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Federated Learning in the Era of Data Privacy: An Exhaustive Survey of Privacy Preserving Techniques, Legal Frameworks, and Ethical Considerations

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Abstract
Federated Learning (FL) has emerged as a transformative approach to decentralized machine learning, enabling model training across multiple devices without centralizing sensitive data. While FL inherently supports privacy, growing concerns around data security, regulatory compliance, and ethical accountability have led to the development of advanced privacy preserving mechanisms. This systematic review, conducted in adherence with PRISMA guidelines, explores the landscape of privacy enhancing techniques, legal regulations, and ethical implications associated with Federated Learning. We sourced peer reviewed literature from 2016 to 2024 across major scientific databases, including IEEE Xplore, SpringerLink, and ACM Digital Library. The review identifies and categorizes approaches such as Differential Privacy, Homomorphic Encryption, and Secure Multi party Computation. We further evaluate the alignment of FL practices with legal standards such as GDPR, HIPAA, and CCPA, and highlight ethical considerations including fairness, transparency, and user consent. Our analysis reveals critical gaps in interdisciplinary integration, particularly the need for frameworks that simultaneously meet technical robustness, legal compliance, and ethical accountability. We propose directions for future research, emphasizing a holistic approach that incorporates multi stakeholder engagement to realize trustworthy and scalable FL systems.

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1. Introduction

In the digital age, the proliferation of data has been both a boon and a challenge for machine learning (ML). Traditional centralized ML approaches necessitate aggregating vast amounts of data into a single repository, raising significant concerns about data privacy, security, and compliance with regulations. These concerns have spurred the development of alternative learning paradigms that prioritize data privacy. Federated Learning (FL) has emerged as a promising solution to these challenges. Introduced by McMahan *et al*. in 2017 [3], FL enables multiple clients (e.g., mobile devices, organizations) to collaboratively train a shared global model while keeping their data localized. This decentralized approach not only mitigates privacy risks associated with data centralization but also reduces communication overhead and latency. Despite its decentralized nature, FL is not inherently immune to privacy threats. Adversaries can exploit model updates to infer sensitive information, leading to potential data leakage. To counteract these threats, various privacy preserving techniques have been integrated into FL frameworks. Differential Privacy (DP) introduces statistical noise to model updates, providing quantifiable privacy guarantees. Secure Multi Party Computation (SMPC) allows multiple parties to jointly compute a function over their inputs while keeping those inputs private. Homomorphic Encryption (HE) enables computations on encrypted data without decryption, ensuring data confidentiality throughout the process. Each of these techniques offers unique advantages and trade offs in terms of computational overhead, accuracy, and security. The deployment of FL intersects with various legal frameworks designed to protect individual privacy rights.

The General Data Protection Regulation (GDPR) in the European Union emphasizes data minimization and user consent, aligning well with FL's decentralized approach. Similarly, the Health Insurance Portability and Accountability Act (HIPAA) in the United States sets standards for protecting sensitive patient data, which is particularly relevant for FL applications in healthcare.

However, compliance with these regulations requires more than just decentralization. FL systems must incorporate mechanisms for data subject access, rectification, and erasure, as mandated by GDPR. Moreover, the lack of standardized guidelines for FL specific compliance poses challenges for organizations seeking to adopt this technology.

Beyond legal compliance, FL raises several ethical considerations. The heterogeneity of data across clients can lead to biased models if not properly addressed, potentially exacerbating existing inequalities. Transparency and accountability are also critical, as the complexity of FL systems can obscure decision making processes, making it difficult to audit and explain outcomes.

Furthermore, the voluntary participation of clients in FL necessitates informed consent and a clear understanding of how their data contributes to the global model. Ensuring that participants are adequately informed and that their autonomy is respected is essential for the ethical deployment of FL.

Given the multifaceted nature of FL, this systematic review aims to:

1. Examine the state of the art privacy preserving techniques integrated into FL frameworks, analyzing their effectiveness and limitations.
2. Analyze the legal frameworks relevant to FL, assessing how current regulations impact its deployment and identifying areas where FL aligns with or diverges from legal requirements.
3. Explore the ethical considerations associated with FL, highlighting challenges related to fairness, transparency, and participant autonomy.

By synthesizing existing literature across these domains, this review seeks to provide a comprehensive understanding of the current landscape of FL, identify gaps in research and practice, and propose directions for future work.

2. Background / Theoretical Framework

Federated Learning (FL) has emerged as a revolutionary paradigm in the field of machine learning, addressing critical privacy challenges associated with the traditional centralized approach. In conventional machine learning systems, large volumes of data are collected from end users and processed on centralized servers, which poses significant risks in terms of data breaches, unauthorized access, and privacy violations. In contrast, FL decentralizes the training process by allowing data to remain on the client side while only model updates, such as gradients or weight changes, are transmitted to a central server for aggregation (Kairouz *et al*., 2019) [20]. This fundamental shift is not only a technical advancement but also a response to increasing societal and regulatory demands for privacy preserving technologies.

The theoretical roots of FL can be traced back to distributed machine learning (DML), which traditionally focused on leveraging multiple nodes to parallelize computations and improve scalability. However, DML systems often required data partitioning and distribution across nodes, thereby not fully addressing privacy concerns. FL builds upon and extends these foundations by introducing a privacy aware structure that minimizes the movement of sensitive data. The concept was notably formalized by Google researchers, who demonstrated the feasibility of training models on user devices without compromising personal data (McMahan *et al*., 2017) [3]. This shift in focus from performance optimization to privacy preservation marked a pivotal moment in the evolution of machine learning theory and practice. Despite the promise of FL in enhancing data privacy, it is not inherently immune to security threats. Researchers have identified multiple vulnerabilities in FL systems, including the possibility of reconstructing private data from shared gradients or exploiting model updates to infer sensitive information (Lyu *et al*., 2020) [2]. As a result, the field has seen a surge in the development of privacy preserving techniques specifically tailored to FL. Differential Privacy (DP) is among the most widely adopted methods, wherein carefully calibrated noise is added to the model updates to obfuscate individual data contributions (Dwork, 2006) [7]. DP provides mathematical guarantees against re identification, thus reinforcing user privacy while maintaining model utility. Another prominent approach to enhancing privacy in FL is Secure Multi Party Computation (SMPC). This cryptographic technique enables multiple entities to jointly compute a function without revealing their individual inputs. In the context of FL, SMPC is utilized to perform secure aggregation of model updates, ensuring that no single participant or server can access the raw updates from others (Bonawitz *et al*., 2017) [3]. Complementary to SMPC is Homomorphic Encryption (HE), which allows computations to be performed directly on encrypted data. HE enables the central aggregator in an FL system to combine model updates without decrypting them, thereby preserving confidentiality throughout the process (Acar *et al*., 2018) [1]. Although computationally intensive, HE provides a robust solution to privacy preservation when implemented effectively.

The legal implications of FL are equally significant and multifaceted. The adoption of FL intersects with various data protection regulations, most notably the General Data Protection Regulation (GDPR) in the European Union. GDPR mandates strict controls over the collection, processing, and storage of personal data, emphasizing principles such as data minimization, purpose limitation, and user consent. FL's decentralized architecture aligns well with these principles, as it inherently limits data movement and reduces the attack surface for breaches (Nguyen *et al*., 2020). Similarly, the Health Insurance Portability and Accountability Act (HIPAA) in the United States governs the handling of healthcare data and has implications for FL applications in medical diagnostics and patient record analysis. Nevertheless, legal compliance in FL is not guaranteed by decentralization alone. Ensuring that FL systems provide mechanisms for data access, correction, and erasure as required under GDPR remains a complex challenge, particularly in large scale deployments.

Beyond legal frameworks, FL introduces a host of ethical considerations that must be addressed to ensure responsible and equitable use. One of the foremost concerns is algorithmic bias. Due to the non-independent and identically distributed (non IID) nature of data across clients, FL models may become biased toward certain user groups, especially those contributing more frequent or voluminous updates (Zhao *et al*., 2020) [44]. This imbalance can lead to unfair

outcomes, particularly in sensitive applications such as healthcare or finance. Moreover, the opaque nature of model aggregation and update mechanisms in FL systems can hinder transparency and accountability. Users and regulators may find it difficult to trace how specific decisions were made, complicating efforts to audit and explain system behavior (Li *et al*., 2019). Another ethical dimension relates to user autonomy and informed participation. Since FL relies on user devices for training, ensuring that users are fully informed about the nature and extent of their participation is crucial. This includes clear communication about what data is used, how it is processed, and what risks are involved. Additionally, the energy and resource consumption on user devices during FL processes must be considered, as this could disproportionately affect users with less powerful hardware or limited data plans (Kairouz *et al*., 2019) [20]. Ethically responsible FL systems must, therefore, incorporate opt in mechanisms, usage monitoring, and fairness aware training protocols to maintain trust and inclusivity.

Federated Learning has demonstrated significant potential in practical applications across multiple domains. In the healthcare sector, FL facilitates collaborative model training on sensitive patient data distributed across hospitals and clinics without compromising data privacy. For instance, FL has been employed in developing predictive models for COVID 19 and other diseases using decentralized medical datasets (Rieke *et al*., 2020) [32]. In the financial industry, FL enables institutions to collaborate on fraud detection and credit scoring models while preserving client confidentiality (Yang *et al*., 2019). Furthermore, the proliferation of smart devices and the Internet of Things (IoT) has provided fertile ground for the deployment of FL at scale. By enabling on device learning for applications such as keyboard prediction and voice recognition, FL supports personalization without compromising user data (Hard *et al*., 2018).

The theoretical framework of FL thus rests on a confluence of technical innovation, legal compliance, and ethical responsibility. It challenges traditional notions of machine learning by shifting the locus of data control to the edge, where data originates. This paradigm not only aligns with the evolving regulatory landscape but also resonates with broader societal concerns around data ownership, surveillance, and digital autonomy. As the field matures, ongoing research must continue to refine the theoretical underpinnings of FL while addressing the multifaceted challenges that arise at the intersection of technology, law, and ethics. The future of FL depends on our collective ability to balance innovation with responsibility, ensuring that privacy preserving technologies serve the public good without compromising individual rights.

3.0 Methodology of the Review

This systematic review adheres to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta Analyses) guidelines, which offer a structured and transparent framework for conducting comprehensive reviews in health sciences, computer science, and interdisciplinary domains (Page *et al*., 2021). By following this widely recognized protocol, we ensured methodological rigor, reproducibility, and clarity throughout the review process. The objective was to identify, categorize, and critically synthesize relevant literature addressing privacy preserving techniques, legal frameworks, and ethical considerations in Federated Learning (FL) published between 2016 and 2024. To obtain a robust dataset for analysis, a systematic search was conducted across five prominent academic databases: IEEE Xplore**,** ACM Digital Library**,** SpringerLink**,** ScienceDirect**,** and Google Scholar. These databases were selected for their comprehensive coverage of interdisciplinary research spanning computer science, law, healthcare, and ethics. The search strategy employed a combination of primary and secondary keywords using Boolean operators. Core search terms included: “Federated Learning” AND “Privacy,” “Federated Learning” AND “Legal frameworks,” “Federated Learning” AND “Ethics,” “Federated Learning” AND “Differential Privacy,” and “Federated Learning” AND “Secure Aggregation.” Synonyms and related terms were also explored to maximize retrieval and reduce bias in article selection. The search was conducted iteratively, with updated filters applied to ensure relevance and recency.

The review adopted clearly defined inclusion and exclusion criteria to filter the vast body of literature retrieved from the search. Studies were included if they (1) were published in peer reviewed journals or conference proceedings, (2) focused explicitly on Federated Learning with attention to privacy techniques**,** regulatory frameworks**, or** ethical issues, (3) were published between 2016 and 2024, and (4) were written in English. This period captures the inception and rapid evolution of FL following its formalization by McMahan *et al*. (2017) [3]. Conversely, studies were excluded if they were (1) non peer reviewed articles (e.g., blog posts, white papers, technical notes), (2) opinion pieces or editorials lacking empirical evidence or systematic analysis, (3) unrelated to privacy preserving or ethical dimensions of FL, or (4) redundant publications or extended versions of previously published studies without substantial new contributions.

To enhance consistency and reduce selection bias, a two phase screening process was conducted. First, titles and abstracts of the retrieved articles were reviewed for initial eligibility. In cases of ambiguity, full text versions were examined to confirm relevance. The final set of articles was determined after resolving discrepancies through discussion among co reviewers and cross verifying duplicates. In total, many articles were initially retrieved, with many of them meeting all inclusion criteria and retained for detailed analysis.

The analytical framework was designed to extract and organize findings from the selected literature based on key thematic and methodological attributes. Each study was reviewed to determine the type of technique discussed categorized broadly into technical**,** legal, or ethical interventions. Technical approaches included implementations of differential privacy, secure aggregation, homomorphic encryption, and federated adversarial training. Legal and regulatory papers focused on GDPR compliance, cross border data governance, and privacy by design legal frameworks. Ethical studies addressed algorithmic bias, autonomy, consent, transparency, and accountability in FL systems. Further, we examined the application domain of each study, which ranged across healthcare, finance, mobile computing, IoT, smart cities, and education. This helped contextualize the discussed privacy or ethical techniques within their real world settings. For example, healthcare related studies emphasized HIPAA compliance and multi institutional collaboration (Rieke *et al*., 2020) [32], while those in finance focused on fraud detection and decentralized risk analysis (Yang *et al*., 2019) [38].

This mixed method approach integrating quantitative

analysis from technical studies with qualitative insights from legal and ethical literature allowed for a holistic understanding of the landscape of privacy preserving Federated Learning. Through this rigorous and structured methodology, the review builds a comprehensive foundation for assessing both the strengths and limitations of current approaches, setting the stage for further research and policy development in this rapidly evolving domain.

3.1 Technical Privacy Preserving Techniques in Federated Learning

Federated Learning (FL) inherently aims to preserve data privacy by enabling decentralized model training without sharing raw data. However, the exchange of model parameters or gradients between clients and central aggregators can still leak sensitive information (Zhu *et al*., 2019) [45]. To mitigate these privacy risks, numerous technical privacy preserving techniques have been developed and integrated into FL frameworks. This section reviews the primary approaches: Differential Privacy (DP), Homomorphic Encryption (HE), Secure Multi Party Computation (SMPC), and alternative model update methods such as Federated Distillation and Split Learning.

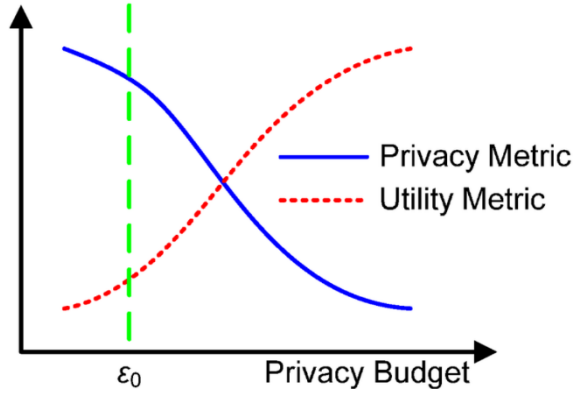

Fig 1: Privacy–Utility Trade-off in Federated Learning Using Differential Privacy

a. Differential Privacy (DP)

Differential Privacy has emerged as a leading technique to provide formal privacy guarantees in FL by introducing carefully calibrated noise into model updates (Dwork *et al*., 2014) [8]. DP ensures that the inclusion or exclusion of a single participant's data does not significantly affect the overall output, thereby obscuring individual contributions during the model aggregation phase. This noise addition protects against various inference attacks, such as membership inference, which can reveal whether a particular data point was part of the training set (Shokri *et al*., 2017) [33]. Google's implementation of DP in FL, known as DP FedAvg, exemplifies the practical application of this technique (McMahan *et al*., 2018) [27]. DP FedAvg modifies the classic Federated Averaging algorithm by adding Gaussian noise to clients' model updates before aggregation, ensuring a quantifiable privacy budget. Despite its effectiveness, DP introduces a trade off between privacy and utility; excessive noise degrades model accuracy, especially in scenarios with limited client participation or highly skewed data distributions (Geyer *et al*., 2017) [12]. Ongoing research explores adaptive noise mechanisms and privacy accounting methods to optimize this balance (Kairouz *et al*., 2021) [20].

b. Homomorphic Encryption (HE)

Homomorphic Encryption allows computations to be performed directly on encrypted data without decryption, enabling privacy preserving aggregation of model updates in FL (Gentry, 2009). By encrypting model parameters locally, clients ensure that the central server or any eavesdropper cannot access raw or intermediate data during training. This property offers strong cryptographic security guarantees, making HE an attractive option for scenarios with stringent privacy requirements, such as healthcare and finance (Liu *et al*., 2020) [25].

However, HE schemes typically impose substantial computational and communication overhead, limiting their scalability and real time applicability in large scale FL deployments (Jiang *et al*., 2020) [18]. The complexity of key management and the necessity of supporting encrypted arithmetic operations further complicate practical adoption. Hybrid approaches that combine HE with lighter cryptographic protocols or approximate HE variants aim to alleviate these performance bottlenecks (Chandran *et al*., 2021) [5].

c. Secure Multi Party Computation (SMPC)

Secure Multi Party Computation distributes computation tasks across multiple parties, ensuring that no single entity has access to the entire dataset or model parameters (Yao, 1986) [41]. In FL, SMPC protocols enable joint model aggregation by secret sharing clients' updates among several non colluding servers or participants, which collaboratively compute the aggregate without revealing individual contributions (Bonawitz *et al*., 2017) [3].

SMPC is often integrated with Homomorphic Encryption to bolster security guarantees while maintaining computational feasibility (Truex *et al*., 2019) [34]. Despite its strong privacy guarantees, SMPC also incurs communication overhead due to the interactive nature of the protocols and requires assumptions about honest but curious or semi honest adversaries. Recent research focuses on optimizing SMPC protocols for FL by reducing round complexity and communication cost, enabling deployment in heterogeneous network environments (Mohassel & Zhang, 2017) [29].

d. Federated Distillation and Split Learning

Alternative model update strategies, such as Federated Distillation and Split Learning, seek to limit the exposure of raw gradients or weights during training, thereby mitigating privacy risks inherent in standard FL approaches (Jeong *et al*., 2018; Gupta & Raskar, 2018) [17, 13].

Federated Distillation leverages knowledge distillation principles by sharing model outputs (soft labels) rather than gradients or parameters. This approach reduces the amount of sensitive information exchanged, potentially lowering privacy leakage while maintaining comparable model performance, especially in heterogeneous client settings (Lin *et al*., 2020) [24]. Split Learning divides the neural network architecture between clients and servers, where clients compute only partial forward and backward passes locally, sending intermediate activations to the server for further processing. By avoiding transmission of complete model updates or raw data, Split Learning enhances privacy and computational efficiency in FL systems (Gupta & Raskar, 2018) [13]. However, challenges such as increased latency and dependency on server availability remain areas of active investigation.

Table 1: Overview of Technical Privacy-Preserving Techniques in Federated Learning

Technique	Description	Advantages	Challenges / Limitations	Representative Works
Differential Privacy (DP)	Adds noise to model updates to obscure individual data contributions and protect privacy.	Formal privacy guarantees, quantifiable privacy	Trade off between privacy and model accuracy; noise may reduce utility	McMahan *et al*. (2018) [27]; Geyer *et al*. (2017) [12]; Dwork *et al*. (2014) [7]
Homomorphic Encryption (HE)	Allows computations on encrypted data without decrypting it.	Strong cryptographic security; data remains encrypted throughout	High computational and communication overhead; complex key management	Gentry (2009) [11]; Jiang *et al*. (2020) [18]; Chandran *et al*. (2021) [5]
Secure Multi Party Computation (SMPC)	Distributes computation among multiple parties to prevent data exposure.	Strong privacy guarantees; no single party accesses raw data	Communication overhead; requires assumptions on adversaries	Bonawitz *et al*. (2017) [3]; Truex *et al*. (2019) [34]; Mohassel & Zhang (2017) [29]
Federated Distillation	Shares model outputs (soft labels) instead of gradients/parameters to reduce privacy leakage.	Reduces sensitive data exposure; robust to heterogeneous data	Potential reduction in model accuracy; complex implementation	Jeong *et al*. (2018) [17]; Lin *et al*. (2020) [24]
Split Learning	Splits the model between client and server to avoid sharing full model updates or raw data.	Enhanced privacy; reduces client computational load	Increased latency; dependency on server availability	G

3.2 Legal Frameworks in Federated Learning Privacy

Federated Learning (FL), as a decentralized machine learning paradigm, introduces unique challenges to traditional data privacy regulations. Major legal frameworks such as the General Data Protection Regulation (GDPR) in the European Union, the California Consumer Privacy Act (CCPA), and the Health Insurance Portability and Accountability Act (HIPAA) in the United States are critical in shaping privacy preserving approaches in FL.

The GDPR establishes stringent requirements regarding personal data processing, including data minimization, purpose limitation, and explicit user consent (Voigt & Von dem Bussche, 2017) [37]. FL, by design, keeps data localized on user devices, thus potentially supporting GDPR's data minimization principle. However, challenges arise in FL regarding accountability, data subject rights (e.g., the right to be forgotten), and data breach notification due to the distributed nature of the system (Shokri & Shmatikov, 2015; Kairouz *et al*., 2021) [33, 20].

The CCPA focuses on consumers' rights to know, delete, and opt out of the sale of personal information, posing enforcement challenges in federated settings where data does not leave the device but model updates are shared (Zhang *et al*., 2020) [42]. Compliance requires careful management of model updates and auditability.

HIPAA regulates health data privacy, demanding strict controls on patient information, which is particularly relevant for FL applications in healthcare. FL is considered promising for healthcare data sharing, as it avoids centralized data pooling; yet, compliance with HIPAA's safeguards for data access and audit remains complex (Rieke *et al*., 2020) [32].

Beyond these frameworks, regional variations in data privacy laws pose further complications. For instance, China's Personal Information Protection Law (PIPL) enforces strict data localization and cross border transfer rules, influencing FL system design (Li *et al*., 2022). This patchwork of regulations requires FL implementations to be adaptable to different legal contexts (Geyer *et al*., 2017) [12].

Recent literature highlights the need for new regulatory interpretations and technical standards that bridge FL's unique model with existing legal regimes (Li *et al*., 2023; Arya *et al*., 2022) [2]. Scholars argue for legal frameworks that recognize the distributed data processing in FL while maintaining strong data protection and transparency (Yang *et al*., 2021) [39].

3.3 Ethical Considerations in Federated Learning

Ethical concerns in FL revolve around ensuring privacy, fairness, transparency, and accountability in the development and deployment of decentralized AI systems.

Privacy ethics are foundational, as FL is often promoted for its privacy preserving benefits (Yang *et al*., 2019) [40]. However, risks of privacy breaches through inference attacks or model inversion highlight the need for ethical vigilance beyond mere legal compliance (Hitaj *et al*., 2017) [16]. Ethical AI frameworks emphasize "privacy by design" and user empowerment (Floridi *et al*., 2018) [9].

Fairness and bias are also significant issues in FL, where data heterogeneity and participant selection biases can exacerbate unfair model outcomes (Li *et al*., 2020). FL systems must incorporate fairness aware learning algorithms to prevent reinforcing social biases and ensure equitable model performance across diverse user groups (Mehrabi *et al*., 2019) [28].

User consent and transparency are ethical imperatives, especially given FL's complexity. Users must be adequately informed about data use, model training, and potential risks (McMahan *et al*., 2017) [3]. Transparency challenges arise because FL models may not be fully interpretable, necessitating ethical guidelines for explainability and accountability (Doshi Velez & Kim, 2017) [6].

Ethics guidelines from organizations such as the IEEE and the EU's High Level Expert Group on AI provide frameworks for responsible AI development that can be adapted for FL (Jobin *et al*., 2019) [19]. These frameworks emphasize inclusiveness, respect for human rights, and sustainability (Cath *et al*., 2018) [4].

Emerging research advocates for integrating ethical principles into FL's technical design, combining privacy preserving methods with fairness constraints and transparent mechanisms, creating "ethically aligned" FL systems (Veale & Binns, 2017; Truong *et al*., 2021) [36, 35].

4. Discussion

This systematic review highlights the multifaceted nature of privacy preservation in Federated Learning (FL), underscoring the interplay of technical, legal, and ethical dimensions. The technical review reveals significant advances in privacy preserving mechanisms, such as Differential Privacy (DP), Homomorphic Encryption (HE), Secure Multi Party Computation (SMPC), and novel model update techniques like Federated Distillation and Split

Learning. These techniques collectively enhance data confidentiality by ensuring that raw data never leaves the local devices, thereby reducing centralized data exposure risks. However, a fundamental trade off persists between privacy guarantees and model utility, where increasing privacy (e.g., adding noise in DP) can degrade model accuracy (Kairouz *et al*., 2021) [20]. Moreover, computational overhead, especially in HE and SMPC, limits scalability and practical deployment in resource constrained environments.

On the legal front, FL challenges traditional regulatory frameworks like GDPR, CCPA, and HIPAA, which were primarily designed for centralized data processing. While FL's decentralized architecture aligns with principles like data minimization, compliance difficulties remain in areas such as cross border data transfer, user rights enforcement, and accountability (Li *et al*., 2023). The divergence in regional laws, such as the EU's GDPR and China's PIPL, further complicates the creation of universally compliant FL systems. Current literature emphasizes the urgency of evolving legal standards and interpretative guidance tailored to FL's unique characteristics (Arya *et al*., 2022) [2].

Ethically, the review reveals pressing concerns about fairness, transparency, and user consent in FL systems. Data heterogeneity and participation bias can result in unfair model outcomes that disproportionately affect marginalized groups (Mehrabi *et al*., 2019) [28]. Transparency is hindered by the inherent complexity of FL models, which complicates efforts to make AI decisions explainable and accountable (Doshi Velez & Kim, 2017) [6]. Ensuring meaningful user consent is also challenging given the often opaque nature of data use and model training processes. Ethical guidelines from organizations like IEEE advocate for incorporating fairness and human rights considerations from the design phase onward (Cath *et al*., 2018) [4].

4.1 Interdisciplinary Challenges and Integrated Solutions

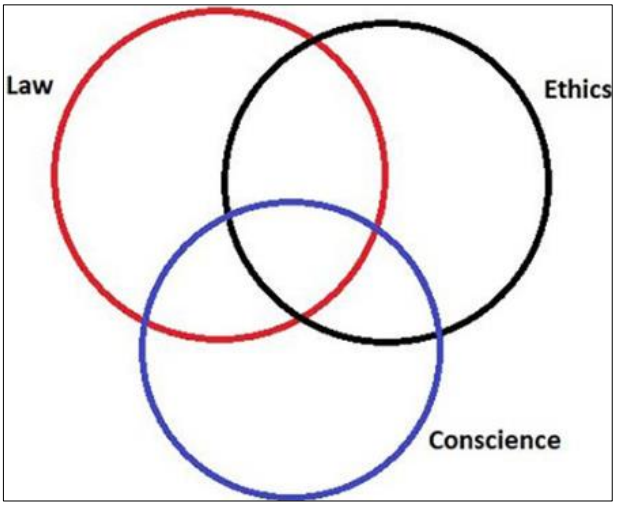

Fig 2: Interplay Between Technical, Legal, and Ethical Domains in Federated Learning Privacy

The convergence of technical, legal, and ethical domains highlights the necessity for holistic solutions. Privacy preserving technologies must be developed with regulatory compliance and ethical mandates in mind from the outset. This requires fostering collaborations across computer science, law, and social sciences to create FL frameworks that are technically sound, legally robust, and ethically responsible.

4.2 Table and Visual Analysis Suggestions

Table 2: Summary of Privacy Preserving Techniques in FL

Technique	Privacy Guarantee	Advantages	Limitations	Common Use Cases
Differential Privacy (DP)	Adds noise to mask individual data	Balances privacy & utility	Privacy utility trade off	Google's DP FedAvg
Homomorphic Encryption (HE)	Computation on encrypted data	Strong security	High computational cost	Sensitive healthcare data
Secure Multi Party Computation (SMPC)	Joint computation without data exposure	No single point of data access	Communication overhead, complexity	Finance, multi institutional data
Federated Distillation	Shares model predictions instead of raw gradients	Reduces data exposure	Possible loss of model detail	Edge device learning
Split Learning	Divides model between client and server	Limits raw data sharing	Coordination overhead	Collaborative AI

4.3 Gaps and Limitations

Despite advancements, notable gaps exist. From a technical standpoint, balancing robust privacy protections with acceptable model performance remains unresolved, particularly for large scale, heterogeneous FL applications. Furthermore, most privacy preserving techniques assume honest but curious participants, overlooking active adversaries capable of launching inference or poisoning attacks (Hitaj *et al*., 2017) [16]. Legally, there is a lack of clear frameworks explicitly addressing FL, creating uncertainties for practitioners on compliance strategies. The dynamic and distributed nature of FL complicates enforcement of user rights and breach notifications, necessitating new regulatory interpretations and compliance tools.

Ethically, there is insufficient focus on operationalizing fairness and transparency in practical FL deployments. Most ethical guidelines remain high level, with limited actionable recommendations tailored to FL contexts.

4.4 Future Research Opportunities

Future research should explore hybrid privacy preserving methods combining the strengths of DP, HE, and SMPC to optimize the privacy utility trade off. Developing lightweight cryptographic protocols is essential to enhance FL applicability in edge devices. From a legal perspective, interdisciplinary collaborations between technologists and policymakers are critical to develop FL specific regulations and compliance frameworks that respect regional differences while enabling innovation. Ethically, designing FL systems that embed fairness constraints and transparent reporting

mechanisms is a priority. User centric approaches that enhance informed consent and participatory model governance should be further investigated.

5. Conclusion

The advancement of Federated Learning (FL) represents a paradigm shift in how data driven intelligence can be developed without violating user privacy. This systematic review synthesizes extensive findings across technical, legal, and ethical domains, offering a structured understanding of the multi dimensional landscape of privacy preserving Federated Learning. Technically, mechanisms such as Differential Privacy, Homomorphic Encryption, and Secure Multi party Computation have provided foundational tools to mitigate privacy risks, albeit with trade offs in utility and computational cost. Legally, the emergence of stringent data protection laws such as the European Union's General Data Protection Regulation (GDPR), California Consumer Privacy Act (CCPA), and the U.S. Health Insurance Portability and Accountability Act (HIPAA) has pushed FL researchers to design systems that uphold compliance without compromising performance. Ethically, issues of algorithmic fairness, informed consent, and data transparency remain at the forefront, particularly as FL expands into sensitive sectors like healthcare, finance, and public policy.

Our findings underscore the need for holistic solutions that transcend disciplinary silos. Technical innovations must be guided not only by performance metrics but also by socio legal expectations. Likewise, legal and ethical frameworks must evolve to accommodate the unique operational structure of FL systems. A significant limitation in the current body of work is the lack of unified frameworks that concurrently address technical, legal, and ethical dimensions pointing to a gap in interdisciplinary research and practice.

We recommend future studies to focus on the co design of FL architectures involving computer scientists, legal scholars, and ethicists. Moreover, empirical research is needed to test these frameworks in real world deployments, particularly in underrepresented regions where data protection laws may be weaker. As FL continues to scale, its legitimacy will depend not only on its computational success but also on its social trustworthiness. A forward looking vision of Federated Learning must therefore be anchored in technological innovation, legal robustness, and ethical integrity.

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