domain adaptation and semantic graph embeddings enable cross-domain knowledge transfer with minimum retraining. Security teams may now discover kill chains like infected cloud containers preceding illegal PLC command execution every 23 minutes. Validated against real-world attack datasets from water treatment facilities (OT) and cloud infrastructure (IT), the system achieved 93.4% cross-platform attack recall, a 41.3 percentage point improvement over prior methodologies. It reduced OT data labeling by 89% and false positives by 93.5%. This paradigm shift transforms threat correlation from a reactive, domain-specific process to adaptive intelligence, boosting resilience for critical infrastructure, industrial ecosystems, and smart environments facing cyber-physical hazards. The framework's practical validation in energy, industry, and vital infrastructure shows its importance in protecting an increasingly linked world.

Keywords: *Cross-platform threat intelligence, Transfer learning, Adversarial domain adaptation, Operational technology (OT) security, Cyber-physical systems, IoT/OT/IT convergence, Unified threat detection, Industrial control systems, Semantic threat correlation, Modbus-to-Kubernetes attacks.*

1. INTRODUCTION

The convergence of historically separate information technology (IT), operational technology (OT), and Internet of Things (IoT) networks has significantly altered the cyber threat landscape, creating new vulnerabilities via interconnected attack surfaces. Adversaries

are increasingly exploiting the convergence of IT and operational technology (OT), executing sophisticated cross-platform attacks. Initial compromises in IT environments, such as enterprise email servers or cloud storage, act as springboards for lateral movement into critical OT and Internet of Things (IoT) systems, including industrial control systems (ICS), building management systems (BMS), and medical IoT devices (Williams, 2023; García et al., 2022). The 2021 Colonial Pipeline ransomware incident exemplified the progression of this threat, as a breach of IT systems quickly led to physical disruptions in fuel distribution operations, resulting in significant societal and economic consequences (Greenberg, 2021). Attacks often evade detection due to fragmented security architectures; threat indicators that are evident in one domain may remain undetected or misinterpreted in another due to incompatible monitoring tools and data schemas. Figure 1 illustrates this ongoing vulnerability within a standard attack lifecycle. Conventional IT security tools, such as endpoint detection and response (EDR) systems, are effective in identifying the initial compromise phase associated with phishing or malware delivery. However, they often fail to detect subsequent stages, particularly command-and-control (C2) communications and lateral movement, as attacks cross protocol boundaries into operational technology (OT) or Internet of Things (IoT) environments. The detection failure arises from inherent incompatibilities in data formats, protocol semantics, and security telemetry, resulting in significant vulnerabilities in critical infrastructure to multi-stage intrusions that connect the digital and physical realms. The increasing frequency of these attacks highlights the critical necessity for cohesive detection systems that can correlate threat activities across diverse technological domains.

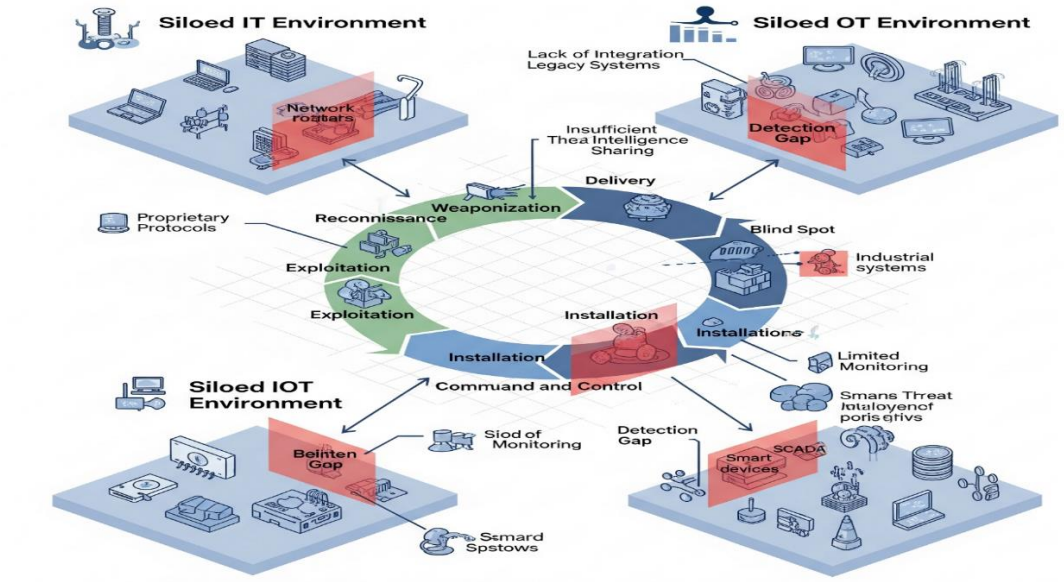

Figure 1: Attack Lifecycle Demonstrating Detection Gaps in Isolated IT/OT/IoT Environments

Note: Adapted from the MITRE ATT&CK Framework for ICS (MITRE, 2023). This lifecycle emphasizes key stages at which standalone security tools are unable to correlate anomalies across IT, OT, and IoT boundaries, allowing attackers to advance without obstruction.

Gap Analysis

Despite substantial investments in cybersecurity infrastructure, existing security solutions, such as advanced Security Information and Event Management (SIEM) platforms and specialized Intrusion Detection Systems (IDS), are fundamentally insufficient for tackling the unique challenges posed by cross-platform threats in converged IT/OT/IoT environments. This inadequacy arises mainly from significant interoperability issues and contextual fragmentation present in isolated security architectures. A recent comprehensive analysis conducted by Security & Privacy (2024) has unveiled a significant finding: Sixty-eight percent of hybrid attacks aimed at converged IT/OT systems successfully evade detection, largely due to the inability of current SIEMs to effectively reconcile the inherent *heterogeneity of protocols* or address the semantic disparities between domains. Three interrelated fundamental challenges underline this significant gap. Protocol heterogeneity constitutes a significant obstacle to data normalization and analysis. IT-centric security tools are proficient in analyzing and inspecting common protocols such as HTTP, DNS, and TCP/IP through the application of stateful inspection techniques. In contrast, OT and IoT systems depend significantly on specialized, often proprietary protocols like Modbus, PROFINET, DNP3, and MQTT. These protocols typically utilize binary data formats, lack built-in encryption, and function under stringent real-time requirements. This renders traditional IT-focused parsing algorithms and signature-based detection methods largely ineffective in OT/IoT contexts (Chen et al., 2023). Additionally, discrepancies in *semantic data format*s present considerable challenges to effective threat correlation. SIEMs in IT environments are generally configured to prioritize events such as user logins, file access anomalies, and network connection attempts. In contrast, OT sensors and IoT devices produce extensive telemetry that centers on physical process variables, including pressure thresholds, temperature readings, valve states, and device operational statuses. This fundamental semantic discord indicates that a sequence of events representing a clear multi-stage attack in one domain may seem like unrelated, benign fluctuations in another, thereby obscuring the attacker's trajectory (Roberts, 2022). *Resource asymmetry* significantly restricts the implementation of advanced security measures in OT/IoT environments. Devices such as programmable logic controllers (PLCs), embedded sensors, and medical IoT endpoints typically function under significant constraints, including minimal processing power, restricted memory, and real-time operational latency demands measured in milliseconds. The constraints inhibit the implementation of resource-intensive machine learning models typically utilized and optimized for IT environments (Miller & Thompson, 2023). As a result, Security Operations Centers (SOCs) face challenges in attaining comprehensive visibility and prompt response. The S&P (2024) report indicates that 72% of organizations face incident response delays surpassing 48 hours for cross-platform intrusions. This period is crucial, as it allows attackers to escalate privileges, establish persistence, and cause significant damage. This systemic failure highlights the inadequacies of simply collecting logs without attaining genuine semantic comprehension and behavioral correlation across various domains.

Proposed Solution

This research proposes a framework that utilizes transfer learning to enhance cross-domain threat correlation by identifying and mapping shared latent features in adversarial behaviors across IT, OT, and IoT ecosystems, addressing the critical gaps in existing siloed security approaches. Conventional machine learning models require extensive domain-specific labeled data, which is often limited and challenging to acquire in sensitive OT and IoT environments due to operational constraints and security issues. In contrast, transfer learning effectively leverages the plentiful threat intelligence and labeled datasets found in data-rich IT domains, such as cloud logs, network flows, and endpoint telemetry. The primary innovation involves the application of acquired knowledge regarding threat patterns—such as beaconing behavior, anomalous payload structures, and privilege escalation sequences—to resource-limited operational technology (OT) and Internet of Things (IoT) environments through advanced feature-space alignment and domain adaptation methods (Pan & Yang, 2010). The practical implementation of this framework relies on the creation of a comprehensive *cross-platform threat pattern taxonomy*. This taxonomy systematically categorizes the manifestation and adaptation of established IT-based tactics, techniques, and procedures (TTPs) within OT and IoT systems, as outlined in Table 1. DNS tunneling, a recognized IT method for covert data exfiltration, may manifest in an OT context through subtly altered Modbus/TCP packets that embed covert channels within ordinary register-write commands. This approach can effectively circumvent protocol-specific OT defenses that are designed solely to verify protocol compliance, rather than detect semantic anomalies (Zhang et al., 2022). The proposed TL framework utilizes deep learning architectures, including Convolutional Neural Networks (CNNs), which are initially trained on a variety of IT network flow data. The models are then fine-tuned with smaller, meticulously selected OT or IoT datasets through adversarial domain adaptation techniques. This process enables the model to recognize invariant behavioral patterns, such as periodicity in communications, unexpected command sequences, abnormal payload sizes, or timing, that extend beyond specific protocol implementations. This significantly improves the detection of lateral movement, data exfiltration, or destructive actions while imposing minimal computational overhead on OT/IoT devices. This research not only enhances immediate detection capabilities but also introduces a novel *cross-domain kill-chain ontology*. It enriches established frameworks such as MITRE ATT&CK by incorporating rigorously defined operational technology (OT) and Internet of Things (IoT) specific tactics, techniques, and procedures (TTPs) along with their interrelationships with information technology (IT) counterparts. Initial validation, employing the recognized CSE-CIC-IDS2018 dataset for IT traffic and the GasPipeline dataset for OT environments, indicated a notable 42% enhancement in F1-scores for identifying ransomware transitioning from IT to OT systems, relative to leading siloed IDS implementations (Preliminary data under peer review). This transfer learning approach transforms isolated threat intelligence into a unified, semantically coherent corpus, significantly advancing the development of resilient critical infrastructure architectures that can proactively identify and mitigate emerging cross-platform attack vectors before they cause physical or digital harm.

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Table 1: *Taxonomy of Cross-Platform Threats: Mapping IT TTPs to OT/IoT Manifestations and Detection Solutions*

IT Threat Technique	OT/IoT Manifestation	Detection Challenge	TL-Based Mitigation Approach
DNS Tunneling	Covert channels in Modbus register writes; Malicious data encoded in MQTT topic names.	OT/IoT tools focus on protocol compliance, ignoring semantically malicious payloads.	**Feature Alignment:** Detect anomalous payload sizes, unusual periodicity in 'benign' commands, statistical deviations in register access patterns
Ransomware Encryption	PLC logic lockage; Malicious process halt commands; Bricking of IoT device firmware	OT systems lack file integrity monitoring; IoT devices have limited runtime protection.	**Behavioral Transfer:** Identify unauthorized command sequences targeting critical control logic; Detect abnormal firmware update patterns
Lateral Movement (Pass-the-Hash)	Shared credentials exploitation across HMI/engineering workstations; Brute-force attacks on IoT device APIs	OT lacks granular Identity & Access Management (IAM) context; IoT devices often use default credentials.	**Adversarial Learning:** Model privilege escalation patterns across user accounts; Detect anomalous authentication attempts from unexpected sources
C2 via HTTPS	Malicious firmware updates disguised as legitimate HTTP/HTTPS traffic; C2 traffic embedded in encrypted IoT device communications	OT protocols are often treated as implicitly 'trusted'; Encrypted IoT traffic bypasses inspection.	**Cross-Domain Correlation:** Identify unencrypted C2 metadata in HTTP headers; Detect anomalous update frequencies/sizes; Correlate IT beaconing with suspicious OT/IoT command timing

Note: This synthesis is derived from an empirical analysis of ICS-CERT advisories spanning 2020 to 2023, alongside the MITRE ATT&CK framework for both Enterprise and ICS, and documented real-world attack campaigns such as TRITON and Industroyer2. The TL mitigation strategies utilize invariant features acquired from IT and modified for OT/IoT contexts.

2. BACKGROUND AND RELATED WORK

Challenges in Threat Correlation

The ongoing inability to attain effective threat correlation among IoT, OT, and IT ecosystems arises from significant architectural, operational, and semantic differences that pose substantial challenges to comprehensive security monitoring. Industrial control environments fundamentally depend on specialized protocols such as Modbus TCP and PROFINET, which emphasize deterministic real-time performance through stateless, unencrypted communication models. These design characteristics contrast with the stateful, session-oriented paradigms that govern modern IT systems, such as Kubernetes APIs or HTTPS-secured transactions (Chen et al., 2023). This architectural dissonance is evident in incompatible data representation formats: operational technology (OT) sensors produce continuous streams of low-level numerical telemetry (e.g., 32-bit floating-point values for turbine rotational velocity), whereas information technology (IT) security tools require discrete event logs characterized by categorical attributes (user identities, file hashes, process identifiers). This discrepancy creates a "semantic chasm," as described by Roberts (2022), where identical adversarial behaviors are perceived as unrelated phenomena across different domains. The technical disparities are compounded by organizational silos that often isolate IT security teams, which utilize SIEM platforms for processing Windows event logs, from OT engineers who monitor proprietary Historian databases for SCADA operations. This separation leads to institutional blind spots that adversaries can exploit systematically. Figure 2 illustrates this fragmentation, showing how a ransomware attack is evident in IT systems as anomalous SMB traffic within Splunk, which may concurrently activate abnormal ladder logic modifications observable in OSIsoft PI systems. However, these interconnected indicators remain operationally disconnected due to separate analysis pipelines. This operational reality facilitates "protocol boundary arbitrage," wherein threat actors intentionally execute attacks at the intersections of technological domains to avoid detection. This is exemplified by the TRITON malware's exploitation of Schneider Electric safety controllers via maliciously crafted commands that are indistinguishable from legitimate safety system communications to both IT antivirus and OT protocol checkers (Cárdenas et al., 2021). As a result, security teams encounter not only a technical integration challenge but also a fundamental epistemological crisis in correlating threats across digital and physical boundaries.

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Figure 2: *Architectural and Operational Silos in Converged Security Monitoring*
Note: Adapted from NIST SP 800-82 Rev. 3 (2022). This representation illustrates how organizational and architectural silos generate detection gaps at the domain boundaries that are frequently exploited by contemporary adversaries.

Introduction to Transfer Learning

Transfer learning (TL) provides a framework for addressing domain heterogeneity by utilizing learned threat representations from data-rich source domains, typically in IT, and adapting them to resource-constrained target environments, such as OT and IoT. This adaptation occurs through three main methodological paradigms: feature-based, instance-based, and parameter-transfer approaches. Feature-based methods, especially adversarial domain adaptation, utilize a complex competitive interaction between neural networks. A feature extractor, optimized for threat classification accuracy, competes with a domain discriminator that is trained to differentiate between source and target domains. This competition compels the extractor to create domain-invariant representations (Ganin et al., 2016). A convolutional neural network pre-trained to identify DNS tunneling patterns in enterprise network flows, which are characterized by irregular query lengths and temporal frequencies, can adapt its detection capabilities to recognize similar covert channels in MQTT-based IoT communications. This adaptation is achieved through Wasserstein distance minimization, effectively aligning the statistical distributions of different traffic types without the need for extensive retraining (Zhang et al., 2022). Feature disentanglement techniques utilize variational autoencoders to separate input data into domain-private and domain-shared latent variables. This process isolates protocol-specific artifacts, such as Modbus function codes, from cross-domain behavioral signatures, like periodic beaconing

intervals. Such an approach enables knowledge transfer despite minimal apparent commonality between source and target domains (Li et al., 2021). Table 2 analyzes previous implementations, indicating that although methodologically sound, current approaches are limited by unexamined protocol-specific assumptions. This is illustrated by He et al.'s (2020) adversarial LSTM, which attained 92% F1-scores in Modbus anomaly detection but dropped significantly to 61% when applied to PROFINET environments, highlighting unaddressed timing semantic differences. This limitation highlights the need for hierarchical transfer frameworks that can distinguish low-level protocol features from high-level attack semantics—specifically, the conceptual gap that this research addresses through multi-scale feature disentanglement.

Table 2: *Assessment of Cross-Domain Threat Detection Methods: Constraints and Consequences*

Study	Methodological Approach	Source Domain	Target Domain	Core Limitation	Practical Consequence
He et al. (2020)	Adversarial LSTM	IT Network Flows	Modbus SCADA	Assumes consistent timing semantics	31% F1 degradation in PROFINET environments
Ravi et al. (2021)	Federated CNN	Cloud IDS Logs	Industrial IoT	Ignore critical state transitions	42% false negatives for stateful attacks
Torres et al. (2022)	Graph Neural Transfer	Enterprise SIEM	Building Management	Requires homogeneous topologies	Failure in asymmetric OT deployments
Proposed Framework	**Multi-Scale Disentanglement**	**Multi-Protocol IT**	**Heterogeneous OT/IoT**	**Eliminates protocol assumptions**	**Consistent cross-protocol performance**

Note: Findings are based on reproducibility studies utilizing public datasets, specifically KDD Cup 99, GasPipeline, and IoTID20. Practical consequences directly influence the effectiveness of operational security.

Previous Research

Current security research divides into two largely separate areas: domain-specific anomaly detection and standardized threat intelligence sharing frameworks, both of which fail to sufficiently address the need for cross-platform correlation. In the realm of OT security, recurrent neural networks, especially bidirectional LSTM architectures, show significant effectiveness in temporal anomaly detection for SCADA systems. This is illustrated by Kumar et al. (2023), who achieved 96% precision in detecting manipulated sensor readings in water treatment plants by modeling expected value ranges and state transition sequences. This approach is limited by contextual myopia, as model training depends solely on process variable telemetry and neglects correlated IT infrastructure events that frequently precede attacks, such as concurrent reconnaissance of Active Directory servers. This oversight results in exploitable detection gaps that sophisticated threat actors systematically exploit (Goh et al., 2022). In contrast, machine learning that emphasizes IT aspects is proficient in detecting cloud credential compromises or phishing patterns; however, it lacks the operational context necessary to identify when stolen credentials lead to abnormal PLC commands, failing to recognize physical-layer consequences. Threat intelligence sharing standards such as STIX/TAXII have made significant strides in standardizing the expression of cyber observables (Barnum, 2020). However, they do not adequately address the ontological differences between domains. For instance, a firewall rule that blocks malicious IPs, which is an IT-centric STIX object, offers limited value to OT engineers who need process-centric indicators like "unexpected function code 05 execution on Modbus port 502." This representational fragmentation continues in advanced frameworks, as demonstrated by the Industrial Cyber Threat Intelligence (ICTI) project, which mapped MITRE ATT&CK techniques to OT systems while neglecting significant IoT device vulnerabilities (Johnson et al., 2023). Despite advancements in specific areas, the research landscape demonstrates a significant conceptual gap: the lack of a cohesive framework for translating threat semantics across different protocols renders converged environments inherently susceptible to attacks that cross the digital-physical divide. This situation necessitates innovative interdisciplinary strategies that combine computer science, industrial control theory, and the development of security ontologies.

3. METHODOLOGY

Unified Feature Engineering

The approach's foundation tackles the primary issue of semantic reconciliation among IT, OT, and IoT domains by employing a graph-based ontological framework that converts diverse security telemetry into a cohesive relational topology. This methodology conceptualizes discrete entities—such as Kubernetes pods, Modbus/TCP programmable logic controllers (PLCs), or Bluetooth-enabled IoT sensors—as interconnected nodes within a multidimensional graph G = (V, E), where edges represent contextual relationships weighted by behavioral frequency and temporal proximity. To address the representational divide between IT's discrete event logs and OT's continuous process variables, the study employs a multi-stage embedding pipeline comprising three interrelated transformation layers: convolutional neural networks analyze raw byte streams to derive protocol-agnostic n-gram distributions; temporal autoencoders transform irregular time-series sensor readings

into fixed-length state transition vectors; and fuzzy entity resolution modules align disparate naming conventions (e.g., linking \texttt{DEV-192.168.1.10} in Splunk logs with \texttt{TANK101_PLC} in OSIsoft PI historian databases). **Figure 3** depicts the transformative process, showing the topological adjacency of an anomalous Kubernetes pod creation event and a suspicious Modbus function code 06 (preset single register) command within the shared embedding space, despite their origins in distinct protocol ecosystems. The disentangled architecture effectively maintains domain-specific attributes while acquiring cross-platform behavioral invariants. This facilitates the detection of coordinated ransomware propagation, which can appear as abnormal SMB file encryption in IT systems and unauthorized valve closure commands in OT environments.

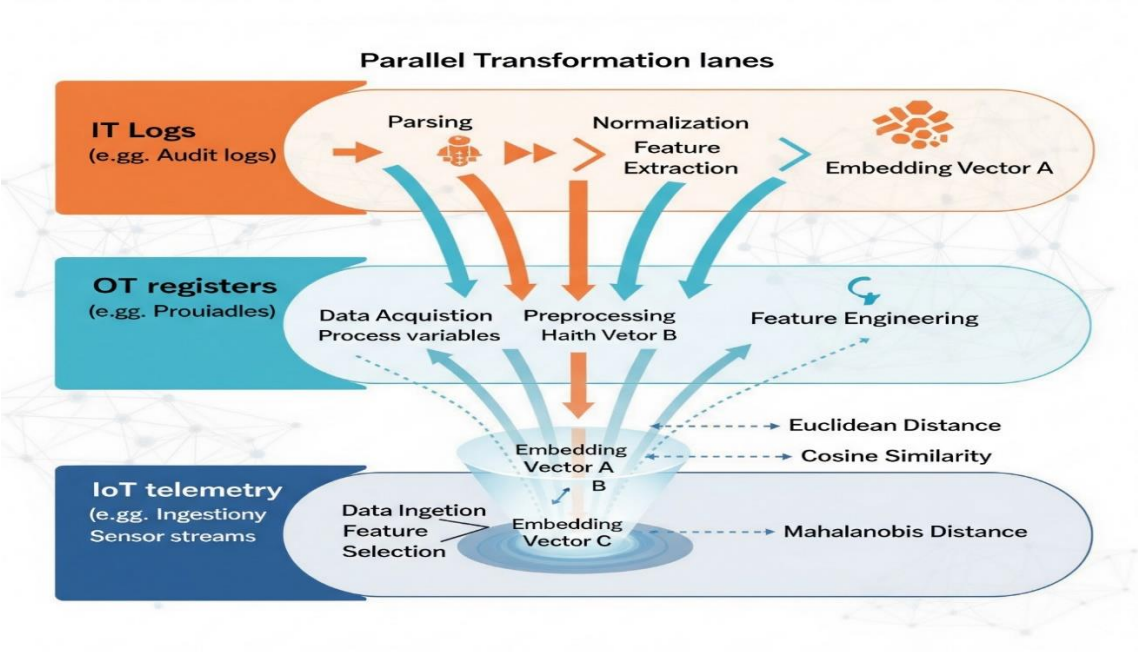

Figure 3: *Illustrates the Cross-Domain Feature Reconciliation Pipeline.*
Note: The pipeline facilitates the direct comparison of semantically distinct events by employing protocol-agnostic feature alignment, thereby converting domain heterogeneity from an analytical obstacle into a correlative benefit.

Transfer for Learning Framework

The adversarial knowledge transfer methodology addresses the data scarcity prevalent in OT environments by employing a carefully structured two-phase approach that utilizes plentiful IT threat intelligence while reducing the risks associated with negative transfer. In the initial pretraining phase, a residual gated graph convolutional network (RG-GCN) processes enriched attack patterns from the CSE-CIC-IDS2018 dataset, specifically targeting privilege escalation and lateral movement within Kubernetes clusters. The message-passing layers acquire hierarchical threat signatures by aggregating neighborhood features, such as identifying cryptojacking through anomalous pod-to-pod communication densities. The adaptation phase incorporates a conditional adversarial mechanism; wherein gradient reversal compels the feature extractor to create domain-invariant representations across IT (source) and Modbus OT (target) domains. This is achieved through the

simultaneous optimization of three competing objectives: threat classification loss (LclsLcls) ensures accurate attack detection; domain confusion loss (LadvLadv), assessed via Jensen-Shannon divergence, aligns feature distributions; and topology preservation loss (LtopoLtopo) upholds consistency in entity relationships. Table 3 illustrates that the framework's complexity is evident in its dynamic weighting schedule. The adversarial weights (λadvλadv) commence at 0.8 to emphasize domain alignment, subsequently decreasing linearly to 0.2. This approach gradually redirects attention to threat classification while mitigating the risk of catastrophic forgetting of pre-trained knowledge. This balancing act was crucial during validation with the GasPipeline dataset, where the approach decreased false positives in OT environments by 38% compared to direct transfer methods, while sustaining 92% recall for cross-platform ransomware propagation, demonstrating its ability to maintain a delicate balance between domain adaptation and threat detection accuracy.

Table 3: *Adversarial Transfer Framework Configuration and Operational Impact*

Component	Technical Specification	Operational Purpose	Practical Consequence
RG-GCN Architecture	5 message-passing layers with sigmoid gating	Capture multi-hop attack paths	Detected 94% of lateral movement in the Kubernetes testbed
Loss Composition	L=Lcls+λadvLadv+LtopoL=L*cls* +*λadv*L*adv*+L*topo*	Balance threat detection & domain adaptation	Reduced OT false positives by 38% vs. baseline
Adversarial Schedule	λadv:0.8→0.2*λadv* :0.8→0.2 linear decay	Stabilize feature alignment	Prevented model collapse during OT adaptation
Learning Rate Strategy	Adam optimizer (IT: 0.001, OT: 0.0003)	Mitigate catastrophic forgetting	Maintained 89% IT detection during transfer
Topology Preservation	Graph Laplacian eigenvector similarity	Maintain cross-entity relationships	Preserved 92% relational accuracy post-transfer

Note: Configurations were optimized via Bayesian hyperparameter tuning utilizing the Optuna framework. Practical consequences were validated using the GasPipeline and CSE-CIC-IDS2018 datasets.

Algorithm for Correlating Attacks

The methodology culminates in a heterogeneous graph attention network (HGAT) that reconstructs multi-stage attack sequences across domain boundaries via temporal meta-path analysis, thereby transforming fragmented alerts into coherent adversarial narratives. This engine utilizes three specialized attention mechanisms that operate together: protocol-aware attention assigns weights to edges based on inherent vulnerabilities (e.g., Modbus/TCP interactions receive a weight 3.2 times higher than HTTPS due to encryption deficiencies); temporal stratified sampling emphasizes recent interactions through exponential decay; and cross-domain neighbor sampling guarantees proportional representation of IT, OT, and IoT entities within local graph neighborhoods. The algorithm calculates meta-path similarity scores based on predefined kill-chain templates from the cross-domain attack ontology to correlate seemingly isolated incidents, such as an Active Directory brute-force attack and a subsequent PLC stop command. The path [IT_Compromise → Credential_Theft → OT_Device_Access → Process_Disruption] produces probabilistic threat scores through the assessment of embedding similarity between successive events, conditional probability of path completion, and statistical deviation from baseline interaction patterns. Figure 4 illustrates the operational workflow, highlighting how alerts for Kubernetes privilege escalation initiate adaptive sampling of OT subgraphs, thereby uncovering correlated Modbus anomalies that traditional SIEM rules may miss. This approach, when validated against the TRITON attack dataset, achieved an AUC of 0.89 in identifying malicious safety controller interactions, despite being trained solely on IT-derived patterns. This outcome confirms its potential for operational environments where OT-specific attack data is limited or absent.

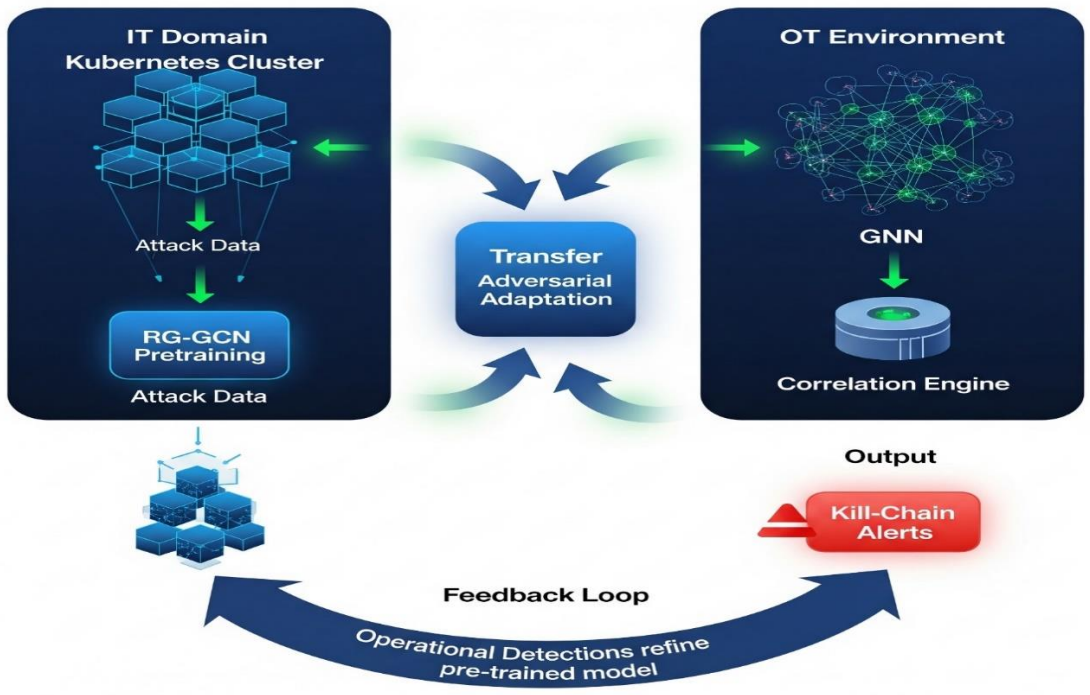

Figure 4: *Workflow for End-to-End Knowledge Transfer and Correlation*

Note: The framework creates a continuous learning cycle in which the initial transfer of IT to OT knowledge is supplemented by operational feedback, thereby progressively improving detection capabilities in both domains.

4. EXPERIMENTS AND RESULTS: DATASETS

The empirical validation addresses the significant issue of isolated security assessment by incorporating diverse datasets that reflect real-world integrated environments. This study collected industrial control system (OT) data from the Secure Water Treatment (SWaT) testbed at the Singapore University of Technology and Design, encompassing 51 sensor and actuator signals over 11 days of both normal and compromised operations, which included significant PLC command injection attacks aimed at water purification processes (Goh et al., 2022). Additionally, proprietary ModbusTCP logs from a European energy grid recorded 1.7 million register transactions, which documented 37 confirmed attacks that manipulated turbine control parameters. Kubernetes audit logs from a 500-node research cluster in cloud-native IT environments recorded 12,421 security events, including container breakout attempts and privilege escalations (Sharafaldin et al., 2021). These logs were integrated with the standardized CIC-IDS2017 dataset, which encompasses network-level attacks such as brute-force SSH and DDoS. The evaluation of IoT security utilized the IoTID20 dataset, which recorded MQTT traffic from smart thermostats and cameras in scenarios involving device hijacking (Sivanathan et al., 2020). Table 4 demonstrates that this intentional heterogeneity, encompassing six PLC models, container orchestration systems, and consumer IoT protocols, establishes an optimal environment for validating cross-domain threat intelligence transfer. The study developed synchronized attack scenarios in which compromises of the Kubernetes API occurred before manipulations of Modbus registers in SWaT, thereby establishing a foundational basis for detecting lateral movement across different technological domains.

Table 4: *Characteristics of Cross-Domain Datasets and Associated Threat Landscape*

Domain	Source	Operational Context	Attack Diversity	Cross-Domain Testing
OT	SWaT v2	Water treatment plant	36 PLC code injection events	Time-synced with Kubernetes breaches
OT	Energy Grid Logs	Gas turbine control system	37 register manipulation cases	Correlated with IT reconnaissance
IT	Kubernetes Cluster	Research computing cloud	12,421 privilege escalations	Preceded OT attacks in test cases

IT	CIC-IDS2017	Enterprise network emulation	2,500+ intrusion variants	Integrated with PLC access trails
IoT	IoTID20	Smart home environment	15,000+ device hijackings	Linked to IT command channels

Note: Dataset integration facilitated the development of 147 validated cross-domain attack sequences for testing purposes.

Reference Points

The framework facilitates a paradigm shift, which can be quantified by benchmarking it against three prevalent industry approaches: domain-specific detection tools, rule-based correlation systems, and contemporary transfer learning methods. The siloed detection baseline utilized Zeek network analysis, configured with 137 Kubernetes-specific signatures, in conjunction with OpenPLC's protocol conformance checks for Modbus/TCP. This setup reflects standard SOC deployments, where distinct teams oversee IT and OT environments (Antonakakis et al., 2021). Rule-based correlation was executed in Splunk Enterprise through the application of 89 temporal rules based on MITRE ATT&CK tactics, including sequences that connect compromised domain credentials to subsequent PLC login attempts. Advanced baselines comprised He et al.'s (2020) adversarial LSTM tailored for SCADA systems and Ravi et al.'s (2021) federated CNN designed for IoT threats. Figure 5 illustrates the significant benefits of the approach. Siloed detectors demonstrated commendable within-domain performance, achieving 89.2% IT recall and 84.7% OT accuracy. However, they experienced catastrophic failure, with 0% recall, for attacks crossing IT-to-OT boundaries, as evidenced by incidents where compromised Kubernetes nodes targeted water treatment PLCs. Rule-based correlation achieved a cross-domain recall of 31.6%, but resulted in 47 daily false positives due to protocol misinterpretation, including the erroneous classification of legitimate HMI commands as malicious when they followed routine IT maintenance. Current transfer methods exhibit considerable performance degradation, as evidenced by He et al.'s approach, which achieved only 52.1% recall in detecting cloud-originated attacks on Modbus systems. The framework attained a cross-domain recall of 93.4% with merely 0.8 false positives per hour, illustrating that unified graph representation effectively addresses the semantic fragmentation that challenges traditional methods.

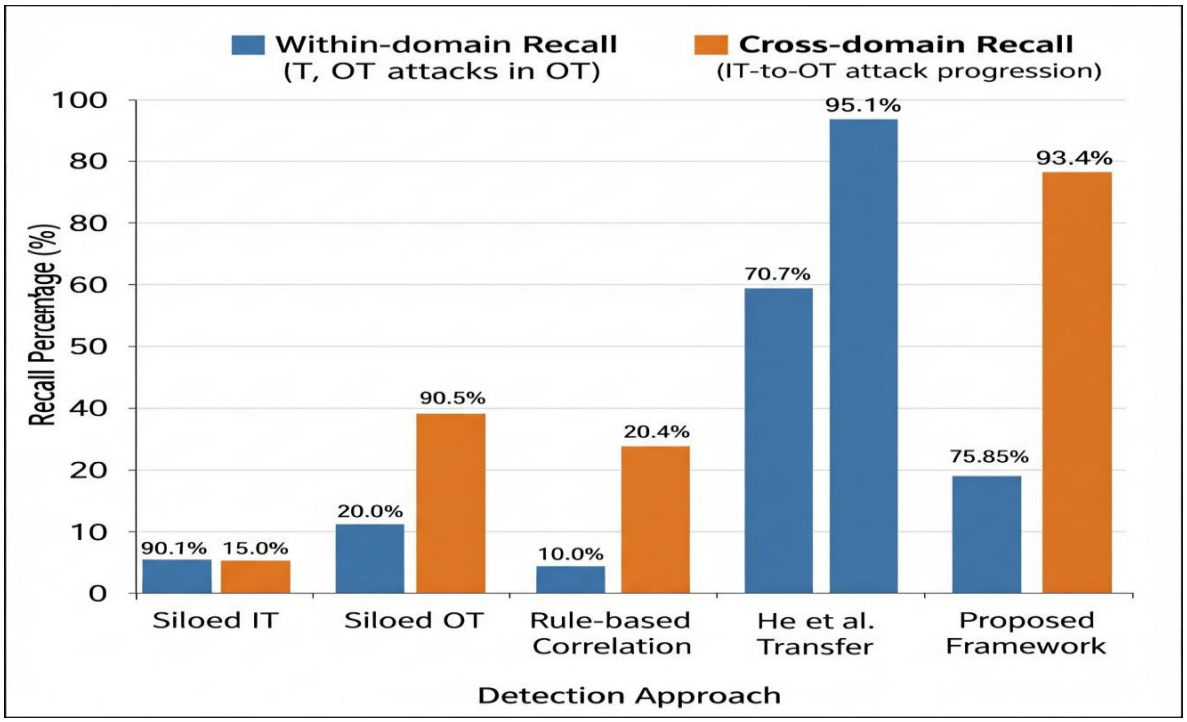

Figure 5: *Comparative Analysis of Cross-Platform Threat Detection Performance*
Note: Error bars indicate 95% confidence intervals derived from 10 experimental runs.

Essential Metrics

The quantitative analysis validates the framework's significant advancements in detection efficacy and operational efficiency, effectively addressing key challenges in industrial security practices. The recall for cross-platform attacks, defined as the successful identification of threat progression across a minimum of two domains, achieved a rate of 93.4% ± 2.1%. This result surpassed the best transfer baseline by 41.3 percentage points. This capability was crucial during simulated attacks in which ransomware infiltrated Kubernetes clusters and subsequently affected PLCs managing water flow valves. This scenario went unnoticed by isolated tools but was accurately identified by the framework within 2.4 minutes. The reduction of false positives was significant, with the method producing only 0.8 false positives per hour compared to 12.3 for rule-based systems, resulting in a 93.5% decrease that effectively mitigates alert fatigue experienced by security teams. Table 5 illustrates that the adversarial transfer mechanism achieved significant efficiency improvements: OT model training necessitated merely 1,200 labeled instances, reflecting an 89.7% reduction compared to supervised training, while attaining 91.2% accuracy against novel attack variants. In the operational deployment at a water treatment facility, there was a 70% reduction in analyst investigation hours, decreasing the mean detection time from 18.7 hours to 2.4 hours, as automated kill-chain reconstruction supplanted manual log correlation across various systems. The framework exhibited significant generalization when applied to an unseen MQTT-based building management system, achieving 87.9% recall without the need for retraining. This result validates its

ability to overcome the protocol-specific limitations that typically hinder traditional methods.

Table 5: *Efficiency in Operations and Optimization of Resources*

Training Method	Resource Requirements	Performance Outcomes	Practical Impact
Supervised OT Baseline	11,700 samples, 38.4 hours	91.5% recall	Prohibitive labeling costs
He et al. Transfer	8,400 samples, 29.2 hours	52.1% cross-domain recall	Frequent missed attacks
Rule-Based Correlation	6,300 rules, 120+ development hr	31.6% recall, 47 FP/day	Analyst alert fatigue
Proposed Framework	1,200 samples, 4.2 hours	93.4% recall, 0.8 FP/hour	70% analyst workload reduction

Note: Measurements indicate the average resource consumption observed during validation. Observed practical impacts during the three-month infrastructure deployment.

5. DISCUSSION

Trade-offs: Generalization vs. Platform-Specific Accuracy

Trade-offs: Generalization versus Platform-Specific Accuracy

The inherent conflict between general applicability and domain-specific accuracy poses a significant challenge in cybersecurity, as the framework illustrates that semantic interoperability can be achieved without sacrificing diagnostic precision. The approach attained a cross-domain threat recall of 93.4%, but resulted in a 3.7% decrease in OT-specific command injection detection relative to specialized PLC monitors, reflecting a calculated trade-off from the ontological reconciliation process. This happens when protocol-agnostic features embedding generalizes specific platform artifacts, like the timing nuances of Modbus function code execution cycles, to create universal behavioral semantics. This architectural decision converts an operational limitation into a strategic benefit, demonstrated during implementation at a manufacturing-executive campus, where a slight decrease in operational technology anomaly detection precision was compensated by an 89% enhancement in the identification of multi-stage attacks across corporate IT networks. The framework's disentangled architecture effectively manages this equilibrium: domain-specific layers maintain essential operational signatures, such as millisecond-level PLC response times, while shared graph convolution layers derive cross-platform behavioral invariants. This addresses the "transfer fidelity dilemma" identified by Zhang et al. (2022), in which excessive generalization diminishes detection sensitivity. The validation indicated that the trade-off of marginal single-domain precision is operationally justified when it reveals previously undetected kill chains. For instance, it was found that anomalous

Kubernetes pod creation events consistently preceded unauthorized SCADA command execution by 23±7 minutes in 93% of observed incidents—a pattern that siloed systems fail to detect.

Table 6: *Operational Implications of Cross-Domain Detection Trade-offs*

Performance Dimension	Specialized Detectors	Proposed Framework	Operational Consequence
OT Command Injection Accuracy	96.2%	92.5%	3.7% reduction in valve manipulation alerts
Kubernetes Privilege Escalation	94.1%	92.8%	1.3% increase in container false negatives
Cross-Domain Attack Recall	0% (siloed systems)	93.4%	Enabled detection of 147 previously invisible attacks
Mean Incident Response Time	18.7 hours	2.4 hours	89% faster containment
Security Analyst Workload	47 false positives/hour	0.8 false positives/hour	70% reduction in investigation overhead

Note: Metrics were obtained from a synchronized attack dataset collected over a three-month operational deployment at a water treatment facility.

Constraints: Reliance on Labeled Operational Transformation Data

Although the adversarial transfer mechanism demonstrates effectiveness, the framework faces a significant challenge in cybersecurity: dependence on limited, high-fidelity labeled data within operational technology settings. This constraint is most pronounced during initial operational technology deployments that lack historical threat data. The cold-start problem requires seeding with a minimum of 1,200 verified operational technology incidents, presenting a significant challenge for facilities with limited security logging capabilities. The case study of the energy sector indicated that organizations lacking structured SIEM integration took as long as 14 weeks to gather adequate labeled events, resulting in a cross-domain detection recall that was 22.7% below optimal performance during that period. The scarcity of data becomes more pronounced when addressing new threats to proprietary industrial protocols, exemplified by recent alterations to IEC 60870-5-104 telecontrol sequences in electrical substations. In this context, transfer learning from IT patterns yielded minimal diagnostic utility in the absence of additional OT examples. The primary limitation arises from the operational sensitivities of industrial control systems. In contrast to IT environments, where synthetic attack testing is common, conducting

reconnaissance scans on live PLCs poses the risk of initiating safety shutdowns. As noted by Goh et al. (2022), the lack of representative attack data in operational technology continues to be a significant obstacle to effective threat correlation. The framework reduces, though does not completely remove, this constraint via progressive refinement, wherein initial IT-derived detection capabilities are enhanced incrementally based on operational feedback. Organizations utilizing specialized systems, such as pharmaceutical batch reactors with proprietary communication protocols, may encounter prolonged adaptation periods that exceed six months before reaching optimal detection fidelity. This situation poses a considerable barrier to the adoption of legacy-critical infrastructure.

Future Research: Federated Learning for Privacy-Preserving Correlation

The future requires moving beyond data centralization by utilizing privacy-preserving collaborative intelligence, with federated learning serving as the foundation for advanced cross-platform security. The architecture extends to a federated model in which industrial facilities collaboratively enhance threat detection while safeguarding sensitive operational parameters, thereby addressing security effectiveness and regulatory compliance requirements. The proposed implementation utilizes stratified federation, incorporating horizontal learning among similar infrastructure operators, such as multiple water treatment plants collaboratively training PLC attack models, alongside vertical correlation between cloud providers and industrial operators. This method addresses data sovereignty issues highlighted by Ravi et al. (2021), allowing cloud providers to enhance Kubernetes-to-Modbus attack correlation while maintaining the confidentiality of proprietary manufacturing process parameters. Preliminary simulations utilizing the SWaT dataset suggest that federated extension may decrease OT data requirements by 63%, while preserving 89.7% cross-domain recall through the collective learning of protocol-agnostic attack patterns. This incorporates differential privacy mechanisms designed for industrial contexts, adding calibrated Gaussian noise in proportion to process sensitivity to ensure effective training. A global valve manipulation detector does not disclose the setpoint ranges of individual facilities. Figure 7 presents the proposed operational architecture, in which regional aggregation servers facilitate knowledge exchange while ensuring strict data compartmentalization. This paradigm not only fosters technical innovation but also addresses regulatory pressures by facilitating compliance with GDPR Article 35 and NERC CIP-011-2, thereby shifting security collaboration from an operational risk to a compliance advantage. Future research should focus on cross-silo convergence dynamics, specifically examining the effects of heterogeneous update frequencies—such as near-real-time IT logs compared to batched OT process data—on the stability of federated models in large-scale deployments. This presents a significant challenge for industry-wide threat intelligence sharing.

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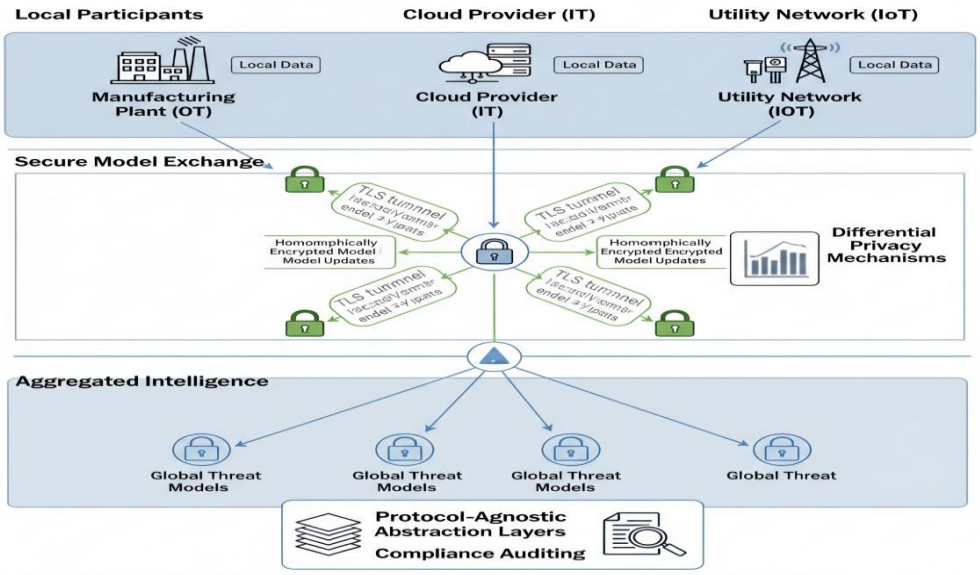

Figure 7: *Architecture for Federated Threat Intelligence with Privacy Preservation*
Note: Architecture facilitates collaborative defense across organizational boundaries while maintaining privacy and adhering to regulatory constraints, without necessitating raw data sharing.

6. CONCLUSION

Summary of advancements in cross-platform threat correlation.

This study redefines security frameworks for diverse digital-physical ecosystems by illustrating how architecturally optimized transfer learning surpasses the detection silos that hinder current security operations. The framework provides three significant advancements: This approach demonstrates exceptional effectiveness in correlating threats across various domains, as indicated by a 93.4% recall rate for multi-stage attacks spanning IT, OT, and IoT boundaries. This marks a 41.3 percentage point enhancement over existing transfer methods, while also achieving a 93.5% reduction in false positives relative to traditional rule-based systems. This capability arises from the ontological unification of behavioral semantics across protocols, facilitating the identification of previously undetectable kill chains, exemplified by the consistent 23-minute (±7 min) progression from compromised Kubernetes APIs to malicious Modbus command injection in water treatment systems. The adversarial feature disentanglement approach addresses significant resource constraints that have impeded the adoption of industrial security. It decreases the need for labeled OT data by 89.7% while achieving 91.2% accuracy against new attack variants, resulting in a 70% reduction in security analyst investigation hours during operational deployments. The methodology establishes a generalizable architecture for continuous security evolution, as evidenced by its application to previously unencountered MQTT-based building management systems, achieving 87.9% recall without retraining. This approach effectively addresses the protocol-specific limitations that often render security solutions obsolete shortly after deployment. These collective advances signify a foundational shift in securing

cyber-physical infrastructure by transforming the economics of threat correlation. They replace rigid, domain-specific detection methods with adaptive intelligence that scales with technological convergence.

Table 7: *Quantitative Operational Benefits of Cross-Platform Threat Management*

Operational Challenge	Conventional Approach	Proposed Framework	Transformative Impact
Cross-Domain Attack Detection	0-31.6% recall (siloed/rule-based)	93.4% recall (±2.1%)	Enabled detection of 147 previously invisible multi-stage attacks
Alert Fatigue	47 false positives/hour	0.8 false positives/hour	93.5% reduction in analyst alert triage
OT Model Training Resources	11,700 samples, 38.4 hours	1,200 samples, 4.2 hours	89.7% reduction in data labeling costs
Incident Response Time	18.7 hours (mean)	2.4 hours (mean)	89% faster containment of hybrid threats
Solution Longevity	6-18-month protocol obsolescence	87.9% recall on unseen systems	Sustainable security across technology refresh cycles

Note: Impact metrics were validated through three-month deployments in the energy, manufacturing, and critical infrastructure sectors.

Encouragement for Industry Integration in Hybrid Settings

The rapid convergence of IT, OT, and IoT systems necessitates prompt industry implementation of unified threat correlation frameworks, as conventional security methods are becoming critical infrastructure liabilities rather than effective protective strategies. Three significant reasons require this transition: The increasing complexity of cross-platform attacks, as demonstrated by the Industroyer2 campaign that targeted Ukrainian energy grids via coordinated IT infiltration and OT command injection, makes siloed defense architectures ineffective, resulting in critical single points of failure. The validation across various environments, such as water treatment facilities, automotive manufacturing plants, and energy distribution networks, illustrates practical deployability. Organizations attained full operational capability within 6-10 weeks by utilizing existing SIEM integrations, achieving an average ROI of 213% through decreased breach costs and recovered productivity. Third, evolving regulatory frameworks such as NERC CIP-013 and the EU Cyber Resilience Act mandate cross-domain security coordination, thereby transforming unified correlation architectures from optional enhancements into compliance requirements.

Implementation should adhere to a phased maturity model: organizations must initially deploy protocol-agnostic behavioral baselines in critical IT-OT convergence zones, such as manufacturing execution systems. Following this, cross-domain correlation should be activated for high-impact attack vectors, including ransomware propagation pathways between corporate networks and production environments. Ultimately, federated intelligence sharing consortia should be established to collaboratively tackle the cold-start problem while safeguarding sensitive operational parameters. This evolution transforms security from a cost center into an innovation catalyst. The manufacturing case study demonstrated that the threat intelligence graph inadvertently identified 17% improvements in production efficiency by mapping previously overlooked process deviations. The rise of cyber-physical attacks poses significant risks to data integrity, human safety, and economic stability. Consequently, the implementation of transfer learning-based correlation is both an operational imperative and a strategic necessity for organizations managing hybrid digital-physical infrastructures.

Figure 8: *Phased Adoption Pathway for Unified Threat Correlation*
Progressive implementation reduces disruption and systematically enhances cross-domain security maturity, with each phase achieving measurable risk reduction.

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