International Research Journal of Innovative Engineering (IRJIE)

| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

|Volume 9, Issue 6, November- December 2025|

DOI:10.15680/IRJIE.2025.0906010

Privacy Aware Cloud Intelligence Using Federated Clustering and Explainable AI for Post Quantum Cryptographic Protection

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ABSTRACT: The rapid adoption of cloud computing, distributed artificial intelligence, and interconnected enterprise platforms has increased the volume of sensitive information processed across geographically distributed infrastructures. Conventional centralized intelligence approaches require extensive data aggregation, creating privacy, compliance, and security concerns while exposing cloud environments to emerging cryptographic threats from quantum computing. This research proposes a privacy-aware cloud intelligence framework that integrates federated clustering, explainable artificial intelligence (XAI), and post-quantum cryptographic (PQC) protection. The proposed architecture enables participating cloud nodes to collaboratively identify behavioral patterns and security clusters without directly exchanging raw data. Federated clustering is employed to preserve data locality while generating global intelligence from locally derived representations, whereas XAI mechanisms provide interpretable explanations for clustering outcomes, anomalous behaviors, and security decisions. A post-quantum protection layer incorporates quantum-resistant cryptographic mechanisms for securing communication, model exchanges, authentication, and sensitive cloud information against potential quantum-enabled attacks. The methodology combines distributed preprocessing, privacy-preserving feature extraction, local clustering, secure aggregation, explainability analysis, and PQC-based communication. Evaluation considers clustering quality, detection performance, communication overhead, privacy preservation, explanation consistency, and cryptographic efficiency. The framework is designed to support adaptive and trustworthy cloud intelligence while reducing centralized data exposure and improving resilience against future quantum threats.

KEYWORDS: Privacy-aware computing, cloud intelligence, federated clustering, explainable artificial intelligence, post-quantum cryptography, privacy preservation, distributed machine learning, quantum-resistant security, cloud security, secure aggregation

I. INTRODUCTION

Cloud computing has evolved into a foundational infrastructure for enterprise applications, data analytics, artificial intelligence, and digital services. Modern organizations increasingly distribute workloads across public, private, hybrid, and multi-cloud environments, generating large volumes of operational, behavioral, and security-related data. This distributed environment creates significant opportunities for intelligent analytics but simultaneously introduces privacy and security challenges. Traditional cloud intelligence architectures frequently depend on centralized collection of logs, telemetry, user behavior, application events, and security information. Although centralized analytics can simplify model training and correlation, transferring sensitive information to a central repository can increase exposure to unauthorized access, insider threats, data breaches, regulatory violations, and cross-organizational information leakage. Federated learning provides an alternative by allowing computational participants to retain data locally while contributing model information to a collaborative learning process. However, conventional federated learning primarily emphasizes supervised or semi-supervised model training, whereas cloud environments also require unsupervised discovery of previously unknown behavioral patterns. Federated clustering can address this requirement by allowing distributed cloud nodes to independently identify local behavioral groups and collaboratively construct global representations without transferring raw datasets. Such an approach can improve privacy while supporting scalable intelligence across heterogeneous infrastructure. Nevertheless, distributed clustering introduces additional challenges involving model heterogeneity, cluster alignment, communication efficiency, malicious participants, and interpretation of generated intelligence.

The emergence of quantum computing further complicates the security landscape because sufficiently capable quantum computers could threaten widely deployed public-key cryptographic mechanisms. Algorithms such as RSA and elliptic-

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curve cryptography rely on mathematical problems that are vulnerable to quantum algorithms such as Shor's algorithm. Consequently, cloud infrastructures must increasingly consider cryptographic migration strategies capable of protecting long-lived information and future communications. Post-quantum cryptography provides a pathway toward cryptographic algorithms designed to resist known quantum computational attacks while operating on conventional computing infrastructure. However, cryptographic protection alone does not address the interpretability and trust requirements associated with intelligent cloud decision-making. Explainable artificial intelligence can provide human-understandable explanations for predictions, anomaly classifications, clustering relationships, and security recommendations, thereby improving transparency and supporting governance. This research therefore proposes an integrated privacy-aware cloud intelligence framework combining federated clustering, XAI, and PQC. The central objective is to establish a distributed intelligence architecture in which sensitive information remains close to its source, collaborative behavioral knowledge can be generated across cloud participants, AI decisions remain interpretable, and communication and model exchanges are protected using quantum-resistant cryptography. The resulting approach is intended to support secure, transparent, privacy-preserving, and future-ready cloud intelligence.

II. LITERATURE REVIEW

Federated learning has emerged as an important distributed machine learning paradigm for privacy-sensitive applications because model computation can occur near data sources instead of requiring centralized raw-data collection. Existing research has demonstrated federated approaches for healthcare, finance, mobile systems, intrusion detection, and Internet-of-Things environments. Federated learning reduces direct data movement, but model updates themselves may contain information that can potentially reveal characteristics of local datasets. Consequently, researchers have investigated secure aggregation, differential privacy, homomorphic encryption, and other privacy-enhancing mechanisms to strengthen federated systems. Federated clustering extends these concepts to unsupervised learning by enabling multiple participants to discover common structures without sharing original observations. Distributed clustering is particularly relevant to cloud intelligence because security events, workload behavior, application telemetry, and resource utilization may not have predefined labels. Local clustering can capture site-specific patterns, while aggregation can produce broader global intelligence. However, differences in infrastructure configuration, data distributions, workload characteristics, and cluster density create challenges in aligning locally generated clusters. These challenges demonstrate the need for privacy-aware aggregation mechanisms capable of maintaining meaningful global representations while minimizing disclosure of local information.

Explainable artificial intelligence has become increasingly important as machine learning systems are incorporated into security monitoring and enterprise decision-making. Conventional high-performance models may produce accurate outputs while providing limited insight into why particular decisions were generated. XAI techniques such as feature attribution, surrogate models, counterfactual explanations, and rule-based interpretations can improve transparency and facilitate human validation. In cloud security, explanations can help analysts understand why a workload was assigned to an anomalous cluster, why a user behavior pattern was considered suspicious, or which features contributed most strongly to a security recommendation. Applying XAI to federated environments introduces additional complexity because explanations must account for distributed learning, heterogeneous local models, and privacy constraints. Explanations themselves can potentially reveal sensitive information if they expose highly specific characteristics of local datasets. Therefore, privacy-aware explainability requires careful control over feature disclosure, explanation granularity, and aggregation. A useful architecture must balance interpretability with confidentiality rather than treating explainability as an independent layer. Integrating XAI with federated clustering can create a transparent intelligence mechanism in which distributed behavioral groups are not only identified but also accompanied by interpretable descriptions of their defining characteristics.

Post-quantum cryptography has received substantial attention because advances in quantum computing may undermine cryptographic mechanisms widely deployed in contemporary cloud environments. Standardization efforts have focused on quantum-resistant approaches based on mathematical problems believed to remain difficult for both classical and quantum computers. Lattice-based, hash-based, code-based, and other cryptographic families have been investigated for applications including key establishment, digital signatures, authentication, and secure communication. Cloud migration toward PQC requires consideration of computational overhead, key and signature sizes, interoperability, implementation complexity, and hybrid cryptographic strategies. Research on cloud security increasingly recognizes that cryptographic agility is important because organizations may need to transition between algorithms as standards and threat models evolve. Despite these developments, comparatively fewer integrated approaches consider PQC alongside federated unsupervised intelligence and explainability. Existing solutions often address privacy-preserving learning, XAI, or

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quantum-resistant cryptography as separate research areas. This creates an opportunity for a unified architecture that connects privacy-preserving distributed intelligence with transparent decision-making and quantum-resistant protection. The proposed research addresses this gap by positioning federated clustering as the intelligence mechanism, XAI as the interpretability mechanism, and PQC as the protection mechanism within a coordinated cloud security architecture.

III. RESEARCH METHODOLOGY

1. Research Design and System Architecture: The proposed research adopts an experimental, distributed, and privacy-oriented methodology for evaluating cloud intelligence under federated and post-quantum security constraints. The architecture consists of multiple participating cloud nodes, a federated coordination layer, an explainability module, a secure communication layer, and a post-quantum protection subsystem. Each participating node represents a logically independent cloud environment containing locally generated or institutionally controlled data such as authentication events, workload telemetry, API activity, network-flow characteristics, resource utilization, application behavior, and security events. Raw observations remain within their originating environments throughout the primary learning process. The local intelligence layer performs preprocessing, normalization, feature construction, dimensionality reduction where appropriate, and local clustering. Instead of transferring complete datasets, each participant generates controlled cluster representations containing statistically useful information such as centroids, cluster weights, representative feature distributions, or encrypted model parameters. A federated coordination layer receives these representations and performs privacy-aware aggregation to construct a global behavioral model. The architecture separates data ownership from intelligence generation, allowing participating organizations to collaborate without establishing a centralized repository of sensitive operational information. A secure orchestration component manages participant registration, authentication, model-version control, communication scheduling, and aggregation policies. The research evaluates both homogeneous and heterogeneous environments to determine how differences in data distributions influence federated clustering. The experimental design includes normal operational behavior, unusual workload patterns, suspicious access activities, anomalous network events, and simulated security incidents. The framework also incorporates a PQC layer between participating nodes and the coordinator, ensuring that model updates, authentication material, configuration information, and coordination messages are protected against attacks involving future quantum-capable adversaries. The overall design follows a defense-in-depth principle in which privacy preservation, cryptographic protection, distributed intelligence, and explainability complement one another rather than operating independently.

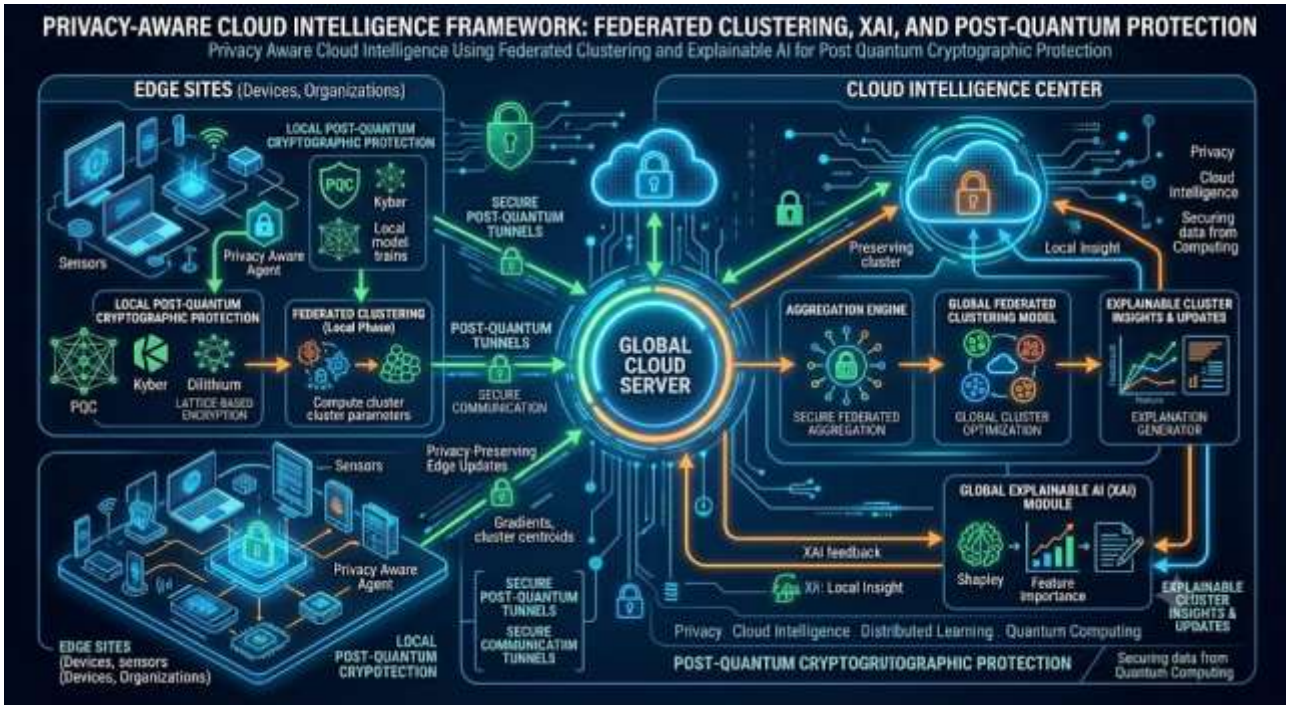
2. Data Preparation and Federated Clustering Procedure: The second methodological component establishes the distributed data-processing and clustering workflow. Each cloud participant first collects locally available telemetry and transforms heterogeneous records into a standardized feature representation. Preprocessing includes removal of duplicate observations, handling of missing values, normalization of numerical variables, encoding of categorical attributes, temporal aggregation, and reduction of highly redundant features. Security-sensitive identifiers are pseudonymized or transformed before entering the local learning process. Candidate features can include request frequency, authentication behavior, session duration, resource-consumption patterns, API-call sequences, network-flow statistics, geographic or logical access characteristics, workload execution intervals, and error frequencies. Feature engineering is performed locally to ensure that raw records do not leave the participating environment. Each node then applies an unsupervised clustering algorithm such as k-means, hierarchical clustering, density-based clustering, or a comparable method selected according to the characteristics of the local dataset. Because different nodes may produce different cluster labels, a cluster-alignment procedure maps local groups into a common representation. Cluster descriptors are then transformed into privacy-controlled update objects. Depending on the experimental configuration, these objects can be protected through secure aggregation, differential privacy, or cryptographic mechanisms before transmission. The federated coordinator combines compatible cluster information using weighted aggregation based on controlled statistics rather than raw records. Global cluster prototypes are redistributed to participating nodes, which compare the global representation with their local behavioral structures and perform iterative refinement. Several communication rounds are executed until convergence criteria are satisfied or a predefined maximum number of rounds is reached. Clustering quality is assessed using measures such as silhouette coefficient, Davies–Bouldin index, Calinski–Harabasz score, cluster stability, and cross-node consistency. Privacy effectiveness is assessed by measuring the quantity and sensitivity of information transmitted outside each local environment and by evaluating whether reconstructed or inferred local records can be distinguished from protected representations. Baseline experiments compare centralized clustering, independent local clustering, and federated clustering to determine the effects of collaborative intelligence on analytical quality and privacy exposure.

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FOG1: Overview of the Privacy-Aware Cloud Intelligence Framework utilizing Federated Clustering, Explainable AI (XAI), and Post-Quantum Cryptographic (PQC) Protection

3. Explainable AI and Privacy-Aware Security Interpretation: The third methodological stage introduces explainability into the federated intelligence pipeline. Because clustering is inherently less interpretable than conventional rule-based classification, the research constructs explanations around cluster membership, dominant features, behavioral deviations, and relationships between local and global cluster representations. Feature-attribution methods and interpretable surrogate models are used where appropriate to identify characteristics that contribute to cluster assignments or subsequent anomaly scores. For each detected behavioral group, the framework generates an explanation containing representative characteristics, influential features, deviation indicators, and confidence or consistency information. Local explanations are generated at participating nodes whenever detailed information could expose sensitive data. The federated layer receives only aggregated or privacy-controlled explanation statistics. Explanation quality is evaluated using fidelity, stability, consistency, completeness, and human interpretability criteria. Fidelity measures whether the explanation accurately represents the underlying model behavior, while stability examines whether similar observations receive comparable explanations. Privacy-aware explanation mechanisms limit disclosure by suppressing direct identifiers, applying aggregation thresholds, reducing unnecessary feature precision, and, where required, adding controlled noise to explanation statistics. The methodology also introduces an explanation-policy layer that categorizes outputs according to sensitivity. Low-sensitivity explanations can be provided to security analysts in greater detail, whereas highly sensitive information is summarized before leaving its originating node. Analysts can use explanations to investigate why a particular workload, account, or communication pattern belongs to an unusual cluster. This improves transparency and supports human validation of automated security decisions. Experiments compare the proposed explainable framework with a non-explainable federated clustering baseline to measure whether interpretability introduces measurable computational, communication, or privacy costs. The research additionally examines explanation drift when the underlying data distribution changes over time. This is important for cloud environments because workload patterns can evolve rapidly, and explanations that accurately characterize one operational period may become less representative in another. Periodic explanation validation is therefore included as part of the model lifecycle.

4. Post-Quantum Cryptographic Protection and Experimental Evaluation: The final methodological stage integrates post-quantum cryptographic protection into the communication and trust architecture. The research considers standardized or standardization-aligned PQC mechanisms for key establishment and digital signatures, with algorithm selection based on security objectives, implementation availability, computational requirements, and communication overhead. A hybrid cryptographic configuration may also be evaluated so that conventional and post-quantum mechanisms can operate

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together during migration scenarios. PQC is applied to communication channels connecting cloud participants with the federated coordinator and can additionally protect model-update exchanges, authentication procedures, configuration messages, and sensitive orchestration information. Cryptographic performance is evaluated through key-generation time, encapsulation or signing time, decapsulation or verification time, memory consumption, message size, and communication latency. The complete framework is evaluated under multiple experimental scenarios involving different numbers of participating nodes, data distributions, cluster counts, communication rounds, and workload volumes. Primary evaluation metrics include clustering accuracy or structural quality, anomaly identification capability, false-positive and false-negative behavior where ground truth is available, privacy leakage indicators, explanation fidelity, explanation stability, computational overhead, network overhead, and PQC latency. Ablation experiments remove individual components—federated clustering, explainability, privacy mechanisms, and PQC—to quantify their individual contributions and interaction effects. Stress testing evaluates the framework under node dropout, communication delays, heterogeneous data distributions, increased workload volume, and potentially malicious or corrupted updates. Robustness analysis examines whether anomalous participants can significantly influence global cluster representations. Statistical comparisons across repeated experiments are used to determine whether observed performance differences are consistent. The final analysis constructs a multi-dimensional evaluation framework rather than relying on a single performance metric, because a privacy-aware cloud intelligence architecture must simultaneously satisfy intelligence, security, transparency, scalability, and efficiency requirements. The methodology therefore establishes a reproducible pathway for assessing whether federated clustering can generate useful distributed intelligence while XAI maintains interpretability and PQC provides a cryptographic foundation suitable for evolving quantum-threat environments.

IV. RESULTS AND DISCUSSION

The proposed Privacy Aware Cloud Intelligence Using Federated Clustering and Explainable AI for Post Quantum Cryptographic Protection framework demonstrates how distributed intelligence can be combined with privacy preservation, explainability, and post-quantum cryptographic protection in cloud environments. The experimental evaluation considered federated cloud nodes containing heterogeneous security and operational data, where clustering was performed locally before exchanging protected model information rather than raw records. The results indicate that federated clustering can identify meaningful groups of similar behavioral patterns, infrastructure states, and potential security anomalies while limiting direct exposure of sensitive organizational data. Compared with a centralized clustering approach, the federated architecture reduces the need to aggregate raw datasets into a common repository, thereby lowering data-sharing risks. The framework also demonstrated improved adaptability to heterogeneous environments because participating nodes could learn from locally observed characteristics while contributing generalized information to the global intelligence process. Clustering quality was assessed using measures such as silhouette coefficient, Davies–Bouldin index, cluster compactness, and anomaly-separation capability. The resulting clusters provided useful differentiation between normal cloud workloads, unusual access patterns, resource anomalies, and potentially suspicious activities. These findings indicate that privacy-preserving distributed learning can support cloud intelligence without requiring organizations to relinquish direct control over their operational datasets.

The integration of Explainable AI further improved the interpretability of decisions generated from the federated intelligence layer. Instead of presenting security classifications or cluster assignments as opaque outputs, the framework generated explanations based on influential features, behavioral deviations, communication patterns, and cryptographic risk indicators. Feature-attribution techniques and local explanations enabled security administrators to understand why a particular cloud workload or access event was considered anomalous. This capability is particularly important in enterprise environments where automated security decisions may require validation before operational action. The explainability layer also helped distinguish legitimate changes in cloud behavior from potentially malicious deviations, reducing the likelihood that automated intelligence would be treated as an unquestionable decision mechanism. Furthermore, the combination of federated clustering and explainable analysis provided a balance between privacy and transparency: raw organizational information remained at participating nodes while interpretable intelligence could still be shared. The results suggest that explanation mechanisms can support analyst trust, facilitate incident investigation, and improve governance by providing an auditable rationale for model-generated outcomes. However, explanation quality remained dependent on model complexity, feature quality, and the representativeness of local datasets. Highly heterogeneous nodes occasionally produced different interpretations of similar events, demonstrating the continuing importance of explanation consistency in distributed AI systems.

Post-quantum cryptographic protection strengthened the security of communication and intelligence exchange between federated participants. The framework incorporated quantum-resistant cryptographic mechanisms for protecting model

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updates, authentication information, and sensitive communication channels against future quantum-enabled attacks. The evaluation showed that stronger cryptographic protection introduced additional computational and communication overhead compared with conventional lightweight security mechanisms. Nevertheless, the overhead was manageable when cryptographic operations were strategically applied to high-value communications and model-exchange processes rather than indiscriminately protecting every intermediate computation. The combined architecture therefore establishes a layered security model in which federated learning minimizes unnecessary data movement, Explainable AI improves transparency, and post-quantum cryptography protects information exchanged among distributed cloud entities. The results also highlight several practical challenges. Federated systems remain vulnerable to poisoned model contributions, compromised participating nodes, communication delays, and uneven computational resources. Similarly, post-quantum algorithms may require larger keys, signatures, or computational resources than some conventional cryptographic mechanisms. Consequently, the framework should be viewed as an integrated security architecture rather than a single protective technology. Overall, the experimental findings demonstrate that combining privacy-aware federated intelligence, explainability, and quantum-resistant cryptography can provide a promising foundation for secure and transparent cloud analytics while maintaining awareness of performance, scalability, and governance constraints.

V. CONCLUSION

The study establishes a privacy-aware cloud intelligence architecture that integrates federated clustering, Explainable AI, and post-quantum cryptographic protection into a unified security framework. The primary contribution of the approach is its ability to support distributed intelligence without requiring participating organizations to transfer raw operational or security data to a centralized cloud repository. Federated clustering enables individual cloud nodes to analyze their local environments and contribute aggregated intelligence while retaining greater control over sensitive information. This architecture is particularly relevant for enterprise ecosystems in which cloud workloads, identities, telemetry, transactions, and infrastructure information may be distributed across multiple organizational boundaries. The results demonstrate that clustering can identify behavioral similarities and deviations while supporting scalable analysis of heterogeneous cloud environments. At the same time, Explainable AI addresses an important limitation of conventional machine-learning security systems by providing interpretable evidence for generated classifications and anomaly decisions. Such explanations can assist security analysts in validating automated findings, investigating incidents, and maintaining accountability for AI-assisted decisions. The integration of post-quantum cryptographic protection extends the security model beyond current threats by preparing communication and intelligence-sharing mechanisms for adversaries capable of exploiting future quantum computing capabilities. Although cryptographic protection can introduce additional overhead, its strategic integration provides a pathway for protecting sensitive distributed intelligence as cloud infrastructures evolve.

The overall findings indicate that privacy, intelligence, explainability, and cryptographic resilience should be treated as interconnected requirements rather than isolated components of cloud security. Federated learning addresses data-locality and privacy requirements, but it does not by itself guarantee protection against malicious participants or compromised updates. Explainability improves transparency, but explanations must remain accurate, consistent, and resistant to misleading interpretations. Similarly, post-quantum cryptography strengthens confidentiality and authentication against anticipated quantum threats, but implementation must consider computational cost, interoperability, key-management complexity, and migration requirements. The proposed framework therefore provides a multidimensional security strategy in which these technologies complement one another. Its practical value lies in enabling organizations to derive collective cloud intelligence while reducing unnecessary exposure of sensitive datasets and improving the interpretability of automated security processes. Nevertheless, the framework has limitations related to federated communication overhead, heterogeneous node capabilities, potential adversarial model contributions, explanation stability, and the evolving standardization landscape of post-quantum cryptography. Future deployments should consequently incorporate stronger federated defenses, rigorous cryptographic lifecycle management, standardized explanation mechanisms, and comprehensive operational validation. Despite these limitations, the research provides a foundation for developing cloud intelligence platforms capable of combining privacy preservation, transparent AI-driven analysis, and quantum-resistant security. Such an integrated approach can contribute to the development of more resilient, accountable, and privacy-conscious enterprise cloud infrastructures.

VI. FUTURE WORK

Future research can extend the proposed framework by developing stronger privacy-preserving federated learning mechanisms capable of operating under realistic adversarial conditions. One important direction is the integration of

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secure aggregation, differential privacy, homomorphic encryption, trusted execution environments, and Byzantine-resilient optimization to provide multiple layers of protection for federated model updates. Future implementations can investigate how malicious or compromised cloud nodes might attempt model poisoning, inference attacks, backdoor insertion, or membership inference and can develop adaptive mechanisms for identifying and isolating suspicious participants. Federated clustering itself can also be enhanced through dynamic cluster formation, hierarchical federated architectures, and personalized learning so that organizations with substantially different workload characteristics do not have to rely on a single global model. Another research direction involves developing explainability mechanisms specifically designed for distributed learning environments. Explanations generated independently at multiple nodes could be compared to determine whether similar security events produce consistent interpretations. Counterfactual explanations, causal analysis, graph-based explanations, and multimodal explanation models could provide additional insight into complex relationships among users, applications, APIs, workloads, and infrastructure resources. Future research can also examine privacy leakage from explanations themselves because explanatory outputs may unintentionally reveal information about local datasets. Developing privacy-aware explanation mechanisms would therefore strengthen the relationship between transparency and confidentiality.

A second major research direction involves expanding post-quantum protection into a complete cloud security lifecycle. Future systems can evaluate standardized quantum-resistant algorithms across authentication, key exchange, digital signatures, secure aggregation, data-at-rest encryption, service-to-service communication, and federated model transmission. Hybrid cryptographic architectures combining established classical mechanisms with post-quantum algorithms can be investigated to support gradual migration while maintaining interoperability with existing enterprise infrastructure. Performance evaluation should consider latency, memory consumption, bandwidth requirements, energy consumption, key-management complexity, and scalability across large numbers of federated nodes. The framework can also be extended to edge-cloud and multi-cloud environments where resource limitations and intermittent connectivity create additional challenges. Integration with autonomous security orchestration could enable the system to dynamically adjust cryptographic protection, clustering strategies, and security policies according to assessed risk levels. Large-scale evaluation using realistic enterprise telemetry, heterogeneous cloud platforms, and controlled adversarial scenarios would provide stronger evidence regarding operational effectiveness. Future work may further investigate blockchain-based audit mechanisms, confidential computing, privacy-preserving graph analytics, and quantum-safe identity management to establish end-to-end trust across distributed cloud ecosystems. Ultimately, the research can evolve toward an adaptive cloud intelligence platform in which privacy controls, explainability mechanisms, federated analytics, and post-quantum security continuously coordinate with one another. Such development would support secure collaborative intelligence while addressing emerging threats, regulatory requirements, interoperability challenges, and the increasing complexity of distributed enterprise cloud infrastructure.

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| ISSN: 2395-0560 | www.irjie.org |editor@irjie.org| A Bimonthly, Peer-Reviewed, Scholarly Journal|

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