

Decentral and Incentivized Federated Learning Frameworks: A Systematic Literature Review

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Abstract—The advent of Federated Learning (FL) has ignited a new paradigm for parallel and confidential decentralized Machine Learning (ML) with the potential of utilizing the computational power of a vast number of IoT, mobile and edge devices without data leaving the respective device, ensuring privacy by design. Yet, in order to scale this new paradigm beyond small groups of already entrusted entities towards mass adoption, the Federated Learning Framework (FLF) has to become (i) truly decentralized and (ii) participants have to be incentivized. This is the first systematic literature review analyzing holistic FLFs in the domain of both, decentralized and incentivized federated learning. 422 publications were retrieved, by querying 12 major scientific databases. Finally, 40 articles remained after a systematic review and filtering process for in-depth examination. Although having massive potential to direct the future of a more distributed and secure AI, none of the analyzed FLF is production-ready. The approaches vary heavily in terms of use-cases, system design, solved issues and thoroughness. We are the first to provide a systematic approach to classify and quantify differences between FLF, exposing limitations of current works and derive future directions for research in this novel domain.

Index Terms—Federated Learning, Blockchain, Mechanism Design, Game Theory, Survey.



1 INTRODUCTION

CENTRALIZED platforms in the domains of search-engines, mobile applications, social-media, chat, music and retail have been dominating the respective industries over the past decades. Business models where digital services are exchanged for user data have developed into high-revenue industries where a few single entities control the global market within the respective domains [1]. The resulting concentration of user data in a small number of entities, however, poses problems such as the risk of privacy data leaks [2] or an increasing power imbalance in favor of market-dominating parties [1], [3], [4] which has caused policymakers to enhance data protection for individuals [5]. The need for confidential AI goes beyond B2C markets, e.g. where entities within the health sector or IoT based industries are prohibited from collaborating on a shared AI model due to sensitive data.

A promising solution that enables the training of machine learning models with improved data security is *Federated Learning* (FL). In FL, complex models such as *Deep Neural Networks* (DNNs) are trained in a parallel and distributed fashion on multiple end devices with the training data remaining local at all times. *Federated Averaging*

(FedAvg) [6] is a widely applied algorithm for FL, where a central authority aggregates a global model from the locally trained models in an iterative process. In theory, FL not only makes previously withheld sensitive data accessible to the machine learning process, but also enables efficient training by taking advantage of the ever-increasing computational power of IoT and mobile devices. Therefore, the technology has the potential to disrupt the contemporary, centralized DNN learning approach towards a decentralized, fair and power-balanced paradigm.

Yet, beyond technical issues, two major design problems remain unsolved: (i) The star topology of FL introduces the risk for single point of failure as well as authority abuse and prohibits use-cases where equal power among participants is a mandatory requirement and (ii) the lack of a practical reward system for contributions of participants hinder this technology from scaling beyond small groups of already entrusted entities towards mass adoption.

Although there exist many proposals of *Incentivized and Decentralized Federated Learning Frameworks* (FLFs), we have not yet seen any full-fledged production-level FLF. To enhance the development towards production-readiness, we took on the challenging task of comparing state-of-the-art solutions despite their heterogeneity in terms of assumptions, use-cases, design choices, special focus and thoroughness by providing a general and holistic comparison framework. Yet, since deep domain knowledge is required across a wide variety of fields, e.g. in blockchain design pattern, game theory, decentralized deep neural network, and security & privacy, we aim to explain concepts concisely to make it easier for experts in a specific domain to follow along.

Specifically, we undertake a *Systematic Literature Review* (SLR) examining all relevant articles from twelve scientific databases in the domain of computer science. 422 results were queried, filtered and examined for relevant articles

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from these databases, resulting in 40 papers remaining after three filtering steps. To the best of our knowledge, this is the first comprehensive survey on the design of both decentralized and incentivized federated artificial intelligence systems. The contribution of this paper is three-fold:

- 1) The first comprehensive systematic survey study on the combined topic of decentralized and incentivized Federated Learning based on the standardized Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) process, ensuring transparency and reproducibility of the work.
- 2) A novel comparison framework for an in-depth analysis of incentivized and decentralized FL frameworks which goes beyond existing survey papers by (i) pointing out the limitations and assumptions of the chosen game-theoretic approaches, (ii) analyzing the existing solutions based on computational and storage overhead on the blockchain, and (iii) an in-depth analysis of the performed experiments.
- 3) Based on the rating and clustering, we have clarified trade-offs in design choices, identified limitations and derived future research directions of decentralized and incentivized Federated Learning frameworks.

The remainder of this paper is structured as follows. In Section 2, we concisely present the technical background of distributed ledger technology and mechanism design in FL systems. In Section 3, we provide an overview of existing surveys on this topic and their respective problem statements. In Section 4, we outline our detailed research questions and introduce our methodology to answer these by conducting a structured literature review. Furthermore, contemporary shortcomings of FLFs are discussed and the SLR is undertaken. Section 5 summarizes the findings and answers the research questions with respect to general applications of the FLFs, Blockchain features, incentive mechanisms and experiments. We derive limitations and further research directions in Section 6. Finally, Section 7 concludes this literature review.

2 PRELIMINARIES

The following sections briefly discuss the fundamentals of Federated Learning, distributed ledger technology, and mechanism design.

2.1 Federated Learning

Federated Learning is a machine learning technique where multiple actors collaboratively train a joint machine learning model locally and in parallel, such that the individual training data does not leave the device. This decentralized approach to machine learning was first introduced by Google in 2016 [6] and addresses two key issues of machine learning: (1) The high computational effort for model training is relocated from a single central actor to a network of data-owning training devices. (2) Since the training data remains on the edge devices, previously inaccessible data

sets of privacy-concerned actors can be integrated into the training process. Thus, "data islands" are prevented.

The *Federated Averaging* (FedAvg) algorithm [6] is a widely adopted optimization algorithm for the FL case, where the calculated gradients for the respective local model training get aggregated and the data stays confidential at all times. The objective is to minimize the empirical risk of the global model θ , such that

$$\arg \min_{\theta} \sum_i \frac{|S_i|}{|S|} f_i(\theta) \quad (1)$$

where for each agent i , f_i represents the loss function, S_i is the set of indexes of data points on each client and $S := \bigcup_i S_i$ is the combined set of indexes of data points of all participants. The most common algorithmic approach to FL problems is Federated Averaging, where the training process is conducted in three communication rounds:

- 1) A central server broadcasts a first model initialization θ_{init} to a subset of participating clients¹.
- 2) These clients individually perform iterations of stochastic gradient descent over their local data to improve their respective local models θ_i on each client.
- 3) In order to create a global model θ , all individual models θ_i are then send back to the server, where they are aggregated (e.g. by an averaging operation). This global model is used as the initialization point for the next communication round.

Optimization algorithms for the FL case are open research [7] and variations of FedAvg exist, e.g. FedBoost [8], FedProx [9], FedNova [10], FedSTC [11] and FetchSGD [12].

Note that the FL setting can range from a few collaborating entities (cross-silo) to a federated system of millions of devices (cross-device).

2.2 Blockchain: A Distributed Ledger Technology

A distributed ledger kept by nodes in a peer-to-peer network is referred to as blockchain, first invented by Satoshi Nakamoto through Bitcoin in 2008 [13]. Cryptographic connections of information enable resistance to alteration and immutability. A peer-to-peer consensus mechanism governs the network, obviating the requirement for central coordination [14]. The introduction of general-purpose blockchains with smart contract capability that supports Turing-completeness [15] has allowed for the creation of decentralized, immutable, and transparent business logic on top of the blockchain. Due to its intrinsic features, this technology is capable of mitigating open issues in the FL context, namely:

- 1) **Decentralization.** Workers are subject to a power imbalance and a single point of failure in server-worker topologies. A malicious server might refuse to pay reward payments or exclude employees at will. Furthermore, a server-worker architecture is

1. clients, workers and agents are used interchangeably

incompatible with a situation in which numerous entities have a shared and equal stake in the advancement of their respective models. Blockchain technologies’ decentralization provides a federal system for entities of equal authority without the need for a central server.

- 2) **Transparency and Immutability.** Data on the blockchain can only be updated, not erased, because every peer in the system shares the same data. In a FL environment, a clear and immutable reward system ensures worker trust. On the other side, each client is audited, and as a result, can be held accountable for malevolent activity.
- 3) **Cryptocurrency.** Many general-purpose blockchain systems include cryptocurrency capabilities, such as the ability to incorporate payment schemes within the smart contract’s business logic. Workers can be rewarded instantly, automatically, and deterministically based on the FL system’s reward mechanism.

Blockchain to ensure equal power. General purpose blockchain systems [15], [16], [17] have the potential to mitigate the first issue of FL by ensuring trust through their inherent properties of immutability and transparency of a distributed ledger, thereby enabling decentralized federations to mitigate dependencies on a central authority.

2.3 Incentive Mechanism

In an environment where it is of utmost importance that pseudo-anonymous clients participate in the FL process, a fair incentive mechanism is required for any realistic setting.

However, the question here is how to design a good incentive mechanism. Simply giving a fixed amount of reward to each worker would not work well as any worker can obtain rewards without doing model updates. A key to answer this question is mechanism design (MD), which is a field of economics and attempts implementing a protocol, system, or rule so that a desired situation (e.g. every participant contributes informed truthful model updates) is realized in a strategic setting, assuming that each participant acts rationally in a game theoretic sense [18].

The purpose of incorporating MD into FL is to incentivize clients to (i) put actual effort into obtaining real and high quality signals (i.e. training the model on local data) and (ii) submit truthfully, without the explicit ability to directly monitor the clients’ behavior. As also mentioned in the previous section, such incentives can be distributed using blockchain’s cryptocurrencies. An appropriately designed mechanism ensures a desired equilibrium when every worker acts rationally and in its own best interest. Such a mechanism has low complexity and is self-organizing, avoiding the need for Trusted Execution Environments (TEE) [19] or secure multi-party computation, yet makes assumptions about the degree of information available.

The process of designing a FL protocol with MD consists of (i) designing a mechanism and (ii) theoretical analysis. The former determines the whole procedure of FL including a reward policy (i.e. how to distribute rewards). A myriad of reward design choices exist: whether

TABLE 1: Comparison of related survey papers.

Ref.	Blockchain	Federated Learning	Incentive Mechanism	Experiment Analysis
[21]	✓	✓	✗	✗
[22]	Partially	✓	✗	✗
[23]	Partially	✓	✓	✗
[24]	✗	✓	✓	✗
[25]	✗	✓	✓	✗
[26]	Partially	✓	Partially	✗
This work	✓ (Detailed)	✓	✓	✓

rewards should be given to the top contributor (i.e. winner-takes-all) or multiple workers and whether rewards should be unequally distributed based on their contribution or equally distributed. When contribution needs to be measured to determine the amount of prizes, this demands a carefully designed reward strategy based on the quality of contributions. Yet, comparing and evaluating workers gradient-updates of FedAvg remains challenging [20]. A game-theoretic analysis is required to ensure that the designed protocol works as planned. Such an approach helps to design a mechanism where the best strategy for all workers leads to a stable equilibrium intended by the system designer. Section 5.3 discusses how FLFs apply mechanism design and how contributions are measured.

3 RELATED SURVEYS AND MOTIVATION OF THIS PAPER

We have identified several survey papers in the context of either mechanism design and FL [22], [23], [25] or blockchain and FL [21], [23], [24]. TABLE 1 shows the comparison of the related survey papers and our own.

Hou *et al.* surveyed the state-of-the-art blockchain-enabled FL methods [21]. They focused on how blockchain technologies are leveraged for FL and summarized them based on the types of blockchain (public or private), consensus algorithms, solved issues and target applications.

The other related survey papers focus on incentive mechanisms for FL [22], [23], [24], [25]. Zhan *et al.* survey the incentive mechanism design dedicated to FL [22]. They summarize the state-of-the-art research efforts on the measures of clients’ contribution, reputation and resource allocation in FL. Zeng *et al.* also survey the incentive mechanism design for FL [23]. However, the difference is that they focus on incentive mechanisms such as Shapley values, Stackelberg game, auction, context theory and reinforcement learning. Ali *et al.* survey incentive mechanisms for FL [24]. In addition to [22] and [23], they summarize involved actors (e.g. number of publishers and workers), evaluation datasets as well as advantages and disadvantages of the mechanisms and security considerations. Tu *et al.* [25] provide a comprehensive review for economic and game theoretic approaches to incentivize data owners to participate in FL. In particular, they cluster applications of Stackelberg games, non-cooperative games, sealed-bid auction models, reverse action models as well as contract and matching theory for incentive MD in FL. Nguyen *et al.* investigate opportunities and challenges of blockchain-based federated learning in edge computing [26].

As revealed from our analysis and summarized in TABLE 1, the existing survey papers lack a holistic view of

decentralized *and* incentivized federated learning which is crucial to spreading the new generation of widely adopted fair and trustworthy FL to the benefit of the data owner. To the best of our knowledge, this paper is the first systematic literature review on the topic of blockchain-enabled decentralized FL with incentive mechanisms.

4 METHOD OF LITERATURE REVIEW

The goal of the following systematic literature review is the identification of decentralized collaborative learning solutions where participation is rewarded. The aim of this study is not only to summarize all major publications, but also to extend the research by having a guideline for current and future practitioners.

Relevant publications are retrieved, filtered, and selected by a methodical procedure. The procedure is inspired by the *Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)* methodology [27]. PRISMA helps authors to improve the reporting of reviews. Within this work, the PRISMA methodology is augmented with the guide for information systems proposed by Okoli *et al.* and Kitchenham *et al.* [28], [29]. The guidelines are a structured approach to conduct a systematic literature review. They consist of five core steps: (i) defining research questions, (ii) searching for literature, (iii) screening, (iv) reviewing, (v) selecting and documenting relevant publication and extracting relevant information. The corresponding flow diagram of the conducted SLR is illustrated in Fig. 1.

4.1 Research Questions

The review and selection of relevant literature is conducted for extracting, preparing, and summarizing relevant information for future researchers. The scope of relevant information is described and limited by five corresponding research questions.

- RQ1 Overview: (i) What are possible applications of FLF? (ii) What problems were solved? (iii) Across which dimensions are the FLF papers heterogeneous?
- RQ2 Blockchain: (i) What is the underlying blockchain architecture? (ii) How is blockchain applied within the FLF and what operations are performed? (iii) Is scalability considered?
- RQ3 Incentive mechanism: (i) How are incentive mechanisms analyzed? (ii) How are the contributions of workers measured?
- RQ4 Federated learning: (i) Is the performance of the framework reported? (ii) How comprehensive are the experiments? (iii) Are non-IID scenarios simulated? (iv) Are additional privacy methods applied? (v) Is the framework robust against malicious participants?
- RQ5 Summary: What are the lessons learned from the review?

4.2 Search Process

We conduct a well-defined search process of relevant publications to allow for reproducibility. The main keywords of interest are “Federated Learning”,

“Blockchain”, and “Game Theory”. Due to the existence of synonyms (e.g. “Collaborative Learning” instead of “Federated Learning”) and abbreviations (e.g. “DLT” instead of “Blockchain”) the search term is extended by taking these variations into account. The final case-insensitive search term is the following:

Search Term

```
("Federated Learning" OR "Federated
Artificial Intelligence" OR
"Collaborative Learning") AND
("Blockchain" OR "Distributed Ledger"
OR "DLT") AND ("Mechanism Design" OR
"Incentive" OR "Reward" OR "Game Theory"
OR "game-theoretical" OR "Economics")
```

We selected 12 of the major computer science publication databases. The search was conducted on November 21, 2021. All search results retrieved at that date were taken as input for further manual inspection. The current results of the query can be obtained by following the hyperlink after each database entry below:

- IEEE Xplore Digital Library ([URL](#))
- SpringerLink Database ([URL](#))
- ACM Digital Library ([URL](#))
- ScienceDirect Database ([URL](#))
- MDPI² ([URL](#))
- Emerald insight ([URL](#))
- Talor & Francis [URL](#)
- Hindawi ([URL](#))
- SAGE ([URL](#))
- Inderscience online ([URL](#))
- Wiley ([URL](#))

After applying the search term, we found 422 publications overall. In addition to this search, the references were screened and 1 more eligible paper was found and included for analysis.

Each publication that we retrieved based on our search was exported or enriched by (i) document title, (ii) abstract, (iii) author names, (iv) publication year, and (v) Digital Object Identifier (DOI).

4.3 Selection Process

The eligibility of the literature corpus that we gathered based on the string was evaluated independently by three researchers. Duplicates were removed and several iterations of manual verification were performed. First, we present the criteria that we applied to include (or exclude) an article for further consideration. Then, we discuss our manual eligibility check.

4.3.1 Inclusion and exclusion criteria

The following three criteria must be fulfilled by an article in order for it to be included for further analysis:

2. As MDPI does not allow for nested search terms, we tried possible keyword combinations such as “Federated Learning” AND “Blockchain” AND “Mechanism Design”

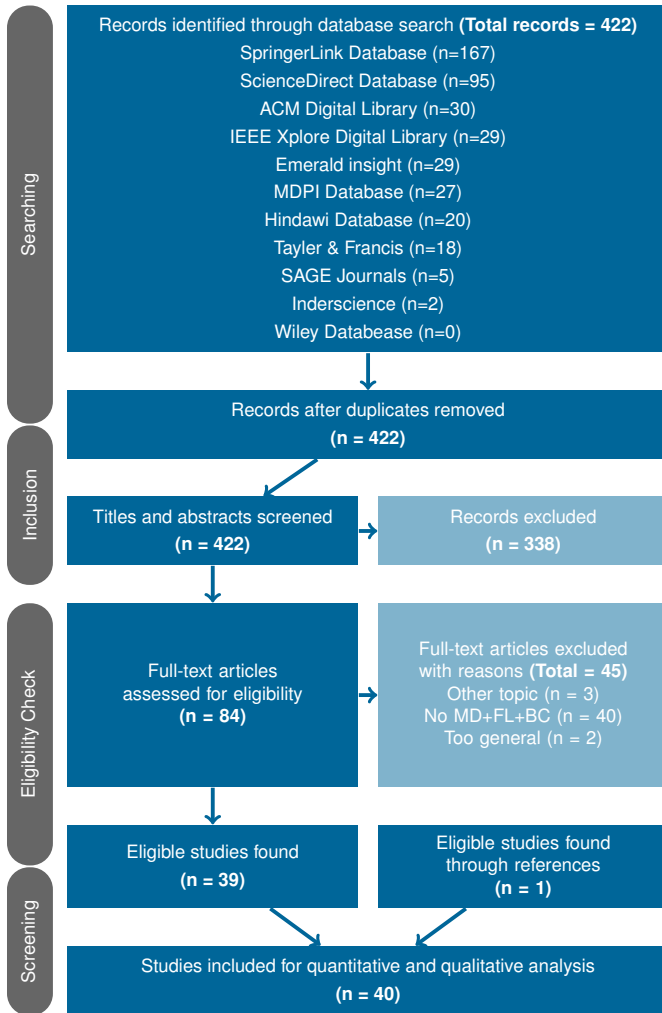


Fig. 1: PRISMA diagram.

- 1) The article must have a direct relation to all of the three search terms (*i*) Federated Learning & (*ii*) Blockchain & (*iii*) Mechanism Design or their respective synonyms.
- 2) The article must be of full length to explain proposed architectures and concepts in depth.
- 3) The article must be written in English.

If the article matched one of the following three criteria, it was excluded from further analysis:

- 1) Articles which do not discuss collaborative learning in the context of both decentralization and incentives. This also covered articles which discuss only two of the three major terms or consider the search terms in a different context.
- 2) Short papers such as poster abstracts because they do not cover enough information to provide a sufficient level of understanding.
- 3) Vague articles which only give a brief overview about the topics, e.g. superficial descriptive articles were excluded.

4.3.2 Manual eligibility check

The following manual eligibility checks were performed by the authors:

- 1) Removal of faulty or correction of incorrect lines in the aggregation file that includes all search results.
- 2) Reading the titles and abstracts of the articles. Each article was marked as follows based on our inclusion criteria, see Section 4.3.1:
 - a) Include, if the article should be included.
 - b) Exclude, if the article should be excluded.
 - c) Not sure, if the article should be re-checked against the defined criteria and briefly discussed.
- 3) The authors compared and discussed their assessments. Disagreements were highlighted and handled as follows: The article was re-checked against the defined criteria and briefly discussed. Sometimes one researcher noticeably misinterpreted the research focus of an article. In that case the article was excluded. In all other cases the article was included.
- 4) Reading parts of or the complete full text in order to get a deeper insight into the research. Then, the article was again voted for inclusion or exclusion.
- 5) The authors compared and discussed their respective selected papers. The same decision levels as described in 2) were used for the comparison.
- 6) The authors read all eligible papers independently and extracted all necessary information.
- 7) Discussion of findings and information exchange.

If the decision on the eligibility of a paper was not clear after further consideration, the authors decided on including the respective article. All included articles were read and relevant information was extracted.

4.4 Screening Process

In order to cover as much structured information as possible, the analysis of the papers was guided by predefined categories regarding the FL framework (TABLE 5), blockchain features (TABLE 6), incentive mechanism features (TABLE 7) and the experiment analysis (TABLE 8). After conducting all steps described above, a total of 40 articles remain that match the initially defined scope of this structured literature review and are further processed to answer the research questions.

5 RESULTS

The following subsections systematically present the results of the literature review by answering the five respective research questions. Each subsection is complemented by an explanatory table that classifies the considered papers according to categories defined in TABLE 4.

5.1 RQ 1: Overview

5.1.1 RQ 1-1: What are possible applications of FLF?

Although most of the surveyed papers do not target specific applications (28 out of 40) due to generalizability of neural networks, some are dedicated to specific applications, namely *Internet of Things* (IoT) (6 out of 40), *Internet of Vehicles* (IoV) (5 out of 40) and *Finance* (1 out of

TABLE 2: Number of papers found and included by publishers.

Publisher	#Papers Found	#Papers Included
Springer	167	5
ScienceDirect	95	1
ACM	30	4
IEEE	29	21+2 ³
Emerald insight	29	0
MDPI	27	3
Hindawi	20	2
Taylor & Francis	18	1
SAGE journals	5	0
Inderscience	2	0
Wiley	0	0
Total	422	39

TABLE 3: Notation table.

Name	Definition
n.s.	Not specified
n.a.	Not applicable
✓	True
✗	False
CS	cross-silo (few clients)
CD	cross-device (many clients)

40). Applications of FLF in special domains may require additional constraints and characteristics. The heterogeneity of the required properties across those domains lead to vast differences in the design choices of function, operations and storage of blockchain, contribution measurement and privacy requirements.

One of the major application scenarios is IoT (e.g. [33], [34], [48]). Sensor-equipped devices collect environmental information and execute model updates thanks to advances in neural engines while edge servers are often assumed to aggregate models that are trained by local sensor devices. For instance, power consumption measured at smart homes can be used for training an AI model of energy demand forecast [57]. Zhao *et al.* propose a FLF for smart home appliance manufacturers to obtain AI models trained with their customers' usage information [34].

Some solved issues pertaining to the IoT-based FL [33], [53]. Zhang *et al.* propose a FL-based failure device detection method that takes into account the fact that sensor readings are often imbalanced since sensors are, in general, not deployed uniformly in a sensing area [33]. They propose a modified FedAvg algorithm called centroid distance weighted federated averaging (CDW_FedAvg) to obtain accurate models when local datasets are imbalanced at the devices. As sensor devices may not have enough resources to solely train neural networks, it is important to determine whether to delegate computationally intensive tasks to edge servers. Qu *et al.* propose an algorithm to determine whether to offload computation to edge servers when

communications between IoT devices and edge computers are unreliable [53].

FL is beneficial to many scenarios in ITS or IoV, e.g. optimized routing, congestion control and object detection for autonomous driving ([37], [44], [49], [61], [63]). Vehicles collect local information and train local models with collected data. Models are often aggregated by devices called RSUs (Road Side Units) and MECs (Mobile Edge Computers) which are often deployed on the road. In IoV, the Cross-Device (CD) setting is often preferred as mostly the same types of sensors are used to measure road condition, and thus the common neural network model structure is shared by vehicles. As different locations have different road conditions, users need locally-optimized models, and thus scalability is a key issue. Furthermore, we need extra protection for users' location privacy. Zou *et al.* propose a FLF for a knowledge trading marketplace where vehicles can buy and sell models that vary geographically [61]. Chai *et al.* propose multiple blockchains to deal with geographically dependent models [44]. Kansra *et al.* integrate data augmentation, a technique to synthetically generate data such as images, into FL to increase model accuracy for ITS such as autonomous driving and road object identification [49]. Wang *et al.* propose a FLF dedicated to the crowdsensing of UAVs (Unmanned Aerial Vehicles) [63]. As UAVs are often equipped with multiple sensors and can be easily deployed to sensing area, a FLF with UAVs has a huge benefit for ITS applications such as traffic monitoring and public surveillance.

The other domain we found in the surveyed papers is finance. He *et al.* proposed a FLF for commercial banks to better utilize customers' financial information [52]. Financial information such as credit level, risk appetite, solvency, movable and real estate owned are crucial sources to understanding the characteristics of customers of financial services. However, it is too sensitive to directly use them for data mining. Hence, a FLF is a viable framework for financial information management.

5.1.2 RQ 1-2: What problems were solved?

The problems solved by the papers can be categorized into (i) the single point of failure/trust issue in FL, (ii) blockchain-related issues, (iii) lack of clients' motivation, (iv) how to fairly evaluate clients' contribution, (v) security and privacy issues.

Most of the papers (29 out of 40) propose a system architecture of FLF to solve the problems of single point of failure/trust in the current centralized server-clients architecture. More specifically, this issue is rooted in the structure of the original FL where an aggregation server is collecting local model updates from clients in a centralized manner. The idea to mitigate this issue is to decentralize the processes involved in FL using blockchain technologies. Each paper proposes operations, functions and protocols processed in and outside the smart contract. Furthermore, some solve the issue of scalability in the FLF (e.g. [44], [48]) and blockchain-related issues such as energy waste of consensus algorithms (e.g. [65], [66]). We will go into the proposed system architectures and blockchain-related issues in Section 5.2.1.

TABLE 4: Definition of columns in the overview tables.

Table	Column	Definition	Possible Values and Examples
FL (TABLE 5)	Application	The field of application of a FLF	Generic, Internet of Things (IoT), ...
	Domains of key contributions	To which domains each paper contribute	System architecture, blockchain, ...
	FL setting	Whether a type of FL is given	CS (cross-silo), CD (cross-device)
	Actors	The key actors in the FLF	Workers, aggregation servers, task publishers, ...
	Setup period	Whether information about the setup of a FLF is included (e.g. who deploys a blockchain)	✓ / ✗
BC (TABLE 6)	Operation on BC	Operations taking place on-chain	Aggregation, payment, coordination, storage
	BC framework	The underlying Blockchain framework applied within the FLF	Agnostic, novel, Ethereum, Corda ...
	Consensus mechanism	The consensus mechanism of BC applied in the FLF	PoW, PoS, PBFT, novel, ...
	Storage on BC	Information that is stored on the Blockchain.	Gradients/model parameters, reputation scores ...
	Storage quantification	Whether the amount of information stored on the BC is analyzed	✓ / ✗
	Storage off-chain	Whether to store data off-chain, such as Interplanetary File System (IPFS)	✓ / ✗
IM (TABLE 7)	Scalability	Whether scalability is considered.	✓ / ✗
	Simulation	Whether profits, rewards or utilities were evaluated via simulation	✓ / ✗
	Theoretical analysis	Whether profits, rewards or utilities were theoretically analyzed	✓ (Used theory) / ✗
	Costs assumed in utility analysis	Cost elements considered for theoretical analysis	Energy consumption, ..., or ✗ if not used
	Metrics for contribution measurement	Metrics used to validate workers' contribution	Accuracy, data size, ... or ✗ if not used
Experiments (TABLE 8)	Validator	Entities that validate workers' contribution	Task requesters, smart contracts, ...
	ML task	Machine Learning task of the experiment	Classification, regression, ...
	Dataset	Datasets on which the experiments are conducted	MNIST, CIFAR10, ...
	Number of Clients	Number of clients within the experiments	
	FL algorithm	FL algorithm applied within the experiments	FedAvg, FedProx ...
	Privacy protection	Whether additional privacy protection methods are applied within the experiments	✓ / ✗
	Non-IID data	Whether experiments are conducted under the non-IID condition	✓ / ✗
	Adversaries	Whether the FNFs robustness is tested with malicious agents	✓ / ✗
	BC implementation	Whether the blockchain part of the FNF is implemented for conducting experiments	✓ / ✗
	Performance	Whether the performance within the experiments of the FL model is measured	✓ / ✗

An incentive mechanism is integrated into FLFs to solve the problem of lack of clients' motivation. The basic idea is to give monetary incentives to clients in return for their effort in training a local model. The incentive mechanism is also leveraged to solve the model poisoning attack which is an attack on a model update to deteriorate the quality of a global model by malicious clients' providing bogus local model updates. The idea for demotivating such attacks is to devise an incentive mechanism that penalizes malicious activities. Furthermore, a reputation score based on contribution is also useful to screen potentially malicious clients. Here, we need a contribution measurement metric to fairly evaluate the quality of clients' model updates and detect the attacks. Details about the proposed incentive mechanisms and contribution measurements will be covered in Section 5.3.

20 out of 40 papers propose approaches to solve issues related to security and privacy. With few exceptions (i.e. attacks on reputation [45], [50] and [66]), both security and privacy issues are rooted in local model updates. The security issue is related to the model poisoning which we mentioned above, while the privacy issue is related to sensitive information that might be leaked from the local updates. We will further summarize the works that solve the security and privacy issues in Section 5.4.

5.2 RQ 2: Blockchain

5.2.1 RQ 2-1: What is the underlying blockchain architecture?

The Blockchain system and its underlying consensus mechanism is an influential part of the FLFs infrastructure. FLFs are heterogeneous in terms of architecture, operation and storage requirements, contribution calculation, actors and applied cryptography. Customized and tailored blockchain solutions may be required with respect to the underlying use-case. Due to its restrictive scalability in terms of computation and storage, most of the analyzed FLFs apply blockchain as a complementary element in

a more complex system, with a few exceptions [30], [39], [54], [58], [59]. Blockchain systems themselves are complex distributed systems, heterogeneous across many dimensions, yet can roughly be categorized into public, private and permissioned Blockchains.

- 1) **Public** Blockchains are open access where participants can deploy contracts pseudoanonymously
- 2) **Private** Blockchains do not allow access for clients outside the private network and require an entity that controls who is permitted to participate
- 3) **Permissioned** blockchains are private blockchains with a decentralized committee which controls the onboarding process

Note that the FLFs that utilize open-source public blockchains such as Ethereum [32], [33], [35], [39], [41], [43], [50], [54], [56], [57], [64], Stellar [51] and EOS [60] were not deployed on the respective public blockchain in the experiments due to the enormous costs this would incur. Hyperledger Fabric [17] or Corda [70] are permissioned blockchains running on private networks, allowing for faster throughput through a limited amount of potential nodes. This makes these frameworks more suitable for applications where blockchain replaces computationally expensive operations such as aggregation or storage of neural network models.

The consensus protocol ensures alignment and finality of a version across all distributed nodes without the need for a central coordination entity. While Proof of Work (PoW) is the most common mechanism applied in Bitcoin and Ethereum, it comes at the cost of wasting computational power on bruteforcing algorithmic hash-calculations for the sole purpose of securing the network. Since many operations within the FLF frameworks are computationally expensive, these tasks can be integrated into the consensus mechanism which creates synergy and might be a better use of resources. Examples for consensus mechanisms can

TABLE 5: Overview of decentral and incentivized FL frameworks. (SA: System Architecture, BC: Blockchain, FL: Federated Learning, IM: Incentive Mechanism, CM: Contribution Measurement, SP: Security & Privacy)

Ref.	Application	FL type	Actors	Setup period	Domains of key contributions					
					SA	BC	FL	IM	CM	SP
[30]	Generic	n.s.	Workers	✓	✓		✓	✓	✓	
[31]	Generic	n.s.	Workers	✓	✓			✓		✓
[32]	Generic	n.s.	Contributors, miners	✓	✓		✓			✓
[33]	IoT	n.s.	Clients, central organization	✗	✓		✓	✓		✓
[34]	IoT	n.s.	Clients, miners	✓	✓					✓
[35]	Generic	n.s.	Agg. server, workers	✓				✓		
[36]	Generic	n.s.	Worker, task publisher, miner	✗				✓		
[37]	IoV	n.s.	MEC, macro base station (MBS), ADV	✗				✓		✓
[38]	Generic	n.s.	Model requester, FL server, clients	✗		✓		✓		
[39]	Generic	CD	Administrator, requester, worker, validator	✓				✓		✓
[40]	Generic	n.s.	Central server, workers	✗				✓		
[41]	Generic	CS	Workers, leaders, aggregation server	✗				✓		✓
[42]	Generic	n.s.	Edge device, fog node, cloud	✓	✓					
[43]	Generic	CS	User, edge, cloud	✗	✓					✓
[44]	IoV	CD	Vehicles, road side units, base stations	✗	✓					
[45]	Generic	CD	Task publisher, workers	✗				✓		
[46]	Generic	n.s.	Participant/trainer, buyer, reporter, data processor	✓	✓			✓		
[47]	Generic	CS	Data owner	✓				✓		
[48]	IoT	CD	Local devices, base stations, mobile edge computing nodes	✓	✓			✓		
[49]	IoV	CD	Vehicle edge nodes, BC nodes	✗	✓		✓	✓		
[50]	Generic	n.s.	Trainer nodes	✓	✓			✓		✓
[51]	Generic	n.s.	Model initiator, computing partner, validator	✗	✓					
[52]	Finance	CS	Follower candidate, leader nodes	✓	✓			✓		
[53]	IoT	CD	Users, edge server, cloud server	✗						
[54]	Generic	CD	Worker nodes	✓	✓					✓
[55]	Generic	n.s.	Task publisher, parties, miners, smart contract	✓	✓					✓
[56]	Generic	n.s.	Requesters, workers, crowdsourcing platform	✗	✓					✓
[57]	IoT	n.s.	IoT device, edge server, central cloud server	✗	✓					✓
[58], [59]	Generic	n.s.	Task requesters, workers	✓	✓			✓		
[60]	Generic	n.s.	Requesters, workers	✗	✓				✓	
[61]	IoV	CD	Road side units (RSUs) as aggregators, MECs, vehicles (workers)	✗	✓			✓	✓	
[62]	IoT	n.s.	Requesters, workers (edge servers), data collectors	✗	✓			✓		✓
[63]	IoV	n.s.	UAVs (sensors, workers), requesters, MECs	✗	✓	✓			✓	✓
[64]	Generic	n.s.	Requesters (cloud servers), data-arbitrators (fog nodes), workers (edge-devices)	✗	✓					
[65]	Generic	n.s.	Requesters, miners	✗	✓	✓		✓	✓	
[66]	Generic	n.s.	Miners, workers	✗		✓				
[67]	Generic	n.s.	Requesters, workers, aggregation servers	✗	✓			✓	✓	✓
[68]	Generic	n.s.	Administrator, requesters, workers, miners	✗	✓			✓		
[69]	Generic	CS and CD	Workers, miners	✗	✓		✓			

be found where the model accuracy is verified (Proof-of-Knowledge [44]), reputation scores are checked (Proof-of-Reputation [36]), the model parameters are securely verified (Proof-of-Federated-Learning [65]), the Shapley-Value is calculated for contribution measurement [38] or verification of capitalizing on efficient AI hardware (Proof-of-Model-Compression [66]).

5.2.2 RQ 2-2: How is blockchain applied within the FLF and what operations are performed?

Blockchain Technology is applied to mitigate the single point of failure and power imbalance of the server-worker topology of traditional FL through a transparent, immutable and predictable distributed ledger. Embedded cryptocurrencies suit the useful property of a real-time reward payments for predefined actions at the same time. In general, Turing-complete smart-contract enabled blockchains allow for a variety of possible complementary features for the FL training process, namely aggregation, payment, coordination and storage:

- 1) **Aggregation** The aggregation of model-parameters, can be performed by a smart contract on top of blockchain [31], [40], [48], [52], [58], [59]. Since blockchain is assumed to be failure resistant, this

strengthens the robustness against possible single-point of failure of an aggregation server. In addition, the deterministic and transparent rules of smart contracts ensure inherent trust with an equal power distribution among participants, while the transparency ensures auditability of contributions. Yet since every node in the blockchain has to compute and store all information, submitting a model to the smart contract for aggregation causes overhead in terms of both computation and storage on the blockchain. Assuming n FL-workers and m Blockchain nodes over t rounds, the blockchain scales with $\mathcal{O}(t * n * m)$ which questions the feasibility of on-chain aggregation.

There are two papers that try to reduce data size for on-chain aggregation. Witt *et al.* [30] proposed a system where 1-bit compressed soft-logits are stored and aggregated on the blockchain saving communication, storage and computation costs by orders of magnitude.

Feng *et al.* [48] employ a framework based on two BC layers where the aggregation process is outsourced to a Mobile-Edge-Server.

- 2) **Coordination** Applying blockchain to coordinate

TABLE 6: Overview of blockchain features.

Ref.	Operations on BC	BC Framework	Consensus Mechanism	Storage on BC	Storage Quantification	Storage Off-chain	Scalability
[30]	Coordination, aggregation, payment		n.a.	1-bit results of all participants	✓(Qualitatively)	n.a.	(Simple computation, low storage)
[31]	Aggregation, payment	Novel (Corda V3.0)	Algorand	Gradients	✗	✗	✗
[32]	Payment	Ethereum	PoW	n.s.	✗	✓(Models on IPFS)	✗
[33]	Payment	Ethereum	PoW	Contribution, Merkle tree	✗	✗	✗
[34]	Payment, Coordination	n.s.	n.s.	FL models	✗	✓(Models on IPFS)	✗
[35]	Payment	Ethereum	PoW	n.s.	✓(gas)	✗	✗
[36]	Storage	novel(TrustRE)	Proof of Reputation (novel)	Reputation scores	✗	✗	✗
[37]	Storage of models	n.s. (novel)	PoW	Model updates	✗	✗	✗
[38]	SV calculation, payment	novel	PoSap	SV value (transactions), Task specification	✗	✗	✗
[39]	Coordination, payment, IPFSStorage	Ethereum	PoW	Task specs (registry contract), task contract	✗	✓(Model params IPFS)	✗
[40]	Storage, Payment, aggregation	n.s.	PoW	Model updates, metadata	✗	✗	✗
[41]	payment	Ethereum (HF)	PoW	PoT record	✓(Gas costs analysis)	✗	✗
[42]	Storage, coordination	n.s.	n.s.	Reputation scores	✗	✓(IPFS)	✗
[43]	Coordination, payment	Ethereum	PoW	Users addresses	✗	✗	✗
[44]beginMH	Storage, payment	n.s.	PoK (Proof-of-Knowledge)	Local models, local loss, signatures	✗	✗	(Hierarchical design)
[45]	Storage	Corda V4.0	PBFT	Reputation scores	✗	✓(Models)	✗
[46]	Coordination, payment, storage	n.s.	Custom (reliability consensus)	Client information, model parameters, crypto settings	✗	✗	(Quick queries)
[47]	Aggregation	n.s.	n.s.	Masked gradients, global model	✗	✗	✗
[48]	Payment, storage, aggregation	Hyperledger fabric	Raft	Local updates	✗	✗	(BC sharding, D2D communication)
[49]	Coordination, Storage	n.s.	n.s.	✗	✗	✗	✗
[50]	Coordination, payment	Ethereum	PoW	IPFS addresses of models	✗	✓(Models on IPFS)	✗
[51]	Coordination, payment	Stellar	n.s.	IPFS addresses of models	✗	✓(Models on IPFS)	✗
[52]	Coordination, aggregation, storage	Hyperledger Fabric	Raft (Apache Kafka)	Local & global models, loss	✗	✗	✗
[53]	Storage	n.s.	Custom	Local & global model parameters	✗	✗	✗
[54]	Private: Coordination, aggregation, storage; Public: Storage, payment.	Hyperledger Fabric, Ethereum Ropsten	Raft, PoW	Private: Parameters; Public: SHA256 hashes of parameters	✗	✗	(Compression, parallelization)
[55]	Coordination, storage, payment	Ethereum (Geth V1.6.4)	PoW	Aggregated models	✗	✗	✗
[56]	Coordination, storage	Ethereum (Truffle)	PoW	Encrypted models	✓(Qualitatively)	✗	(Use of Elgamal)
[57]endMH	Coordination	Ethereum (Geth)	PoW	Aggregated local updates	✗	✗	✗
[58], [59]	Coordination, aggregation, payment, storage	n.s.	n.s.	Task information, voting results, (model updates) ¹	✗	✗	✗
[60]	Payment, storage	EOS, Hyperledger Fabric	n.s.	Hashes of model updates, data size	✗	Model updates	✗
[61]	Coordination, payment, storage	n.s.	n.s.	Models	✗	✗	✗
[62]	Storage	Agnostic (consortium)	PBFT	Model updates	✗	✗	✗
[63]	Storage	n.s.	PoW	Task information, model updates, aggregated models	✗	✗	✗
[64]	Storage	Ethereum	PoW	Reputation scores	✗	Model parameters	✗
[65]	Payment, storage	Custom	PoFL (Proof-of-Federated-Learning)	Model updates	✗	✗	✗
[66]	Payment, storage	Custom	PoMC (Proof-of-Model-Compression)	Model updates	✗	✗	✗
[67]	Storage	n.s.	n.s.	Signatures of servers, reputation scores and contributions	✗	✗	✗
[68]	Coordination, storage, payment	Agnostic	n.s.	Task information, voting results, model updates	✗	✗	✗
[69]	Storage, payment, aggregation	Custom	PoW	Model updates, computation time	✗	✗	✗

and navigate the FL process allows for decentralization without heavy on-chain overhead. Instead of aggregating the model on-chain, letting the blockchain choose a leader randomly can ensure decentralization [34], [44], [54], [68]. Another way blockchain coordinates the FL process is by enabling the infrastructure for trust-less voting atop of the blockchain. Voting on the next leader (aggregator) [51], [52] or on each others contributions [58], [59], [68] further democratizes the process. Beyond explicit coordination operations like voting or leader selection, the implicit function of storing crucial information and data for the FL process, [30], [39], [56], [61], verifying correctness of updates [34], [54] or keeping the registry of active members [30], [31], [38], [39], [58], [59] is crucial for the FL workflow and implies coordination through blockchain as an always accessible, verifiable, transparent and immutable infrastructure.

- 3) **Payment** Many general-purpose blockchain systems include cryptocurrency capabilities and therefore allow for the incorporation of instant, automatic and deterministic payment schemes defined by the smart contract's business logic. This advantage was capitalized on by 26 of the 40 FLF we analyzed. Section 5.3 discusses the details of applied payment schemes in the context of reward mechanisms and game theory.
- 4) **Storage** Decentralized and publicly verifiable storage on the blockchain facilitates auditability and trust among participants. Even though expansive, since all blockchain nodes store the same information in a redundant fashion, it might make sense to capitalize on the immutability and transparency feature of blockchain and store information where either a shared access among participants is required or where verifiability of the history is required to hold agents accountable for posterior reward calculations [36]. In particular,

machine learning models [31], [37], [40], [44], [46], [47], [52], [53], [54], [58], [59], reputation scores [36], [42], User-information [30], [31], [38], [39], [58], [59] and Votes [30], [58], [59] are stored on-chain of the respective FLF.

5.2.3 RQ 2-3: Is the framework scalable?

Especially if the FLF is intended to be used with hundreds to millions of devices, the scalability of the framework is an important characteristic. In particular, (i) storing large amounts of data such as model-parameters and (ii) running expansive computations on the blockchain e.g. aggregating millions of parameters, calculate expansive contribution measurements like Shapley Value or privacy-preserving methods hinder the framework to scale beyond a small group of entrusted entities towards mass adoption. To overcome the scalability-bottleneck of storage, some FLF applied an Interplanetary-File-System (IPFS) [71], where data is stored off-chain in a distributed file system, using the content-address as a unique pointer to each file in a global namespace over all computing devices [32], [34], [39], [42], [45], [50], [51], [60], [64]. Other FLF are based on novel design choices to tackle the scalability-issues: Witt *et al.* [30] applied compressed Federated Knowledge Distillation, storing only 1-bit compressed soft-logits on-chain. Chai *et al.* [44] design a hierarchical FLF with two blockchain layers to reduce the computational overhead by outsourcing computation and storage to an application specific sub-chain. Similarly, Feng *et al.* [48] propose a two-layered design, where the transaction efficiency of the global chain is improved through sharding. Bao *et al.* [46] employ an adaption of counting bloom filters (CBF) to speed up blockchain queries in the verification step of their FLF. Desai *et al.* [54] combine public and private blockchains, with the former storing reputation scores for accountability and the latter used for heavy computation and storage. Furthermore, the authors apply parameter compression for further scalability improvements.

5.3 RQ 3: Incentive Mechanism

We found that 45% (18 out of 40 papers) of the surveyed papers measured workers' rewards via simulation while 35% (14 out of 40 papers) of them theoretically analyzed their incentive mechanisms. In the following, we study these 14 papers in terms of how they are theoretically analyzed and how participants' contribution is measured and utilized for their analysis.

5.3.1 RQ 3-1: How are incentive mechanisms analyzed?

In general, there are three steps for theoretical analysis. The first step is to determine what entities' behavior is examined. In FL, such entities could be workers and task requesters. The second step is to model the entities' utilities or profits. They can be often obtained by taking into account the expectation of possible profits and costs. The last step is to analyze the defined utilities or profits. We will see how each step is conducted in the literature.

The first step is to determine entities to be analyzed. In most cases, workers are at least chosen as an entity as the idea of giving incentives is to motivate workers. Some papers also choose entities that pay rewards (e.g. task requesters) as we want to make sure that they are also profitable even if they pay rewards to workers.

The second step is to define the utilities or profits of entities. A utility is a one-dimension measurable unit that quantifies an entity's value on an outcome and can be positive (e.g. rewards for workers and a value of AI models for task requesters) and negative values (e.g. a computation cost for workers and a total amount of payout for task requesters). Utilities and profits can be derived by subtracting costs from payouts. Although the elements of payouts are relatively straightforward (e.g. rewards for work contribution), defining cost elements often depends on the assumed application scenarios. Typical costs in the surveyed papers are computation, electricity (e.g. [40], [44], [45], [58], [59], [63]), data acquisition (e.g. pictures and sensor readings [61], [62], [63]) and privacy leakage due to model updates (e.g. [62], [63], [65]). Even multiple cost factors can be considered (e.g. [61], [62], [63]).

The last step is to analyze the defined utilities and profits to ensure the robustness of designed incentive mechanisms and derive the optimal strategies and reward allocation. It is up to us to determine what to analyze with utilities. For example, the most simple yet crucial analysis would be to prove that it is worthwhile for workers to join a FL task by showing that their profits are non-negative. Weng *et al.* and Bao *et al.* modeled requesters' and/or workers' profits with given rewards and costs proved that their profits are non-negative [31], [46]. Utilities can be used to derive task requesters' and workers' optimal strategies by finding a point where utilities are maximized. By proving the existence of such a point, we can derive an equilibrium, which is a condition where entities (e.g. workers) cannot be better off deviating from their optimal strategies. Finding an equilibrium would be a strong proof that a designed mechanism is stable. For instance, if workers can control what data size they use for a task, then the factor of data size should be in workers' utility, and we can derive the optimal data size by maximizing the utility

(e.g. by finding first- and second-order conditions) [59]. It is also used to determine optimal prices for tasks. Wang *et al.* propose a Q-learning-based approach to determine the optimal prices so that utilities are maximized via iterative learning processes [63]. Similarly, Zou *et al.* derive the optimal prices for workers with first- and second-order conditions when the value of data, transmission quality and communication delay are the factors to determine their competitiveness and costs [61]. Hu *et al.* propose a two-stage optimization method to determine the optimal values on data and their prices in order by solving an Euler-Lagrange equation of their utilities. These kinds of two-stage optimization game are often formalized as the Stackelberg game. Jiang and Wu [40] and Chai *et al.* [44] propose optimal incentive mechanisms with the Stackelberg game, in which two parties sequentially determine their actions according to other party's action. More specifically, a party called leader moves first and the other party called follower moves accordingly. Jian and Wu propose a Stackelberg-game-based incentive mechanism for FL [40]. An aggregation server (a leader) first provides a task's deadline and rewards to workers (followers). Workers then determine how much they should train by maximizing their utilities with the information provided by the server. The server then determines the optimal reward by maximizing its utility with the feedback by the workers. Chai *et al.* also propose a Stackelberg game to analyze their incentive mechanism in IoV [44]. Aggregation servers (RSUs) are leaders while workers (vehicles) are followers, and aggregation servers first suggest prices and workers determine how much data they should collect and use for training so that both entities' utilities are maximized in order.

It is interesting to see that the process of FL with an incentive mechanism can be seen as a contract or contest. Specifically, a task requester proposes a contract with task description and its reward and workers can determine whether or not to sign such a contract and how much resource they will provide [45]. A FL process can be also seen as a contest as workers need to work first, which incurs irreversible costs due to computation, whereas their rewards are not guaranteed at the time of model update submission. Toyoda *et al.* give an incentive analysis based on the contest theory [58], [59]. Workers' utilities are used to derive how much effort workers' should exert to a task under the risk of not gaining prizes, while requesters' utility is used to determine how a prize should be split to workers.

5.3.2 RQ 3-2: How are the contributions of workers measured?

Incentive mechanisms require a measurement of contribution by each client to fairly distribute rewards to workers. However, it is not an easy task as we cannot see their actual work and have to measure workers' contribution only from their model updates. For this, we need to determine (i) metrics for contribution measurement and (ii) validators that measure metrics.

The metrics used in the literature can be categorized into absolute and relative ones. The absolute metrics are metrics that can be measured without others' local model updates. For instance, a loss function can be measured from a local model and a global model, and the difference of them can

TABLE 7: Overview of incentive mechanisms and contribution measurement.

Ref.	Simulation	Theoretical analysis	Costs assumed in utility analysis	Metrics for contribution measurement	Validator
[30]	✓	✓	Generic	Correlation of predictions (Peer truth serum for FD, relative)	Smart contract
[31]	✗	✓	✗	n.s.	n.s.
[32]	✗	✗	✗	Accuracy (validation scores) (absolute)	Miners
[33]	✓	✗	✗	Accuracy, data size (absolute)	Aggregation server (central server)
[34]	✓	✗	✗	Euclidean distance of model updates (relative, reputation)	Miners
[35]	✓	✗	✗	Data size (absolute)	Smart contract
[36]	✓	✗	✗	Accuracy (predictions), energy consumption, data size (absolute, reputation)	Task requesters
[37]	✗	✗	✗	Accuracy (loss) (absolute)	MEC servers
[38]	✓	✗	✗	Accuracy (loss) (relative, Shapley values)	Miners
[39]	✗	✗	✗	Accuracy (loss, marginal) (relative, rank)	Validators
[40]	✓	✓ (Stackelberg game)	Computation cost	Accuracy, data size (absolute)	n.s.
[41]	✗	✗	✗	n.s.	n.s.
[42]	✗	✗	✗	n.s.	n.s.
[43]	✗	✗	✗	Data size (absolute)	Task requesters
[44]	✓	✓ (Stackelberg game)	Computation cost	Accuracy (loss) (absolute)	Aggregation servers (RSUs)
[45]	✓	✓ (Contract theory)	Energy consumption	RONI [72] for IID, FoolsGold [73] for non-IID (reputation)	Task requesters
[46]	✗	✓	Generic	n.s.	Workers
[47]	✓	✗	✗	Generic (Shapley values)	Smart contract
[48]	✗	✗	✗	n.s.	n.s.
[49]	✗	✗	✗	Accuracy (generic, marginal) (absolute)	n.s.
[50]	✓	✗	✗	Accuracy (generic) (relative)	Workers
[51]	✗	✗	✗	n.s.	Validators
[52]	✓	✗	✗	Euclidean distance of model updates (relative, Shapley values)	n.s.
[53]	✓	✗	✗	Communication delay, energy consumption (absolute)	Aggregation servers (cloud servers)
[54]	✗	✗	✗	Speed of model submission (absolute)	n.s.
[55]	✗	✗	✗	n.s.	n.s.
[56]	✗	✗	✗	Accuracy, data size (absolute, reputation)	Task requesters
[57]	✗	✗	✗	Data size (absolute)	Aggregation servers (edge servers)
[58], [59]	✗	✓ (Contest theory)	Computation cost	Accuracy (generic) (relative, rank by voting)	Workers
[60]	✗	✗	✗	Data size (absolute)	Workers
[61]	✓	✓	Cost of data acquisition and communication	Accuracy (loss) (absolute)	Aggregation servers (RSUs)
[62]	✓	✓	Cost of sensing and privacy	n.s.	n.s.
[63]	✓	✓ (Reinforcement learning)	Cost of sensing, privacy and energy	Data size, sensing capacity (absolute)	Aggregation servers (MECs)
[64]	✗	✗	✗	n.s.	n.s.
[65]	✓	✓	Privacy leakage cost	Accuracy (absolute)	Blockchain nodes
[66]	✗	✗	✗	n.s.	n.s.
[67]	✓	✓	✗	Accuracy (loss) (absolute, reputation)	Workers
[68]	✗	✗	✗	Accuracy (generic) (relative, rank by voting)	Workers
[69]	✗	✗	✗	Computation time (absolute)	Miners

be used as a metric for contribution measurement. Although the majority of absolute metrics are based on accuracy (e.g. [32], [33]) and data size (e.g. [35], [40]), other factors are also proposed such as energy consumption (e.g. [36], [53]) and computation time [69]. Some combine multiple metrics (e.g. [36], [56]). Absolute metrics are generally straightforward but hard to validate. For instance, as only the model updates are submitted to an aggregation server in FL, no one can judge whether workers honestly claim the data size used for their model updates. In contrast, the relative metrics can be measured by comparing one’s output with others’ and this somewhat solves such a difficulty. For instance, Zhao *et al.* propose a metric based on the Euclidean distance of workers’ model updates [34]. Likewise, Witt *et al.* propose that workers are to submit an unlabeled public dataset’s labels predicted with their own local models and calculate the correlation of their labels as a metric [30]. This metric is integrated into the computation of reward distribution based on peer truth serum [74] for the FL setting. Voting is another approach to relatively determine workers’ contribution. For instance, workers in the next round of FL are to choose best updated models in the previous round using their own local datasets and rank them by voting [58], [68].

The above metrics can be also used to measure workers’ reputation. If the same workers are assumed to join different tasks, reputation scores calculated with workers’ past contribution can be a reliable factor to determine reward amount. Some works propose the reputation of workers based on their past contribution (e.g. [34], [36], [45], [56]). For instance, Kang *et al.* propose to calculate workers’

reputation based on direct opinion by a task requester and indirect opinions by other task requesters [45].

Even if workers’ individual contribution is measured, it does not guarantee that rewards are fairly given to workers. Hence, it is important to determine how rewards should be distributed based on the metrics. The Shapley value is an approach to fairly determine payouts to workers based on their contributions [75]. Three papers propose to use the Shapley value for fair reward distribution [38], [47], [52]. Liu *et al.* propose to use it with the metric of accuracy [38]. He *et al.* compared their Shapley-value-based method with three approaches, namely (i) equal distribution, (ii) a method based on individual contribution, and (iii) a method called the labor union game where only the order of submission is taken into account to contribution measurement, and found that the Shapley-value-based method outperforms the others in terms of workers’ motivation and fairness [52]. Ma *et al.* propose a method to calculate Shapley values even if model updates are masked to preserve workers’ privacy [47].

The next question we must answer is who validates such metrics. From our study, validators can be classified into (i) aggregation servers (e.g. [33], [37], [44]), (ii) task requesters (e.g. [36], [45], [56]), (iii) validators whose task is only to measure contribution ([39], [51]), (iv) blockchain nodes (e.g. [32], [65], [69]), (v) workers (e.g. [50], [67], [68]) and (vi) smart contracts (e.g. [30], [35], [47]). Some of the works assume that aggregation servers, task requesters or validators are expected to possess datasets to calculate the metrics discussed above. As reviewed in Section 5.2.1, some propose custom blockchains dedicated

to FL, and the validation process is integrated into its block generation process, making blockchain nodes validators. In some scenarios, aggregation servers, task requesters and blockchain nodes can be validators since local models are collected by them. However, datasets for validation may not be always available. As we have seen above, some metrics can be calculated without validators. Furthermore, metrics based on the correlation of predicted labels do not require any validation dataset and can even be measured in a smart contract [30].

5.4 RQ 4: Experiments

Conducting experiments is a key element of FLF development for two reasons. Firstly, the implementation of an example testifies to the feasibility of the approach and gives the authors the chance to identify weaknesses of their frameworks, e.g., poor scalability. Secondly, conducting experiments allows the comparison of the proposed approaches with each other, e.g., based on the accuracy of the models on standardized test sets. We screened the papers for experiments, and when present, examined them according to nine criteria (TABLE 8).

5.4.1 RQ 4-1: Is the performance of the framework reported?

The large majority of papers report results of their experiments expressed in either loss, accuracy, or F1 score (84.8%, 28 out of 33 papers with experiments). The remaining instead focus on the performance of their novel group-based Shapley value calculation for contribution measurement [47], the user interface [38], the computational effort and adversarial influence [54], or game-theoretic quantities such as utility values and rewards [63]. We note that comparability of the approaches is not given through the conducted experiments, since even when using the same data sets and the same evaluation metrics, different experimental scenarios are investigated. In conclusion, to obtain insightful results, experiments should compare the performance (accuracy and computational effort) of an incentivized, decentralized FL system in a standardized challenging environment (non-IID, adversaries) with either the performance of a traditional centralized FL system or the performance of a locally trained model without FL. Ideally, the effectiveness of incentive mechanism and decentralization efforts are reflected in the FLF performance through a holistic experimental design.

5.4.2 RQ 4-2: How comprehensive are the experiments?

First, it was found that the majority of publications do include experiments. Only seven of 40 papers did not conduct experiments [42], [49], [51], [52], [58], [59], [64]. However, the analysis also shows that only 45% of the experiments implement the actual blockchain processes (15 out of 33 papers with experiments). Instead the distributed functionality was simulated or its impact estimated. For instance, Mugunthan *et al.* [50] focus on the evaluation of the frameworks' contribution scoring procedure by simulating collusion attacks on the FL procedure. The effect of introducing blockchain to the FL framework was accounted for by estimating the per-agent gas

consumption. Similarly, Chai *et al.* [44] conduct experiments specifically designed to investigate the Stackelberg-game-based incentive mechanism. The authors accomplish this without implementing the blockchain processes.

To test the FL functionality of the framework, a ML problem and a dataset must be selected. For the ML application and the dataset used, we observe a high homogeneity. Almost all experiments realize classification problems and use publicly available benchmark datasets. The most common are MNIST (handwritten digits) [77] and its variations, as well as CIFAR-10 (objects and animals) [78]. Only Rathore *et al.* [57] and Li *et al.* [37] did not perform classification tasks. Rathore *et al.* [57] performed object detection on the PASCAL VOC 12 dataset [79]. Object detection typically combines regression and classification through predicting bounding boxes and labeling them. Li *et al.* [37] applied their FLF to autonomous driving and minimized the deviations in steering-wheel rotation between a human-driven and simulation-driven vehicle. This corresponds to a regression task.

As to the number of training data holders, the experiments considered between one [37] and 900 [55] clients. In general, one would expect papers specifying cross-silo settings to test with fewer (<100 [23]) and papers specifying cross-device settings to test with more (>100) clients. Of the frameworks clearly designed for a cross-device application, it is noticeable that only Kang *et al.* [45] and Desai *et al.* [54] conduct experiments with 100 participants or more. On the contrary, Rahmadika *et al.* [41] test with as many as 100 participants, although only designing a cross-silo framework.

Regarding the FL algorithm, the classic FedAvg [6] is mainly used. Furthermore, in some experiments algorithms are used that mitigate the problem of catastrophic forgetting (Elastic Weight Consolidation (EWC) [32]), reduce the communication overhead (Federated Knowledge Distillation (FD) [30], signSGD [54]), or show more robust convergence for non-IID and other heterogeneous scenarios (FedProx [39], Centroid Distance Weighted Federated Averaging (CDW_FedAvg) [33]). Chai *et al.* [44] and Mugunthan *et al.* [50] design custom FL algorithms. Specifically, Chai *et al.* [44] propose a FLF with two aggregation layers in order to promote scalability. In their FL algorithm, nodes in the middle layer aggregate the local model updates of associated nodes in the lowest layer. This semi-global model is then fine-tuned by the middle layer nodes based on data collected by the middle layer nodes themselves. Finally, nodes in the top layer aggregate the fine-tuned-models from the middle layer nodes into a global model which is eventually passed back to the lowest layer nodes. All aggregations are weighted by the training dataset size. Mugunthan *et al.* [50] propose a FLF where all clients evaluate and score the differentially encrypted locally trained models of all other clients. These scores are reported to a smart contract which computes an overall score for each local model. Eventually, each client aggregates the global model from all local models, weighted by the overall score.

5.4.3 RQ 4-3: Are non-IID scenarios simulated?

In real-world applications of FL, the training data is often not independent and identically distributed (non-IID)

TABLE 8: Overview of experiments. (BCWD = Breast Cancer Wisconsin Data Set, BT = Blockchain Tampering, DGHV = Dijk-Gentry-Halevi-Vaikuntanathan Algorithm, DP = Differential Privacy, ECC = Elliptic Curve Cryptography, HE = Homomorphic Encryption, HDD = Heart Disease Data Set, KDD = Knowledge Discovery and Data Mining Tools Competition, RP = Random Model Poisoning, RSA = Rivest-Shamir-Adleman Cryptosystem, RT = Reputation Tampering, SA = Secure Aggregation [76], SP = Systematic Model Poisoning, ZKP = Zero-Knowledge Proof, 2PC = 2-Party Computation)

Ref.	ML Task	Dataset	#Clients	FL Algorithm	Privacy protection	Non-iid	Adversaries	BC implem.	Performance
[30]	Classification	EMNIST	10	FD	✗	✓	✓ (RP, SP)	✗	✓
[31]	Classification	MNIST	4-10	FedAvg	✓ (HE (Paillier))	✗	✗	✓	✓
[32]	Classification	MNIST	5	FedAvg, EWC	✓ (DP, HE)	✓	✗	✗	✓
[33]	Classification	Custom	4	FedAvg, CDW	✓ (n.s.)	✓	✗	✓	✓
[34]	Classification	MNIST	10	FedAvg	✓ (DP)	✗	✓ (RP)	✗	✓
[35]	Classification	MNIST	25	FedAvg	✓ (n.s.)	✗	✗	✓	✓
[36]	Classification	MNIST, CIFAR10	n.s.	n.s.	✗	✗	✗	✗	✓
[37]	Regression	Real time AD video	1	n.s.	✓ (HE (DGHV), ZKP)	✗	✗	✗	✓
[38]	Classification	MNIST	n.s.	FedAvg	✓ (SA)	✗	✗	✓	✗
[39]	Classification	MNIST	5	FedAvg/ FedProx	✓ (Symmetric encryption)	✗	✓ (RP)	✓	✗
[40]	n.s. (NLP assumed)	Reddit, Celeba	5-75	n.s.	✗	✗	✗	✗	✓
[41]	Classification	MNIST	100	Custom	✓ (Ring signature, HE(RSA), Rabin, ECC)	✗	✗	✓	✓
[42]	✗	✗	✗	✗	✗	✗	✗	✗	✗
[43]	Classification	Mathworks Handwritten	10	FedAvg	✓ (Pairing-based cryptography, ECC)	✗	✗	✓	✓
[44]	Classification	MNIST, CIFAR10	6	Custom	✓ (Asymmetric cryptography, digital signatures)	✗	✓ (RP)	✗	✓
[45]	Classification	MNIST	100	FedAvg	✗	✓	✓ (RP, RT)	✓	✓
[46]	n.s.	n.s.	10	n.s.	✓ (n.s.)	✗	✗	✓	✓
[47]	Classification	ORHD dataset	9	FedAvg	✓ (SA)	✓	✗	✗	✗
[48]	Classification	MNIST	30	n.s.	✗	✗	✗	✗	✓
[49]	✗	✗	✗	✗	✗	✗	✗	✗	✗
[50]	Classification	Adult Census, KDD	50	Custom FedAvg	✓ (DP)	✓	✓ (RP, SP, RT)	✗	✓
[51]	✗	✗	✗	✗	✗	✗	✗	✗	✗
[52]	✗	✗	✗	e.g. FedAvg (FATE)	✓ (HE)	✗	✗	✗	✗
[53]	Classification	Custom	3-4	FedAvg	n.s.	✗	✓ (RP)	✗	✓
[54]	Classification	CIFAR10	100	FedAvg, signSGD	✓ (n.s.)	✓	✓ (SP)	✓	✗
[55]	Classification	FMNIST	900	FedAvg	✓ (HE (Paillier))	✓	✓ (RP)	✓	✓
[56]	Classification	BCWD, HDD	3	FedAvg	✓ (HE (Elgamal))	✗	✗	✓	✓
[57]	Classification, Regression	PASCAL VOC 2012	5-10	FedAvg	✓ (HE)	✗	✗	✓	✓
[58], [59]	✗	✗	✗	✗	✗	✗	✗	✗	✗
[60]	Classification	MNIST	10	FedAvg	✗	✓	✗	✓	✓
[61]	Classification	MNIST	50	n.s.	✗	✗	✗	✗	✓
[62]	Classification	FEMNIST	35, 105, 175	n.s.	✗	✓	✗	✗	✓
[63]	Classification	MNIST	n.s. ⁵	n.s.	✗	✗	✗	✗	✗
[64]	✗	✗	✗	✗	✗	✗	✗	✗	✗
[65]	Classification	CIFAR-10	20, 50, 100	n.s.	✓ (HE, 2PC)	✗	✗	✗	✓
[66]	Classification	ImageNet	20	n.s.	✗	✗	✓ (RP, BT)	✓	✓
[67]	Classification	MNIST, CIFAR-10	10	FedAvg	✗	✗	✓ (RP, SP)	✗	✓
[68]	Classification	MNIST	50	FedAvg	✗	✗	✗	✗	✓
[69]	Classification	MNIST, CIFAR-10	2-6	FedAvg	✗	✓	✗	✗	✓

between the clients. This effects the performance of the global model and adds an additional layer of complexity with respect to contribution measurement. Hence, how we simulate non-IID scenarios with open datasets is crucial. In 11 publications and for various benchmark datasets, non-IID scenarios were considered. For the example of the MNIST dataset, Witt *et al.* [30] simulate different levels of non-IID scenarios following the Dirichlet distribution as it can easily model the skewness of data distribution by varying a single parameter. Martinez *et al.* [60] split the dataset in overlapping fractions of various size, whereas Kumar *et al.* [32] divide the dataset so that each trainer only possesses data from two of the ten classes. In a less skewed setting, Kumar *et al.* allocate data from at most four classes to each trainer, with each class being possessed by two devices.

5.4.4 RQ 4-4: Are additional privacy methods applied?

Even though FL’s core objective is to maintain confidentiality through a privacy-by-design approach where model parameters are aggregated instead of training data, there remain innumerable attack surfaces [80]. Therefore, the presented frameworks employ additional privacy-preserving mechanisms which can be divided into two groups. (i) Mechanisms that encrypt or obfuscate gradients and prevent malicious parties to draw conclusions about the data set. (ii) Mechanisms that hide the identity of participating parties. A classification of the employed privacy-preserving methods can be seen in Fig. 2.

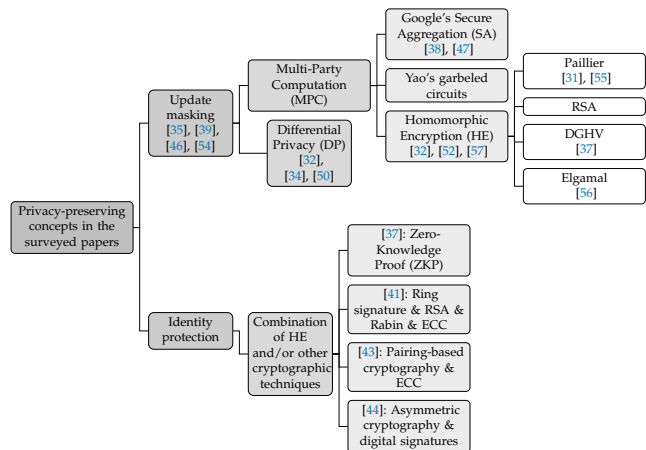


Fig. 2: Privacy-preserving concepts employed in survey papers. (DGHV = Dijk-Gentry-Halevi-Vaikuntanathan Algorithm, ECC = Elliptic Curve Cryptography, RSA = Rivest-Shamir-Adleman Cryptosystem. Papers with unspecified methods are added to next highest node.)

The methods of the first group can be further divided into (i) approaches that are based on cryptographic secure multi-party computing (MPC), and (ii) approaches that are based on differential privacy (DP).

MPC refers to cryptographic methods by which multiple participants can jointly compute a function without having to reveal their respective input values to the other

participants. MPC approaches include three groups of methods [76]. (i) Google’s secure aggregation (SA) [76] is specifically designed to achieve low communication and computation overhead and to be robust towards device dropout. It has been employed by Liu *et al.* [38] and Ma *et al.* [47]. Beyond implementing SA, the latter develops a group-based Shapley-value method for contribution measurement, since the native Shapley-value method cannot be applied to masked gradients. (ii) Yao’s garbled circuits have not been applied to any of the analysed frameworks, but are mentioned here for completeness. (iii) While Yao’s garbled circuits were developed for 2-party secure computing, homomorphic encryption (HE) allows for higher numbers of participants [76]. As shown in Fig. 2, HE has been employed in several works [31], [37], [52], [56], [55], [57]. For that, different implementations of the homomorphic idea have been chosen, such as the Pallier cryptosystem, the Elgamal cryptosystem, or the Dijk-Gentry-Halevu-Vaikuntanathan Algorithm (DGHV). Li *et al.* [56] choose the Elgamal cryptosystem that is less computationally expensive than other HE approaches.

DP refers to a method where noise drawn from a probability density function $p_{noise}(x)$ with expected value $\mathbb{E}(p_{noise}(x)) = 0$ obfuscates the individual contribution with minimal distortion of the aggregation. DP has been employed by Mugunthan *et al.* [50], Zhao *et al.* [34], and Kumar *et al.* [32], with the latter combining the use of HE and DP. However, the fewer clients participate in the DP process, the heavier the distortion of the aggregated model, introducing a trade-off between privacy and model accuracy. Zhao *et al.* [34] mitigate the loss in accuracy by incorporating a novel normalization technique into their neural networks instead of using traditional batch normalization (e.g. [32], [50]). Besides MPC and DP, another technique for data set protection is chosen by Qu *et al.* [65]. Instead of the clients sharing masked gradients, the FLF relies on requesters sharing masked datasets in the model verification step. This prevents other workers from copying the models while testing and evaluating them. HE and 2-party computation (2PC) are used. Zhang *et al.* [39], Desai *et al.* [54], Bao *et al.* [46], and Rahmadika *et al.* [35] also rely on the masking of gradients but do not specify the privacy-preserving mechanisms.

The second group of frameworks targets the protection of participants’ identities through cryptographic mechanisms. For that, Rahmadika *et al.* [41] combine ring signatures, HE (RSA), Rabin algorithm, and elliptic curve cryptography (ECC), while Chai *et al.* [44] incorporate digital signatures and asymmetric cryptography approaches, and Rahmadika *et al.* [43] perform authentication tasks through pairing-based cryptography and ECC. Only one framework implements measures for both masking gradients as well as hiding identities. Li *et al.* [37] use DGHV for masking gradients and Zero-Knowledge Proof (ZKP) for identity protection.

Finally, He *et al.* [52] specifically address the problem of aligning entities. This problem occurs for vertical federated learning where different parties hold complementary information about the same user. The parties have to find a way of matching these information without disclosing the identity of their users. To solve this problem, He *et*

al. employ Encrypted Entity Alignment which is a protocol for privacy-preserving inter-database operations [52].

5.4.5 RQ 4-5: Is the framework robust against malicious participants?

The experiments consider and simulate different types of adversaries, where some publications consider multiple types of attacks. Four groups of attack pattern were identified in the publications: random model poisoning, systematic model poisoning, reputation tampering (RT), and blockchain tampering. The most common attack considered in the experiments is random model poisoning. This includes attacks, where local models are trained on a randomly manipulated data set ([39], [45], [50], [67]) or where random parameter updates are reported ([53], [30], [45], [34], [44], [55], [66]). For instance, malicious agents in [39] use a training dataset with intentionally shuffled labels, whereas in [55] the parameter updates are randomly perturbed with Gaussian noise. Kang *et al.* [45] analyse the effects of a bad or manipulated data set by providing 8% of the workers with training data where only a few classes are present, and another 2% of the workers with mislabeled data. Kang *et al.* quantify the insufficiency of the dataset using the earth mover’s distance.

The second most commonly simulated type of attack is systematic model poisoning where the attackers manipulate the model through well-planned misbehavior. In [54], a fraction of workers colludes and manipulates their image classification data sets by introducing a so-called trojan pattern: the malicious agent introduces a white cross to a certain fraction of a class, e.g., to 50% of all dog pictures in an animal classification task and re-labels these data points as horse pictures. This creates a backdoor in the model that cannot be detected by subjecting the model to dog or horse pictures which will be correctly classified. However, pictures with the trojan pattern will be misclassified. Other forms of systematic model poisoning can be found with Witt *et al.* [30], Mugunthan *et al.* [50], Gao *et al.* [67].

The third type of attack that was simulated is reputation tampering (RT). Here, malicious agents intentionally provide colluding agents with perfect reputation or voting scores [45], [50]. The fourth type of attack is blockchain tampering [66]. Here, malicious miners intentionally fork the blockchain and prevail by building a longer branch faster than the honest miners.

5.5 RQ 5: Summary: What are Lessons Learned?

The inherent complexity of FLF leads to heterogeneity of the scientific research across the dimensions (i) application, (ii) overall design, (iii) special focus on open issues and (iv) details and thoroughness.

Application Although the majority of analyzed works offer application independent frameworks (classified as “generic” in Table 5) other FLF are applied across IoT, Industrial-IoT (IIoT), IoV and Finance. The heterogeneity of the required properties across those domains causes differences in the design choices of function, operations and storage of blockchain, contribution measurement and privacy requirements.

Variety of possible design choices In addition to the domain specific influence on the system architecture, design

choices about the FL algorithms, communication protocol, applications of blockchain within the ecosystem, blockchain technology (existing or novel), storage and operation on blockchain, security trade-offs, mechanism design, contribution measurement, etc. add to the complexity and overall variety of such systems. For example, some works apply blockchain as the outer complementary layer [36] while blockchain is the core infrastructure for coordination, storage, aggregation and payment in other FLFs [30], [39]. Furthermore, some works developed application specific blockchain systems, while others tried to embed a FLF on top of existing blockchain frameworks such as Ethereum for cheaper and pragmatic deployment. Our survey exposes a similar variety in the choice of the contribution measurement: The spectrum reaches from computationally lightweight correlation of answers on a public dataset [30] as a proxy for contribution as opposed to the Shapley value, a measurement with strong theoretical properties but massive computational overhead [38], [52].

Special Focus The aforementioned complexity as well as its novelty result in many open issues across a broad spectrum. Many works therefore focus on solving specific issues such as enhanced privacy [31], [37], [41], [51], novel blockchain systems [33], [38], bandwidth reduction [53], novel contribution measurements [30], [38], [53] or game theory (e.g. [40], [45]), as the major contribution which further complicates a holistic comparison of FLF.

Thoroughness The analyzed papers also vary heavily in provided detail and thoroughness, ranging from first concepts, lacking details in terms of important specifications such as performance, specific function, operation and storage on blockchain, contribution measurement, robustness, experiments and privacy to theoretically detailed and experimentally tested solutions. None of the analyzed papers are production-ready.

5.5.1 Standards for better comparability

For better reproducibility, implementability and comparability we suggest to consider and define the following elements when designing a FLF.

System model and architecture:

- Assumed application
- Type of FL (i.e., CD vs CS, horizontal vs vertical)
- Entities (including attackers)
- Setup (e.g., who manages a system, who deploys it)
- Role of blockchain within the FLF (e.g., what part does blockchain replace, what functions/operations)
- Blockchain design (e.g., consensus algorithms, blockchains, smart contracts)
- Non-blockchain design (e.g., off-chain storage, privacy protection, authentication)
- Procedures (e.g., flowcharts and diagrams)
- Theoretical analysis of the incentive mechanism
- Specification of clients' contribution measurement
- Possible attacks (e.g., system security, data privacy)

Performance analysis:

- Quantitative performance analysis
- Scalability analysis
- Security analysis of the assumed attacks

6 FUTURE RESEARCH DIRECTIONS

We discuss possible future research directions towards mass adoption of FLFs. We raise six promising research directions for blockchain, incentive mechanism and FL.

6.1 Blockchain

6.1.1 Towards better scalability

One of the major factors of the applicability of a FLF is its ability to scale beyond small groups towards mass adoption. Out of the 40 papers, only 6 mentioned and considered scalability within the design of their respective FLF.

Blockchain offers trust, immutability and decentralization for the operations and the information stored on it, yet is particularly influential on the overall scalability. The scalability is determined by (i) the function of blockchain in the FLF, (ii) operations performed onchain, (iii) blockchain framework and (iv) the amount of storage onchain. Blockchain becomes a scalability bottleneck

- 1) if it is part of the operating core infrastructure of the FLF (e.g. [30]) and not only a complementary outer layer technology (e.g. [36])
- 2) if heavy operations such as aggregation or reward calculation are performed on-chain [38]
- 3) if the blockchain framework is public and used outside the realm of the FLF or the consensus mechanism is resource-intensive (Proof of Work)
- 4) if heavy amount of information are stored on the blockchain such as model updates

A promising future research direction is the application of Zero-Knowledge Succinct Non-Interactive Argument of Knowledge (ZK-SNARKs) [81] in the FLF context. ZK-SNARKs is a promising cryptographic technology that allows a *prover* to prove to a *verifier* that a computation has been executed without revealing the program itself. As verification can be fast and easily done on the smart contract, it might improve the scalability of blockchain-enabled FLF dramatically.

6.1.2 Thorough complexity analysis

FLF specific blockchain systems claim to solve important shortcomings of existing blockchain frameworks, e.g. replacing the computational overhead of the Proof of Work systems with computational heavy tasks in FLF like model parameter [65] or reputation verification [36] or calculate the contribution measurement [38]. Other FLF specific blockchain systems utilize efficient AI hardware [66] or enhance the overall privacy for the FLF processes [31]. Yet a widely ignored topic in the scientific literature is the incurred deployment and maintenance cost of unproven novel blockchain systems in practice. Introducing a new, highly complex infrastructure introduces security risks and requires a large team of experts to run and maintain such a system in practice. Deployment on already existing blockchain frameworks may mitigate the additional complexity and risks but might be less efficient.

Developing simple and robust application specific blockchain systems, stress-testing them under realistic assumptions and thoroughly analysing their theoretical properties is an important future research direction towards production-ready FLFs.

6.2 Incentive Mechanisms

6.2.1 Realistic and computational feasible contribution measurement

Measuring workers' contribution is open research and varies heavily in the analyzed literature. So far, five major contribution measurements are considered in the literature.

- 1) **Honest Report/Full Information** rewards are calculated on the basis of the clients report of the amount of data, local accuracy or local loss. Yet reward systems based on such simplified assumptions may not be applicable in any real-world scenario as the dominant strategy for an individual-rational agent is dishonest behavior (report the best possible outcome without costly model-training). Applying Trusted Execution Environments might solve the issue, yet might be an infeasible technical requirement for mobile, edge or IoT devices.
- 2) **Reputation systems** Reward mechanisms based on the clients' reputation or majority voting are an interesting research avenue, promising to relax heavy verification and control mechanics for high reputation clients. How to quantify the reputation in a fair and robust fashion remains open research.
- 3) **Direct Measures** Direct Measurement such as assessing each client's model update on a public dataset/testset requires (i) a trusted central authority performing such tests and (ii) limits scalability due to the computational overhead.
- 4) **Exact Measures** The Shapley value of cooperative game theory is a common method for measuring the contribution of an agent in FL due to its desired properties of efficiency, symmetry, linearity and null-player, yet comes at the cost of heavy computational overhead (even when optimized [82], [83]) limiting the scalability of the framework and questioning the practicability of this approach.
- 5) **Correlation based Measures** Without having access to the ground truth, the reward is calculated based upon the correlation of the reported signals of peers. This implicit approach does not require an explicit contribution measurement and therefore avoids computational overhead.

Correlation based reward mechanisms such as Correlated Agreement (CA) [84], [85] or Peer-Truth Serum [30] are an interesting future research direction because their lightweight computation allows for potential execution atop of blockchain.

6.2.2 Realistic clients' behavior

Theoretical analysis of the designed incentive mechanisms, as performed by 12 out of 40 papers, requires simplifications and assumptions with respect to (i) information availability (ii) uniformity in utility functions or (iii) individual rationality which might not guarantee the robustness of the mechanisms in a real-world scenario. Specifically, as clients are humans, they may not follow their optimal strategies derived by analysis. For instance, not all clients would take the cost of energy consumption into account when

determining their strategies. We suggest taking humans' behavioral bias (e.g. prospect theory [86], [87]) as well as non-quantifiable measures (e.g. utility of privacy) into the theoretical analysis of incentive mechanisms.

6.3 Federated Learning

6.3.1 Performance evaluation under realistic conditions

While many papers conducted performance evaluation, they often did not consider realistic scenarios: (i) rather well-known benchmark datasets such as MNIST and CIFAR-10 are chosen (29 out of 34⁶ experiments on classification) and (ii) the non-IID setting is only applied in 11 out of 34 papers. Furthermore, inconsistencies between the targeted FL setting (i.e. CS, CD) and number of clients in the experiments are observed. In particular, FLFs that assume CD should simulate a large number of clients, however, only Kang *et al.* [45] and Desai *et al.* [54] conducted experiments with 100 participants or more (TABLE 8).

To better evaluate FLFs, we suggest using datasets dedicated to FL (e.g. LEAF [88]) as well as simulating different levels of non-IID data among clients (e.g., Dirichlet distribution [30]). Deployment on clusters of inexpensive computers such as Raspberry Pi [89] might realistically simulate large-scale FL scenarios under the CD assumption.

6.3.2 Beyond supervised FL and Federated Averaging

Another open research domain is the application of FLFs to machine learning tasks beyond supervised learning: tasks such as natural language processing, user behavior analytics or unsupervised learning tasks might rely on more complex neural network architectures. This in turn might require new or adapted model aggregation algorithms that might come with new implications for the incentive design and blockchain integration. In addition, assuming heterogeneity of clients with different hardware and restrictions requires flexibility on the Neural Network choice (e.g., Federated Knowledge Distillation [30]).

6.3.3 Towards lightweight privacy-preserving FL

Despite FL being a data privacy preserving technology by design, research has shown that certain characteristics of the underlying training data sets can be inferred from the global model and that additional privacy preserving measures are recommended. Our review shows that two classes of security concerns are targeted by the publications, namely (i) leakage of data set characteristics and (ii) disclosure of participant identities. Although a substantial number of papers (20 out of 40 publications) address one of these concerns, only a single paper addresses both [37]. Moreover, preventing data set leakage through DP or MPC inflicts trade-offs. Specifically, DP comes with a trade-off between data security and model accuracy, while MPC comes with a trade-off between data security and computation complexity, and it might thus not be applicable with a large number of participants [47]. It is worth noting that the model accuracy of DP cannot be inherently improved due to intentionally added noise. Hence, it would be important to explore lightweight MPC algorithms [76] to accommodate a large number of clients for privacy-preserving FL.

6. 6 papers out of 40 did not run experiments

7 CONCLUSION AND OUTLOOK

FL is a promising new AI paradigm, focused on confidential and parallel model training on the edge. In order to apply FL beyond small groups of entrusted entities, a decentralization of power as well as compensation for participating clients has to be incorporated into the Federated Learning Framework. This work traversed and analyzed 12 leading scientific databases for incentivized and decentralized FLFs based on the PRISM methodology, ensuring transparency and reproducibility. 422 results were found and 40 works analyzed in-depth after three filtering rounds. We overcame the challenge of heterogeneity of FLFs in terms of use-cases, applied focus, design choice and thoroughness by offering a comprehensive and holistic comparison framework. By exposing limitations of existing FLFs and providing directions for future research, this work aims to enhance the proliferation of incentivized and decentralized FL in practice.

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