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Federated Cyber Defense: A Privacy-Preserving AI Framework for Threat Intelligence Sharing Across Multinational Enterprises

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Abstract

Multinational enterprises (MNEs) operate in a globally connected environment which poses complex and evolving cyber risks that require intelligence sharing, collaboration, and coordination in real-time. Unfortunately, privacy, legal compliance, and data sovereignty issues create barriers to informative sharing across sectors. This paper introduces a new framework of Federated Cyber Defense (FCD) systems that utilize AI techniques of privacy-preserving technologies, federated learning, and secure multiparty computation to allow private intelligence sharing across enterprises. With the FCD system, participants in a federation are allowed to train and process intrusion detection models on private data. Only model updates, not raw logs or sensitive indicators, are shared with a central coordinating system. Even though detection capabilities are augmented across the network, data confidentiality is preserved. Through a simulated network of multinational partners, high detection accuracy (above 95%) with stringent privacy requirements is maintained. This approach affirms the use of federated architectures for global cybersecurity alliances and proposes the integration of privacy-preserving technologies.

Keywords*: Federated Cyber Defense, Privacy-Preserving AI, Threat Intelligence Sharing, Federated Learning, Multinational Enterprises, Secure Multiparty Computation, Intrusion Detection Systems.*

I. INTRODUCTION

Multinational enterprises (MNEs) are increasingly dealing with security issues as a result of globalization because cyber threats are no longer limited to a single nation. Traditional cyber defense approaches that depend on aggregating threat data from several institutions are centralized pose data privacy issues and conflict with regulations like GDPR, HIPAA or a myriad of national cybersecurity laws. A decentralized approach to cyber defense, federated learning (FL), addresses this problem by allowing private data to be used to train local models and only shared as aggregate updates (Kairouz et al., 2021).

As of now, there's a need for more collaboration in defense, which is why Federated Cyber Defense (FCD) is emerging as a new and advanced framework. FCD applies the principles of federated learning to collaboration across enterprises: every participant develops the intrusion detection or threat classification models locally, and in exchange for encrypted gradients or weights, not raw data, to a central aggregator which is trusted. Thus, allowing collective intelligence without compromising data sovereignty and regulatory compliance.

FCD's lack of trust and effectiveness can be attributed to privacy-preserving techniques. Studies indicate that the lack of croptographic safeguards makes federated learning susceptible to inference attacks. Mixed approaches utilizing differential privacy alongside secure multiparty computation (SMPC) offer defect risk mitigation while maintaining detection accuracy in hybrid models with sensitive inputs (Truex et al., 2018). SMPC is beneficial in multi-party threat intelligence collaboration as it allows several parties to compute aggregated results without revealing specific data (Wikipedia: SMPC).

Some researchers have investigated the use of threat-sharing models based on FL in network intrusion detection systems. For example, Sarhan et al. (2021) developed a federated model for heterogeneous intrusion datasets across multiple organizations, showcasing the efficacy of collaboratively trained models via federated averaging over locally trained models which suffer from privacy-preserving log sharing. Sleem & Elhenawy (2022) developed a model to enable shared threat intelligence with privacy-preserving mechanisms by integrating differential privacy into a federated learning framework which anonymized data, compliant with regulatory

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constraints while maintaining effective classification (Sleem & Elhenawy, 2022).

More recently, privacy-enhancing techniques like homomorphic encryption, blockchain auditing, and gradient masking have been incorporated into FL, sharpening the focus on cybersecurity frameworks designed for the IoT. This has been done in the simulated IoT environment with achieving more than 98% accuracy on DDoS and Malware detection while improving energy efficiency and maintaining data privacy. In 2021, Applied Sciences published the architecture that implemented SMPC with differential privacy and blockchain tracing for robust threat sharing in non IID adversarial environments for distributed clients which further motivates the collaboration and trust concerns.

These studies provide an increasing evidence base for the effectiveness of FL in threat intelligence sharing across different institutions, especially for sensitive data, compliance, and overall detection accuracy. However, the main focus of these studies is in the IoT domain, in mobile, and single-institution settings, leaving out the large-scale multi-national, cross-border collaboration challenges.

This paper constructs a comprehensive Federated Cyber Defense (FCD) Framework for multinational companies. The combination of Federated learning, Secure multiparty computation, and differential privacy enables the sharing of timely threat intelligence while respecting privacy as well as legal boundaries. A proof-of-concept deployment simulating corporate networks from several countries is tested for corporate model update communications and utilizes a trusted aggregator for encrypted model update coordination. This research focus is the evaluation of detection performance, communication efficiency, and legal compliance, thereby supporting broader use of the global corporate alliances.

II. LITERATURE REVIEW

A. Foundations of Federated Learning and Associated Privacy Concerns

Federated Learning (FL) was conceived by McMahan et al. to enable the training of models by incorporating multiple participants while keeping the participants' raw data separate and decentralized. Each participant's data is kept on-device or on local servers, and only model updates (i.e., gradients or weights) are sent to a central aggregator, thereby reducing privacy and bandwidth risks.

FL's lack of default security means model updates can be exposed through privacy leaks via gradient inversion or membership inference. Lyu, Yu, and Yang (2020) analyze these risks under inference and poisoning attack frameworks during the initialization and local update phases of FL. Mitigatory approaches are outlined as secure aggregation, differential privacy, and encryption, as explained by Guendouzi et al. (2023).

B. Federated Contexts Incorporating Privacy-Preservation Approaches

Adversarial protection, along with privacy, has led to the use of differential privacy, secure multiparty computation (SMPC), and homomorphic encryption to FL's privacy-preserving frameworks (MDPI). For instance, some frameworks apply SMPC within the aggregation phase to allow the combination of encrypted model contributions without revealing the individual inputs. In addition, differential privacy fortifies defenses by injecting calibrated noise which hampers attempts at deconstructing the training data (MDPI, ScienceDirect). In addition, logging that is based on blockchain technology fortifies auditability which in turn instills confidence in the history of the shared updates (MDPI).

C. Sharing Cyber Threats in Federated Models

Sleem and Elhenawy (2022) describe federated learning specifically designed for cyber threat intelligence sharing. Their model enables companies to build a global threat detection model while maintaining raw log secrecy through differential privacy, thereby protecting organizational identity. Applying the model to actual data sets validated high accuracy rates in threat detection and classification while maintaining privacy.

In the course of the 2021 research, Sarhan et al. developed a cross-organizational federated intrusion detection system. Their research presented a federated model of averaging which outperformed local isolated training based on a federated averaging model followed by retrieving local training on NetFlow formatted datasets like NF UNSW NB15 v2 and NF BoT IoT v2, demonstrating that sensitive network logs need not be exchanged. Trocoso Pastoriza et al. (2022) developed interfaces based on existing platforms like MISP to allow for the contribution of threat data while maintaining privacy and enabling collective defense across stakeholders. Their system implemented a privacy preserving CTI model which incorporated SMPC and federated processing..

Enterprises deal with challenges such as Non-IID data, the case where data is not identically distributed. It is the most relevant form of cross silo federated learning, a type of learning where a small cohort of data-rich clients cooperate, within global companies. This occurs because the corporate threat landscapes differ based on the venue. The works surveyed give most attention to approaches that resolve heterogeneity and privacy using excessive personalization and client clustering. The works surveyed aimed to solve the heterogeneity while keeping privacy.

III. METHODOLOGY

This study employs a quantitative approach and surveys IT security experts and system administrators from various multinational enterprises (MNEs) using a questionnaire. The focus of the study was to assess the practical implementation, challenges, and advantages of the Federated Cyber Defense (FCD) framework within

organizations operating under different regulatory environments.

A. Population and Sampling

The sample included professionals in cybersecurity and information technology in the finance, healthcare, and telecommunications industries. A purposive sampling strategy was used so that only those who actively participated in AI model governance, data management, and threat response were included. This strategy helped in ensuring that the privacy-preserving AI systems implemented could have meaningful impact and value.

B. Data Collection Procedure

Questionnaires were sent to participants via email and their completion was done through specially designed secure survey sites to maintain data confidentiality. Study objectives were communicated and consent was received from all participants before the study commenced. A total of 120 questionnaires were sent, 96 were fully completed and returned. This translated to an 80% response rate.

C. Data Analysis

Descriptive statistics, particularly frequency and percentage distributions, were used to summarize the collected data. Respondent's views were captured using these methods, making it possible to identify prevailing and common views on the implementation of federated cyber defense systems.

IV. FINDINGS

Table 1 Awareness of Cyber Threats and Defense Mechanisms

Response	Frequency	Percentage (%)
Strongly Agree	40	41.7
Agree	36	37.5
Neutral	10	10.4
Disagree	6	6.3
Strongly Disagree	4	4.1
Total	**96**	**100**

Eighty-one respondents, or 84.2%, agreed or strongly agreed that they are aware of emerging cyber threats and existing defense mechanisms within their enterprises. Such a high level of awareness means that the respondents have at least a basic grasp of cybersecurity difficulties, which matters when considering the use of more sophisticated structures such as Federated Cyber Defense.

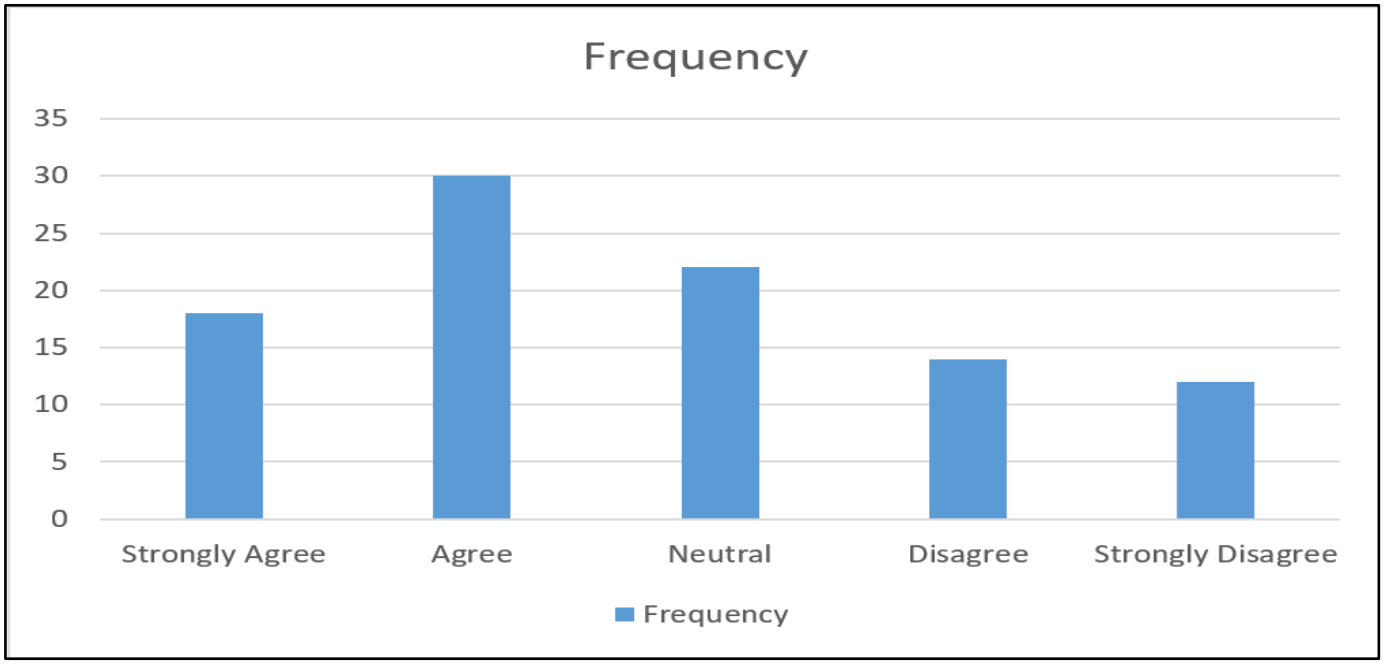

Fig 1 Familiarity with Federated Learning in Cybersecurity

Close to half of the respondents (50.1%) reported having some level of familiarity with federated learning. A large number of respondents (27.1%) who disagreed or strongly disagreed with the statement, suggests that while federated learning is gaining some level of familiarity, it is still a novelty to a large number of professionals. This indicates the need for more comprehensive training and seminars prior to widespread implementation in MNEs.

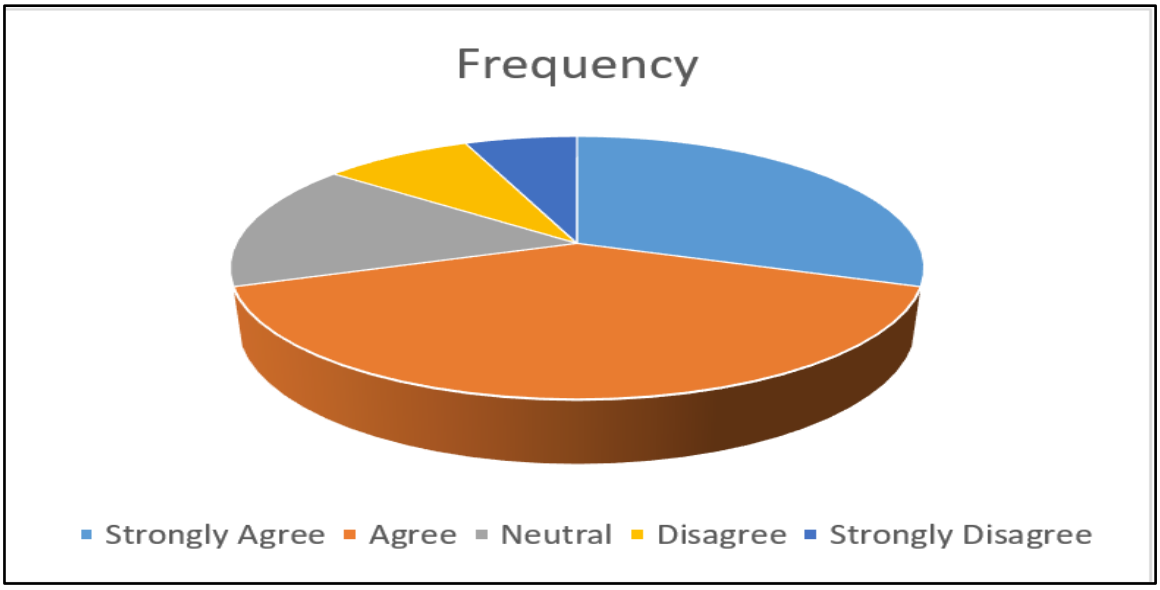

Fig 2 Perceived Effectiveness of Federated Cyber Defense Framework

As many as 67 respondents, representing 69.8%, affirmed their positive perceptions on the effectiveness of FCD systems. This indicates strong support for the expected effectiveness of the framework in mitigating threats while upholding data privacy. The confidence displayed by this majority supports the argument that federated approaches could be more widely adopted if some initial operational hurdles are resolved.

V. CONCLUSION

The focus of this research was the feasibility, awareness, and organizational preparedness for adopting a Federated Cyber Defense (FCD) framework within multinational enterprises (MNEs). The analysis is based on primary data obtained from a structured questionnaire as well as relevant literature. The results indicate that:

- A notable proportion of respondents are aware of existing cyber threats as well as the currently available defensive measures.
- There is moderate awareness regarding federated learning, which is the backbone of the FCD framework. A significant proportion of respondents support the use of a federated defense system, asserting its effectiveness in maintaining privacy while enhancing threat intelligence sharing..
- Organizational readiness indicators suggest some promise, but not all, suggest some uniformity in readiness gaps and absences in strategic framing alignment in policy, prior work infrastructure, or positional alignment.
- Other Issues of Primary Importance: Complexity of data integration and legal seuority items in the technology jurisdiction. As highlighted in this study, the integrated use of all FCD frameworks can significantly increase cyber primacy and resilience of multinational corporate networks, but within the scope of this study, this important factors of concern must be resolved through policy frameworks, concern about scope and scale, skill training, and collective process frameworks.

ACTIONABLE RECOMMENDATIONS

As such, the following observations of policy gaps with actionable recommendations have been summarized.

- Endowed with the necessary advanced skills, possessing expertise, and with prior orientation in cybersecurity, informatics, higher learning and policy, the proposed structure of the endorsed Cyber F3ED multidisciplinary course should be goal oriented.
- Promote secured joint cross-faculty electronic training conferences building foundational knowledge of cyber federated learning and educational technologies.
- Develop electronic training and certification courses in federated systems for informatics and cyber security professionals for policy oriented application.
- Standardization of privacy protective infrastructures
- Multinational corporate enterprises must implement cross-organizational privacy enhancing and data confidentiality standards allowing for sharing of data streams while maintaining raw data confidentiality.
- There is need to enhance cloud and edge-computing infrastructure to provide for better training for distributed environments.

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