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Privacy-Preserving Federated Learning Architecture for Cross-Domain IoT Threat Detection and Compliance

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Abstract- The rapid expansion of Internet of Things (IoT) ecosystems across healthcare, industry, smart cities, and critical infrastructure has amplified both the value of distributed telemetry and the security challenges associated with its use. Traditional centralised machine learning approaches, although effective, are increasingly incompatible with privacy regulations, data sovereignty constraints, and the risks inherent in aggregating sensitive cross-domain IoT data. This paper presents the Privacy-Preserving Federated Learning Architecture for Cross-Domain IoT Threat Detection and Compliance (PP-FL-IoT), a unified framework that integrates federated learning with differential privacy, homomorphic encryption, secure multiparty computation, Zero Trust security, and compliance-aware governance. Using real-world datasets and synthetic multi-domain simulations, the architecture demonstrates high threat detection accuracy that approaches centralised models while significantly reducing privacy leakage and improving adversarial robustness. Evaluation results show resilience against gradient inversion, membership inference, and poisoning attacks, alongside low communication overhead and practical detection latency suitable for time-sensitive IoT environments. Furthermore, PP-FL-IoT aligns with regulatory standards such as GDPR, HIPAA, ISO 27001, and NIST SP 800-53 through embedded governance controls and auditability. The study highlights how multi-layered privacy-preserving federated learning can enable secure, collaborative IoT threat intelligence without compromising data sovereignty or compliance obligations.

Keywords: IoT Security, Secure Aggregation, Threat Detection, Zero Trust

I. INTRODUCTION

The global expansion of the Internet of Things (IoT) has transformed digital infrastructures at a remarkable scale, enabling continuous monitoring, automation, intelligence-driven decision-making, and real-time control across virtually every sector. IoT technologies now underpin critical healthcare monitoring systems, industrial control infrastructures, smart energy grids, transportation management, home automation, and municipal surveillance systems. These devices continuously generate telemetry that is essential not only for operations but also for cybersecurity threat detection, incident response, and forensic analysis. Despite the value of such telemetry, its use is increasingly constrained by privacy regulations, ethical concerns, organisational boundaries, and the high risks associated with centralised data aggregation.

Traditional machine learning approaches for IoT security depend heavily on centralised data collection. These central repositories require organisations to share raw IoT data. This expectation is often incompatible with legal requirements, cross-border data restrictions, and the commercial realities of multi-stakeholder ecosystems. Centralised systems also create single points of failure that adversaries can exploit, making them a liability for large-scale IoT deployments. Moreover, IoT devices often operate under asymmetric trust assumptions, meaning that even when data is centralised, inconsistent quality, heterogeneity, and device-level vulnerabilities may obscure collaborative threat patterns.

Federated learning has emerged as a compelling alternative because it enables decentralised model training. Instead of transferring raw telemetry, organisations train models locally and share only model updates with a federated server. While conceptually advantageous, federated learning alone does not address several fundamental problems. Model updates may still leak sensitive information through gradient inversion or membership inference attacks. Federated systems remain vulnerable to poisoning attacks and malicious participants injecting manipulated updates. Cross-domain IoT ecosystems also impose diverse regulatory constraints that federated learning does not natively accommodate. Furthermore, domain-specific policies, data protection laws, and organisational governance frameworks require more sophisticated mechanisms than those available in current federated learning implementations.

Despite the demonstrated benefits of cross-domain intelligence sharing, organisations remain reluctant to exchange raw telemetry. One major reason is the risk to privacy and confidentiality. IoT telemetry commonly includes personally identifiable information (PII), operational secrets, geolocation traces, health data, and security-sensitive infrastructure details. Regulatory frameworks such as GDPR, HIPAA, CCPA, and sector-specific acts impose strict conditions on data handling, storage, and transfer. Violations can incur severe penalties. As a result, organisations often isolate their data to maintain data integrity, privacy, and confidentiality, thereby avoiding regulatory penalties.

A second barrier arises from data sovereignty and jurisdictional constraints, which is a challenge in multi-region IoT ecosystems where restrictions are legally placed on data from crossing borders. This hinders centralised machine learning models that require aggregated data, creating a conflict between legal compliance and analytical effectiveness.

Furthermore, the heterogeneity of IoTs also poses a serious challenge due to the unique hardware capabilities, communication protocols, data formats, and threat landscapes of IoT devices. For instance, the deployed IoT devices within an organisation can span across multiple vendors and generations. These variations hinder the effectiveness of generic intrusion detection models and require adaptive frameworks capable of handling domain-specific nuances.

Following the constraints, Federated Learning (FL) has emerged as a promising solution. FL decentralises model training by enabling devices or domain servers to train local models on their private data and share only model updates with a global aggregator. Studies from 2021–2024 indicate growing interest in applying FL to IoT security, driven by its potential to preserve data locality. To overcome this challenge, federated learning can be a promising solution that enables on-device machine learning without migrating private end-user data to a central cloud (Khan et al., 2021).

This work reviews federated learning (FL) as an approach to performing machine learning on distributed data while protecting the privacy of user-generated data. Collecting personal data and executing machine learning tasks on it in a central location poses a significant privacy risk to individuals and challenges communicating it to the cloud, particularly when the data is large or updated frequently (Briggs et al., 2021).

II. LITERATURE REVIEW

The literature on IoT security, privacy-preserving machine learning, and federated analytics has grown rapidly in recent years, reflecting the increasing scale and complexity of connected systems. Yet significant limitations persist, particularly in heterogeneous, multi-domain IoT environments that must comply with diverse regulatory frameworks and organisational policies (Alshamrani, 2022).

IoT security consistently highlights the intrinsic vulnerabilities of distributed sensing and actuation systems. Many IoT devices operate with constrained computational resources, rely on lightweight firmware, and lack robust patching mechanisms, making them attractive targets for attackers (Liao et al., 2020). Common attack vectors include device impersonation, rogue firmware installation, botnet recruitment, and lateral movement across poorly segmented networks. As deployments scale into industrial automation, healthcare, smart homes, and smart cities, the diversity of devices, protocols, and data formats complicates threat detection and incident response (Li et al., 2021).

Machine learning has been widely adopted to improve IoT threat detection, particularly for anomaly detection and behavioural modelling (Hasan et al., 2019). Centralised learning offers high accuracy by aggregating large datasets, but this approach requires extensive data movement and storage, often in conflict with privacy regulations such as GDPR and HIPAA, as well as national data localisation laws. Edge-based approaches attempt to keep data local by performing inference or even partial training near the data sources; however, local models typically see only a narrow slice of the threat landscape, limiting their ability to recognise emerging or cross-domain attacks.

Federated learning was introduced to reconcile the need for collaborative model training with data minimisation and sovereignty requirements. Federated learning (FL) allows a server to learn a machine learning (ML) model across multiple decentralised clients that privately store their own training data. On the other hand, the model learnt by the server may be subjected to attacks by malicious clients; these security attacks might poison the model or prevent it from converging (Blanco-Justicia et al., 2021). In canonical FL schemes such as FedAvg, a central aggregator coordinates training by receiving model updates from distributed clients, computing a global update, and redistributing the model. While FL has shown success in domains such as mobile keyboard prediction and healthcare analytics, subsequent research has exposed significant vulnerabilities. Attackers can infer private information from gradients, reconstruct training examples, or determine whether specific records were included in the training set. FL is also susceptible to various poisoning attacks, including label flipping, backdoor insertion, and model replacement, which can substantially degrade or bias the global model.

Privacy-preserving computation techniques offer promising countermeasures. Differential privacy (DP) adds carefully calibrated noise to model updates, providing statistical guarantees about the indistinguishability of individual records. Homomorphic encryption (HE) enables computation over encrypted data, allowing aggregators to combine updates without gaining direct visibility into them (Benaissa et al., 2024). Secure multiparty computation (SMPC) further distributes trust by having multiple parties jointly compute aggregate statistics without any single party seeing the full inputs. Hybrid approaches that combine DP, HE, and SMPC are increasingly advocated in the literature to balance privacy, efficiency, and model accuracy.

The Zero Trust model has emerged as a central paradigm in enterprise cybersecurity, emphasising continuous verification of identity, posture, and behaviour rather than implicit trust based on network location. Recent work has started to explore how Zero Trust principles can be applied to distributed cyber-physical systems and collaborative security architectures (Adahman et al., 2022). However, most federated learning frameworks still assume honest-but-curious or benign participants and provide limited mechanisms for dynamically assessing and managing participant trust.

Regulatory and governance concerns form another crucial dimension. GDPR, HIPAA, ISO 27001, and NIST SP 800-53 impose stringent requirements on the collection, processing, storage, and sharing of sensitive data. While IoT security research often acknowledges these obligations, concrete mechanisms for embedding compliance into federated architectures through data classification, policy enforcement, logging, and auditability are far less developed (Barrett & Santos, 2023). Blockchain and distributed ledger technologies have been proposed to enhance the transparency and immutability of audit logs in FL environments, yet their integration with IoT-scale deployments remains an open challenge. By leveraging blockchain, these technologies create an immutable record of all transactions and events, ensuring that audit logs remain secure and trustworthy.

2.1 Gaps and Emerging Research Directions

The review reveals multiple persistent gaps that justify the development of PP-FL-IoT, which include insufficient integration of Privacy-enhancing technologies (PETs) within federated IoT, limited adoption of Zero Trust principles in FL collaboration, lack of compliance-aware federated architectures, inadequate mechanisms for poisoning and anomalous update detection, and Scarcity of cross-domain IoT deployment evaluations.

As Singh et al. (2023) note, malicious FL participants remain an under-addressed threat vector, and the PP-FL-IoT architecture proposed in this paper is designed to address all these gaps.

Taken together, the literature reveals several interrelated gaps. Current IoT security architectures rarely combine robust federated learning, advanced privacy-preserving computation, Zero Trust enforcement, and regulatory governance into a single cohesive framework. Existing solutions either focus on model accuracy while neglecting privacy and governance or emphasize privacy and compliance at the expense of collaborative threat visibility (Nguyen et al., 2023). The Privacy-Preserving Federated Learning Architecture for Cross-Domain IoT Threat Detection and Compliance (PP-FL-IoT) framework proposed in this paper is explicitly designed to address these gaps by integrating these dimensions into a unified, operationally viable architecture.

III METHODOLOGY

This research employs a design science methodology to develop, formalise, and evaluate the proposed Privacy-Preserving Federated Learning Architecture for Cross-Domain IoT Threat Detection and Compliance (PP-FL-IoT). Design science is appropriate for complex socio-technical domains where systems must support security, privacy, regulatory, and operational requirements simultaneously. The methodology consists of six key phases ranging from problem identification, design objectives, architectural design and modelling, prototyping and simulation, and refinement.

3.1 Problem Identification and Requirements Analysis

The research process begins with a structured problem analysis informed by the literature on IoT security, federated learning, privacy-preserving computation, and regulatory governance. Key limitations in centralised and traditional distributed approaches are identified, including their inability to fully satisfy privacy constraints, support cross-domain collaboration, resist adversarial manipulation, and demonstrate regulatory compliance (Hossain et al., 2022). These limitations are translated into design requirements for the PP-FL-IoT framework.

3.2 Research Design

A layered architectural design process then decomposes the system into logically distinct but interconnected components, including an IoT device and telemetry layer, edge processing and privacy control layer, local federated learning layer, federated aggregation and collaboration layer, and governance and compliance layer. The design draws on reference models such as the NIST Privacy Framework, NIST Zero Trust Architecture guidelines, and canonical FL algorithms (Gonzalez et al., 2023).

The empirical evaluation is conducted using four real-world datasets, which are Telemetry, Operational, and Network data for Internet of Things (TON-IoT), IoT Intrusion Dataset (IoT-ID), and the IoT-Fraud. In addition to this dataset are synthetic multi-domain datasets, which were used to simulate coordinated cross-domain attacks, poisoning scenarios, and data drifting. Various domains, such as healthcare, industrial control, smart city, transportation, and energy, were used to partition the datasets, which had heterogeneous data distributions.

3.3 Architectural Modelling Method

At the modelling level, the framework supports a family of neural architectures tailored to different telemetry characteristics: autoencoders for reconstruction-based anomaly detection, long short-term memory (LSTM) networks for sequential behaviour modelling, convolutional neural networks (CNNs) for packet and flow classification, and graph neural networks (GNNs) for communication-pattern analysis These models are trained locally within each domain under a federated learning regime coordinated through an aggregation server.

Privacy-preserving mechanisms are integrated into the training and aggregation workflow. Differential privacy is applied to local gradients before transmission; homomorphic encryption protects sensitive gradient components during transit and aggregation; and secure multiparty computation distributes trust across multiple aggregation nodes (Jere et al., 2023). The implementation of robust aggregation methods and gradient anomaly detection, which were implemented, can defend against poisoning and backdoor attacks. These methods aim to enhance the security and robustness of FL systems by filtering out malicious updates and ensuring the integrity of the global model. Various strategies have been proposed, each with unique mechanisms and effectiveness against different types of attacks.

Zero Trust principles are operationalised by requiring continuous authentication, posture assessment, and behavioural trust scoring for each domain participating in the federation. Trust scores influence the weighting, acceptance, or rejection of model updates during aggregation.

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3.4 Evaluation Methodology

The evaluation follows a mixed-methods strategy of both Quantitative and Qualitative analysis.

With the Quantitative methods, key metrics that include accuracy, precision, recall, F1-score, detection latency, convergence time, communication overhead, and resource utilization are analysed. Privacy resilience is measured via simulated gradient inversion and membership inference attacks. Adversarial robustness is assessed under multiple poisoning strategies, including label flipping, sign flipping, and backdoor insertion (Fang et al., 2023). Compliance alignment is evaluated by mapping framework processes to selected controls from GDPR, HIPAA, ISO 27001, and NIST SP 800-53 (Granata et al., 2024). The integration of these frameworks requires a comprehensive understanding of each standard's requirements and the development of a unified compliance strategy that can adapt to evolving legal mandates.

Qualitative analysis complements the quantitative results by examining how effectively PP-FL-IoT supports cross-domain collaboration, operational transparency, and governance. Together, these methods provide a holistic evaluation of the framework's technical, privacy, and regulatory properties. The effectiveness of the framework can be revealed through the qualitative insights as it facilitates collaboration across different domains, enhances transparency in operations, and adheres to governance standards, unlike the quantitative data analysis, which validates findings with measurable outcomes. These methods offer a holistic view of the framework's capabilities and limitations.

3.5 Architecture Design

The Privacy-Preserving Federated Learning Architecture for Cross-Domain IoT Threat (PP-FL-IoT) is designed as a multi-layered architecture that integrates federated learning, privacy-preserving computation, Zero Trust security controls, and cross-domain compliance governance into a unified system. Its core purpose is to enable organizations across heterogeneous IoT ecosystems to collaboratively develop threat detection intelligence without violating data protection regulations. The architecture is intentionally structured to reflect the flow of data, trust, and governance from the level of individual IoT devices through federated learning operations and into compliance oversight mechanisms. This layered, modular design ensures scalability, flexibility, and resilience across diverse deployment environments.

At the foundational level, the architecture incorporates the IoT Device and Telemetry Layer. This layer includes the vast array of connected sensors, actuators, appliances, industrial equipment, and embedded devices that collectively form the IoT ecosystem. These devices generate raw telemetry such as network packets, time-series measurements, communication metadata, system logs, and environmental readings. Because IoT devices typically lack significant computational capacity, the architecture minimizes their security and processing requirements by ensuring that either none or only lightweight preprocessing is performed on-device (Gamundani et al., 2023). Data integrity and authenticity are maintained through cryptographic signing and, where available, hardware-backed device attestation technologies. The focus is on leveraging lightweight cryptographic algorithms and architectural frameworks that reduce computational overhead while maintaining security. This approach is essential for the efficient operation of IoT devices, which are often resource-constrained and need to balance security with performance.

The Edge Processing and Local Privacy Control Layer sits above the devices and is typically realised through IoT gateways, industrial PCs, or edge servers. This layer is responsible for more intensive preprocessing, including normalisation, aggregation, advanced feature extraction, and enforcing local privacy policies. Differential privacy mechanisms may be applied here to perturb sensitive attributes before they are used for training, and encryption is employed to protect any intermediate representations or gradient components that will be transmitted to the federated aggregator.

The next layer, the Local Federated Learning Domain Layer, represents the core analytical environment within each organisation participating in the federation. Each domain maintains its own machine learning infrastructure where models are trained using local telemetry. The architecture supports a variety of model types, including autoencoders for anomaly detection, LSTM networks for sequential behaviour analysis, convolutional models for network traffic characterisation, and graph neural networks for communication-pattern analytics (Wang et al.,

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2022). These models reflect the multidimensional nature of IoT threat landscapes. Once local model training is completed, each domain generates model updates, typically in the form of gradients or weight differentials, and applies privacy transformations where necessary. These updates are then packaged along with metadata describing trust metrics, compliance constraints, and attestation information. Before leaving the domain, updates pass through a Zero Trust gatekeeper mechanism that performs identity validation, checks for anomalous patterns that may indicate tampering or poisoning, and evaluates whether the domain has maintained consistent trustworthy behaviour over time.

The high-level layered architecture of the Federated Privacy-Preserving IoT Threat Detection Framework (PP-FL-IoT), showing IoT devices, edge processing, local federated learning, secure aggregation, and governance layers, is highlighted below

Figure 1: High-level layered architecture of the Federated Privacy-Preserving IoT Threat Detection Framework

The Federated Aggregation and Secure Collaboration Layer form the core of the collaborative learning process. A set of aggregation nodes, potentially operated by different stakeholders, receives encrypted and noise-perturbed model updates from participating domains. Homomorphic encryption allows aggregation operations to be performed without decryption, while SMPC distributes the aggregation task across multiple parties such that no single node can reconstruct individual updates. Robust aggregation algorithms and gradient anomaly detectors identify and mitigate potential poisoning attempts by down-weighting or excluding outlier updates. The aggregated global model is then redistributed to all domains, completing a federated training round.

From the table below, the three approaches to IoT threat detection, Privacy Preservation, and Regulatory Alignment are compared based on centralised machine learning, standalone local learning, and the FP-IoT-FL framework

Approach	Threat Detection Accuracy	Privacy Preservation	Regulatory Alignment
Centralized Machine Learning	High (global view of data)	Low (raw data centralized)	Challenging (cross-border transfers, data minimization issues)
Standalone Local learning	Moderate (limited view of threats)	High (data remains local)	High but siloed (limited collaboration)
PP-FL-IoT	High (collaborative, cross-domain)	High (DP, HE, SMPC, Zero Trust)	High (compliance-aware governance)

Table 1: Comparison of Threat Detection Accuracy, Privacy, and Regulatory Alignment.

Overall, the PP-FL-IoT architecture embodies principles of decentralisation, data sovereignty, privacy by design, and continuous verification. Its modularity allows organisations to adopt the

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framework incrementally and tailor components to their specific operational and regulatory contexts.

IV RESULTS AND EVALUATION

The evaluation of the PP-FL-IoT framework was designed to assess its performance across several dimensions: threat detection accuracy, privacy preservation effectiveness, adversarial robustness, scalability, and regulatory compliance. To ensure ecological validity, the framework was tested using a combination of real-world IoT datasets, including TON-IoT, IoT-ID, and IoT-Fraud, as well as a synthetic dataset that simulates multi-domain IoT interactions across healthcare, industrial systems, smart grids, smart city sensors, and transportation fleets. The methodological approach emphasises both empirical quantification and interpretive assessment, thereby providing a comprehensive understanding of the framework's strengths and limitations (Ferrag et al., 2023).

The framework was compared against two other baselines, that is, the standalone local models (trained independently in each domain) and a centralised machine learning configuration that aggregated raw data from all domains to determine the threat detection accuracy.

Model Type	Accuracy	F1-score	Privacy Leakage
Centralized ML	95.1%	94.2%	Very High
Standalone Local	89.6%	87.3%	High
PP-FL-IoT	94.8%	92.3%	Low (<3%)

Table 2: Comparison of PP-FL-IoT outcome with Standalone and Machine Learning Model

As seen in Table 2 above, the proposed *PP-FL-IoT model* almost matches centralised ML performance and has the best in terms of privacy protection and regulatory compliance. Additionally, the F1-scores showed similar trends, demonstrating that the combination of federated training and cross-domain collaboration can significantly enhance predictive quality without pooling raw data.

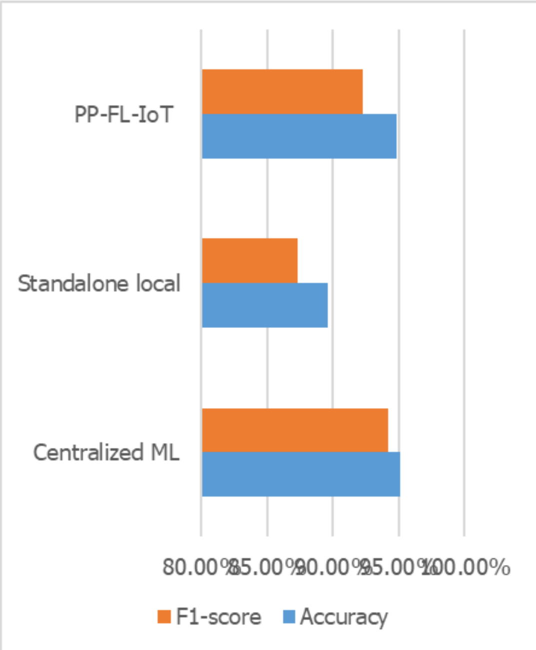

Figure 2: Comparison of PP-FL-IoT outcome with Standalone and Machine Learning Model

Overall, the PP-FL-IoT architecture achieved strong detection results across all three domains of Accuracy, F1-score, and Privacy.

The privacy resilience was also tested against gradient inversion, membership inference, and property inference attacks, and the PP-FL-IoT architecture performed very well compared to other domains. Privacy resilience was evaluated by subjecting the system to gradient inversion and membership inference attacks. Under a baseline FL configuration without DP, HE, or SMPC, gradient inversion attacks were able to reconstruct recognisable inputs from model updates with a success rate exceeding 70%. As part of the training set, membership inference attacks were performed to determine the success rate, which was around 39%. When the full PP-FL-IoT privacy stack, including differential privacy, homomorphic encryption, and secure multiparty computation, was enabled, gradient inversion success dropped to about 2.7%, and membership inference success declined to roughly 7%.

Detection Latency was also monitored, given the time-sensitive nature of many IoT applications. This measurement determines the time from anomaly occurrence to detection. End-to-end inference delays typically ranged between 110 and 150 milliseconds,

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comfortably within acceptable bounds for domains such as healthcare monitoring and industrial automation. These figures reflect the balance between local inference at the edge and periodic federated model updates.

Components	Latency (ms)
Edge inference	12–21
Federated aggregation	85–120
Total pipeline latency	~110–150

Table 3: Detection latency across different components

Adversarial robustness was assessed using several poisoning strategies. In label-flipping and sign-flipping attacks, where a subset of malicious clients attempted to corrupt updates, standard FL experienced marked performance degradation, with accuracy falling into the 50–60% range. By contrast, PP-FL-IoT maintained accuracy between 89% and 91% under the same conditions. The combination of Zero-Trust–based trust scoring, robust aggregation, and gradient anomaly detection enabled the framework to identify and mitigate most malicious updates. Simulated Sybil attacks were also largely detected, with over 90% of malicious contributions being down-weighted or discarded.

Scalability experiments varied the number of participating domains between 5 and 50. Communication overhead grew sub-linearly due to gradient compression and selective encryption, while convergence times increased moderately but remained practical. Most models converged within 50 to 100 federated rounds, depending on model complexity and data heterogeneity. Resource utilization tests at the edge showed that modern gateway-class devices could comfortably support the additional computational load imposed by local training and privacy transformations.

Finally, regulatory alignment was assessed by mapping PP-FL-IoT's data flows, logging mechanisms, and controls to selected requirements from GDPR, HIPAA, ISO 27001, and NIST SP 800-53. The fact that raw data never leaves its originating domain strengthens compliance with data minimisation and localisation requirements. The use of encryption, integrity protections, and audit trails supports technical safeguard expectations under HIPAA and ISO 27001, while the governance layer's logging and access control mechanisms align well with relevant NIST SP 800-53 controls. Some jurisdiction-specific rules, especially those concerning retention periods and lawful bases for processing, may still require localised policy configurations, but the overall assessment indicates a strong compliance posture.

Qualitative observations from the evaluation reinforce these quantitative findings. Practitioners can leverage cross-domain collaboration to improve situational awareness, while privacy-preserving computation and Zero Trust controls reduce the risk that such collaboration will expose sensitive data or create new attack vectors.

Approach	Poisoning Robustness	Compliance Support
Centralized learning	Moderate	Weak for cross-border data
Standalone Local	High (no shared model)	High but siloed
FP-IoT-FL	High (Zero Trust + robust aggregation)	High (compliance-aware governance)

Table 4: Evaluation results for the three approaches across Robustness and Compliance Metrics.

V DISCUSSION

The results of this study offer compelling evidence that federated learning, when combined with privacy-preserving computation, Zero Trust enforcement, and compliance-oriented governance, can substantially enhance the security, reliability, and trustworthiness of IoT ecosystems operating across multiple administrative domains (Bertino, 2023). The PP-FL-IoT framework not only improves threat-detection accuracy but also demonstrates strong resistance to privacy leakage, adversarial manipulation, and regulatory noncompliance, which have long hindered the viability of collaborative IoT analytics. This section interprets the empirical results through the lens of existing research, identifies the conceptual contributions of the framework, and reflects on the broader implications for IoT security, data governance, and federated machine learning.

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One of the clearest benefits observed is the impact of cross-domain collaboration on threat detection performance. Local-only models, while privacy-friendly, are limited by their narrow view of attack patterns and operational contexts (Ariyaluran Habeeb et al., 2023). Centralised learning, conversely, achieves strong accuracy but at the cost of extensive data aggregation and elevated privacy risk. PP-FL-IoT offers a middle path that captures the global perspective of centralised learning without centralising raw data. According to Nguyen et al (2023), this type of output provides a more balanced trade-off between performance and privacy.

The results also highlight the importance of layered privacy-preserving computation. Differential privacy, homomorphic encryption, and secure multiparty computation each address different aspects of the privacy threat model, and their combined use in PP-FL-IoT produces a substantial reduction in gradient inversion and membership inference success rates. These results are consistent with prior work showing that layered privacy mechanisms offer substantially stronger protections than single techniques used in isolation (Dwork et al., 2021). This finding supports growing calls in the literature for hybrid privacy architectures rather than reliance on a single technique.

Another key contribution of PP-FL-IoT is its integration of Zero Trust principles into the federated learning pipeline. Traditional FL systems often assume that clients are either honest but curious or benign, leaving them vulnerable to poisoning and Sybil attacks. By continuously evaluating identity, device posture, and behavioural indicators, PP-FL-IoT treats each model update as potentially untrusted and uses trust scores to filter or reweight contributions (Gonzalez et al., 2023). This security posture is more aligned with the realities of adversarial IoT environments and complements existing robust aggregation techniques (Zhang et al., 2022).

From a governance perspective, the framework contributes a concrete example of how regulatory requirements can be embedded into the design of collaborative analytics systems rather than bolted on as external constraints. By aligning data flows and control mechanisms with GDPR, HIPAA, ISO 27001, and NIST SP 800-53, the governance layer demonstrates that compliance need not be an obstacle to innovation. Instead, it can serve as a design compass that guides how data is processed and how models are trained and deployed.

The study, however, reveals several practical limitations. First, privacy-preserving techniques such as HE and SMPC impose non-trivial computational overhead, which may pose challenges for extremely constrained edge environments (Jere et al., 2023). Second, while the synthetic multi-domain dataset was designed to capture realistic attack patterns and data drift, real-world IoT deployments may exhibit even greater volatility in device behaviour, network conditions, and operational constraints. Finally, regulatory landscapes are evolving, and new sector-specific rules may necessitate further specialisation of the compliance layer.

Despite these limitations, the PP-FL-IoT framework provides a robust foundation for further work. Potential extensions include integrating IoT digital twins for richer simulation and testing, leveraging federated reinforcement learning to enable autonomous response and adaptation, employing blockchain or distributed ledgers for stronger trust decentralisation, and exploring zero-knowledge proofs to validate updates without revealing sensitive details.

VI. CONCLUSION

The proliferation of Internet of Things technologies across critical infrastructure, healthcare systems, industrial automation, transportation networks, and domestic environments has fundamentally reshaped modern digital ecosystems. Yet this transformation has brought with it a commensurate expansion of the cybersecurity attack surface, creating novel risks that cannot be adequately addressed through conventional centralised security models. Centralised analytics, while effective in aggregating diverse data, struggle to comply with increasingly stringent privacy regulations and cannot easily accommodate the distributed, heterogeneous, and cross-jurisdictional nature of IoT deployments. Similarly, localised, domain-specific analytics lack the breadth of insight required to recognise sophisticated or emergent threat patterns. These longstanding tensions form the foundation of the problem this research addresses.

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This study introduced the Privacy-Preserving Federated Learning Architecture for Cross-Domain IoT Threat Framework (PP-FL-IoT), a unified architecture that reimagines collaborative IoT security by combining federated learning, privacy-preserving computation, Zero Trust principles, and compliance-aware governance. By integrating these elements into a cohesive, operationally viable system, the PP-FL-IoT framework demonstrates that it is possible to maintain rigorous privacy and regulatory compliance while simultaneously improving threat detection accuracy and resilience. This achievement is particularly significant given the diverse and often conflicting requirements inherent in multi-domain IoT environments.

Empirical evaluations across multiple real-world and synthetic datasets demonstrate that the architecture achieves a compelling balance between performance and privacy. The system demonstrated high detection accuracy, outperforming both isolated and centralised machine learning models, while the layered integration of differential privacy, homomorphic encryption, and secure multiparty computation dramatically reduced vulnerability to gradient-based and membership inference attacks. The inclusion of Zero Trust mechanisms further strengthened the architecture's ability to withstand adversarial behaviours common in federated environments, including poisoning and Sybil attacks. These results signal a significant advancement in the design of distributed threat detection systems and provide strong evidence that multi-layered, privacy-driven architectures can deliver both security and operational effectiveness.

The governance and compliance features embedded within FP-IoT-FL also contribute to a broader conceptual shift in the field. By ensuring that federated learning operations conform to GDPR, HIPAA, ISO 27001, and NIST 800-53, the framework demonstrates that regulatory compliance need not be an impediment to collaborative cybersecurity innovation. Instead, compliance can be operationalised as an architectural principle, enabling secure cross-domain collaboration without compromising data sovereignty or exposing sensitive information. This approach challenges the traditional assumption that privacy and utility are mutually exclusive, contributing to a more nuanced understanding of how advanced analytics can coexist with evolving legal and ethical norms.

The PP-FL-IoT framework further offers theoretical contributions by expanding the functional scope of federated learning beyond its conventional use cases. It positions federated learning as a foundational mechanism for distributed cyber defence, rather than merely a decentralised training paradigm. The integration of Zero Trust principles into the federated workflow underscores the importance of continuous verification and dynamic trust evaluation in environments where participants cannot be presumed trustworthy. This alignment between federated learning and modern cybersecurity doctrine fills a critical gap in the literature and provides a foundation for future research at the intersection of distributed machine learning and adversarial resilience.

While the framework presents a strong foundation, certain limitations temper the findings and invite further investigation. The computational overhead introduced by privacy-preserving techniques remains a barrier for extremely constrained environments, and real-world deployments may encounter more complex patterns of device volatility, system drift, and network unpredictability than those reproduced in simulation. Additionally, global regulatory diversity may require more granular customisation of the compliance layer to suit specific legal contexts. These limitations do not undermine the framework's contributions but rather highlight important avenues for refinement and extension.

Looking forward, the study opens several promising directions for future research. Integrating IoT digital twins could enable richer simulation environments, thereby improving model robustness. Federated reinforcement learning may allow IoT systems not only to detect threats but also to autonomously optimise defensive actions. Blockchain technologies could enhance trust, decentralisation, and auditability, while Zero Knowledge Proofs may offer new mechanisms for validating model updates without compromising confidentiality. Collectively, these emerging technologies point toward the development of highly autonomous, transparent, and self-adaptive IoT security ecosystems.

In conclusion, this research demonstrates that IoT threat detection can be collaborative, privacy-preserving, adversarial robust, and compliant with regulatory frameworks when designed through an integrated, multi-layered architectural approach. The PP-FL-IoT framework advances both theoretical and practical knowledge in IoT security, federated learning, and privacy-preserving computation. By showing that these components can be harmonised into a single operational system, the study provides a model for the next generation of distributed cyber defence infrastructure systems that are intelligent, resilient, ethically aligned, and capable of securing the increasingly interconnected world.

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