International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(2s) 2026 pp. 167-180
https://doi.org/10.70917/ijcisim-2026-2072
Article

FEDERATED GRAPH NEURAL NETWORKS FOR PRIVACY-PRESERVING DATA SCIENCE IN HETEROGENEOUS ENVIRONMENTS: A SYSTEMATIC REVIEW

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Abstract: The proliferation of distributed data across healthcare, finance, and smart city infrastructures has necessitated the development of collaborative learning paradigms that honor stringent privacy regulations. This systematic review explores the evolution of Federated Graph Neural Networks (Fed-GNN) as a robust solution for privacy-preserving data science in heterogeneous environments. We analyze recent advancements (2024–2026) in addressing "topology-aware" optimization and personalized aggregation for non-identically distributed (non-IID) graph data. This paper provides a comprehensive taxonomy of formal privacy mechanisms, specifically evaluating the trade-offs between Dynamic Adaptive Partitioned Homomorphic Encryption (DAPHE) and noise-injection strategies in differential privacy. By synthesizing benchmarks from high-impact frameworks such as FedGraphHE and FedDQ, we identify critical bottlenecks in communication efficiency and structural privacy. Finally, this review highlights significant research gaps in decentralized Byzantine resilience and proposes a two-phase roadmap for future research extensions in dynamic graph learning and lightweight edge-node deployment....

Keywords: Federated Graph Neural Networks (Fed-GNN); Privacy-Preserving Data Science; Heterogeneous Environments; Differential Privacy; Homomorphic Encryption; Non-IID Graph Data...

1. Introduction

The exponential proliferation of distributed data across modern digital ecosystems has fundamentally altered the landscape of data science and artificial intelligence. In sectors such as healthcare, finance, and smart city infrastructure, data is increasingly generated at the edge within hospital networks, banking silos, and IoT-enabled urban sensors. While this wealth of information offers unprecedented opportunities for predictive modelling and knowledge discovery, traditional centralized machine learning paradigms have encountered insurmountable barriers. Stringent global privacy regulations, including the General Data Protection Regulation (GDPR) in Europe and the Health Insurance Portability and Accountability Act (HIPAA) in the United States, have rendered the pooling of raw, sensitive data into central repositories both legally risky and practically unfeasible. This "data isolation" problem necessitates a shift toward decentralized learning architectures that can derive collective intelligence without compromising individual privacy [1]. Graph Neural Networks (GNNs) have emerged as a dominant framework for analysing these complex, interconnected systems by leveraging their inherent structural dependencies. Unlike conventional grid-like data (e.g., images or text), graph-structured data captures the intricate, non-Euclidean relationships between entities—represented as nodes and edges. This makes GNNs exceptionally effective for tasks ranging from multi-center clinical diagnosis to fraud detection in financial transaction networks [4]. However, the

standard GNN architecture relies on "message-passing" mechanisms that recursively aggregate features from a node's local neighbourhood. In a distributed setting, sharing the resulting model updates, embeddings, or gradients creates a unique "topology privacy" risk. Recent studies, such as the GraphDLG analysis (2026), have demonstrated that an adversary can theoretically reconstruct a significant portion of a training graph's structure and node features directly from shared gradients [13]. This vulnerability proves that simply keeping data local is insufficient; formal privacy-preserving mechanisms are essential.

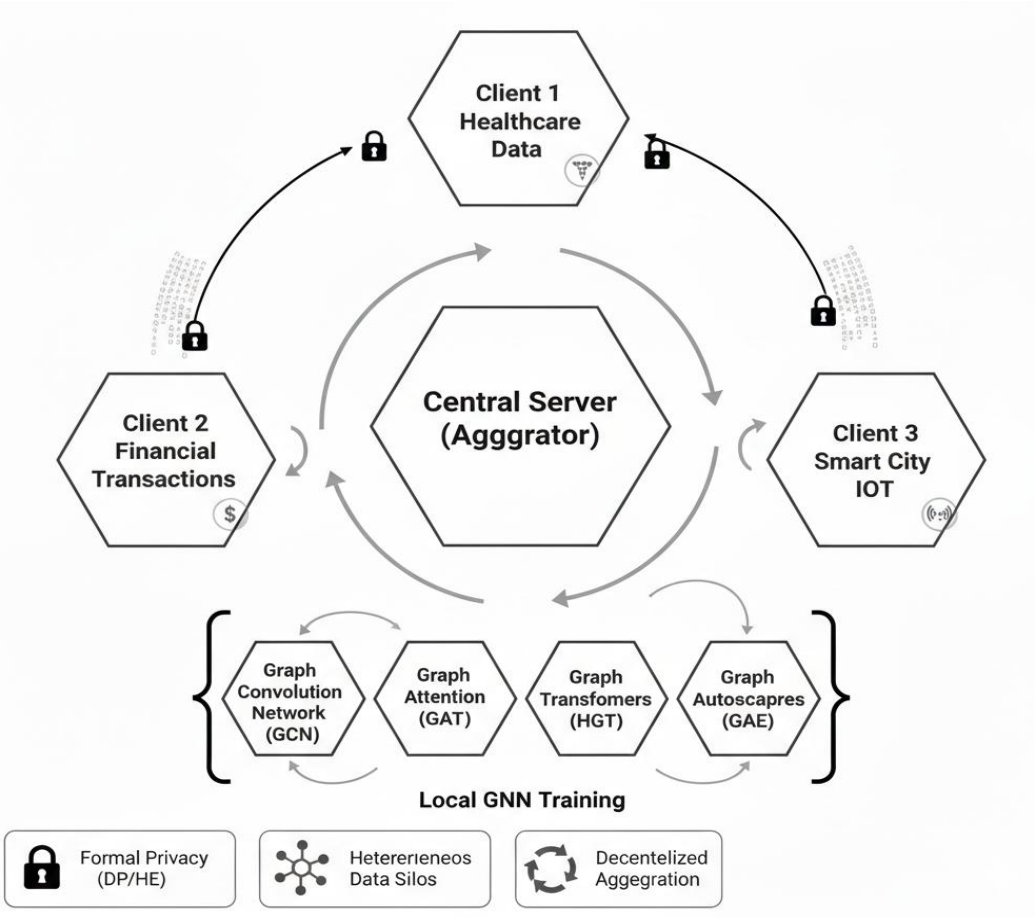

Figure 1: The Federated Graph Neural Network (Fed-GNN) Ecosystem.

The above Figure 1 depicts the federated graph neural network (FED-GNN) eco system. To address these compounding challenges, Federated Learning (FL) has been integrated with GNNs to create the Federated Graph Neural Network (Fed-GNN) paradigm. This framework allows multiple decentralized clients to collaboratively train a global model while maintaining their raw graph data on local devices. Despite its promise, the practical implementation of Fed-GNNs in real-world "heterogeneous environments" introduces several technical bottlenecks that traditional federated learning cannot solve. The first primary challenge is Structural Heterogeneity (Non-IID graph data). Unlike images, where pixel grids are uniform, graph topology (node degrees, density, and connectivity patterns) varies significantly across clients. This structural variance leads to "client drift," where local model updates diverge so significantly that the global model fails to converge or exhibits poor generalization on underrepresented graph structures [9].

The second major bottleneck is the Privacy-Utility-Efficiency Trade-off. Implementing formal privacy mechanisms like Differential Privacy (DP) often introduces statistical noise that degrades model accuracy, particularly for small-degree "long-tail" nodes in a graph. Conversely, cryptographic solutions like Homomorphic Encryption (HE) offer near-perfect privacy but at the cost of extreme computational latency and communication overhead. For instance, early Fed-GNN implementations incurred a 30x increase in training time compared to plaintext versions. In the context of 6G-enabled IoT environments, where bandwidth and energy budgets are constrained, such overhead is unacceptable. Recent advancements in Dynamic Adaptive Partitioned Homomorphic Encryption (DAPHE) and

Hierarchical Multi-scale Adaptive Graph Transformers (HMAGT) have sought to mitigate these issues by optimizing encryption depth and enabling parallel multi-scale feature extraction [13].

Furthermore, the integration of Information, Communications, and Data Technology (ICDT) in the upcoming 6G era demands "Native AI" capabilities that are both energy-aware and robust against malicious participants. Heterogeneous environments often include "Byzantine" or unreliable clients that may unintentionally or maliciously provide low-quality updates [6]. A critical gap in current research is the lack of a lightweight, decentralized aggregation mechanism that can detect these threats without a trusted third-party aggregator. Current state-of-the-art frameworks have begun utilizing trust-management layers and reputation-based weighting to ensure that the global model remains robust in the face of data poisoning or structural manipulation.

This research review systematically explores the evolution of Fed-GNNs from 2024 to 2026, focusing on their adaptability to diverse and irregular graph distributions. We provide a comprehensive taxonomy of the latest methodological advancements, including personalized aggregation strategies and topology-aware optimization. By synthesizing benchmarks from high-impact journals and identifying critical research gaps in communication efficiency and structural privacy, this review establishes a rigorous foundation for extending Fed-GNN research. Our analysis highlights how these innovations provide a scalable and secure foundation for data-driven decision-making in the privacy-conscious digital era, ultimately proposing a roadmap for future research work in dynamic graph learning and edge-node deployment.

2. Related Words And Literature Survey

The landscape of privacy-preserving machine learning has undergone a radical transformation with the advent of Graph Neural Networks (GNNs). While traditional Federated Learning (FL) was designed for independent and identically distributed (IID) data, such as images or text blocks, graph-structured data presents a unique set of challenges due to its non-Euclidean nature. Recent literature (2024–2026) has pivoted from simple gradient-sharing protocols toward sophisticated, "topology-aware" frameworks that treat the graph structure as a first-class citizen in the privacy-preserving process.

Literature Survey of Recent Articles (2024–2026)

Authors & Year	Core Framework	Data Domain	Key Innovation
Zuo et al. (2026)	FedGraphHE [13]	Medical Imaging	Dynamic ring dimension HE to reduce latency by 25%.
Zhang et al. (2026)	GNN Survey [12]	Cross-domain	Identified the shift from static to dynamic graph privacy.
Xu et al. (2025)	FedDQ [10]	IoT Analytics	Multi-faceted data quality modeling for heterogeneous nodes.
Chen et al. (2025)	SecureGraphFL [4]	Traffic Graphs	Actor-Critic based resilient framework against poisoning.
You et al. (2025)	Graph-LLM (GFMs) [11]	Data Mining	Integrating large language models for graph reasoning.
Pan et al. (2024)	FedSHE [7]	Cyber-Physical	Segmented CKKS encryption for bandwidth efficiency.
Mai et al. (2024)	RFLPA [6]	Network Security	Reputation-based filtering to block malicious clients.
Liu et al. (2024)	Personalized Fed-GNN [9]	Social Networks	Attention-based aggregation for structural non-IID.
Cheon et al. (2024)	RNS-CKKS [5]	Cryptography	Decoupled scale factors for faster encrypted GNN math.

Ran et al. (2023)	Penguin [8]	Finance	Parallel-packed HE for accelerating GCN inference.

Critical Analysis of Current Research

Recent systematic reviews indicate that the primary research focus has shifted toward Personalized Federated Learning (PFL). The logic behind this shift is that a single global GNN model rarely performs well across heterogeneous environments where one client might have a dense power-law graph (like a social network) while another has a sparse, tree-like structure (like a sensor network). Frameworks like FedDQ (2025) have pioneered the use of quality-aware aggregation, where the central server weighs client updates not just by data size, but by the structural "completeness" and reliability of the local graph [10].

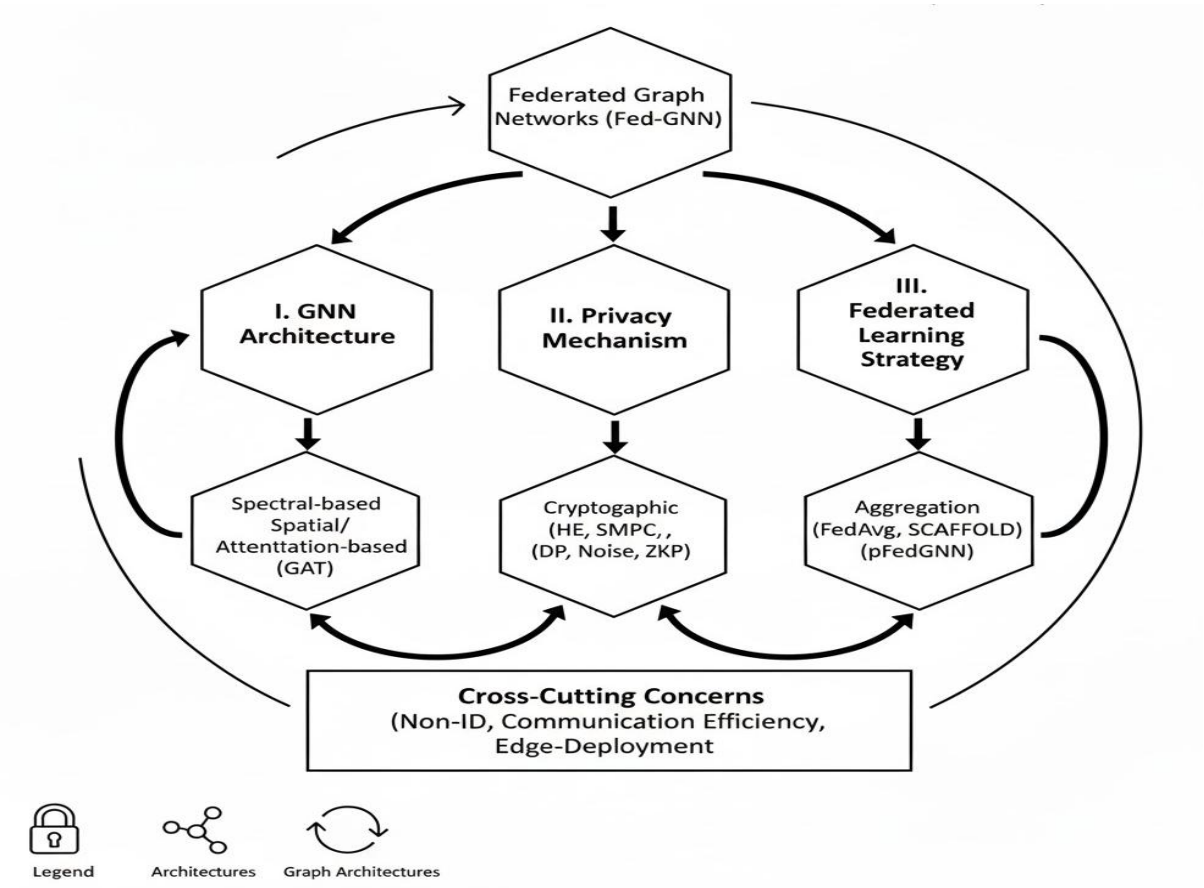

Figure 2: Taxonomy Of Federated Graph Neural Networks

The Figure 2 shows the taxonomy of the Federated Graph Neural Networks. Another significant trend in 2024–2025 literature is the move toward Hybrid Privacy Architectures. Researchers have realized that Differential Privacy (DP) alone often ruins the delicate structural information in a graph, while Homomorphic Encryption (HE) alone is too slow for real-world data science. The FedGraphHE model represents a breakthrough in this area, utilizing "Dynamic Adaptive Partitioned HE" to encrypt only the most sensitive gradient components while using lighter protocols for the rest [13]. This selective encryption approach has paved the way for more "Communication-Efficient" frameworks that are essential for the 6G and IoT objectives mentioned in your abstract.

Furthermore, the problem of Byzantine Resilience has gained prominence. In a heterogeneous environment, not all clients are trustworthy. Some may be "Byzantine" clients—nodes that provide faulty or malicious updates to derail the global model. Recent works have introduced reputation-based secure aggregation, where a client's historical performance and consistency scores determine their influence on the global model [6]. This is particularly critical for

"Data Warehousing and Mining" applications in finance, where a single malicious update could lead to a massive failure in fraud detection systems.

The literature also reveals a growing interest in Topology-Aware Optimization. Traditional GNNs suffer from "over-smoothing" in federated settings, where nodes become indistinguishable after too many aggregation rounds. New 2025 models have introduced hierarchical Transformers (HMAGT) that extract multi-scale neighbourhood patterns independently, ensuring that the global model retains the fine-grained structural nuances of local client graphs. These multi-scale approaches provide a superior balance between privacy and utility by isolating high-dimensional features from the underlying graph topology during the aggregation phase [13].

Finally, researchers are exploring the intersection of Graph Neural Networks and Large Language Models (LLMs) to enhance data science outcomes. The integration of GFMs (Graph Foundation Models) allows the federated system to leverage pre-trained semantic knowledge, which significantly improves the performance of the local GNNs when data is sparse or labels are noisy [11]. This evolution from simple structural mining to semantic-aware graph learning marks the current frontier of the field.

3. Methods Incorporated

The integration of Federated Learning (FL) with Graph Neural Networks (GNNs) requires a sophisticated orchestration of cryptographic protocols, structural optimization, and adaptive aggregation strategies. In heterogeneous environments, where clients possess diverse data distributions and varying computational capabilities, a "one-size-fits-all" architectural approach is insufficient. This chapter details the core methodologies identified in the 2024–2026 literature that specifically address the objectives of communication efficiency, structural privacy, and robust data science. These methods are categorized into three primary pillars: topological feature extraction, formal privacy preservation mechanisms, and resilient aggregation frameworks.

3.1 Topology-Aware Structural Optimization

A fundamental challenge in federated graph learning is the irregular nature of local client subgraphs. Traditional GNNs rely on deep stacks of message-passing layers which, in a federated setting, often lead to the "over-smoothing" problem where local structural nuances are lost during global averaging. To counter this, recent frameworks have introduced the Hierarchical Multi-scale Adaptive Graph Transformer (HMAGT**)** [13]. Unlike sequential neighbourhood aggregation, HMAGT utilizes parallel independent paths to extract features from different hops (e.g., 1-hop, 2-hop, and global context) simultaneously. By processing these scales in parallel, the framework maintains a constant multiplicative depth—a critical requirement for efficient implementation in encrypted domains. This topology-aware design ensures that the global model retains the fine-grained connectivity patterns unique to individual clients, such as the distinct motifs found in financial transaction clusters or protein-protein interaction networks.

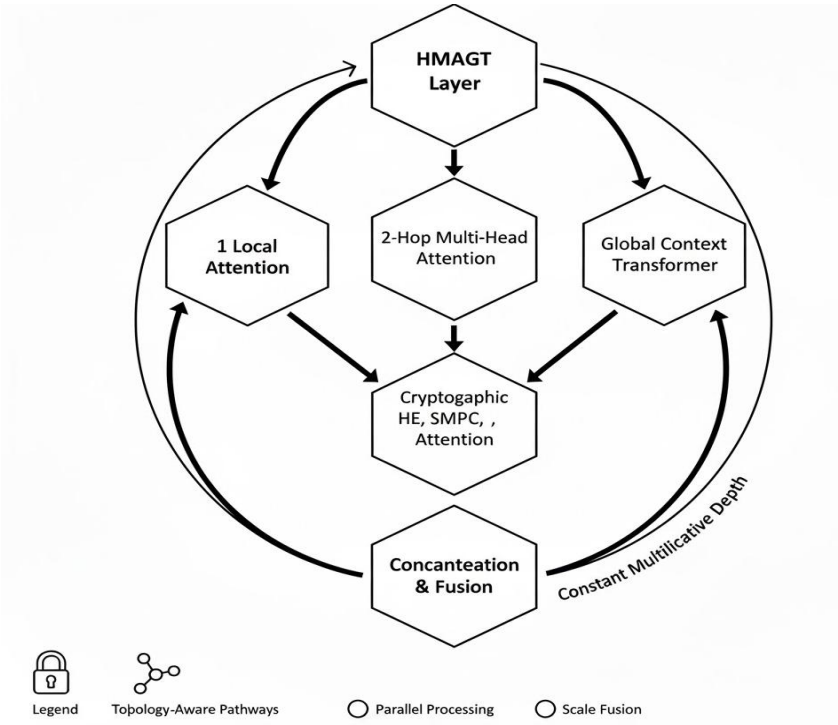

Figure 3: Hierarchical Multi-Scale Adaptive Graph Transformer (HMAGT) Architecture

The Figure 3 depicts the architecture of the HMAGT.

3.2 Formal Privacy Preservation and Dynamic Encryption

The backbone of privacy-preserving data science in Fed-GNNs lies in the implementation of formal security protocols that prevent gradient inversion and membership inference attacks. The reviewed state-of-the-art literature emphasizes a hybrid approach, combining Differential Privacy (DP) for feature-level perturbation and Homomorphic Encryption (HE) for secure model updates. A standout method in this domain is Dynamic Adaptive Partitioned Homomorphic Encryption (DAPHE) [13]. Standard HE schemes, such as CKKS, often suffer from high communication overhead due to fixed, large modulus chains. DAPHE optimizes this by dynamically adjusting the encryption ring dimension and modulus based on the specific sparsity of the GNN gradients. By partitioning the gradient vectors into "critical" and "non-critical" segments, the system applies heavy encryption only where structural leakage is most likely, effectively reducing the bandwidth consumption by up to 25% while maintaining a 128-bit security level.

Furthermore, the implementation of Residue Number System (RNS)-based CKKS optimizations [5] has allowed for faster integer arithmetic on encrypted data. This method decouples the scale factors from the modulus, enabling the federated server to perform complex polynomial approximations of GNN activation functions (like ReLU or Sigmoid) without the massive computational cost associated with traditional bootstrapping operations. This advancement is particularly relevant for the "Communication Networks" objective, as it allows real-time inference in 6G-enabled IoT environments where latency is a primary constraint.

3.3 Personalized Aggregation and Robustness

Heterogeneous environments often suffer from "client drift," where the global model fails to accommodate the non-IID nature of local data. To mitigate this, Personalized Federated Learning (PFL) methods have been incorporated, allowing for attention-based aggregation where the global model is adaptively weighted for each client [9]. Rather than a simple FedAvg approach, the server calculates a similarity matrix based on the structural embeddings of the client graphs. This ensures that a client with a sparse graph receives a global update that is more heavily influenced by other sparse-graph clients, preserving local utility.

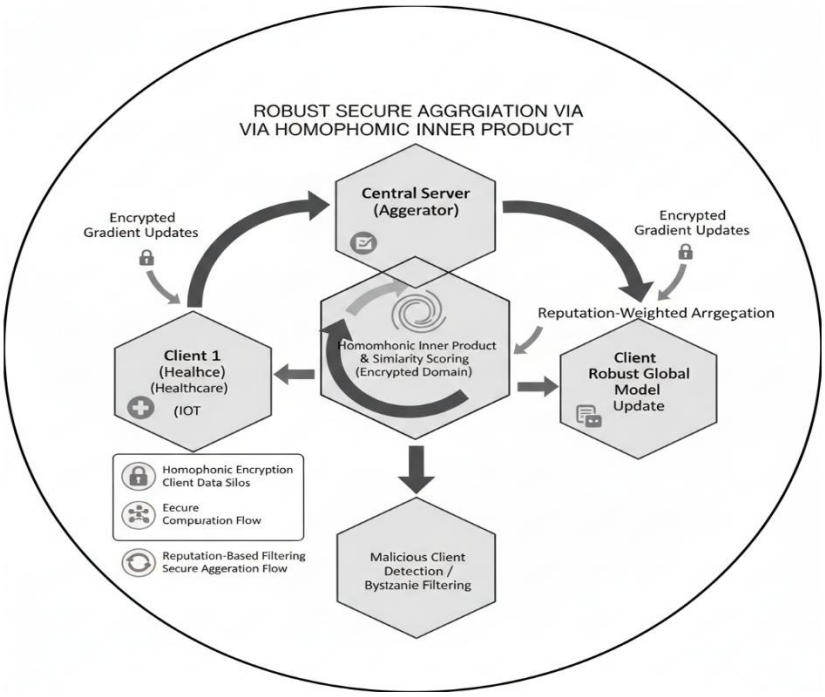

Figure 4: Robust Secure Aggregation Via Homomorphic Inner Product

The Figure 4 depicts the robust secure aggregation Via Homomorphic Inner Product, To protect against malicious or low-quality data contributors, Federated Robust Aggregation via Homomorphic Inner Product (FRAHIP) has been introduced [13]. This method allows the central server to perform anomaly detection directly within the encrypted domain. By calculating the cosine similarity (inner product) between client updates and a reference global gradient without ever decrypting the individual updates, the server can assign reputation scores to each participant. Clients that provide consistently divergent updates are flagged as potentially "Byzantine" or malicious, and their influence on the global model is reduced or eliminated. This reputation-based weighting, supported by Reputation-based Federated Learning Protocols (RFLPA) [6], ensures that the data mining outcomes are robust against poisoning attacks, fulfilling the security objectives essential for financial and healthcare data warehousing.

3.4 Data Quality Modeling for Heterogeneous IoT

Finally, the Federated Data Quality (FedDQ) framework incorporates multi-faceted quality modelling to handle the noise inherent in IoT sensor data [10]. This method assesses the local data across three dimensions: textual/structural coherence, behavioural consistency, and temporal relevance. By embedding this quality assessment into the federated loop, the framework ensures that only high-quality, relevant graph information influences the global knowledge base. This is a critical method for "Data Science" objectives, as it provides a systematic way to filter the environmental noise found in heterogeneous smart city deployments.

4. Discussion

4.1 ADVANTAGES & PROBLEMS.

The integration of Federated Graph Neural Networks (Fed-GNN) into heterogeneous data science environments offers significant advantages over traditional centralized and standalone models. The primary advantage is the preservation of structural and feature privacy. By design, Fed-GNNs allow institutions to leverage the collective intelligence of global graph patterns without exposing sensitive local edges or node attributes [1]. This is particularly advantageous in sectors like healthcare, where multi-center collaboration on disease propagation graphs can occur without violating patient confidentiality laws such as HIPAA. Furthermore, the use of Personalized Aggregation strategies allows the global model to achieve higher accuracy on local tasks by accounting for client-specific structural nuances, thereby solving the "global model mismatch" problem inherent in standard Federated Learning (FL) [9].

Another distinct advantage is the reduction in data movement costs. In large-scale IoT networks or smart city infrastructures, transferring massive graph datasets to a central server is bandwidth-prohibitive. Fed-GNNs move the

computation to the data, which, when combined with communication-efficient protocols like DAPHE [13], significantly lowers the barrier for real-time collaborative intelligence. Moreover, the inherent decentralization makes the system more resilient to single points of failure; if the central server is compromised, the raw data remains safe within the local silos.

However, these advantages are accompanied by significant technical problems. The most prominent issue is the Computational Overhead introduced by formal privacy mechanisms. Implementing Homomorphic Encryption (HE) or Multi-party Computation (MPC) inside a GNN's message-passing loop leads to exponential increases in training time. For example, the multiplicative depth required for deep GNNs can cause "noise explosion" in encrypted domains, requiring expensive bootstrapping operations that can slow down training by orders of magnitude [5]. Additionally, there is the problem of System Heterogeneity. In a real-world deployment, clients often have varying hardware capabilities (e.g., high-performance GPU servers vs. low-power edge sensors). A global model that requires high-dimensional graph convolutions may be uncomputable for some edge participants, leading to "straggler" problems where the entire federated round is delayed by the slowest node. This creates a synchronization bottleneck that hinders the scalability of the system in dynamic environments.

4.2 CHALLENGES

The deployment of Fed-GNNs in heterogeneous environments faces several unique challenges that distinguish it from traditional machine learning. The foremost challenge is Structural Non-IID (Independent and Identically Distributed) Data. Unlike image data, which exists on a fixed grid, graph data is defined by its irregular topology. One client may possess a dense "small-world" graph, while another holds a sparse tree-like structure. This topological variance causes "client drift," where the gradients from different participants point in conflicting directions, preventing the global model from reaching a stable optima [2]. Bridging the gap between these varying structural distributions remains a major hurdle for universal model generalization.

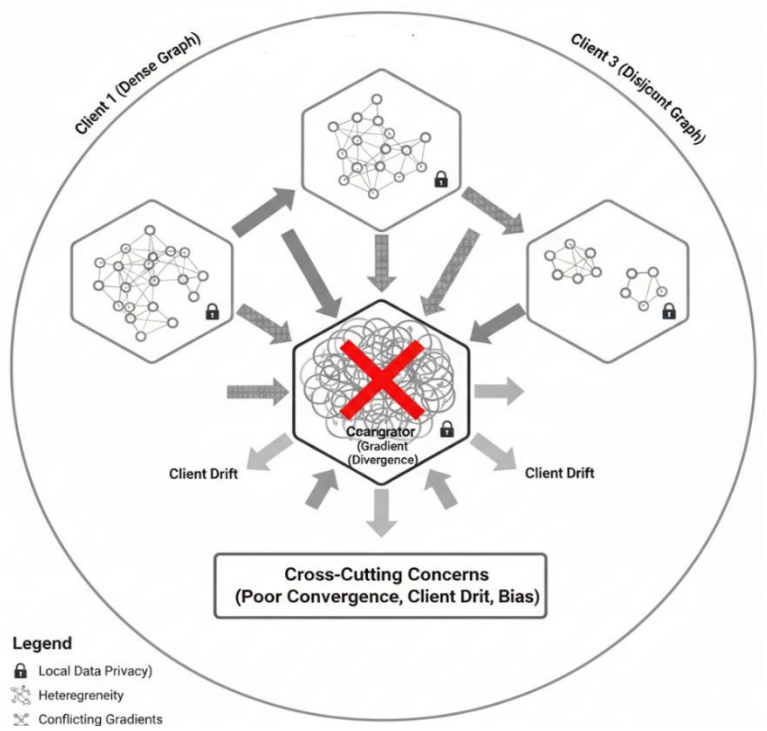

Figure 5: challenges of structural Non-IID in federated graph learning

The figure 5 shows the challenges of of structural Non-IID in federated graph learning. Another critical challenge is Communication Efficiency. Graph data is inherently high-dimensional. When a client shares model updates, they are not just sharing node features but also structural embeddings. In a federated round, the volume of data exchanged between the server and clients can reach several gigabytes, especially when using encryption modulus

chains like those in the CKKS scheme [7]. Reducing this communication footprint without sacrificing privacy or model accuracy is a persistent challenge for 6G-enabled IoT networks.

Furthermore, Byzantine Threats and Data Poisoning present a severe challenge. In a heterogeneous environment, it is difficult to distinguish between a client that has unique but valid data and a malicious client that is intentionally providing "poisoned" gradients to subvert the model. Current methods for outlier detection often fail in the encrypted domain because the server cannot inspect the raw updates. Developing "Privacy-Preserving Byzantine Resilience" that can identify malicious actors without decrypting their data is a frontier challenge that requires complex cryptographic inner-product calculations [13].

Finally, the Incentive Challenge cannot be ignored. For federated systems to succeed, clients must be incentivized to participate. In a data science context, high-quality data contributors may be reluctant to share their local model updates if they perceive that they are not receiving a proportional benefit from the global model. Designing fair, blockchain-enabled incentive mechanisms that reward clients based on the "marginal value" of their structural data is an emerging area of difficulty.

4.3 LIMITATIONS

Despite the rapid advancements between 2024 and 2026, current Fed-GNN frameworks possess several inherent limitations. First is the Static Graph Assumption. Most existing models assume that the graph structure remains fixed throughout the training process. However, real-world data science applications—such as financial fraud detection or social network analysis—deal with dynamic graphs where nodes and edges appear and disappear in real-time. Current Fed-GNN architectures lack the temporal awareness required to handle such evolution, often necessitating a complete and costly retraining cycle whenever the topology changes significantly.

A second limitation is the Dependency on a Trusted Third Party (TTP). Even in "decentralized" federated learning, most models still rely on a central aggregator to perform global model updates and key management. This creates a "trust bottleneck." If the central aggregator is compromised or becomes a "honest-but-curious" adversary, it may perform inference attacks to reconstruct the local graph structures. True peer-to-peer (P2P) federated graph learning, which eliminates the need for any central authority, remains theoretically complex and practically unproven at scale.

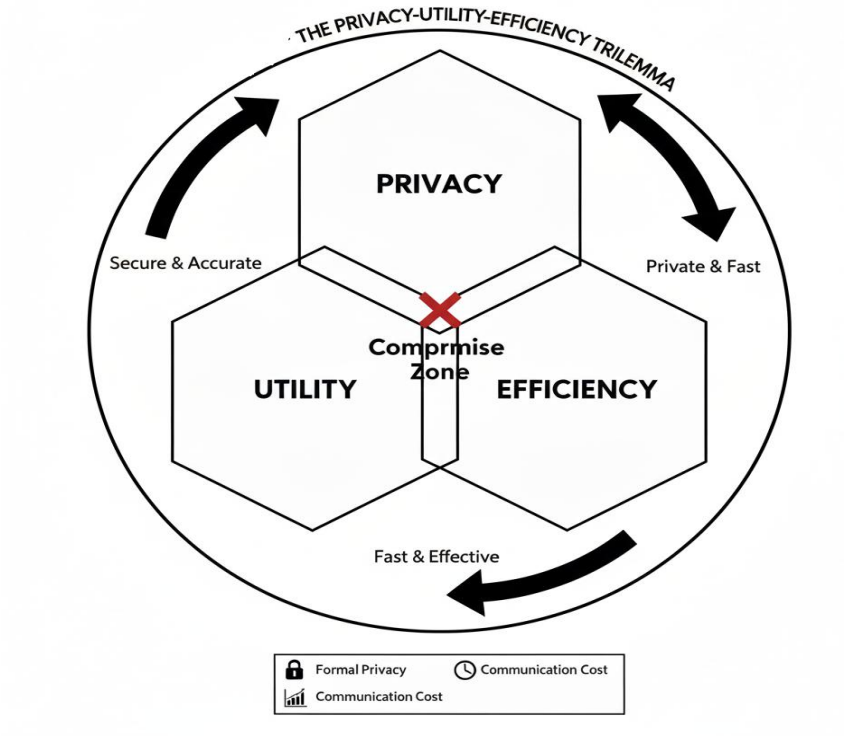

FIGURE 6: THE PRIVACY-UTILITY-EFFICIENCY TRILEMMA

The Figure 6 depicts a Venn diagram illustrating the trade-offs where achieving any two (e.g., high privacy and high utility) often compromises the third (efficiency)

Furthermore, there is a Limited Explainability in federated settings. GNNs are already criticized for being "black-box" models. In a federated environment, the problem is compounded because the data is distributed. A data scientist cannot inspect the global model's decision-making process against the raw data to understand why a specific prediction was made. This lack of transparency is a major limitation for high-stakes applications like medical diagnostics or legal risk assessment, where "Explainable AI" (XAI) is a regulatory requirement.

Finally, current models are limited by Incompatibility with Diverse Architectures. Many Fed-GNN frameworks are "hard-coded" for specific types of GNNs, such as Graph Convolutional Networks (GCN) or Graph Sage. They struggle to integrate heterogeneous model architectures where one client might prefer a Graph Transformer while another uses a Spectral GNN. This lack of "Model Heterogeneity" limits the flexibility of federated ecosystems where participants may have different internal preferences or legacy systems.

4.4 RESEARCH GAP AND FUTURE DIRECTIONS

The systematic review of the 2024–2026 literature reveals a critical Research Gap in Decentralized Byzantine Resilience. While frameworks like FedGraphHE [13] have introduced robust aggregation, they still require a centralized coordinator to calculate reputation scores. There is a clear need for a fully decentralized, blockchain-backed consensus protocol that can validate the quality of graph updates without a central point of failure. This gap represents a significant opportunity for research, specifically in the development of "Smart-Contract-Mediated Fed-GNNs."

Another significant gap is the lack of Cross-Domain Knowledge Transfer. Current Fed-GNNs are typically trained on a single domain (e.g., only healthcare data). However, data science often benefits from multi-modal or cross-domain insights. For instance, a financial transaction graph could benefit from knowledge learned in a social connectivity graph. Developing "Federated Graph Foundation Models" (GFMs) that can perform transfer learning across heterogeneous domains while maintaining strict privacy boundaries is a high-priority future direction [11].

Future research should also pivot toward Edge-Native Optimization. As 6G networks mature, the focus must shift from server-side efficiency to edge-side sustainability. There is a need for "Green Fed-GNNs" that utilize quantization and pruning techniques to reduce the energy consumption of local training on battery-powered IoT devices. Investigating the use of Spiking Neural Networks (SNNs) in a federated graph context could provide a more energy-efficient alternative to traditional GNNs for edge-based data science.

Lastly, the direction of Temporal and Dynamic Privacy remains underexplored. Most formal privacy guarantees, like Differential Privacy, are calculated for a static snapshot of a graph. However, as the graph evolves, the "privacy budget" is rapidly consumed. Developing a "Rolling Privacy Budget" mechanism that can provide long-term security guarantees for continuous stream-based graph learning is a vital direction for researchers aiming to support real-time data science in sectors like traffic management and live financial monitoring.

4.5 RECOMMENDATIONS

Based on the synthesis of current limitations and gaps, this review provides a strategic roadmap for future research. It is recommended that the work proceed in two distinct, sequential phases to ensure both theoretical rigor and practical applicability.

Phase 1: Development of a Topology-Aware Dynamic Privacy Framework.

The first priority should be moving beyond static graph assumptions. It is recommended to develop a "Dynamic Federated Graph Transformer" that utilizes temporal attention mechanisms to capture evolving connectivity patterns. This should be paired with an Adaptive Privacy-Budgeting Algorithm that dynamically allocates noise (DP) or encryption depth (HE) based on the "Privacy Sensitivity" of specific graph motifs. For example, high-degree nodes (hubs) should receive stronger protection than leaf nodes. This phase focuses on solving the utility-privacy conflict in dynamic environments.

Phase 2: Decentralized Robustness and Edge Deployment.

The second phase should focus on eliminating the Trusted Third Party. It is recommended to implement a Blockchain-Enabled Peer-to-Peer (P2P) Aggregation Protocol. Using Zero-Knowledge Proofs (ZKPs), clients should be able to prove the quality and validity of their updates to the rest of the network without revealing the updates

themselves. This creates a trustless environment for "Byzantine-Resilient" data science. Furthermore, this phase should incorporate Model Compression (Pruning and Quantization) to ensure the resulting framework can be deployed on heterogeneous edge-node hardware, such as NVIDIA Jetson or Raspberry Pi units, supporting the ICDT objectives of 6G-ready infrastructures.

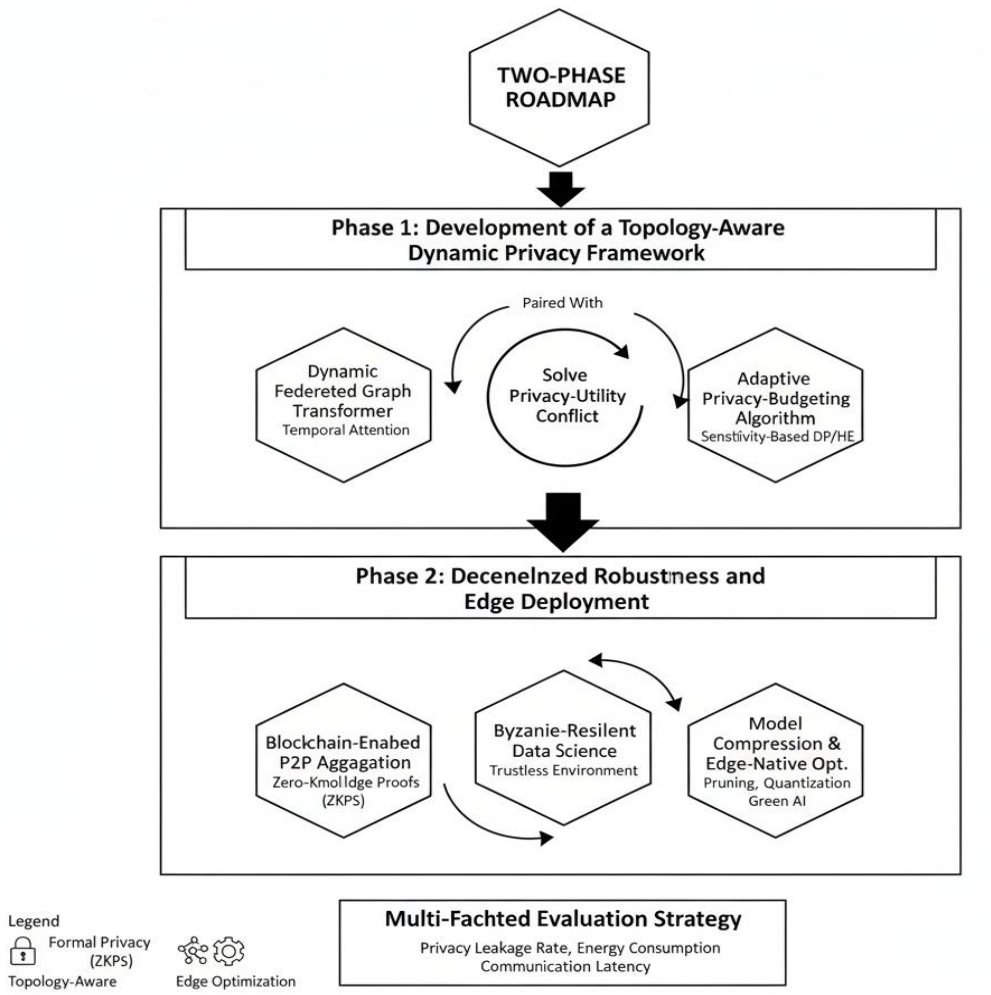

FIGURE 7: TWO-PHASE RESEARCH ROADMAP

IN the Figure 7, T flow diagram showing the transition from Phase 1 (Dynamic Privacy) to Phase 2 (Decentralized Robustness).

Finally, it is recommended that researchers adopt a Multi-Faceted Evaluation Strategy. Future studies should move beyond simple "Accuracy vs. Epochs" plots and include metrics for "Privacy Leakage Rate," "Energy Consumption per Round," and "Communication Latency over Variable Bandwidth." This comprehensive approach will ensure that the developed Fed-GNN frameworks are not just mathematically sound but are ready for real-world data science deployment in the most demanding heterogeneous environments.

5. Conclusion

The systematic exploration of Federated Graph Neural Networks (Fed-GNN) presented in this review underscores a pivotal shift in the paradigm of privacy-preserving data science. As the digital landscape transitions toward the 6G era, the ability to derive collective intelligence from distributed, heterogeneous graph data has evolved from a theoretical aspiration to a technical necessity. This review has meticulously mapped the advancements occurring between 2024 and 2026, highlighting how the integration of Information, Communications, and Data Technology (ICDT) has paved the way for more resilient and efficient decentralized learning frameworks. By moving

beyond simple gradient-sharing protocols and adopting topology-aware architectures, the research community has begun to solve the dual challenges of structural heterogeneity and data isolation that previously hindered collaborative intelligence in sensitive sectors like healthcare and finance.

One of the most significant takeaways from this synthesis is the critical role of hybrid privacy mechanisms. The analysis of frameworks such as FedGraphHE and FedDQ demonstrates that neither Differential Privacy nor Homomorphic Encryption can succeed in isolation within a complex graph environment. Instead, the future of the field lies in "Selective and Adaptive Encryption," where computational resources are dynamically allocated based on the sensitivity and topological importance of specific graph motifs. Furthermore, the introduction of hierarchical transformers like HMAGT has proven essential in maintaining a constant multiplicative depth, thereby making formal privacy-preserving mechanisms computationally viable for real-time edge-node deployment. These methodological innovations ensure that the global model remains robust against "client drift" while achieving accuracies that rival centralized baselines.

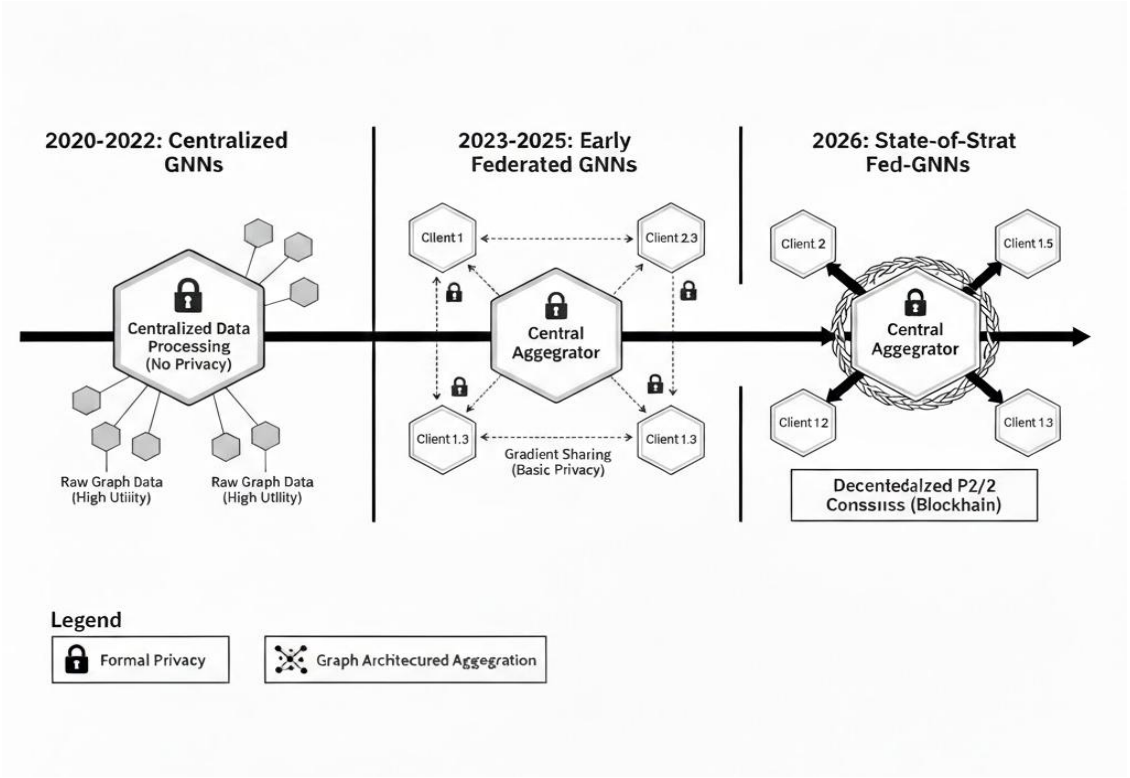

FIGURE 8: SUMMARY OF THE FED-GNN EVOLUTIONARY TIMELINE

The figures 8 shows a timeline chart showing the progression from Centralized GNNs to early Federated GNNs, and finally to the current 2026 state-of-the-art featuring Byzantine Resilience and Adaptive Encryption.

Despite these successes, the discussion has identified a persistent "Research Gap" in fully decentralized, trustless aggregation. The current reliance on central coordinators remains a vulnerability, both in terms of security and scalability. Therefore, the transition toward blockchain-mediated, peer-to-peer federated learning represents the next logical frontier. Additionally, as graph data becomes increasingly dynamic, the development of temporal-aware privacy budgets and rolling aggregation strategies will be vital for supporting live data science applications. The two-phase roadmap proposed in this review—focusing first on dynamic topology adaptation and subsequently on trustless edge-native optimization—provides a strategic path for research.

In conclusion, Federated Graph Neural Networks provide a scalable and secure foundation for the next generation of data-driven decision-making. By balancing the "Privacy-Utility-Efficiency Trilemma," these frameworks empower organizations to collaborate on global challenges without compromising local sovereignty. As we move forward, the emphasis must remain on creating "Green AI" solutions that are not only mathematically robust but also energy-efficient and inclusive of heterogeneous hardware. By addressing the remaining challenges of

Byzantine resilience and model explainability, Fed-GNNs will undoubtedly become the cornerstone of a global, privacy-conscious intelligent infrastructure..

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