

A Comprehensive Survey on Edge Data Integrity Verification: Fundamentals and Future Trends

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Recent advances in edge computing have pushed cloud-based data caching services to edge, however, such emerging edge storage comes with numerous challenging and unique security issues. One of them is the problem of edge data integrity verification (EDIV) which coordinates multiple participants (e.g., data owners and edge nodes) to inspect whether data cached on edge is authentic. To date, various solutions have been proposed to address the EDIV problem, while there is no systematic review. Thus, we offer a comprehensive survey for the first time, aiming to show current research status, open problems, and potentially promising insights for readers to further investigate this under-explored field. Specifically, we begin with stating the significance of the EDIV problem, the integrity verification difference between data cached on cloud and edge, and three typical system models with corresponding inspection processes. Then, we synthesize a universal criteria framework that an effective verification approach should satisfy. Subsequently, we adopt a schematic development timeline to reveal the research advance on EDIV in a sequential manner, followed by a detailed review on the existing EDIV solutions. Finally, we highlight intriguing research challenges and possible directions for future research.

Additional Key Words and Phrases: Edge Data Integrity Verification, Edge Computing, Security, Internet of things

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1 INTRODUCTION

The global number of deployed mobile and **Internet-of-Things (IoT)**s devices has been rapidly increasing as a result of the current growth in 5G and beyond networks [1]. It will surpass 25.4 billion in 2030 according to the technical report [2]. These devices are applied as the core building blocks of smart applications to carry out the most basic yet essential activities such as detecting [3], actuating [4], and controlling [5]. It is insufficient to depend just on those low-performance devices to properly complete complex activities, e.g., smart transportation arrangements [6–8], smart medical treatments [9–11], and smart vehicle control [12–14]. Instead, high-performance computing infrastructures are required to offload calculation tasks and facilitate

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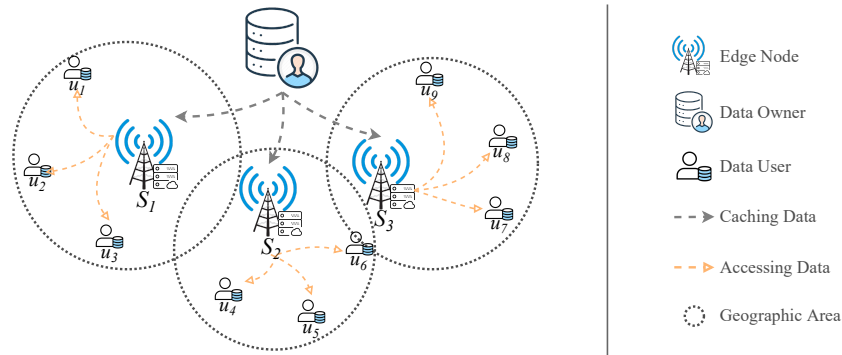


Fig. 1. Example of edge storage. A data owner caches multiple data replicas to geographically distributed edge nodes (denoted by S_1, S_2, S_3) to serve nearby data users (denoted by $u_i, i \in \{1, 2, \dots, 9\}$) with ultra-low data access latency.

decision-making. Undoubtedly, **cloud computing (CC)** [15–17] is the most well-known of such technologies. In this environments, **cloud infrastructure providers (CIPs)**, e.g., One Drive¹, Amazon², and Google Drive³, deliver data caching services in a centralized manner to support large-scale data access [18, 19]. Yet, cloud computing is not capable of perfectly matching the demands of mobile/IoT services due to the concerns like geographical unawareness [20], bandwidth limitations [21], a lack of real-time services [22], and unpredictable data access latency [23]. To this end, an emerging paradigm named **edge computing (EC)** [24–26] is spawned as one of the 5G and beyond key enabler technologies to facilitate latency-sensitive or geo-aware applications, e.g., autopilot [27], virtual reality [28], and video analytics [29]. The detailed definition and origin of EC can refer to [30]. Motivated by EC, **data owners (DOs)** are allowed to outsource popular data on **edge nodes (ENs)** for serving nearby **data users (DUs)** with better user experience [31], as shown in Fig. 1. Due to such benefits over CC, EC has grown dramatically in the last several years [32]. The Market Study Report⁴ predicts that the edge data centre market is expected to exceed \$20 billion by 2026.

Unfortunately, this promising computing paradigm still faces alarming security challenges in practice [33–36]. Different from cloud facilitated by mega-scale data centres, edge nodes are usually deployed at base stations or access points and deployed by different **edge infrastructure providers (EIPs)** [37]. This edge caching strategy is much more distributed, dynamic, and volatile [38], making the integrity of cached data corrupted easily and frequently. Plus, various attacks against EC-related infrastructures have significantly increased in recent years [39]. For instance, Mirai virus, which was released in August 2016 and managed to infiltrate more than 65,000 IoT devices within the first 20 hours of that release [40–42], is one of the most famous assaults to have ever taken place in reality. Over 178,000 domains were knocked down as a result of DDoS assaults launched against edge nodes a few days later using botnets created from these infected devices [43]. IoTReaper and Hajime, two Mirai variants that were discovered shortly after, were thought to have infected more than 378 million IoT devices in 2017 [34, 44]. These IoT botnet assaults were estimated to have cost over 100 million USD in damages since the initial Mirai botnet was found in 2016 [34, 45, 46]. More intuitively, researchers have found that various factors may lead to data loss in real-world scenarios. Based on the report from Kroll Ontrack⁵, 67% data loss is

¹<https://www.microsoft.com/en-us/microsoft-365/onedrive/online-cloud-storage>

²<https://aws.amazon.com/>

³<https://www.google.com/drive/>

⁴<https://www.gminsights.com/industry-analysis/edge-data-center-market>

⁵<https://www.techradar.com/how-to/world-of-tech/management/how-to-recover-lost-business-data-1304303/2>

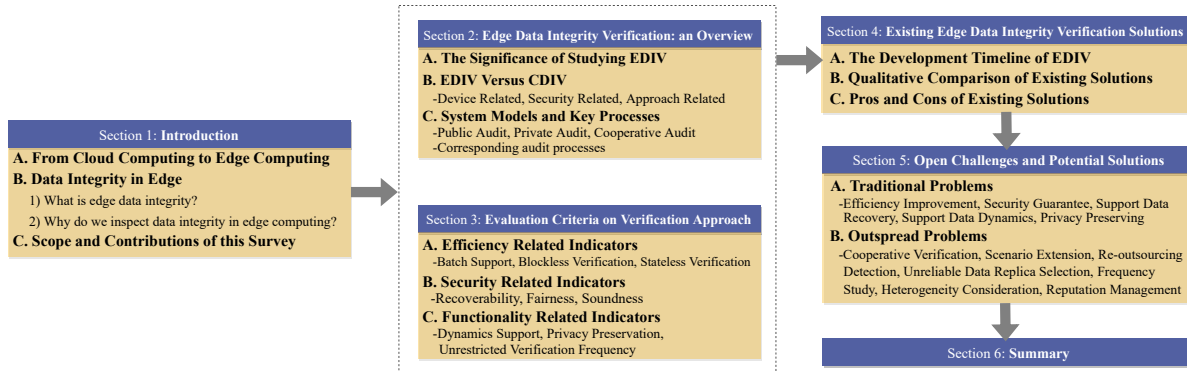


Fig. 2. Roadmap of the survey

caused by hard drive crashes or system failure, 14% is blamed for human error, and 10% is a result of software failure.

The above-mentioned examples and statistics clearly illustrate the unsatisfactory state of edge data security. Outsourcing data to edge nodes results in the separation of data ownership and management, and thus data owners and data users are unable to always trust edge nodes because they may misuse data management permissions and expose data to security risks [47]. Consequently, a variety of issues must be addressed before subscribing edge data caching services. For example, *how do data owners trust EIPs and ensure that outsourced data is integral all the time? How to properly audit cached data without retrieving the whole data collection? How to maintain the stable operation of integrity audit while data owners modify outsourced data?* All of the aforementioned problems could be handled by an **edge data integrity verification (EDIV)** approach, which entails creating a solution that allows data owners or (and) users to identify the integrity of outsourced data in the edge environment (referred to it as the EDIV problem hereafter [48]). EDIV investigation is of particularly practical importance for edge-based services/applications since critical business decisions depend mostly on accurate edge data and if it is corrupted, any decision based on that is suspect. We further emphasize its significance in Section 2.1. To date, numerous great achievements have been made for the EDIV problem, such as verification efficiency improvement [48] and data privacy guarantee [49], however, all these articles have proposed specific EDIV solutions targeting on corresponding fields, exposing the lack of a systematic and comprehensive review of them. We would like to note that **cloud data integrity verification (CDIV)** problem has been paid lots of attention in the last decade and has formed some related reviews, e.g., [50–55]. However, EDIV has several fundamental discrepancies with CDIV and needs to be independently investigated, which will be articulated in Section 2.2. Overall, the purpose of this work is to narrow this gap while motivating new insights into data integrity in edge computing domains.

1.1 Scope and Contributions

To the best of our knowledge, **this is the first survey to look into data integrity verification in edge computing environments**, i.e., the EDIV problem. We begin with describing the motivation of studying EDIV problems and then providing a comprehensive comparison between CDIV and EDIV. Afterwards, three typical system models with corresponding key processes are covered. Simultaneously, we demonstrate a set of criteria that an effective EDIV approach should satisfy. Then, depending on their design aims, we comb through a taxonomy of EDIV solutions, ranging from 2019 to 2022. Finally, we highlight unresolved challenges and make recommendations for further research. This is done to clarify the link between CDIV and EDIV, as well as to promote

Table 1. List of key abbreviations

Abbr.	Definition	Abbr.	Definition	Abbr.	Definition
IoTs	Internet-of-Things	CC	Cloud Computing	CIP	Cloud Infrastructure Provider
EC	Edge Computing	DO	Data Owner	EN	Edge Node
DU	Data User	EIP	Edge Infrastructure Provider	EDIV	Edge Data Integrity Verification
CDIV	Cloud Data Integrity Verification	SLA	Service Level Agreement	TPA	Third Party Auditor
EDI	Edge Data Integrity	PDP	Provable Data Possession	POR	Proof of Retrievability

future development and integration of EDIV. More significantly, we provide a valuable resource for follow-up researchers and amateurs. To conclude, the primary contributions of this survey are overviewed as follows.

- We clarify the gravity and significance of the EDIV study and summarize its uniqueness compared with CDIV. Besides, the system models along with key processes of EDIV are introduced in detail.
- We synthesize a universal criteria system that a satisfactory EDIV solution is expected to meet, which can be further applied to assess the quality of EDIV methods.
- According to the established criteria, a development timeline is given to outline the evolution of existing efforts for the EDIV problem. Plus, current solutions are properly classified into three types, while emphasizing their advantages and exposing their shortcomings.
- We identify a list of open issues and further exploit future research directions including traditional and outspread ones to promote dedicated efforts on the EDIV problem. Notably, some of the valuable directions have barely or even never been investigated yet. We hope it could provide some insight for follow-up researchers.

1.2 Paper Organization

The remainder of this survey is structured as follows. The motivation and overview of the EDIV problem are presented in Section 2. In Section 3, we propose a series of criteria regarding the evaluation of existing EDIV solutions. A development timeline and taxonomy on EDIV are structured and the existing works are reviewed accordingly in Section 4. In Section 5, several future research directions and potential solutions are introduced, while a summary is provided in Section 6. For clarity, we illustrate the organization of this work in Fig. 2, and key acronyms are outlined in Table 1.

2 EDGE DATA INTEGRITY VERIFICATION: AN OVERVIEW

In order to better understand the scope and breadth of the EDIV problem, in this section, we state the significance of EDIV investigation. Then, we explicitly present the discrepancy between CDIV and EDIV. Further, we provide a summary of three commonly-used system models, along with a short introduction to the corresponding key processes concerning the EDIV problem-solving strategies.

2.1 The Significance of Edge Data Integrity Verification

To some extent, data cached on cloud is more reliable and stable than on edge nodes [56, 57], since cloud servers have adequate resources to achieve computation-intensive inspection tasks, while edge nodes often can not afford to perform the same level of integrity assurance [58]. In reality, however, data corruption accidents occur frequently even in cloud. According to a comprehensive study [59], existing cloud data corruption detection schemes are quite insufficient. Specifically, only 25% of data corruption problems are reported correctly, 42% are undetected, and 21% receive imprecise error reports. They also found that the detection system raises

12% false alarms. Real examples include but not limited to the following ones. Jeff Bonwick, the ZFS⁶ creator, mentioned that a fast database named Greenplum⁷ faces undetected data corruption every 10 to 20 minutes⁸. Additionally, NetApp⁹ conducted 41-month real-world research on more than 1.5 million hard disk drives and identified over 400,000 undiscovered data corruptions, including more than 30,000 undetectable by hardware RAID controllers [60]. Besides, during the course of six months and involving around 97 petabytes of data, CERN¹⁰ discovered that approximately 128 megabytes of data got irreversibly corrupted [61].

The above analysis clearly reveals that detecting data corruption is a challenging problem in cloud domains, let alone in dynamic edge computing environments. Briefly, studying the EDIV problem has the following significance from the utility perspective.

Cut Data Owners' Loss. Edge data corruption has a lasting impact on data owners' businesses. For recoverable data, detecting corruption as soon as possible can help data owners recover correct data in a timely way, so that effective measures could be taken to shrink the gaps left by corruption [60, 62]. For unrecoverable data, identifying corruption efficiently can assist data owners in designing emergency plans to minimize unnecessary delay and possible loss of business reputation and revenue [63]. Furthermore, inspecting **edge data integrity (EDI)** presents a critical aspect to reduce the customer churn rate, increase data users' trust and respect, and reestablish client relationships.

Boost EIPs' Reputation. In practical terms, there are thousands of EIPs around the world, each of which is renowned in certain geographic areas. For instance, Optus [64] is highly accepted in Australia, and IBM is more prestigious in America. Business competition can be fierce, especially in fast-moving edge computing markets where data owners often shop around for cost-effective EIPs [65]. A satisfying EDIV solution can help EIPs defend their market position and build their competitive advantage.

Remedy Deficiency. In real production environments, edge nodes adopt internal data and metadata checksumming [66] to detect data corruption [67]. In some cases, although EIPs have bounded by **service level agreements (SLAs)** [68, 69] to ensure data integrity, data owners can not solely rely on such agreements, because edge data operational details are not transparent to the data owners and EIPs may be untrusted [70], i.e., EIPs may not conduct required data integrity check mechanisms to actively report corruption for keeping a good industry reputation. Even if EIPs are assumed to be totally honest and self-actualized, outsourced data replicas could be manipulated or lost due to accidental activities [71], which can be a nightmare for data owners and an embarrassment for EIPs. Thus, an effective EDI external verification approach can be regarded as a supplement to internal checksumming, supporting data owners and EIPs to detect corruption shortly.

2.2 Edge Data Integrity Verification Versus Cloud Data Integrity Verification

The detailed comparison between EDIV and CDIV is summarized in Table 2. In brief, there are three key distinctions. First, *edge nodes as data carriers lead to device-related discrepancies including the number, location, capacity, and providers of devices.* In this respect, edge nodes' protection systems are more brittle than those of cloud servers', and therefore a variety of attacks that could be ineffectual against cloud servers can seriously endanger the integrity of data cached on edge [74, 75]. Second, *data cached on edge suffers from a greater diversity of attacks.* Obviously, attack diversification hugely raises the corruption undetected probability [36]. Because of it, even if corruption occurs, most data owners/users might not be able to notice it. Third, *diverse question scenarios bring in different problem-solving approaches.* The challenges of creating an integrity verification mechanism for edge computing are directly attributed to this aspect. The majority of CDIV schemes in use

⁶<https://en.wikipedia.org/wiki/ZFS>

⁷<https://greenplum.org/>

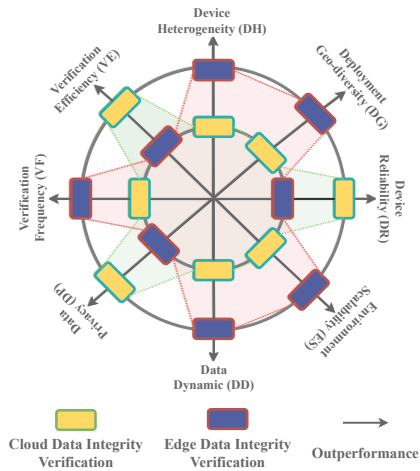
⁸<https://queue.acm.org/detail.cfm?id=1317400>

⁹<https://www.netapp.com/>

¹⁰<http://home.cern/>

Table 2. Cloud Data Integrity Verification Versus Edge Data Integrity Verification

Cat.	Sub-category	CDIV	EDIV
Device Related	The number of devices	• limited number of cloud servers	• large-scale edge nodes
	Device location	• remote and centralized, long distance from data users, less mobility	• at the edge of the network and distributed, close to data users, high mobility
	Device capacity	• more secure, less scalability, more latency, virtually unlimited resources	• less secure, more scalability, less latency, fewer resources
	Device provider	• big companies	• less powerful entities, e.g., small companies
Security Related	The number of risks	• less outside security risks	• more risks, more likely to be attacked
	The type of risks	• fewer types of risks, free from the single point failure problem [72]	• specific threats, e.g., breaking network access, unknown stakeholders or determining resource locations, single point failure problem [73]
Approach Related	Assumption	• Almost enough resources support complex inspection schemes.	• Limited resources can not conduct complex inspection tasks.
	Trust model	• CIPs ensure data integrity.	• EIPs are responsible for data integrity.
	Main function	• verification	• verification, localization, and geo-assurance
	Main feature	• less limitation	• more lightweight for every participant
	Inspection way	• one-by-one inspection	• inspection in a parallel way
	Inspection frequency	• less, having centralized control	• more due to a higher level of threats, lack of centralized control



Features	CDIV ¹	EDIV ¹
DH [78]	□ similar data centers	■ inequale edge nodes
DG [78]	□ one or several locations	■ numerous locations
DR [79]	■ strong security guarantee	□ weak assurance mechanism
ES [80]	□ change infrequent	■ easy extension
DD [81]	□ steady data	■ dynamic data
DP [34]	■ powerful privacy protection	□ weak protection policy
VF [48]	□ low-frequency	■ high-frequency
VE [48]	■ high-efficiency	□ low-efficiency

1: ■ high-performance; □ low-performance.

Fig. 3. A comparative visual summary between edge data integrity verification and cloud data integrity verification

today are coarse-grained [76], which is unfit for edge computing because of the more complex systems and applications. Fine-grained and lightweight integrity verification approaches are necessitated in edge computing environments [77].

Table 3. Review on existing internal attacks regarding EDIV

Attack Type	Description
Spoofing Attack [87]	• Dishonest DO/DU/TPA checks the received proofs and claims an incorrect verification result.
Replay Attack [88]	• Dishonest EN deduces the latest integrity proof from previous-generated ones.
Forgery Attack [89]	• Dishonest EN forges an integrity proof to bypass the integrity check.
Replace Attack [90]	• Dishonest EN replaces a damaged block with another intact block saved by itself to try to pass the verification.
Data Leakage Attack [91]	• Dishonest TPA deduces outsourced data during the verification protocol.
Outsourcing Attack [92]	• Dishonest EN intercepts integrity proofs created by other ENs as its own proof.
Byzantine Attack [93]	• Dishonest EN tampers with honest ENs' integrity proofs when returning the integrity proof.
Collusion Attack [94]	• Dishonest ENs collude together to corrupt the cached data to deceive DO/DU/TPA.

We further state the key differences from a high-level point of view in Fig. 3, where each of the edges indicates one of the features that cloud and edge exhibit discrepancy in data integrity. It can be deduced from the radar graph and the table that edge nodes are more heterogeneous and follow geo-diversity deployments [78]. Plus, data privacy leakage during integrity verification occurs more often in edge because it broadens the real-world attack surface from the perspective of weak computation power, attack unawareness, protocol heterogeneity, and coarse-grained access control [34]. Furthermore, data dynamic issues should be considered more rigorously in edge, as data cached on edge is changed faster than on cloud [81]. Besides, since edge nodes have less reliability [79], verification frequency in edge domains should be higher. Finally, verification efficiency currently achievable is hard to match existing CDIV solutions due to highly scalable edge environments.

2.3 System Models and Key Processes

EDIV problems usually happen in data-driven services that take advantage of edge computing architectures [82–84], where edge nodes are always expected to involve in the process of integrity verification for the ease of security concerns of both data owners and data users [85]. Due to the limitations of processing and storage capacities of data owners/users, sometimes the integrity check is performed by a **third party auditor (TPA)** [86]. To sum up, there are four types of entities related to the EDIV problem:

- **Data Owner (DO):** It could be an Application vendor, developer, etc. It outsources its latency-sensitive data on multiple geographically distributed edge nodes to serve nearby DUs, as shown in Fig. 1. To enhance user experience, it queries data and requests for data integrity verification on edges.
- **Data User (DU):** It may be an IoT device, mobile subscriber, etc. It would check the integrity of queried data, because of self-interest concerns, by the interaction with edge nodes like the cases presented in Fig. 4 and Fig. 5.
- **Edge Node (EN):** It could be an access point, base station, etc. As illustrated in Fig. 1, it caches data replicas for DOs, can be reached by nearby DUs with low access latency, and assists in the completion of integrity check.
- **Third Party Auditor (TPA):** It could be an agency, certification body, etc. It performs an external and independent audit of the integrity of data cached on remote ENs for DOs/DUs, as displayed in Fig. 5. Typically, TPAs have powerful computing and storage capabilities.

We further identify a number of EDIV-related attacks that are targeted to damage verification processes and launched by EDIV participants (i.e., DO, DU, EN, and TPA), as summarized in Table 3. Please note that there is a strong correlation between those attacks and security assumptions adopted in solutions. For example, if TPA is supposed to be fully trustworthy, data leakage attacks never happen in the verification process.

Generally, a system model defines the purpose and context for approach usage. More specifically, it describes what kind of participant is involved and what assumption is held [95]. Notably, not all of the entities mentioned above are included in each existing EDIV solution. We extract three generic system models in brief, including private audit, public audit, and cooperative audit. These models mainly differentiate on what participants are engaged. In private audit, it is the data owner/user that verifies EDI. However, the data owner/user is not totally trustworthy, as it may deliberately claim incorrect verification results to obtain monetary or service compensation from EIPs [96]. Thus, *from the edge nodes' perspective, it is impossible to determine whether verification results are reliable or not*. To eliminate this concern and alleviate the verification burden on data owners/users, public audit occurs, in which TPA acting as a trusted agency fulfills integrity inspection [97, 98]. On the downside, *the security of EDIV is hard to guarantee if TPA is byzantine*. Very recently, cooperative audit comes into follow-up researcher's sight to improve verification fairness. In this case, blockchain or other distributed technologies are adopted to enable edge nodes to collectively finish inspection tasks without the participation of TPA or even data owners/users [99–101]. We introduce these three system models with key processes as follows.

2.3.1 Private Audit. As shown in Fig. 4, a data owner/user inspects outsourced data using a *Challenge-Response* mechanism, in which it interacts with multiple edge nodes via message exchange, and EDI can be ensured with a high probability if edge nodes provide correct integrity proofs [48, 102]. The key process of private audit is as follows.

- **Challenge(.)** \rightarrow *chal.message(.)*: DO/DU runs this randomized algorithm to build and send a challenge message *chal.message(.)* to each EN.
- **Response(*d*, *chal.message(.)*)** \rightarrow *resp.message(r)*: This randomized algorithm is run by each EN to prove the integrity of cached data replicas *d*. It takes as input the challenge message *chal.message(.)* and cached data replicas *d*, and then returns a response message *resp.message(r)* with integrity proof *r*.
- **Verification($\cup\{resp.message(r)\}$)** \rightarrow (τ , \perp , $\{id\}$): DO/DU runs this deterministic algorithm. It takes as input the set of received response messages and determines whether the corresponding data replicas are integral. If proofs are verified in a batch way, it further locates corrupted data replicas.

2.3.2 Public Audit. As presented in Fig. 5, a data owner/user authorizes TPA to complete EDIV for ease of the verification burden [49, 86]. In this case, the data owner/user sends an inquiry message to TPA, and then TPA is responsible for checking data integrity, following the same *Challenge-Response* mechanism. After finishing it, TPA returns verification results back to the data owner/user. The key process of public audit is as follows.

- **Inquiry(.)** \rightarrow *inq.message(.)*: This algorithm is run by DO/DU. It outputs an inquiry message *inq.message(.)*.
- **Challenge(*inq.message(.)*)** \rightarrow *chal.message(.)*: TPA runs this randomized algorithm to build and send a challenge message *chal.message(.)* to each EN.
- **Response(*d*, *chal.message(.)*)** \rightarrow *resp.message(r)*: This randomized algorithm is run by each EN to prove the integrity of cached data replicas *d*. It inputs the challenge message *chal.message(.)* and cached data replicas *d*, and sends back a response message with an integrity proof *r*.
- **Verification($\cup\{resp.message(r)\}$)** \rightarrow (τ , \perp , $\{id\}$): TPA runs this deterministic algorithm. It takes as input the set of response message $\cup\{resp.message(r)\}$, and determines whether the corresponding data replicas are integral.
- **Answer(τ , \perp , $\{id\}$)** \rightarrow *ans.message(.)*: The algorithm is run by TPA. It takes as input the verification result, and sends an answer message *ans.message(.)* to DO/DU.

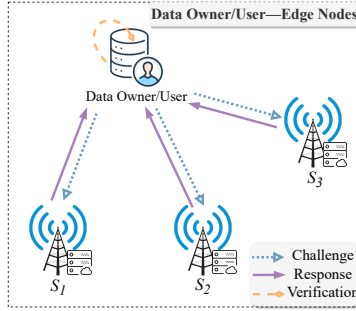


Fig. 4. Private audit process

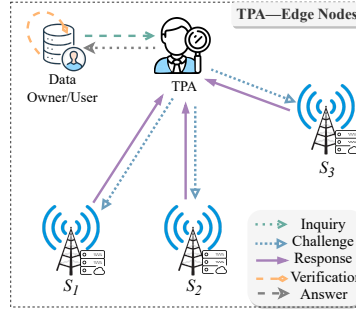


Fig. 5. Public audit process

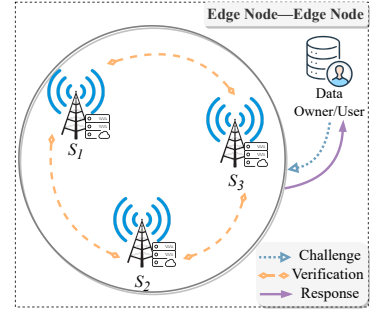


Fig. 6. Cooperative audit process

2.3.3 Cooperative Audit. In the last two years, the mentality of EDIV problem-solving is further enlarged. Edge nodes check data integrity by themselves without the interaction with a data owner/user or TPA [103, 104], as illustrated in Fig. 6. In this case, edge nodes usually adopt consensus algorithms to reach an agreement about the integrity status of cached data replicas, and directly return the verification result that all agree on to the data owner/user. The key process is demonstrated as follows.

- **Challenge(.)** \rightarrow *chal.message(.)*: DO/DU runs this deterministic algorithm to build and send a challenge message *chal.message(.)* to ENs.
- **Verification(*chal.message(.)*)** \rightarrow $(\tau, \perp, \{id\})$: ENs collaboratively run this deterministic algorithm. It inspects cached data replicas and locates corrupted ones.
- **Response($\tau, \perp, \{id\}$)** \rightarrow *resp.message(.)*: This algorithm is run by one or multiple ENs to return the verification result to DO/DU.

3 EVALUATION CRITERIA ON VERIFICATION APPROACH

In this section, we explore a number of evaluation criteria to discover the pros and cons of existing EDIV solutions. This set of criteria is also employed to assess the quality of verification approaches. A brief classification of the criteria that would be covered in this survey and the methodologies are illustrated in Fig. 7 to highlight the relationship among these indicators, followed by the detailed description below.

First, substantial effort is required to make problem scenarios well-defined, relatively complete, and coherent. Existent EDIV solutions can be categorized into two ties from the scenario support perspective, including multi-replica and multi-owner. Notably, in edge domains, we usually do not investigate single-replica storage cases (i.e., DO caches one data replica on a single EN) because of two reasons: (1) existing EDIV solutions could be directly adopted to handle the EDIV problem with imperceptible modification; (2) single-replica is unable to support low-latency services for geographically distributed DUs, which deviates from the objective of EC [105].

Specifically, multi-replica support represents that the solution is designed for and works well in multi-replica scenarios, where a single DO deploys its data replicas in multiple geo-distributed ENs to serve various users in different regions, like the example presented in Fig. 1. Supporting multi-replica is one of the fundamental characteristics of effective EDIV solutions. In this case, three key issues call for special attention: (1) *geo-assurance*: edge nodes may cache only one or two replicas of the original data, while claiming that they are storing the number of replicas specified by the data owner [53], and thus data owners need to verify that edge nodes actually store the specified number of replicas; (2) *efficiency improvement*: even though single replica verification schemes can be extended to multi-replica scenarios, but the audit costs would go up exponentially with the increase of the number of replicas, thus limiting their application; (3) *data dynamics*: outsourced data may be frequently

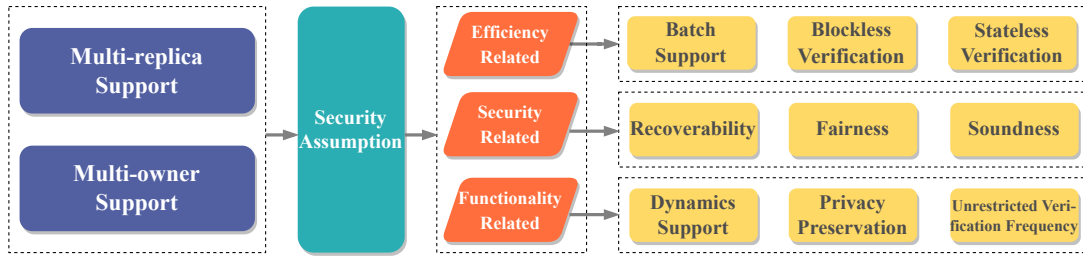


Fig. 7. Evaluation criteria of edge data integrity verification solutions

added, deleted, or modified by data owners. The verification schemes should work well under such dynamic operations [106].

Multi-owner support denotes that the solution can inspect multiple data replicas for multiple data owners, simultaneously. In contrast to the schemes for a single data owner with multiple replicas, this type of scenarios should not only consider *geo-assurance*, *efficiency improvement*, and *data dynamics*, but also take *owner dynamics* into account. Intuitively, it seems unnecessary to develop additional methods for multi-owner, since most solutions for multi-replica can be extended to this one in an obvious way, but it is unfeasible in practice. If multi-replica solutions are trivially extended to support multi-owner with data integrity assurance, each data owner has to perform the same verification workflow to interact with all corresponding edge nodes. In particular, the edge node that caches numerous data replicas from various data owners may suffer high computation and communication overhead, as it has to process multiple audit requests from dissimilar data owners at the same time [107]. Clearly, these trivial extensions could incur a new performance bottleneck and a tremendous workload on edge nodes. Thus, digging into multi-owner scenarios to design appropriate EDIV approaches is meaningful and critical in reality.

Founded on specific scenarios, we describe the concept of *security assumption* that is the backbone when designing EDIV approaches and directly related to the classified criteria [108]. Generally, security assumption is associated with four entities, i.e., data owners, data users, edge nodes, and TPAs. Each of them may be assumed as *untrusted*, *semi-trusted*, or *trusted*. Clearly, different assumptions lead to various cases and further need different approaches to handle them. For example, if TPA is supposed to be fully trusted, we do not bother to design a privacy-preserving EDIV method. In contrast, if it does not hold, privacy issues should be jointly considered. Next, we elaborate on specific indicators.

3.1 Efficiency Related Indicators

EDIV efficiency consists of three aspects including computation, storage, and communication, which further derives three indicators, i.e., batch support for computation efficiency improvement, blockless verification for communication efficiency improvement, and stateless verification for storage efficiency improvement. We articulate them separately as follows.

3.1.1 Batch Support (BS). Batch support refers to that a method could inspect the integrity of multiple data replicas simultaneously [109]. It is a general indicator for both multi-replica and multi-owner scenarios. Its main purpose is to improve computation efficiency so that data replicas can be inspected more frequently over a fixed time interval. To date, lots of related work, e.g., [49, 86], supports batch verification, especially in edge computing environments.

3.1.2 Blockless Verification (BV). Blockless verification refers to that an approach should not ask data owners/users or TPAs to retrieve outsourced data replicas from the remote edge nodes for verification purposes [110]. This is a prerequisite for all EDIV solutions, since it is an unnecessary and communication-consuming task to access the whole data replicas (particularly with big sizes) cached on edge nodes and check integrity. In blockless verification, it is small-sized integrity proofs (e.g., hash strings) that are generated and transferred to the data owner/user or TPA for proof verification, which reduces communication overhead fundamentally.

3.1.3 Stateless Verification (SV). Stateless verification means that neither a data owner/user/TPA nor an edge node requires to cache previous verification results in order to perform future audits [111]. In short, every challenge request both from data owners/users or TPAs is time-independent, which aims to save storage space for each side. This is an indirect requirement of data integrity methods. Otherwise, it may result in a situation in which keeping prior audit states becomes a storage burden for each participant.

3.2 Security Related Indicators

In addition to efficiency-related metrics, a number of security attributes should be taken into consideration when designing an appropriate EDIV approach. From a high-level point of view, an EDIV scheme would be more practical if it could recover the corrupted data replica after identifying it. Furthermore, fairness is another important indicator, as keeping fair is the basis of incentives that motivates edge nodes to act normal and perfect. Last, soundness ensures that EDIV solutions can secure against various types of attacks during verification so that yielding a correct verification result. Next, we introduce them in detail.

3.2.1 Recoverability (Re). Recoverability refers to that an EDIV solution can not only find out the corrupted data replicas but also complete data recovery to avoid an unpleasant situation [112]. This property fills the gaps left by corruption so that protects EIPs' reputation and guards data owners to keep user experience.

3.2.2 Fairness (Fa). Fairness is displayed in two aspects. First, from edge nodes' perspective, a satisfactory solution should ensure that data owners/users can not deliberately assert incorrect verification results [113], i.e., edge nodes are capable of telling whether or not inspection results can be trusted. Accordingly, malicious data owners/users are impossible to damage the reputation of EIPs. Second, from data owners/users' perspective, a feasible solution should provide protection against legitimate but malicious edge nodes who may collude to obtain a misleading verification result [114], especially in cooperative audit cases. Unequivocally, fairness is a key indicator for both edge nodes and data owners/users [115].

3.2.3 Soundness (So). Soundness refers to that an edge node is unable to pass verification unless it provides a correct integrity proof [116]. If an edge node can pass a challenge request without holding the data or with corrupted data, the data owner/user is incapable of detecting data corruption in a timely manner, resulting in potentially far-reaching business ramifications. Therefore, the soundness property of data integrity verification approaches guarantees data reliability and is a necessity for approach design.

3.3 Functionality Related Indicators

EDIV is a wide-range problem, and solutions may have lots of appendant sub-functions besides integrity verification and corruption localization, such as, dynamic verification, privacy preservation, and unrestricted verification frequency. Obviously, the more the EDIV approach supports, the better it is.

3.3.1 Dynamic Verification (DV). Dynamic verification refers to that an EDIV approach can work steadily when the cached data replicas are updated by data owners [117]. It is an important indicator, as data dynamics is a fundamental characteristic and often occurs in edge computing environments. An approach supporting dynamic verification property would be more practical, especially in industry.

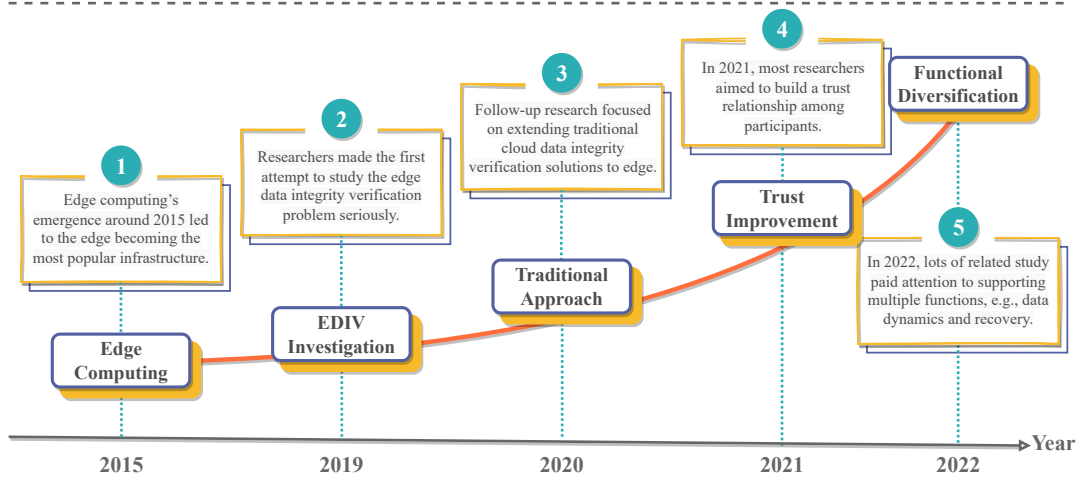


Fig. 8. Development timeline of edge data integrity investigation

3.3.2 Privacy Preservation (PP). Privacy preservation requires that TPA has no personal knowledge of the sensitive information of data owners/users, data replicas, and edge nodes while yet validating the integrity of outsourced data [118]. Privacy leakage often occurs in public audit cases owing to the curious TPA involvement, but it is uncommon in private or collaborative audits.

3.3.3 Unrestricted Verification Frequency (UVF). Unrestricted verification frequency implies that there should be no limits on the number of challenges issued by a data owner/user or TPA for integrity validation [119]. It is also known as unbounded inquiries. EDIV is a continuous process, in which a data owner/user or TPA runs the verification procedure at regular intervals to detect data corruption. The computation efficiency of the data integrity completion has a direct impact on the frequency of challenge requests. If the verification procedure of a data integrity method is computationally demanding, the data owner/user or TPA would adopt it less frequently, and consequently, unrestricted verification frequency will suffer.

4 EXISTING EDGE DATA INTEGRITY VERIFICATION SOLUTIONS

In this section, we summarize the development process of EDIV problems and then survey the literature advances. We explore the following databases: Web of Science, Google Scholar, IEEE Xplore and ACM library to search papers based on the keywords: edge data integrity, integrity attack, edge computing, data security, and integrity in edge. By adopting the criteria presented in Fig. 7, we review existing EDIV approaches in a qualitative way. Besides, we figure out the pros and cons of them. For ease of understanding and interpretation, we list EDIV approaches in the taxonomy Table 4 to summarize the qualitative aspects. Further, we outline the key contributions and limitations of each reference work in Table 5, Table 6, and Table 7 for private audit, public audit, and cooperative audit, respectively.

Overall, EDIV is a novel problem and still in its initial stage. Briefly, the problem has undergone four years of development since its birth. Fig. 8 depicts a schematic layout of the EDIV problem development process. It has made some attractive progress and achievement over the past few years but also endured frustrations and setbacks. In the following, we illustrate several stages of the evolution of EDIV solutions.

Table 4. Qualitative Comparison of Existing Solutions

Category	Ref.	Scenario ¹	Security Assumption ²	Effi. Related ³			Secur. Related ³			Funct. Related ³		
				BS	BV	SV	Re	Fa	So	DV	PP	UVF
Private Audit	[48]	O-E	TO-UE	○	●	●	○	○	●	○	●	●
	[102]	O-E	TO-UE	●	●	●	○	○	●	○	●	●
	[120]	O-E	TO-UE	○	●	●	○	○	●	○	●	●
	[121]	O-E	TO-UE	●	●	●	○	○	●	●	●	●
	[122]	O-E	TO-UE	●	●	●	○	○	●	●	●	●
Public Audit	[86]	U-T-E	TU-ST-UE	●	●	●	○	●	●	○	●	●
	[123]	O-T-E	TO-TT-SE	●	●	●	●	●	●	○	○	●
	[124]	O-T-E	TO-ST-TE	○	●	●	○	●	●	●	○	●
	[125]	O-T-E	TO-ST-TE	○	●	●	○	●	●	●	●	●
	[126]	O-T-E	UO-UT-TE	○	●	●	○	●	●	○	○	●
	[49]	U-T-E	TU-ST-UE	●	●	●	○	●	●	○	●	●
	[127]	U-T-E	TU-TT-SE	○	●	●	○	●	●	○	●	●
Cooperative Audit	[128]	E-E	TE-TE	○	●	●	○	○	●	○	●	●
	[129]	E-E	UE-UE	○	●	●	○	●	●	○	●	●
	[130]	E-E	TE-TE	○	●	●	○	○	●	○	●	●
	[103]	E-E	TE-TE	○	●	●	●	○	●	○	●	●
	[131]	E-E	UE-UE	○	●	●	○	○	●	○	●	●
	[104]	E-E	UE-UE	○	●	●	○	○	●	○	●	●

1: O-E (DO and ENs); U-T-E (DU, TPA, and ENs); O-T-E (DO, TPA, and ENs); E-E (among ENs).

2: TO-UE (trusted DO and untrusted ENs); TU-ST-UE (trusted DU, semi-trusted TPA and untrusted ENs); TO-TT-SE (trusted DO and TPA, semi-trusted ENs); TO-ST-TE (trusted DO and ENs, and semi-trusted TPA); UO-UT-TE (untrusted DO and TPA, and trusted ENs); TU-TT-SE (trusted DU and TPA, and semi-trusted ENs); TE-TE (trusted ENs); UE-UE (untrusted ENs). [Please note that semi-trusted denotes honest-but-curious.]

3: ● (support); ● (uncertainty); ○ (non-support) for efficiency (Effi.), security (Secur.), and functionality (Funct.) related indicators.

- 2015: *The emergence of edge computing*. The roots of edge computing reach back around 2015, while it is also well-known as fog computing [132] or cloudlet computing [133]. The aim is to explore the feasibility of performing computations on edge nodes through which network traffic is directed.
- 2019: *The emergence of EDIV problems*. Edge data integrity was not valued much before 2019, until Tong *et al.* [86] published the first work on the EDIV problem from the data users' perspective.
- 2020: *The focus on traditional approaches*. In 2020, lots of related work was proposed, but the trend is to extend traditional CDIV approaches to the edge domain without identifying the unique characteristic of edge. As we discussed in Section 2.2, there are several essential discrepancies between edge and cloud when integrity inspection.
- 2021: *The focus shifted to trusted improvement*. In 2021, EDIV solutions generalized and extended the CDIV solutions space to enable better performance. In this year, most of related work paid much attention to trust improvement, as in edge, trust issues become more crucial than cloud. Instead of being limited to traditional approaches, EDIV solutions have generated their own specific and clear development routes.

Table 5. Summary of Recent Advances in EDIV Solutions for Private Audit

Cat.	Ref.	Year	Contributions	Limitations
Private Audit	Li <i>et al.</i> [48]	2020	<ul style="list-style-type: none"> – It proposes a novel data structure named variable Merkle hash tree. – It reduces verification complexity via sampling technology. – It defends against replay and forgery attacks. 	<ul style="list-style-type: none"> – It offers a probabilistic integrity guarantee, inducing some unpredictable consequences brought by undetected corruption. – It does not consider the trust issue of data owners, as well as the data dynamics and recovery issues. – It has high traffic over backhaul networks.
	Li <i>et al.</i> [102]	2021	<ul style="list-style-type: none"> – It provides a deterministic integrity guarantee. – It supports batch verification so that efficiency could be improved. 	<ul style="list-style-type: none"> – It fails to take the security of data owners into account. – It can not repair corrupted data replicas or work well in data dynamic scenarios.
	Cui <i>et al.</i> [120]	2021	<ul style="list-style-type: none"> – It inspects data integrity at a block level. – It aims at designing a low computation overhead solution. 	<ul style="list-style-type: none"> – It has some security issues like spoofing attacks and forgery attacks. – It can not repair corrupted data and does not consider data dynamics.
	Qiao <i>et al.</i> [121]	2021	<ul style="list-style-type: none"> – It supports batch auditing and provable dynamic update. 	<ul style="list-style-type: none"> – It can not ensure fairness or support data recovery.
	Ding <i>et al.</i> [122]	2022	<ul style="list-style-type: none"> – It supports batch verification. – It proposes a new data structure named index-single linked table to support data dynamics including insertion, deletion, and modification. 	<ul style="list-style-type: none"> – It is incapable of handling various security concerns such as forgery attacks. – It can not repair corrupted data replicas.

2022: *The focus tied to functional diversification.* From 2022 to the present, researchers begin designing a more general EDIV strategy with a variety of functions. For example, they have developed integrity verification approaches in edge computing environments with data recovery and data dynamic support.

Traditionally, the design philosophy of CDIV schemes almost entirely relies on **provable data possession (PDP)** [134] or **proof of retrievability (POR)** [135]. In brief, PDP schemes are probabilistic since they employ random block sampling for verification rather than considering the entire data replica. Specifically, the original data are preprocessed to create some metadata that is stored with original data and adopted later to verify the integrity of the cached data replica. This type of scheme can detect data corruption but fails to recover it. Another well-known strategy, POR, overcomes such drawbacks, enabling to provide data recovery by using the redundant encoding of data. Technically, these two most-commonly used CDIV schemes are interchangeable. In fact, most existing EDIV approaches are variants of PDP or POR. Next, we review them in detail.

4.1 Private Audit

Some studies concentrate on private audit, in which the data owner/user is responsible for integrity verification, no need of TPA involvement in the whole verification process, comb-outing privacy leakage issues brought by TPA. However, the fairness issue occurs accordingly, since neither data owners/users nor edge nodes are suitable to conduct proof verification due to trust concerns [136]. Next, we go over related works in depth.

Li *et al.* [48] (2020) propose a lightweight sampling-based probabilistic approach, namely EDI-V, aiming to auditing the integrity of multiple data replicas cached on a large scale of edge nodes. Meanwhile, they develop a

Table 6. Summary of Recent Advances in EDIV Solutions for Public Audit

Cat.	Ref.	Year	Contributions	Limitations
Public Audit	Tong <i>et al.</i> [86]	2019	<ul style="list-style-type: none"> – It can verify data integrity on the edge nodes without downloading the data from them. – Both the pre-download strategy of edge nodes and the query pattern of data owners are preserved against TPA. 	<ul style="list-style-type: none"> – It is hard to ensure that TPA is totally trustworthy. – The study mainly focuses on privacy preservation and fails to tackle other unique challenges in edge. – It is a variant of the PDP scheme that limits verification efficiency.
	Liu <i>et al.</i> [123]	2020	<ul style="list-style-type: none"> – It considers data recovery by using one-way linked information tables. – It supports batch verification and thus verification efficiency can be improved. 	<ul style="list-style-type: none"> – It relies on an unrealistic assumption, i.e., TPA is totally trustworthy. – It barely considers possible attacks.
	Wang <i>et al.</i> [124]	2021	<ul style="list-style-type: none"> – It considers multiple scenarios including single edge, multiple edges, and a joint of multiple edges and the cloud. – The proposed approach is privacy-preserving. 	<ul style="list-style-type: none"> – It can not guarantee that TPA can be trusted. – It does not support batch verification, data recovery and dynamics.
	Chen <i>et al.</i> [126]	2021	<ul style="list-style-type: none"> – It crowdsources auditing tasks to multiple auditors to solve the untrusted TPA issues by using blockchain. – It proposes an unbiased selection algorithm to select TPA from the auditor committee and designs an incentive mechanism to force TPA to act honestly. 	<ul style="list-style-type: none"> – It does not consider data recovery and dynamics. – It does not consider protecting the privacy of data owners. – It fails to tackle possible attacks, such as collusion attacks.
	Wang <i>et al.</i> [125]	2022	<ul style="list-style-type: none"> – It is an extension of [124], which has the same merits as it. They further propose an optimization strategy based on a matrix index to support data dynamics. – It adopts a novel integrity proof generation method by using algebraic signature. 	<ul style="list-style-type: none"> – It has the same limitations as [124], except for data dynamics support.
	Tong <i>et al.</i> [49]	2022	<ul style="list-style-type: none"> – It is an extension of [86], in which caching strategy optimization problems are investigated to store verification tags on edge nodes for communication cost reduction. 	<ul style="list-style-type: none"> – It has the same limitations as [86].
	Liu <i>et al.</i> [127]	2022	<ul style="list-style-type: none"> – The proposed scheme can provide the property of key exposure resistance in auditing. – It provides privacy-preserving property. 	<ul style="list-style-type: none"> – It does not support batch verification, data recovery and dynamics. – TPA may be malicious during EDIV.

new data structure, variable Merkle hash tree, to facilitate audit accuracy by maintaining sampling uniformity. From the security view, EDI-V is able to defend against replay and forge attacks, while it just ensures a probabilistic integrity guarantee, which incurs security risks resulting in undetected corruption. Besides, it does not offer support to data dynamics and recovery. Moreover, the characteristic of the non-support of batch verification further constrains its practicability in large-scale edge systems. To achieve efficiency improvement, they have gone one step further to develop a deterministic EDIV approach named EDI-S [102] (2021) in order to support

batch verification. However, EDI-S still can not fulfill corrupted data recovery or seamlessly extent to inspect dynamic data. Then, Cui *et al.* [120] (2021) exploit a PDP-based EDIV framework named ICL-EDI by using homomorphic tags, aiming to design a low-computation solution. Like the above-described approaches, it does not support data recovery and dynamics, and is easy to be damaged by various attacks.

Similarly, Qiao *et al.* [121] (2021) develop a lightweight auditing scheme, namely EDI-SA, inspired by the shuffle algorithm and the bucket sorting algorithm. EDI-SA involves an improved sampling strategy to randomly choose data blocks to be verified. Based on algebraic signature [137], EDI-SA achieves low computation overhead and supports both batch auditing and provable dynamic update. However, it does not ensure fairness, similar drawbacks marked in other private audit based approaches. Afterwards, Ding *et al.* [122] (2022) present EDI-DA, an integrity batch verification scheme. They also design a new data structure called index-single linked table to support data dynamic operation, which improves update efficiency and the practicability of the approach. On the downside, it can not carry out data recovery and still faces some security problems like forgery attacks.

4.2 Public Audit

In some cases, it is not practically feasible for the data owner/user to remain online all the time for EDIV [138]. Hence, the data owner/user could delegate this responsibility of integrity verification to TPA to liberate itself from this heavy computing task, which derives public audit. From a statistical perspective, public audit is the most popular scheme in academia at present. In public audit, privacy issues, e.g., data leakage and user anonymity, are associated uniquely, although fairness can be achieved naturally.

The first EDIV-related paper was published by Tong *et al.* [86] (2019), in which they propose two integrity checking protocols entitled ICE-basic and ICE-batch based on TPA without privacy violation. ICE-basic and ICE-batch are developed for the cases where data users inspect data integrity on a single edge node and multiple edge nodes, respectively. Even if ICE-batch supports batch verification, the verification efficiency is limited significantly due to that the proposed scheme is a variant of PDP that has been validated as not efficient enough for EDIV. Besides, they assume that TPA is fully trusted, which is hard to ensure in practice. Very recently, the same authors extended this paper in [49] (2022), where they try to design an effective tag cache strategy to reduce verification communication costs. Neither papers consider data dynamic and recovery. Additionally, Liu *et al.* [123] (2020) focus on a more specific integrity verification scenario-enterprise multimedia cached on edge nodes-and design an integrity auditing scheme by using homomorphic authenticator [139] in order to enhance computation efficiency. Meanwhile, they employ one-way linked information tables to achieve data recovery in a highly efficient manner. The advantage of it is that batch verification and data recovery are considered and handled well, and yet they barely investigate associative security, privacy, and data dynamic issues.

Furthermore, Wang *et al.* [124] (2021) exploit a ZSS signature [140] based EDIV scheme named ZSDIVMEC with the TPA engagement, which supports privacy protection and data dynamics. They take full consideration of three usages including a single edge node, multiple edge nodes, and a joint of multiple edge nodes and a central cloud. However, batch verification is neglected, which may limit its efficiency. Furthermore, data recoverability is not discussed so that further work is needed for practicability enhancement. The same research team refines this publication and yields [125] (2022). In the newest paper, they adopt algebraic signature [141] to design a lightweight EDIV framework and simultaneously design an optimized strategy for the support of data dynamics. Because it is an extension of their previous one [124], they have the same advantages and disadvantages, except better supporting data dynamics, making it more practical in reality. Recently, Chen *et al.* [126] (2021) point out that edge environments need a different trust model compared with cloud computing paradigms, as edge storage is more decentralized and thus more vulnerable to various security risks. Consequently, they devise a blockchain-based intelligent crowdsourcing audit scheme named Crowdauditing to improve the credibility of TPAs. It totally changes the verification scheme by using an auditor committee rather than fully relying on a

Table 7. Summary of Recent Advances in EDIV Solutions for Cooperative Audit

Cat.	Ref.	Year	Contributions	Limitations
Cooperative Audit	Alazeb <i>et al.</i> [128]	2019	– It employs rule-based intrusion detection methods to find malicious access.	– It does not include experimental evaluations. – It does not support batch verification, data recovery, fairness, and data dynamics.
	Yue <i>et al.</i> [129]	2020	– It eliminates TPA by using blockchain to increase trust. – It proposes a sampling strategy to reduce verification overhead, especially for the large data replica.	– It has a high communication overhead incurred by blockchain. – It just considers the scenario that involves one data replica with multiple shards.
	John <i>et al.</i> [130]	2020	– It explores several machine learning-based classifiers to check the integrity of electrocardiogram data. – It conducts extensive experiments to show the corruption detection performance produced by different machine learning algorithms.	– It does not support batch verification, data recovery, fairness, and data dynamics. – It regards the EDIV problem as the outlier detection tasks, rather than following the mainstream problem-solving perspective.
	Li <i>et al.</i> [103]	2021	– It does not need TPA involved. – It can repair corrupted data replicas automatically.	– It does not achieve batch verification and data dynamics. – It does not consider possible attacks due to the assumption of no byzantine edge nodes.
	Duan <i>et al.</i> [131]	2022	– Trust can be enhanced due to no TPA engaged.	– It does not take data dynamics and recovery into consideration.
	Li <i>et al.</i> [104]	2022	– It does not need TPA involvement. – It designs an incentives mechanism to motivate edge nodes well behaved. – It tailor-makes a consensus algorithm.	– It offers a probabilistic integrity guarantee by sampling a proportion of data blocks. – It designs specifically for honest edge nodes, rather than from the DO/DU's perspective.

single TPA to achieve integrity inspection. Smart contract technology is used to collaborate with each party ensuring the reliability of audit results. Furthermore, an incentive mechanism is carefully constructed to drive auditors providing honest audit results for rewards maximum. Due to the adoption of blockchain and smart contract, TPA trusted issues can be well resolved, compared with other public audit schemes. However, it pays less attention to verification efficiency improvement, privacy protection, and data recovery and dynamics.

Very recently, Liu *et al.* [127] (2022) design a EDIV scheme based on bilinear pairing [140] and certificateless cryptography [142]. The scheme provides the property of key exposure resistance in storage auditing and supports privacy-preserving. However, the adoption of TPA is not convincing in terms of the reliability of the verification result. Besides, verification efficiency and other additional features like data recovery and dynamics support are not rigorously considered as well.

4.3 Cooperative Audit

As we mentioned before, private audit has fairness issues as it is the data owner/user that verifies integrity without the confirmation of edge nodes. Public audit is able to compensate for this limitation but hard to ensure that TPAs are totally trustworthy from the other participant's perspective, which may lead to potential security

risks. To overcome this drawback, numerous works recently head to collaborative audit, in which edge nodes collaborate with each other to check EDI without TPA or even data owners/users' involvement. In that case, both the verification fairness issue and the TPA trusted issue can be eliminated naturally. We articulate the publications on cooperative audit in the following.

Alazeb *et al.* [128] (2019) focus on healthcare systems to detect malicious transactions by using a rule-based strategy. It is much more like an intrusion detection system, where edge nodes identify malicious behaviors that may corrupt data integrity according to specific corruption detection regulations. However, there are no experimental evaluations to validate their idea, which undermines the credibility of the proposed approach regarding follow-ups. Besides that, intrusion detection-based integrity verification is still a probabilistic method, and thus the accuracy needs to be studied further. Notably, this approach can not ensure fairness, as data owners are unable to participate in the verification process. Moreover, Yue *et al.* [129] (2020) restore blockchain and exploit a decentralized EDI sampling verification scheme in edge-cloud storage scenarios. Merkle tree with random challenging numbers is adopted and analyzed for system performance optimization. Additionally, they develop rational sampling strategies to address the problem of limited resources and high real-time requirements, making verification more effective. It keeps fairness because blockchain, as a third party, inspects integrity proofs for both the data owner and edge nodes. Nevertheless, it does not consider batch verification, data recovery, and dynamics issues.

In addition, John *et al.* [130] (2020) explore several machine learning-based classifiers to check the integrity of electrocardiogram data. The feature vectors are derived from low complexity kurtosis and skewness [143] based signal quality indices. The approach is more like [128], as both of them solve EDIV problems from the corruption detection perspective, rather than depending on interactive verification via *Challenge-Response* mechanisms. The best part of it is that extensive experiments are conducted to evidence which machine learning model is the most suitable one for integrity corruption detection. It seems an ensemble of three neural networks using bagging with appropriate structures exhibits the best performance during testing for all the parameters considered with 99.47% accuracy. From the utility point of view, this work saves lots of experiment simulation burden for researchers who would like to devote to this topic. However, due to the model-centric design, batch verification, fairness, data recovery, and dynamics are not investigated.

One step further, Li *et al.* [103] (2021) propose the CooperEDI scheme to inspect EDI in a distributed manner. CooperEDI employs a distributed consensus mechanism to form a self-management edge caching system. Edge nodes cooperatively ensure the integrity of cached replicas and repair corrupted ones. It rigorously considers data recovery problems but neglects computation efficiency and data dynamics. Although CooperEDI does not involve TPA, fairness is still hard to ensure since edge nodes may collude to generate incorrect verification results and the data owner can be only notified of corruption passively without knowing if the verification results are authentic and effective. Moreover, they fail to study how to secure against potential attacks such as byzantine attacks. Recently, they present EdgeWatch [104] (2022), a collaborative EDIV framework, by leveraging blockchain. EdgeWatch collaborates with edge nodes to complete verifying a data replica cached on a certain edge node, and at the same time, the incentive mechanism is designed to motivate other edge nodes to join together into EDI inspection processes in a fast and honest way. The corresponding consensus algorithm is carefully designed to make edge nodes reach consensus. However, in practice, data owners who expect to check the integrity of outsourced data are always not edge nodes, so we argue that EdgeWatch has limited application scenarios. Very recently, Duan *et al.* [131] (2022) claim that it is impossible to avoid the collusion of edge nodes with malicious intruders. To solve it, they explore a blockchain-based verification protocol based on a distributed virtual machine agent that is an edge data integrity monitoring framework. In this way, trusted verification can be achieved without depending on a TPA. However, it does not support batch verification, fairness, data recovery, and dynamics.

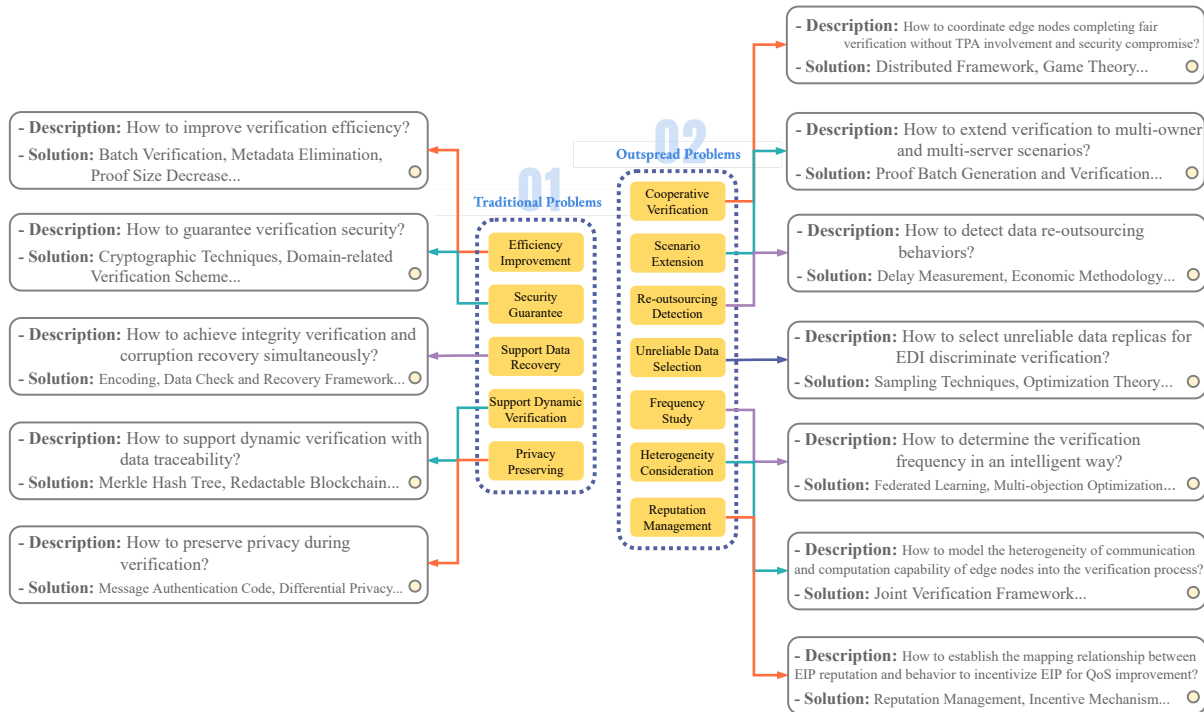


Fig. 9. Future research directions and potential solutions for the edge data integrity verification problem

5 OPEN CHALLENGES AND POTENTIAL SOLUTIONS

So far, we have witnessed mostly the beneficial progress of reviewed approaches that address the data integrity issues existing in edge domains, and albeit this is potential to intrigue researchers to investigate more, we also should raise awareness when it comes to the practicability and flexibility of existing technologies. In this section, we aim to outline and discuss currently known limitations in the literature we have reviewed, while offering outspread challenges that have been paid less or even no attention yet, hoping to motivate future research.

5.1 Traditional Problems

In cloud computing environments, efficiency improvement, security guarantee, data recovery, dynamic verification, and privacy-preserving are most commonly focused on by researchers when designing integrity inspection solutions. Those problems also exist in edge computing scenarios and are required to be further studied from different angles due to the uniqueness of edge environments.

5.1.1 How to improve verification efficiency? Integrity verification efficiency is a fundamental issue which directly determines the practicability of EDIV solutions. Three aspects are specifically involved in terms of efficiency, including computation, storage, and communication complexity. Overall, batch verification is a common choice for reducing computation complexity [48, 86]. The rapid expansion of 5G networks leads to the major performance bottleneck of EDIV solutions shifting from communication to computation. In this context, a more efficient batch verification scheme is required to satisfy stringent computing latency requirements. Regarding storage complexity, as edge nodes always cache additional metadata for future integrity verification, how to inspect

EDI without keeping metadata is a challenging yet promising research direction for storage reduction. One possible solution is to encourage data owners to store original data as well. In this way, both edge nodes and data owners could validate integrity without metadata engaged in the verification process. At last, the communication efficiency of data integrity schemes is involved in three ways: the original data transmission to edge nodes, the data owners/users launching the verification procedure, and integrity proofs sent reverse. Besides, in the case of dynamic data, the communication overhead also includes data updates. A direct implementation of communication efficiency improvement is to reduce the size of integrity proofs, which is worth in-depth study.

5.1.2 How to guarantee verification security? With the emergence of many new technologies integrated with edge, the openness of edge should be an advantage but also become a threat to its users. Data integrity schemes are subject to various attacks, as presented in Table 3, which leads to that some existing EDIV solutions are neither safe nor dependable if the attacks are launched successfully without being detected in a timely manner. Additionally, the *Challenge-Response* mechanism is vulnerable to data leakage attack if the proof generation method is not semantically secured. Numerous cryptographic techniques, such as multiProver zero-knowledge proof [144] and Homomorphic Verifiable Tag [145], have been widely applied in existing works to achieve security goals, while it is still far from satisfactory due to efficiency issues. Since different security assumptions are held in various cases, it is reasonable to design a domain-related verification scheme with comprehensive theoretical security analysis.

5.1.3 How to achieve integrity verification and corruption recovery simultaneously? When data owners detect that their outsourced data has become corrupted, they expect the damaged data to be entirely recovered. Existing integrity check techniques achieving data recovery rely mostly on encoding methods, such as error correcting code [146] and network coding [147], but they are only effective for low damage percentage and require a significant amount of computation overhead. Therefore, it is critical to devise novel EDIV approaches with data recovery support. To tackle it, a collaborative data check and recovery framework could be used. In brief, after identifying corruption, the edge nodes with corrupted data replicas could interact with nearby normal edge nodes to ask for the correct one. In this way, corruption could be recovered with low communication overhead.

5.1.4 How to support dynamic verification with data traceability? The outsourced data is dynamic by nature in edge computing environments. It is subject to regular modification by data owners. Thus, offering support for dynamic operations on outsourced data is also critical for an auditing protocol. Edge nodes must update data strictly according to data owners' requirements to guarantee the correctness and timeliness of data. However, existing methods that support data dynamics, such as Merkle hash tree [148] and index hash table [149], have inevitable drawbacks that can not be ignored. Specifically, Merkle hash tree requires substantial amounts of supplementary validation information to ensure the validity of data updates. Index hash table is only effective for modification, since the insertion and deletion operations disrupt the sequence structure of the original table, adding extra costs. Furthermore, edge nodes only cache the most recent version of the data, while historic versions being deleted. However, in certain cases, data owners/users not only expect edge nodes to deliver the latest data block, but also seek to access historical versions, which necessitates data traceability. Supporting data updates with data traceability is a valuable issue for EDIV in future development trends. An intuitive solution is to use redactable blockchain to trace the historical versions and verification results in the long term.

5.1.5 How to preserve data privacy during verification? Data privacy guarantee has always been a critical prerequisite in SLA for developing edge caching services. A publicly auditable technique should not expose the privacy information to TPA, or TPA should be able to undertake the audit of the owner's data without fear of learning data content. Using message authentication codes (MACs) on the owner's data is one way for ensuring privacy. During an audit, TPA challenges the integrity of randomly selected data blocks and their MACs. The edge node responds with a sequence of data blocks as well as the MACs, and then the integrity

of the data is checked by TPA. This solution, however, has the following disadvantages: (1) a linear sequence of data blocks is acknowledged to TPA, directly violating the privacy-preserving agreement between the data owner and TPA; (2) the communication and computation complexity varies linearly with sampled block size; (3) audit cost can be very high if bandwidth between TPA and edge node is limited; and (4) it only supports static data files. Consequently, existing privacy-preserving EDIV systems are not perfectly feasible in reality. To this end, differential privacy [150] could be explored to handle this problem. If integrity proof is processed with differential private mechanisms, data privacy could be preserved but some noise is injected into it, and thus a novel proof verification approach is required. While with the prevalence of batch verification and a large number of interactions, this side effect can be mitigated because the noise usually complies with the Laplace mechanism where the mean value is equal to zero.

5.2 Outspread Problems

Aside from the concerns discussed in Section 5.1 which exist in both cloud and edge, the following issues are particularly prevalent in edge.

5.2.1 *How to coordinate edge nodes completing fair verification without TPA involvement and security compromise?*

In recent years, the general trend of the development of EDIV is to let edge nodes themselves achieve integrity verification, i.e., cooperative verification, due to the following two reasons: (1) releasing the assumption of trusted TPAs and meanwhile keeping fairness; (2) making most of communication overhead occurring in backhaul networks, instead of backbone networks to greatly reduces communication overhead. To date, there are lots of attempts focusing on this direction, like [129]. Some of them, e.g., [104, 129], try to adopt blockchain to replace TPAs for public audit, however, they are not aware of potential security risks brought by blockchain itself, e.g., outsourcing attacks [92] and byzantine attacks [93]. Besides, others, such as [103], apply traditional distributed algorithms, e.g., Raft [151], Paxos [152], to make edge nodes communicate with each other for EDI inspection tasks under the assumption of no byzantine edge nodes. How to release unrealistic assumptions and simultaneously ensure edge nodes behave honestly during cooperative verification needs to be investigated further. This might be tackled by game theory which targets on logical decision-making to guarantee honest behavioral relations.

5.2.2 *How to extend verification to multi-owner and multi-server scenarios?* Existing EDIV solutions only consider the case of EC domains with one data owner and multiple edge nodes. However, as we mentioned in Section 3, these solutions can not be directly extended to support multiple data owners with data integrity assurance due to verification efficiency and scenario heterogeneity issues. *To date, research on the EDIV problem with multi-owner and multi-server has not been carried out yet.* One potential solution is to tailor-make an efficient proof batch generation method for edge nodes to improve proof generation efficiency and accordingly develop a proof batch verification approach for proof verification efficiency enhancement. With careful design, the approach could well fit in such complicated edge environments.

5.2.3 *How to detect data re-outsourcing behaviors?* SLAs restrict the EIP's ability to preserve data in a certain geographic region at the granularity level of city, state, time zone, or political boundaries. Nevertheless, dishonest EIPs may relocate data owners' data to a third-party data centre, which usually has less computation and communication capacities, in breach of SLAs for saving storage space or enhancing profit. Undoubtedly, such malicious data re-outsourcing acts may conflict with the preferences of data owners and jeopardise their legitimate rights and interests, and worse than that, it might indirectly make data available to other governments, who can review it via search warrants or any other legal means, which invades sensitive data privacy, especially defense data. The common *Challenge-Response* mechanism can not provide proof that data cached in untrusted edge nodes is not re-outsourced to other economical ones, especially in collusion network architectures. *There is no*

relevant study on re-outsourcing detection in edge storage so far. An intuitive solution is to simply measure the network delay of different distances. Clearly, it could not prevent untrusted edge nodes from re-outsourcing data to some other nearby yet cost-effective edge nodes. In this case, fast detection of intentional dishonesty or breach of re-outsourcing is critical for data owners/users. It may be addressed by economic methodologies, such as incomplete information dynamic game models.

5.2.4 How to select unreliable data replicas for EDI discriminate verification? Existing EDIV solutions indiscriminately inspect all data replicas for data owners/users in each verification round [48, 86, 102, 123, 153]. In fact, it is not likely for the majority of data replicas to be corrupted by various faults or cyberattacks simultaneously [103], and thus data owners/users are able to merely verify a part of unreliable data replicas in each round due to efficiency and cost-effectiveness concerns [154, 155]. Indeed, some researchers [156] have exploited a sampling-based method that supports inspecting partial data replicas by adopting a straightforward sampling technique, i.e., proportionally stratified sample [157], in cloud computing environments. Obviously, this approach is neither reasonable nor tenable in real-world scenarios. To handle this issue, it is possible to adopt a dynamic selection process based on the optimization theory. The problem could be modeled as a constrained optimization problem by jointly considering the inherent property of data replicas and the performance of cache services (e.g., quality of service (QoS) [158]), and the (approximate) optimal solution could be derived by various optimization algorithms, e.g., simplex method [159], lagrangian multiplier method [160], and genetic algorithm [161].

5.2.5 How to determine the verification frequency in an intelligent way? Although substantial work has been devoted to the EDIV problem, they depend almost exclusively on the round-based *Challenge-Response* mechanism that is invoked periodically at time intervals of a specified duration. In that case, verification frequency is one of the most fundamental problems for approach design and directly affects verification accuracy. *Despite the fact that extensive research is underway on the improvement of EDIV efficiency, none of them have rigorously considered the unlimited verification frequency property*, as shown in Table 4. They all focus on designing EDIV approaches from the one-round perspective. Nevertheless, studying verification frequency is significantly essential for approach practicability. More specifically, if EDI is inspected frequently through the *Challenge-Response* mechanism, the computation and communication cost on both sides becomes extremely high. Instead, if setting a low frequency, corruption behaviors may not be found and corrected promptly, which may cause huge losses to data owners/users. Therefore, it is reasonable to work out an (approximate) optimal trade-off among verification frequency, verification accuracy, and resource consumption, regarding EDIV. The direct solution is to let edge nodes collectively train a frequency selection model by using federated learning, if there is enough training data with a large number of verification-related features e.g., inspection results and times. In practice, however, it is usually hard to obtain training datasets, making this direct implementation inapplicable. In this case, multi-objective optimization algorithms, e.g., non-dominated sorting genetic algorithm II [162], could be used to derive such a trade-off.

5.2.6 How to model the heterogeneity of communication and computation capability of edge nodes into the verification process? Although existing EDIV solutions provide high detection efficiency with relatively low overhead, their applicability is very limited as they totally rely on an implicit assumption, that is the edge nodes have the same computation and communication capability throughout the inspection execution. However, we have observed that not all the processes of edge nodes experience the same level of resource availability at exactly the same time in real-world cases. Thus, the edge node having adequate resources can adopt a complex yet accurate EDIV method, i.e., interaction verification through the conventional *Challenge-Response* mechanism, but others may be incapable of employing it at the same speed. If the solution fully depends on this interaction for EDI assurance, it is hard to ensure the feasibility due to the decentralized distribution of edge nodes and heterogeneity of resource requirements. *No research has attempted to release this unrealistic assumption when*

designing EDIV solutions until now. To this end, we plan to design a joint verification framework to handle it. Specifically, data replicas can be filtered first by edge nodes in a flexible way according to their available resources. By doing so, honest edge nodes would report identified corruption actively. However, it is not adequate to merely let edge nodes do inspection tasks due to the existence of dishonest edge nodes. A joint interaction verification at a relatively low frequency is needed to detect corruption that is not trustily reported by malicious edge nodes, which unlocks the better performance of EDIV under a more practical assumption.

5.2.7 How to establish the mapping relationship between EIP reputation and behavior to incentivize EIP for QoS improvement? We have witnessed the emergence of a variety of EIPs over the last few years. AWS, Microsoft, Google, and IBM are a few examples of companies that apply the combined strength of edge nodes to provide data caching services. Collaboration among edge nodes has enabled more efficient use of network capacity, but it may also present new system risks. Cryptographic techniques, often known as hard security measures, offer only partial solutions by ensuring data integrity. An edge node can be a valid member of a collaborative group and hence pass the standard cryptographic security tests. It might, however, purposefully report misleading measurement findings in order to acquire extra value at the expense of others. Soft security risks are the name given to this type of danger. In this context, trust and reputation management systems have the potential to combat such soft security concerns effectively, since there is a strong positive correlation between EIP reputation and cached data reliability [70], i.e., prestigious EIPs are more likely to keep cached data replicas intact for securing competitive advantage. Technically, each EIP could be associated with a reputation value, which is updated based on the reliability of his cached data and further serves as one of the pathways to achieve EDI discriminate verification. Apart from designing an effective and satisfactory EIP reputation management system, developing an incentive mechanism to motivate EIPs behaving honestly during EDIV is also a pressing problem. We plan to develop a tailor-made incentive mechanism. If we adopt the credit as an example, then the credit is distributed to every EIPs in proportion to their honest behaviors. For the EIP that behaves better in the process of EDIV, it could gain more credits and accordingly has a higher possibility to be selected by data owners for data caching.

6 SUMMARY

Edge computing is an emerging research field that has inspired intense interest in edge security, especially in EDIV investigation. Given the scarcity of a detailed review on the EDIV-related topic in the open literature, this paper provided a thorough survey of various EDIV methodologies. We began with discussing the significance and uniqueness as well as the typical system models with corresponding key processes for the study of data integrity assurance in edge. Then, the comprehensive approach evaluation criteria were developed, followed by the discussion and comparison of recently advanced EDIV designs. Finally, we highlighted alarming challenges and presented future directions. The EDIV problem is still in its infancy and will quickly mature in the future years for providing generic and versatile solutions. We expect that this survey will generate great attention in this emerging area and motivate more research efforts toward the satisfactory investigation of data integrity verification in edge domains.

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