Toward Sustainable and Trustworthy Federated Learning: A Review of Energy Efficiency, Blockchain, and Verifiability

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***Abstract*—Federated Learning (FL) is an emerging method to train machine learning models without the data getting centralized. By not centralizing the data, FL is compatible with security-conscious sectors like healthcare, finance, and IoT. However, despite this benefit, FL currently encounters three key issues hindering mainstream adoption, including high energy consumption during distributed training, the requirement for trust amongst the users, and the absence of good verifiability to ensure the result is proper and not adulterated.**

In the past few years, researchers have attempted to solve each of these problems individually. Initiatives under Green FL work towards minimizing the carbon and energy footprint. Blockchain-enabled solutions incorporate mechanisms for trust among clients as well as incentives. Cryptographic and auditing mechanisms allow for some extent of verifiability. The majority of the above works consider the problems in isolation. What is still absent is an integrated picture that examines their interplay, trade-offs, and the potential for common frameworks.

This paper surveys 45 papers from 2021 to 2025 that relate to energy awareness, blockchain incorporation, or verifiability in FL. We categorise each paper with the straightforward coding scheme (Yes, Partial, No) on the three dimensions and study overlaps. The results show blockchain as the most progressed strand, energy-efficiency dealt with moderately, while verifiability remains the least studied. The paper ends with gaps, open issues, and future work towards sustainable and trustworthy FL.

***Index Terms*—Federated Learning, Blockchain, Energy Efficiency, Verifiability, Distributed Machine Learning, Green AI**

I. Introduction

A. Background

Federated Learning (FL) is a distributed machine learning paradigm that allows several parties to jointly train a single model without sharing their raw data [1]. In such a way, privacy is maintained; therefore, it is tempting to use it in sensitive areas such as healthcare [2], finance, or even the Internet of Things (IoT) [3]. Besides that, FL is used in schools (for instance, FL in the ImageNet benchmark for medical imaging) [4] and in industries (for example, Google's Gboard that makes use of FL to enhance typing predictions [5], and Apple's Siri where personalized models are locally trained on devices [6]). These cases are some of the ways through which FL manages to keep both data privacy and the benefits of joint learning.

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B. Key Challenges

Despite the fact that FL holds enormous promise, it runs into three main challenges that obstruct wide use of its technology [7]:

- **Energy consumption:** When such training is spread over a large number of clients and edge devices, the computation and communication costs are going to increase [8]. As a result, the energy and carbon footprints also rise [9]. Another study confirms increasing energy demands during FL operations across distributed devices [10].
- **Trust and incentives:** Along with security, clients should be comfortably assured of how their data and contribution are handled [11]. There should also be a system that provides fair incentives to encourage continuous participation [12]. Trust handling mechanisms such as blockchain and smart contracts have been proposed for the same [13]. Moreover, secure data sharing and verifiable model updates are critical for incentivizing participation [14].
- **Verifiability:** The current architectures of FL do not provide strong enough guarantees that every step of the training and the outcomes achieved are actual and not altered [15]. Techniques like zero-knowledge proofs have been proposed to verify model correctness in FL systems [16]. Similarly, enclave-based verifiable systems have been developed to validate federated model updates [17]. However, real-world applications still lack reliable and enforceable verifiability guarantees [18].

C. Gaps in Existing Surveys

There are a number of surveys; however, they are concentrated only in one single dimension such as energy, trust, or verifiability without considering all these aspects simultaneously [4]:

- Energy-efficient or "Green FL" reviews (e.g., Thakur et al., 2025) only deal with sustainability aspects of FL [5], [7], [16].
- Blockchain-enabled FL surveys (e.g., Jiang et al., 2024) talk the most about trust and incentives that come up with FL [8], [9], [17], [18].
- Verifiable FL surveys (e.g., Sun et al., 2025) mention cryptographic protection while not referring to energy or blockchain [12], [19], [20].

This separation leads to a lack of understanding of the trade-offs and synergy between those three major aspects [21], [22].

D. Our Contribution

Rather than analyzing energy efficiency, blockchain, and verifiability separately, this paper concurrently addresses all of these issues in FL [22]. Firstly, we comprehensively survey 45 studies from 2021 up to 2025, secondly, we use a three-dimensional taxonomy to code Yes/Partial/No for each dimension as well as to point out categories that are intersecting and those that are underexplored [4], [23]. Compared to previous works, this combined view makes it possible to be aware of the areas where development is achieved as well as to be able to locate those in which there is still a lack of work [2], [15].

E. Paper Structure

The remainder of the paper is organized as follows:

- Section 2 – Methodology and selection process
- Section 3 – Taxonomy framework
- Section 4 – Literature analysis of 45 works
- Section 5 – Discussion and future directions
- Section 6 – Future Research Directions
- Section 7 – Conclusion

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II. Methodology

A. Search Strategy

The review implemented a systematic approach that took inspiration from the PRISMA guidelines [4]. Various wireless libraries were used to access the most pertinent articles: IEEE Xplore, ACM Digital Library, SpringerLink, ScienceDirect, and arXiv. The following sets of keywords were combined to represent the wide signal of studies introduced [1]:

- "Federated Learning" OR "Collaborative Learning"
- "Blockchain" OR "Distributed Ledger"
- "Energy Efficiency" OR "Carbon" OR "Green AI"
- "Verifiability" OR "Auditing" OR "Zero-knowledge Proofs"

It was done to ensure that the paper references of the domains as well as the broader surveys are included.

B. Timeframe

The time of the publication was limited to between January 2021 and March 2025. This represents the period when a lot of attention has been given to energy-saving and reliable federated learning [5], [22].

C. Screening and Selection

- **Initial filtering** – The level of relevance of the information from titles and abstracts was judged.
- **Full-text perusal**- Articles about FL and of technical nature were only selected.
- **Eligibility check** – Only peer-reviewed journal articles, conference papers, and high-quality preprints were included [21], [23]

From a first set of records of 260, duplicates, and off-topic works were removed leaving 45 final studies [4].

D. Coding Framework

The characteristics of the studies were described by three fields:

- **Energy/Carbon-awareness (E):** Did the study report energy consumption or carbon emissions? [5], [16].
- **Blockchain integration (B):** Was blockchain technology used for coordination, incentives, or security?
- **Verifiability (V):** Did the work include mechanisms to prove correctness or detect tampering?

The following scale was used for the coding of each dimension:

- **Y (Yes)** –One dimension was thoroughly discussed in the paper.
- **P (Partial)** –The dimension was referred to or briefly discussed.
- **N (No)** – The dimension was not addressed.

E. Final Dataset

The final dataset consists of 45 papers without copies. A 7-column summary table (Reference, Authors, Title, Venue, Focus, E/B/V, coding, Notes) was created to map each of them. This dataset is the foundation of the taxonomy and the study that follows.

III. Taxonomy Framework

A. Motivation for the Taxonomy

Federated Learning is a rapidly growing field of research, but the majority of studies have only addressed one or two aspects of the problem [1], [21]. In order to compare these works evenly, a three-dimensional taxonomy was created. This taxonomy reflects whether a research work explicitly discusses:

B. Coding Dimensions

Every article was thoroughly studied and then graded according to its alignment with three binary/partial dimensions:

- **Energy/Carbon (E):**
  - **Y (Yes):** The paper was about a concrete energy-saving or carbon-aware method.
  - **P (Partial):** The paper contained only a brief mention or an indirect impact on energy of the proposed method.
  - **N (No):** The paper has not taken energy into account.
- **Blockchain (B):**
  - **Y (Yes):** Blockchain was the main engine of the proposed framework.
  - **P (Partial):** Blockchain was mentioned but not fully implemented.
  - **N (No):** The paper does not contain any blockchain features.
- **Verifiability (V):**
  - **Y (Yes):**The work explicitly provides components that facilitate the verification or auditing of the system.

– **P (Partial):** The work refers to verifiability, but the aspect is somewhat shallow.
– **N (No):** The paper has not introduced any verification features.

C. Taxonomy Structure

On the basis of these three dimensions, the possible classes of papers investigated were:

- **Single-focus works:**a paper, which treats only one dimension (e.g., Green FL without blockchain or verifiability) in detail.
- **Dual-focus works:**the combination of two dimensions in the respective works, e.g., blockchain + energy or blockchain + verifiability studies.
- **Triple-focus works:** the fewest overlapping studies that only attempted to combine all three aspects (just one paper from our dataset).

D. Representation in the Study

The classification system has been relied on to assign labels to all 45 papers under review. A 7-column comparative table alongside numerous graphs (bar charts, Venn diagrams, and timelines) in the Results section were used to visualize the findings. Thus, we could monitor the areas where studies are moving forward and where very large gaps remain [4].For example, Figure 1 depicts that the number of publications dealing with energy-aware, blockchain-enabled, and verifiable federated learning has been increasing gradually from 2021 to 2025, which can be interpreted as the worldwide growing interest in sustainable AI. Besides that, Figure 2 shows how the 45 papers are spread over the three main dimensions: energy, blockchain, and verifiability. A significant disparity is apparent, as most studies are focusing on blockchain while the verifiability aspect remains quite challenging. These snapshots offer surveys of research progress and thematic gaps that Section 4 lays down for the detailed discussion.

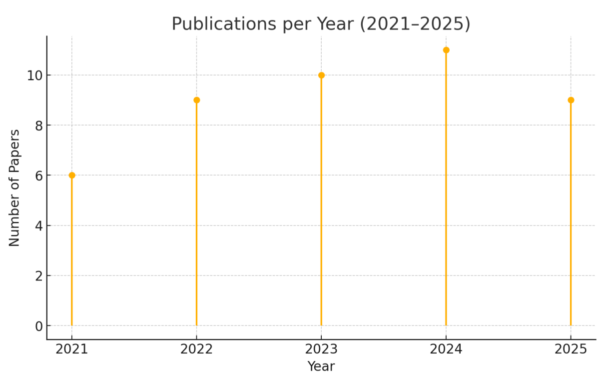

Fig. 1: Publications per year (2021–2025)

IV. Literature Analysis

A. Overview of the Dataset

The author has gone through 45 studies published from 2021 to 2025, which include a balanced mix of journal articles,

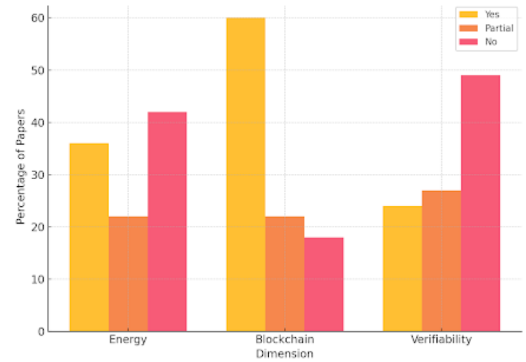

Fig. 2: Distribution of 45 reviewed papers across Energy, Blockchain, and Verifiability dimensions.

conference papers, and preprints – representing both academic and industry-driven research [4]. The dataset is quite varied in terms of domains, ranging from healthcare, IoT, finance to mobile services, which shows that there is a lot of interest in the use of Federated Learning (FL) for sustainable and trustworthy purposes.Table II (located in Appendix) provides a concise and organized summary of these works, specifying publication details, focus areas, and coding results for energy awareness (E), blockchain integration (B), and verifiability (V). Such a summary allows us to see how the researchers' work is spread over the three main dimensions and also to identify the first gaps that are discussed in the next sections.

B. Publication Trends

Rising interest in sustainable and trustworthy Federated Learning (FL) is reflected in the number of publications, which have more than doubled from 2021 to 2023 [9], [21]:

- 2021 – 6 papers
- 2022 – 9 papers
- 2023 – 10 papers
- 2024 – 11 papers
- 2025 – 9 papers

As can be seen from Figure 1, the research activity has gradually increased, reaching its maximum in 2024. Despite a small decline in 2025, the total amount of work remained quite high, indicating that this cross-cutting theme still attracts a strong response from both academia and industry. This steady rise is consistent with the overall global emphasis on energy-efficient AI, blockchain-based trust mechanisms, and verifiable learning systems – three components that are nowadays considered as key to the long-term scalability and ethical deployment of FL.

C. Coverage by Dimension

The coding of 45 articles was carried out with the aim to examine how these papers have addressed the three main issues of Energy (E), Blockchain (B), and Verifiability (V) by using the Y/P/N scale - Yes (explicitly addressed), Partial (mentioned or indirectly considered), and No (not discussed). The breakdown of various codes is given as follows:

- **Energy (E):**16 Yes, 10 Partial, 19 No
- **Blockchain (B):**27 Yes, 10 Partial, 8 No
- **Verifiability (V):** 11 Yes, 12 Partial, 22 No

The results depicted in Figure 2 show that the community is mainly focused on blockchain as the most widely open dimension of consideration, with nearly two-thirds of the papers reviewed providing a blockchain-based trust or coordination framework [8], [9]. Energy efficiency gets some attention, usually, when it is the case of wireless or IoT-based FL [5], [16], [24], whereas the aspect of verifiability is the least considered. The scarce focus on verifiability suggests that although privacy-preserving methods have been developed, the community still seems to lack trained techniques for the correctness and the possibility of an audit in FL outcomes [21].

D. Key Observations

The review of 45 papers selected for analysis reveals a range of ongoing research developments as well as several open questions that need to be addressed with respect to the development of sustainable and trustworthy Federated Learning (FL).

One of the major points indicates the usage of blockchain technology as the main method to solve problems related to trust, accountability, and incentive mechanisms in FL. In general, many authors suggest to use distributed ledger technologies in securing aggregation, decentralized orchestration, or token-based reward systems [8], [9], [11]. Besides this, several papers coordinate smart contract-based or blockchain-supported data integrity solutions [10], [18], [25] and thus confirm the increasing agreement that FL suffers from the lack of trust guarantees and that blockchain can effortlessly remedy this problem by decentralization and immutability [21].

Moreover, the second point is about energy efficiency. The issue of energy saving is touched upon by several works, but only a few of them publish actual measurements of energy usage or carbon emission [5], [16], [26]. Most energy-aware methods work on indirect tasks such as communication compression, device/client selection, or model quantization [24], [27], [28], without the provision of standard sustainability metrics. This supports the idea that "Green FL" is still largely a theoretical concept and that quantitative carbon-accounting processes in FL are at an early stage [16].

Third, verifiability, i.e., the capability of an external entity to audit FL updates or to verify the correctness of the training process, is the dimension which has attracted the least number of inquiries out of the three. A very limited number of research works put forward end-to-end verifiable learning pipelines making use of zero-knowledge proofs, secure enclaves, or publicly verifiable secret sharing (PVSS) [12], [13], [15], [23], [29]. Moreover, the problems of scalability, computational overhead, and deployment practicality are still poorly addressed even in these works [21].

Lastly, the most important point of this survey is that it does not reveal any research that would combine the three aspects of energy efficiency, blockchain-based trust, and verifiability into a single framework [4], [22]. The absence of triple-focus" architectures thus clearly indicates the existence of a new research frontier which has not been explored yet: the construction of FL systems that can provide simultaneously sustainability, transparency, and cryptographically verifiable at scale.

Table II (located in Appendix) goes further in confirming these insights by providing the grouping of the studies by the main techniques used. Studies on energy-aware topics usually implement quantization or adaptive scheduling, those enabled by blockchain employ custom consensus or smart contracts, and researches concentrating on verifiability use zero-knowledge proofs or zk-SNARK pipelines [7], [12], [18], [24], [28]. This organized comparison serves as a transition to the discussion of the methodology in the following section

E. Fragmentation of Research

The survey reiterates that Federated Learning (FL) is still a fragmented extensively researched area [1], [21]. The majority of the experiments concentrate only on one or two of the three significant issues-energy efficiency, blockchain-based trust, and verifiability without any attempts to combine them into a single architectural framework [5], [8], [22]. Therefore, there is a limited level of understanding of these interactions in FL dimensions in the field.

In the 45 papers evaluated, only one paper sets out the design that considers all three aspects altogether [15], [22]. This points to a considerable chasm in the research field: despite the increasing community's interest in the sustainability and trust of FL, the community has not yet converged on holistic system designs that jointly support energy efficiency, decentralization, and cryptographic accountability [21]. Instead of integrating their work, researchers have followed parallel but disconnected research threads, as noted in [1].

F. Trade-offs and Tensions

The trade-off between sustainability, security, and scalability is a recurring point in the reviewed articles [5], [27], [30], [31]. Although blockchain facilitates better transparency and decentralization, it requires more computational and communication resources. As a result, the total energy consumption of FL systems goes up [6], [25]. On the other hand, energy-saving measures like quantization, pruning, and client selection lower energy consumption but at the cost of accuracy and neutrality among the participants [32].

Along with zero-knowledge proofs (ZKPs) and trusted execution environments (TEEs), verification mechanisms gain in transparency but they are so computationally heavy that they become unfeasible for low-power or large-scale devices [19], [24], [29], [33] . The real challenge faced by researchers and system designers is to come up with lightweight as well as

TABLE I: Common Techniques Used Across Reviewed Works.

Category	Techniques / Algorithms	Representative Works
Energy Optimization	Quantized CNN, Opportunistic FL, Energy-aware Scheduling	Han et al. (2024), Li et al. (2024), Xu et al. (2024)
Blockchain Integration	Proof-of-Federated-Learning, Smart Contracts, BFT Consensus	Zhao et al. (2022), Lin et al. (2024), Ren et al. (2024)
Verifiability	Zero-Knowledge Proofs (ZKP), PVSS, zk-SNARKs	Rao et al. (2024), Lee et al. (2025), Zhang et al. (2025)
Incentive Mechanisms	Token-based Rewards, Multi-stage Incentives	Wu (2025), Jiang et al. (2024)

secure frameworks that could combine these conflicting goals. The balancing of sustainability, openness, and scalability, which is still one of the most difficult questions in FL research, is the problem of finding the trade-off between them [4], [34].

G. Lack of Standardization

Besides, the lack of benchmarking and standards is another major hurdle that comes up in this review [4], [9]. The number of studies that only carry out experiments on shared datasets or give sufficient details of their energy and carbon usage is very few. The lack of standardized evaluation tools makes fair comparison between proposed methods unfeasible [5], [35].

On top of that, numerous studies are limited to specific domains such as healthcare, IoT, or edge computing [2], [36], each of which employs its own proprietary or simulated datasets, thus making it hard for the results to be reproduced and generalized over various industrial sectors. The FL community must commit to carbon-aware benchmarks that are common and evaluation protocols that are open if they really want to foster development. Setting up standardized datasets along with guidelines for energy reporting will not only ensure techniques get fairly compared but also make research results reproducible [10], [22].

H. Emerging Trends

On the one hand, these sorts of trends, despite the fragmentation, offer opportunities for the field to develop new sustainable and verifiable FL systems of the next generation [1], [4]. Carbon-Aware FL Frameworks: There have been a few studies which started to incorporate energy and carbon tracking into the training processes [32], [35]. The frameworks measure the energy consumption of the device level dynamically and modify the engagement of the clients so as to have the least possible impact on the environment [16]. Hybrid Blockchain Architectures: Those scientists who are conducting research by applying off-chain storage, lightweight consensus models, and hierarchical blockchains are trying to solve the problems of latency and computation burden of the traditional blockchain systems [18], [25], [27]. Advances in Verifiable FL: Even though it is still a very specialized area, developments in verifiability through zk-SNARKs, TEEs, and cryptographic audits indicate that accountability is drawing more interest [12]–[14].

These methods come with the ability to present proofs of the correctness of training even when there is no central supervision [24]. Individually, these research trends reflect the transition from purely conceptual frameworks to resource-aware, practical, real-world system implementations, and collectively, they demonstrate the community's step closer to the release of these systems [20].

I. Key Research Gaps

A careful review of 45 sustainable and trustworthy research works in Federated Learning (FL) reveals three fundamental research gaps distinctly:

1) **Lack of Carbon Profiling:**It is found that very few FL studies actually report detailed measurements of energy usage or carbon emissions. In the absence of standard environmental metrics, most of the sustainability claims made are just theoretical and are not backed by empirical evidence [3], [5], [16], [35]. Even in the case of recently introduced "Green FL" frameworks, as per the observations made by [22], [37], reporting is mostly limited to the energy at the communication level, and not the entire end-to-end carbon cost.
2) **Limited Scalability of Verification:**Present methods for verifiability - which mainly leverage zero-knowledge proofs, secure enclaves, or verifiable aggregation techniques [12]–[15], [20], [24] - are resource-intensive and have difficulties in scaling up in large or heterogenous FL settings. In most instances, these cryptographic protocols are only at the proof-of-concept stage and have not been put to the test in real production environments.
3) **Absence of Integrated Architectures:**There is no research that depicts a comprehensive FL system that tackles energy efficiency, blockchain-based trust, and end-to-end verifiability all at the same time. The majority of the work only commits to one or two of these aspects and are at the conceptual or prototype level [8], [17], [34]. The research discussed in Table II (located in Appendix) indicates that work on energy optimization, blockchain integration, and cryptographic auditing are three separate tracks that seldom come together.

Addressing these issues will take the joint efforts of different specialists such as machine learning experts, distributed systems engineers, cryptographers, and sustainable computing experts. It is only through such a merger that we can hope to see FL platforms not only being scalable but also ethically sound and aware of the system-level resources.

V. Future Research Directions

The above discussion shows that while Federated Learning (FL) has gradually moved towards more decentralization and privacy protection, the journey towards sustainability and verifiability is still long. Tackling the energy, trust, and transparency trio requires careful innovation at various levels - from the basic protocols to system-level integration and evaluation frameworks.

A. Carbon-Aware Benchmarks

One critical thing that needs to be done is the creation of standardized, carbon-aware benchmarks. In most studies, Federated Learning researchers only give the accuracy of their models and the time of convergence and do not provide the energy or carbon costs related to the process [3], [5], [16]. This situation has two significant effects:

1) sustainability claims remain largely qualitative rather than quantitative, and
2) fair comparison across different studies becomes increasingly unreliable.

A subsequent study should provide publicly accessible benchmarking suites that log and disseminate outcomes of environmental metrics such as GPU/CPU energy consumption, communication overhead, and carbon footprint per training round. Just as ImageNet changed vision research, a thoughtfully created "Green FL Benchmark" could set the single measurement standard throughout the world [35].

Furthermore, benchmarking should not limit to static metrics only — the dynamic energy monitoring during the FL lifecycle (client selection, aggregation and verification) can expose the real-time efficiency trade-offs [22], [38]. The integration of these measurements into open repositories like TensorBoard or Weights & Biases will also help foster the support of transparency and reproducibility. Thus, researchers as well as industry practitioners are jointly enabled to guarantee that FL models, aside from being accurate, are also "green".

B. Lightweight Verification Mechanisms

Verification is at the center of the trustworthiness of FL; however, the existing verification methods are very resource-intensive and, thus, are unsuitable for large networks [12]–[14]. Certain types of cryptographic tools, such as zero-knowledge proofs (ZKPs), trusted execution environments (TEEs), or secure multiparty computation (SMPC) give correctness guarantees, but they require a lot of processor cycles — which in a manner goes against energy efficiency [15], [20].The next step would be the search for lightweight but still trustworthy verification mechanisms. Some possible tracks of future research include:One of them could be Probabilistic verification, where only a very small part of updates is selected at random for revision thus combining low auditing costs [23] with high reliability.Another one is Hierarchical verification layers, letting edge devices check partial results locally before getting them combined with other partial results for global aggregation [24], [38]. Finally, there is Post-hoc verification via audit trails that use cryptographic fingerprints of model updates rather than full proof generation [39].At the same time, privacy-preserving auditing systems that exploit the benefits of federated aggregation [40] and verifiable computation must also be researched. Equipping the verification process with resource-efficient techniques will thus move the community toward wide-scale FL deployments, which are scalable, verifiable and sustainable for billions of devices.

C. Hybrid Blockchain–FL Architectures

Even though blockchain technology ensures mutability, openness, and trust, energy and throughput take a toll on it. For example, Proof-of-Work (PoW)-powered consensus mechanisms are not compatible with the indeed already highly distributed nature of Federated Learning (FL) environments [17], [36].The upcoming architectures can rely on hybrid blockchain networks that keep the pros and cons of decentralization alongside the gains in efficiency [25], [27], [41], [42].Some of the potential ways for innovation are:An execution model that contains off-chain computation but retains on-chain commitments, so the FL changes can hardly be verified unless the blockchain is fully replicated [43], [44].Consensus mechanisms such as Proof-of-Stake (PoS) or Proof-of-Authority (PoA) that draw very little energy from the one utilized by the Proof-of-Work (PoW) process [37].

Conceptualizing of either hierarchical or sharded ledgers that is designed around multiple local blockchain based on specific domain co function handling before reaching syntax to a global chain [17], [41].What is more, edge computing nodes that are connected with blockchain can be the key to a smoother nearby area that has less time lag between training and verification cycles [25], [27], [36].On account of such blend systems, blockchain may see itself no longer as an energy-heavy load that slows it down; instead it becomes one of the scalable trust layers that compliments sustainable FL [17], [27], [37], [41], [42] .

D. Incentive and Governance Models

The concept of sustainability is not just a technical issue — it also calls for the implementation of economic and social incentives, which will ensure that participation is continuous and honest [26], [40], [45]. Federated systems are depending on users who voluntarily contribute the data and computing power. However, without a suitable reward system, the engagement will fade over time [11], [45].The areas of future research should be the development of tokenized incentive frameworks that not only encourage participants to provide more data but also higher quality data and energy efficiency [29], [40]. For example:Those nodes that manage to train in a more efficient manner and lower carbon emissions can receive "green credits" that can be traded in blockchain-based marketplaces [33], [37].Governance patterns by means of Decentralized Autonomous Organizations (DAOs) may direct Federated Learning (FL) systems in a more open way, giving access to the participants for voting on changes or ways of rewards [11], [26], [36].

Multi-layered trust systems can, for instance, pair blockchain-based reputations with energy metrics in order to verify that trustworthy and sustainable contributors are given priority access [35], [39].It will require cooperation between computer scientists, economists, and policymakers to bring about such a scenario where economics, ethics, and sustainability are perfectly interwoven in the Federated Learning (FL) system within the next decade [26], [37], [40], [45].

E. Cross-Domain Testbeds

The other angle is the development of experimental cross-domain testbeds for FL.At present, the majority of studies are confined to very specific verticals, i.e., healthcare, IoT, or finance, in which datasets and assumptions of each are isolated [2], [17], [36]. This significantly limits the extent to which the results can be generalized and also prevents the identification of domain-agnostic trade-offs [4].The creation of multi-domain FL testbeds that represent dissimilar surroundings (energy-limited IoT nodes vs. hospital servers, for example) will allow researchers to check their designs in real, mixed conditions [7], [45]. These testbeds should consist of:Device diversity found in the real world (smartphones, sensors, and edge servers).Changing energy limitations and network variability [6], [16].Modules for blockchain integration and verifiability auditing [8], [11], [24].Such a testbed does not have to be only for academic use but can also be a tool for guiding policy and regulatory frameworks, especially in areas like healthcare and the autonomous car industry, where both privacy and accountability are issues of concern [2], [17], [40]. Moreover, these are infrastructures that can also promote interdisciplinary collaboration, allowing the comparative studies between FL algorithms in the academic world, and those in the industrial world [4], [9], [36], [41].

F. Roadmap for the Decade to Come

Along with the research possibilities, we put forward a community three-phase roadmap sketching out ways of reaching truly sustainable and verifiable federated systems [5], [9], [16], [22], [37]:

Short-Term (1–2 years):

- Form the open benchmarks for carbon and energy measurement [3], [16], [35].
- Build prototypes for lightweight verification methods and hybrid consensus models [12], [13], [27].
- Start convening interdisciplinary research groups concentrating on green and verifiable FL [5], [20], [22].

Medium-Term (3–5 years):

- At large scales, design and test hybrid blockchain–FL frameworks [8], [17], [25], [36].
- Combine energy monitoring with incentive mechanisms in domain-specific pilots (healthcare or smart-city environments, for example) and then deploy them [2], [26], [40].
- Fund open research initiatives that host standardized metrics and datasets [6], [7], [22].

Long-Term (5–10 years):

- Standardize often carbon-aware and verifiable AI under IEEE, ISO, or academic consortia [37], [38].
- Create sustainability certifications that are recognized globally for FL systems [10], [40].
- Motivate governments and organizations to implement FL solutions that not only show model accuracy but are also environmentally friendly and transparent [4], [17], [40], [45].
- This outline is a prediction of a future where federated learning systems gradually shift from being privacy-preserving to having sustainability certificates and being audit-ready [9], [16], [32], [37], [38], thus, at every juncture of their lifecycle, they remain accountable.

G. Conclusion

Federated Learning (FL) is one of the main methods for distributed and privacy-preserving model training, which has gained a lot of attention in recent years. Despite this, the broad use of FL is still dependent on solving three main issues-how to make it energy efficient, ensuring trust mechanisms, and providing verifiability.This systematic review of 45 studies published between 2021 and 2025 focused on these three dimensions of FL. The results indicate that trust frameworks based on the blockchain have been the major focus of the research; energy efficiency initiatives have been moderate, and measures of verifiability are the least developed among the other aspects. Moreover, in only one instance were all three dimensions integrated, which is an indication of the separated state of current research.

The current situation is further illuminated by the review that points out different trade-offs: while blockchain incorporation allows for openness, the energy used for this can be higher. These contradictions epitomize the urgent need for designs that are lightweight, composable, and aware of their carbon impact to be able to combine the concerns for sustainability and security. The future of this field is dependent on addressing the need for standardized benchmarks in which one will be a hybrid blockchain–FL system and the others will be scalable verification frameworks. There is a recommended phased roadmap — the starting point is open, carbon-aware benchmark creation, then the next step is hybrid trust-efficiency frameworks, and the final stage is the setting of sustainable AI governance standards that are internationally aligned.

Federated Learning can be both sustainable and trustworthy, thus integrating the three pillars of energy efficiency, trust, and verifiability. The integration is a technical achievement and at the same time, it is a moral and practical need in FL deployment across the different domains such as healthcare, IoT, and finance, where privacy, accountability, and sustainability coexist.

REFERENCES

[1] B. Liu, N. Lv, Y. Guo, and Y. Li, "Recent advances on federated learning: A systematic survey," Neurocomputing, vol. 597, p. 128019, Sept. 2024, doi: 10.1016/j.neucom.2024.128019.

[2] M. Baucas, P. Spachos, and K. Plataniotis, "Federated Learning and Blockchain-enabled Fog-IoT Platform for Wearables in Predictive Healthcare," 2023, arXiv. doi: 10.48550/ARXIV.2301.04511.

[3] A. Yousefpour et al., "Green Federated Learning," Aug. 01, 2023, arXiv: arXiv:2303.14604. doi: 10.48550/arXiv.2303.14604.

[4] N. Rodríguez-Barroso, M. García-Márquez, M. V. Luzón, and F. Herrera, "Challenges of Trustworthy Federated Learning: What's Done, Current Trends and Remaining Work," 2025, arXiv. doi: 10.48550/ARXIV.2507.15796.

[5] D. Thakur, A. Guzzo, G. Fortino, and F. Piccialli, "Green Federated Learning: A New Era of Green Aware AI," ACM Comput. Surv., vol. 57, no. 8, pp. 1–36, Aug. 2025, doi: 10.1145/3718363.

[6] X.-T. Dang, B.-M. Vu, Q.-S. Nguyen, T.-T.-M. Tran, J.-S. Eom, and O.-S. Shin, "A Survey on Energy-Efficient Design for Federated Learning over Wireless Networks," Energies, vol. 17, no. 24, p. 6485, Dec. 2024, doi: 10.3390/en17246485.

[7] A. Agiollo, P. Bellavista, M. Mendula, and A. Omicini, "EneA-FL: Energy-aware orchestration for serverless federated learning," Future Gener. Comput. Syst., vol. 154, pp. 219–234, May 2024, doi: 10.1016/j.future.2024.01.007.

[8] W. Ning et al., "Blockchain-Based Federated Learning: A Survey and New Perspectives," Appl. Sci., vol. 14, no. 20, p. 9459, Oct. 2024, doi: 10.3390/app14209459.

[9] J. Liu et al., "Enhancing trust and privacy in distributed networks: a comprehensive survey on blockchain-based federated learning," Knowl. Inf. Syst., vol. 66, no. 8, pp. 4377–4403, Aug. 2024, doi: 10.1007/s10115-024-02117-3.

[10] S. Zhu, R. Li, Z. Cai, D. Kim, D. Seo, and W. Li, "Secure verifiable aggregation for blockchain-based federated averaging," High-Confid. Comput., vol. 2, no. 1, p. 100046, Mar. 2022, doi: 10.1016/j.hcc.2021.100046.

[11] L. Cassano, J. D'Abramo, S. Munir, and S. Ferretti, "Trust and Resilience in Federated Learning Through Smart Contracts Enabled Decentralized Systems," 2024, doi: 10.48550/ARXIV.2407.06862.

[12] A. A. Bellachia, M. A. Bouchiha, Y. Ghamri-Doudane, and M. Rabah, "VerifBFL: Leveraging zk-SNARKs for A Verifiable Blockchained Federated Learning," 2025, arXiv. doi: 10.48550/ARXIV.2501.04319.

[13] J. Guo, K. Vaswani, A. Paverd, and P. Pietzuch, "VerifiableFL: Verifiable Claims for Federated Learning using Exclaves," 2024, arXiv. doi: 10.48550/ARXIV.2412.10537.

[14] D. Commey, B. Appiah, G. S. Klogo, and G. V. Crosby, "ZKP-FedEval: Verifiable and Privacy-Preserving Federated Evaluation using Zero-Knowledge Proofs," 2025, arXiv. doi: 10.48550/ARXIV.2507.11649.

[15] J. R. Nouri, "Verifiable AI: Anchoring Model Outputs and Synthetic Media with Cryptographic Proof-of-Origin Systems," 2025, SSRN. doi: 10.2139/ssrn.5273427.

[16] V. Bolón-Canedo, L. Morán-Fernández, B. Cancela, and A. Alonso-Betanzos, "A review of green artificial intelligence: Towards a more sustainable future," Neurocomputing, vol. 599, p. 128096, Sept. 2024, doi: 10.1016/j.neucom.2024.128096.

[17] Y. Jiang et al., "Blockchained Federated Learning for Internet of Things: A Comprehensive Survey," ACM Comput. Surv., vol. 56, no. 10, pp. 1–37, Oct. 2024, doi: 10.1145/3659099.

[18] Z. Wang, Q. Hu, M. Xu, Y. Zhuang, Y. Wang, and X. Cheng, "A Systematic Survey of Blockchained Federated Learning," June 01, 2024, arXiv: arXiv:2110.02182. doi: 10.48550/arXiv.2110.02182.

[19] Y. Sun, S. Zhou, and D. Gündüz, "Energy-Aware Analog Aggregation for Federated Learning with Redundant Data," 2019, arXiv. doi: 10.48550/ARXIV.1911.00188.

[20] Z. Xing et al., "Zero-Knowledge Proof-based Verifiable Decentralized Machine Learning in Communication Network: A Comprehensive Survey," 2023, doi: 10.48550/ARXIV.2310.14848.

[21] E. Hallaji, R. Razavi-Far, M. Saif, B. Wang, and Q. Yang, "Decentralized Federated Learning: A Survey on Security and Privacy," IEEE Trans. Big Data, vol. 10, no. 2, pp. 194–213, Apr. 2024, doi: 10.1109/TBDATA.2024.3362191.

[22] T. M. Fernández-Caramés and P. Fraga-Lamas, "A Comprehensive Survey on Green Blockchain: Developing the Next Generation of Energy Efficient and Sustainable Blockchain Systems," 2024, arXiv. doi: 10.48550/ARXIV.2410.20581.

[23] X. Gao et al., "VeriFi: Towards Verifiable Federated Unlearning," 2022, arXiv. doi: 10.48550/ARXIV.2205.12709.

[24] C. Lee, J. Heiss, S. Tai, and J. W.-K. Hong, "End-to-End Verifiable Decentralized Federated Learning," 2024, arXiv. doi: 10.48550/ARXIV.2404.12623.

[25] S. Ren, E. Kim, and C. Lee, "A scalable blockchain-enabled federated learning architecture for edge computing," PLOS ONE, vol. 19, no. 8, p. e0308991, Aug. 2024, doi: 10.1371/journal.pone.0308991.

[26] H. Xu, "Blockchain-Enabled Multi-stage Incentive Framework for Federated Learning," Thesis, 2025. Accessed: Oct. 27, 2025. [Online]. Available: https://opus.lib.uts.edu.au/handle/10453/188068

[27] S. Li, Q. Hu, and Z. Wang, "PoFEL: Energy-efficient Consensus for Blockchain-based Hierarchical Federated Learning," Aug. 15, 2023, arXiv: arXiv:2308.07840. doi: 10.48550/arXiv.2308.07840.

[28] A. Mukherjee and R. Buyya, "EnFed: An Energy-aware Opportunistic Federated Learning in Resource Constrained Environments for Human Activity Recognition," 2024, arXiv. doi: 10.48550/ARXIV.2412.00768.

[29] Y. Zhang, D. Zeng, J. Luo, Z. Xu, and I. King, "A Survey of Trustworthy Federated Learning with Perspectives on Security, Robustness, and Privacy," 2023, arXiv. doi: 10.48550/ARXIV.2302.10637.

[30] A. Khan and others, "Securing Federated Learning with Blockchain: A Systematic Review," Springer AI Rev., 2023, doi: 10.1007/s10462-023-10419-8.

[31] L. Wu, W. Ruan, J. Hu, and Y. He, "A Survey on Blockchain-Based Federated Learning," Future Internet, vol. 15, no. 12, p. 400, Dec. 2023, doi: 10.3390/fi15120400.

[32] D. Thakur, A. Guzzo, and G. Fortino, "Hardware-algorithm co-design of Energy Efficient Federated Learning in Quantized Neural Network," Internet Things, vol. 26, p. 101223, July 2024, doi: 10.1016/j.iot.2024.101223.

[33] A. Qammar, A. Karim, H. Ning, and J. Ding, "Securing federated learning with blockchain: a systematic literature review," Artif. Intell. Rev., vol. 56, no. 5, pp. 3951–3985, May 2023, doi: 10.1007/s10462-022-10271-9.

[34] A. Zekiye and Ö. Özkasap, "Blockchain-based Federated Learning for Decentralized Energy Management Systems," 2023, arXiv. doi: 10.48550/ARXIV.2306.17186.

[35] A. S. Luccioni and A. Hernandez-Garcia, "Counting Carbon: A Survey of Factors Influencing the Emissions of Machine Learning," 2023, arXiv. doi: 10.48550/ARXIV.2302.08476.

[36] D. C. Nguyen et al., "Federated Learning Meets Blockchain in Edge Computing: Opportunities and Challenges," IEEE Internet Things J., vol. 8, no. 16, pp. 12806–12825, Aug. 2021, doi: 10.1109/JIOT.2021.3072611.

[37] S. R. Rammohan, K. Chakravarthi, N. Sharma, S. Sharma, and M. Natarajan, "Systematic Survey on Energy Conservation Using Blockchain for Sustainable Computing Challenges and Roadmaps," Int. J. Adapt. Control Signal Process., vol. 39, no. 2, pp. 247–265, Feb. 2025, doi: 10.1002/acs.3948.

[38] K. Balan, R. Learney, and T. Wood, "A Framework for Cryptographic Verifiability of End-to-End AI Pipelines," 2025, arXiv. doi: 10.48550/ARXIV.2503.22573.

[39] A. Korneev and J. Ramon, "A Survey on Verifiable Cross-Silo Federated Learning".

[40] T. Q. D. Pham, K. D. Tran, K. T. P. Nguyen, X. V. Tran, L. Köehl, and K. P. Tran, "A new framework for prognostics in decentralized industries: Enhancing fairness, security, and transparency through Blockchain and Federated Learning," 2025, arXiv. doi: 10.48550/ARXIV.2503.05725.

[41] M. Rahmati, "Energy-aware federated learning for secure edge computing in 5G-enabled IoT networks," J. Electr. Syst. Inf. Technol., vol. 12, no. 1, p. 13, May 2025, doi: 10.1186/s43067-025-00203-2.

[42] E. Gabrielli, G. Pica, and G. Tolomei, "A Survey on Decentralized Federated Learning," 2023, arXiv. doi: 10.48550/ARXIV.2308.04604.

[43] Y. Wang, H. Peng, Z. Su, T. H. Luan, A. Benslimane, and Y. Wu, "A Platform-Free Proof of Federated Learning Consensus Mechanism for Sustainable Blockchains," 2022, doi: 10.48550/ARXIV.2208.12046.

[44] B. Chhetri, S. Gopali, R. Olapojoye, S. Dehbash, and A. S. Namin, "A Survey on Blockchain-Based Federated Learning and Data Privacy," June 29, 2023, arXiv: arXiv:2306.17338. doi: 10.48550/arXiv.2306.17338.

[45] E. Moore, A. Imteaj, S. Rezapour, and M. H. Amini, "A Survey on Secure and Private Federated Learning Using Blockchain: Theory and Application in Resource-Constrained Computing," IEEE In-

ternet Things J., vol. 10, no. 24, pp. 21942–21958, Dec. 2023, doi: 10.1109/JIOT.2023.3313055.

APPENDIX

ADDITIONAL TABLE

Legend: E = Energy/Carbon-awareness, B = Blockchain integration, V = Verifiability mechanisms. Y = Yes, N = No, P = Partial.

Ref.	Authors / Year	Title (short)	Venue	Focus	E/B/V	Note
[1]	Liu et al., 2024	Recent Advances on FL: A Systematic Survey	Neurocomputing	FL survey	N/N/N	Broad FL; lacks blockchain or energy scope.
[2]	Baucas et al., 2023	FL and Blockchain-enabled Fog-IoT Platform for Wearables	arXiv	Healthcare BFL	Y/Y/P	Secure FL for healthcare; limited verification.
[3]	Yousefpour et al., 2023	Green Federated Learning	arXiv	Energy-efficient FL	Y/N/N	Energy metrics analyzed; no blockchain link.
[4]	Rodríguez-Barroso et al., 2025	Challenges of Trustworthy Federated Learning	arXiv	Trustworthy FL	P/P/P	Highlights trust and reliability issues.
[5]	Thakur et al., 2025	Green Federated Learning: New Era of Green Aware AI	ACM CSUR	Green FL (survey)	Y/N/N	Covers green AI and energy optimization.
[6]	Dang et al., 2024	Energy-Efficient Design for FL over Wireless Networks	Energies (MDPI)	Wireless FL energy	Y/N/N	Focuses on energy-efficient communication.
[7]	Agiollo et al., 2024	EneA-FL: Energy-Aware Orchestration for Serverless FL	FGCS	Energy-aware orchestration	Y/N/N	Optimizes energy and runtime scheduling.
[8]	Ning et al., 2024	Blockchain-Based FL: Survey and New Perspectives	Appl. Sci. (MDPI)	BFL taxonomy	P/P/P	Surveys BFL models; minimal energy detail.
[9]	Liu et al., 2024	Enhancing Trust & Privacy in Distributed Networks	Knowl. Inf. Syst.	Privacy in BFL	P/P/P	Focuses on privacy and blockchain trust.
[10]	Zhu et al., 2022	Secure Verifiable Aggregation for Blockchain-based FL	High-Confidence Comput.	Verifiable BFL aggregation	N/Y/Y	Uses proofs for verifiable aggregation.
[11]	Cassano et al., 2024	Trust and Resilience in FL Through Smart Contracts Enabled Systems	arXiv	Smart-contract FL	P/Y/P	Smart contracts enhance trust and resilience.
[12]	Bellachia et al., 2025	VerifBFL: Leveraging zk-SNARKs for Verifiable BFL	arXiv	Verifiable BFL	Y/N/Y	zk-SNARKs ensure verifiable FL.
[13]	Guo et al., 2024	VerifiableFL: Verifiable Claims for FL Using Exclaves	arXiv	Verifiable FL	Y/N/Y	Hardware enclaves ensure verifiable training.
[14]	Commey et al., 2025	ZKP-FedEval: Privacy-Preserving Federated Evaluation	arXiv	ZKP-based FL	Y/N/N	Uses ZKPs for private model evaluation.
[15]	Nouri, 2025	Verifiable AI: Proof-of-Origin for Model Outputs	SSRN	Verifiable AI pipelines	Y/Y/Y	Tracks AI outputs with cryptographic proofs.
[16]	Bolón-Canedo et al., 2024	Review of Green Artificial Intelligence	Neurocomputing	Green AI survey	Y/N/N	Focuses on sustainable and low-carbon AI.
[17]	Jiang et al., 2024	Blockchained Federated Learning for IoT: Survey	ACM CSUR	IoT BFL survey	P/P/P	Explores IoT BFL frameworks and trust.
[18]	Wang et al., 2024	Systematic Survey of Blockchained Federated Learning	arXiv	BFL survey	P/P/P	Classifies blockchain roles in FL.
[19]	Sun et al., 2019	Energy-Aware Analog Aggregation for FL with Redundant Data	arXiv	Energy-aware scheduling	Y/N/N	Reduces communication energy in FL.
[20]	Xing et al., 2023	ZKP-based Verifiable Decentralized ML	arXiv	Verifiable decentralized ML	Y/P/Y	Integrates ZKPs for model transparency.
[21]	Hallaji et al., 2024	Decentralized Federated Learning: Security & Privacy Survey	IEEE Trans. Big Data	Decentralized BFL	P/Y/P	Discusses privacy and trust in DFL.
[22]	Fernández-Caramés et al., 2024	Comprehensive Survey on Green Blockchain	arXiv	Green blockchain systems	Y/N/N	Reviews sustainable blockchain designs.
[23]	Gao et al., 2022	VeriFi: Towards Verifiable Federated Unlearning	arXiv	Verifiable FL unlearning	Y/Y/P	Enables verified unlearning with proofs.
[24]	Lee et al., 2024	End-to-End Verifiable Decentralized Federated Learning	arXiv	Verifiable decentralized FL	P/P/Y	Ensures full-chain verification in FL.
[25]	Ren et al., 2024	Scalable Blockchain-enabled FL for Edge Computing	PLOS ONE	Edge-based BFL	Y/Y/N	Edge FL improves trust and scalability.
[26]	Xu, 2025	Blockchain-enabled Multi-stage Incentive Framework for FL	Thesis (UTS)	Incentive BFL	Y/P/P	Incentive design enhances trust and fairness.
[27]	Li et al., 2023	PoFEL: Energy-efficient Consensus for Blockchain-based FL	arXiv	BFL + energy consensus	Y/P/P	Reuses FL energy in blockchain consensus.
[28]	Mukherjee et al., 2024	EnFed: Energy-aware Opportunistic FL in HAR Systems	arXiv	Energy-aware FL	Y/N/N	Lowers device energy via adaptive FL.
[29]	Zhang et al., 2023	Survey of Trustworthy Federated Learning	arXiv	Trustworthy FL (Survey)	P/P/P	Reviews FL trust, privacy, and robustness.
[30]	Khan et al., 2023	Securing FL with Blockchain: Systematic Review	Springer AI Review	Security/Privacy in BFL	P/P/P	Discusses FL security using blockchain.
[31]	Wu et al., 2023	Survey on Blockchain-Based Federated Learning	Future Internet (MDPI)	BFL Survey	P/P/P	Summarizes BFL models and challenges.
[32]	Thakur et al., 2024	Hardware-Algorithm Co-design for Energy-Efficient FL	Internet Things (Elsevier)	Energy-efficient FL	Y/N/N	Optimizes FL using quantized models.
[33]	Qammar et al., 2023	Securing FL with Blockchain: Literature Review	Artif. Intell. Rev.	BFL security survey	P/P/P	Focuses on security and auditability in BFL.
[34]	Zekiye et al., 2023	BFL for Decentralized Energy Management Systems	arXiv	Energy management BFL	Y/Y/N	Applies BFL to smart grid management.
[35]	Luccioni et al., 2023	Counting Carbon: Survey on ML Emission Factors	arXiv	Green AI (carbon study)	Y/N/N	Studies carbon footprint in ML training.
[36]	Nguyen et al., 2021	FL Meets Blockchain in Edge Computing: Opportunities	IEEE IoT J.	Edge BFL opportunities	P/P/P	Early study of FL–blockchain synergy.
[37]	Rammohan et al., 2025	Energy Conservation Using Blockchain for Sustainable Computing	Int. J. Adapt. Control Signal Process.	Green blockchain survey	Y/N/N	Reviews blockchain energy-saving methods.
[38]	Balan et al., 2025	Cryptographic Verifiability of End-to-End AI Pipelines	arXiv	Verifiable AI pipelines	P/Y/Y	Proposes cryptographic proofs for AI pipelines.
[39]	Korneev et al., 2025	Survey on Verifiable Cross-Silo Federated Learning	arXiv	Cross-silo verifiable FL	Y/Y/P	Reviews enterprise-focused verifiable FL.
[40]	Pham et al., 2025	Framework for Fair, Transparent Decentralized Industries	arXiv	Decentralized BFL fairness	Y/P/P	Enhances fairness and transparency via BFL.
[41]	Rahmati, 2025	Energy-Aware FL for Secure Edge Computing in IoT Networks	J. Electr. Syst. Inf. Technol.	Energy-aware FL	Y/N/N	Manages energy use in 5G-enabled FL.
[42]	Gabrielli et al., 2023	Survey on Decentralized Federated Learning	arXiv	Decentralized FL (Survey)	P/P/P	Analyzes DFL privacy and architecture.
[43]	Wang et al., 2022	Platform-Free Proof of FL Consensus Mechanism	arXiv	Sustainable BFL consensus	Y/P/P	Introduces eco-friendly FL consensus.
[44]	Chhetri et al., 2023	Blockchain-Based FL and Data Privacy: Survey	arXiv	Privacy in BFL	P/P/P	Focuses on BFL privacy mechanisms.
[45]	Moore et al., 2023	Secure and Private FL Using Blockchain: Theory & Applications	IEEE IoT J.	Secure BFL applications	P/P/P	Addresses FL security in IoT networks.

TABLE II: Additional Comparative Table of Surveyed Works Including Energy Awareness (E), Blockchain Use (B), Verifiability (V).