Data Management for Future Wireless Networks: Architecture, Privacy Preservation, and Regulation

Xuemin (Sherman) Shen, Cheng Huang, Dongxiao Liu, Liang Xue, Weihua Zhuang, Rob Sun, and Bidi Ying

Abstract

Next-generation wireless networks (NGWN) aim to support diversified smart applications that require frequent data exchanges and collaborative data processing among multiple stakeholders. Data management (DM), including data collection, storage, sharing, and computation, plays an essential role in empowering NGWN. However, DM for NGWN faces two significant challenges: stakeholders' data cannot be easily managed across different trust domains under a distributed network architecture; and privacy preservation requirements of personal data become more rigorous under new privacy regulations. To explore possible solutions to address the challenges, we first investigate the state-of-the-art architecture designs for DM and emphasize advantages of a blockchain-based DM architecture. Then we summarize existing privacy-preserving techniques in terms of advantages and challenges when being applied to DM. In addition, we review recent privacy regulations with their impacts on DM and discuss the existing solutions with privacy regulation compliance based on blockchain. Finally, we identify further research directions for achieving DM with privacy preservation.

Introduction

With the rapid advancement of wireless communication networks, smart devices can be connected through reliable and seamless wireless connections. It is revolutionizing our daily lives by providing various smart applications, such as smart transportation systems and e-healthcare systems [1]. As wireless networks continue to evolve, the next-generation wireless networks (NGWN) will further unleash the power of connectivity with a virtualized network architecture and the assistance of artificial intelligence (AI) [2]. To achieve the full potential of NGWN, a key enabler is the wealth of user data. First, massive connected smart devices can lead to the generation of user data at an unprecedented rate. Second, the evolving computing and storage infrastructure at the network edges makes the data collection and pre-processing more convenient. Third, AI-based data processing poses high requirements on the volume, dimension, and quality of collected user data for accurate training and evaluation of AI models. Therefore, data management (DM) will play a critical role in NGWN in terms of data collection, data storage, data sharing, and data computation [3].

DM faces significant technical challenges in NGWN [4]. First, multiple data stakeholders from different industrial sectors, such as mobile operators, technology vendors, data centers, and application providers, need to collaboratively manage the life cycle of user data. For instance, user data can be generated at smart home appliances provided by technology vendors, transmitted through NGWN, stored and processed at data centers, and finally utilized by application providers for marketing analysis and product development. The complex DM process requires frequent data exchanges and distributed data processing among data stakeholders with dynamic degrees of mutual trust. As a result, a reliable and trustworthy architecture for DM is required. Second, data privacy regulations are taking effect and significantly reshaping the privacy landscape of NGWN. In particular, the European General Data Protection Regulation (GDPR) [5] defines legal requirements on DM of personal user data from different aspects:

- It grants users a wide range of legal rights to obtain information and control operations on their personal data.
- It requires "restricted processing" over personal data, where a set of privacy-preserving techniques can be adopted to enhance user identity privacy and data confidentiality.
- It requires privacy compliance for data life cycle events to enforce obligations of data stakeholders [6].

Any data stakeholder failing to comply with the GDPR requirements on DM may face severe financial and legal consequences. Without proper solutions to DM with privacy preservation under the GDPR, there will be significant data barriers for data stakeholders in NGWN.

This survey article aims at providing a comprehensive understanding of DM in NGWN under privacy regulations. In the following section, we discuss architecture specifications for DM by investigating various existing solutions based on cloud computing, fog computing, and blockchain. In comparison, we emphasize the advantages of blockchain-based DM architectures. Following that, we summarize a wide range of traditional privacy-preserving techniques and discuss the use

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Xuemin Shen, Cheng Huang, Dongxiao Liu (corresponding author), Liang Xue, and Weihua Zhuang are with the University of Waterloo; Rob Sun and Bidi Ying are with Huawei Technologies Canada.

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cases and challenges when applying them to DM. Then we present state-of-the-art DM solutions under the GDPR. We present research challenges on achieving DM in NGWN under the GDPR and discuss potential solutions. Finally, we conclude this study and discuss further research directions.

Data Management Architecture: From Centralization to Decentralization

In this section, the existing architectures for DM are discussed in terms of centralized and decentralized architectures.

Centralized Architecture: Fog to Cloud

One of the most popular DM architectures is based on cloud computing [7], where applications are deployed on virtual machines in cloud servers to store and process their data in centralized databases. This architecture has brought many advantages, such as cost-effective storage and efficient data analytics, since cloud servers have massive computational and communication resources.

However, the cloud-based architecture may not be suitable for the complicated DM in NGWN, since a centralized solution may suffer from various attacks, such as the single point of failure and remote hijacking attacks, which can cause unexpected data leakage. At the same time, the concept of fog computing [8] is introduced and integrated with a cloud-based architecture to meet the DM requirements of location awareness, low latency, and real-time data processing. A fog-to-cloud DM architecture [8] is illustrated in Fig. 1. In the architecture, data are collected from distributed sources including vehicles, sensors, and computers to be processed and temporarily stored in the fog layer. After being pre-processed, the data are uploaded to a cloud platform for data sharing and analysis. Compared to cloud-based architectures, this fog-to-cloud DM architecture is more hierarchical and provides more flexibility. At the same time, data privacy policies specified by the data owners can be enforced in fog computing to achieve fine-grained data access control. However, as fog nodes are usually restricted in storage and processing capabilities and the provided functionality can be highly vendor-dependent, they may pose limitations on DM architecture design.

The centralized architecture is widely considered in many research works on DM under a common assumption that the cloud and fog nodes are honest in data storage and processing. Nevertheless, in reality, they may be subject to potential security breaches and may misuse user data for self-interest without user awareness. Under this circumstance, not only may sensitive user data be exposed, but also the functionalities of the deployed services are affected. Hence, to improve the security and robustness of DM, decentralized architectures have been proposed in recent years.

Decentralized Architecture: Blockchain

In comparison with the centralized DM architectures, a decentralized architecture can mitigate the reliance of a single trusted entity and is a preferred approach to DM. In particular, blockchain is a promising distributed architecture that mainly

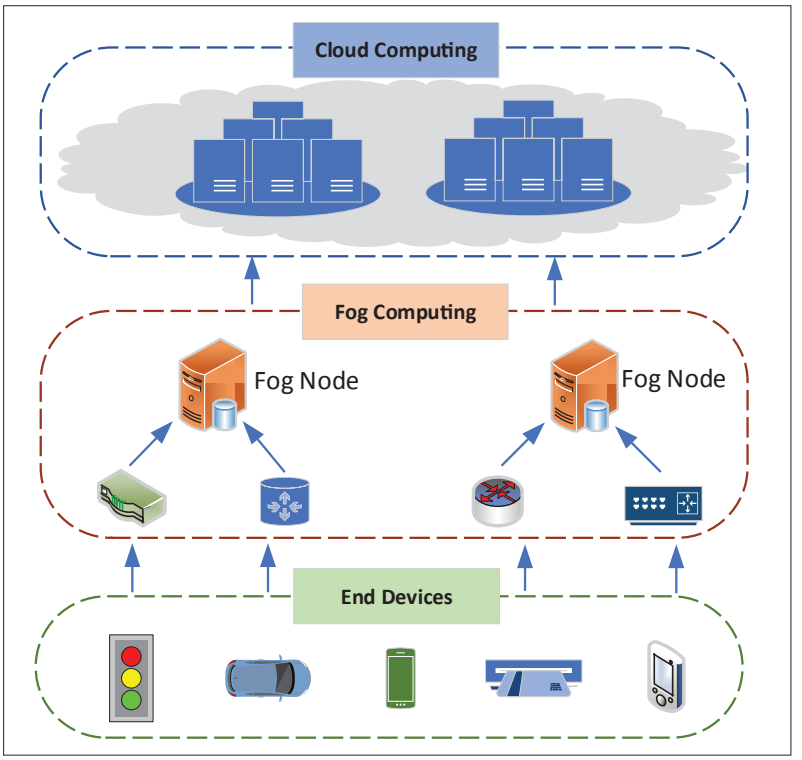

FIGURE 1. Fog-to-cloud data management architecture.

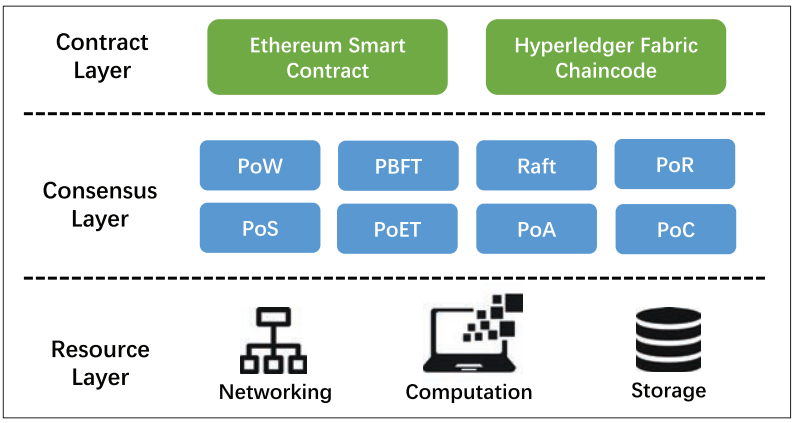

FIGURE 2. Blockchain layers and components.

consists of three layers: resource layer, consensus layer, and contract layer, as shown in Fig. 2. The resource layer defines three basic components in the blockchain. Networking components can facilitate peer-to-peer (P2P) communication among distributed nodes. Computation components allow the distributed nodes to perform necessary computation operations, such as data hash and signature. Storage components are vital for storing transaction data of the blockchain. The consensus layer includes different consensus protocols, such as proof of work (PoW) and proof of stake (PoS), to provide different security and scalability guarantees. The layer relies on the networking components for distributed nodes to communicate and maintain a consistent view of the blockchain. Many cryptographic computations can also be implemented by consensus protocols with the computation components. The consensus layer, smart contracts, and chaincodes [9] are deployed to support various functions and applications for blockchain users.

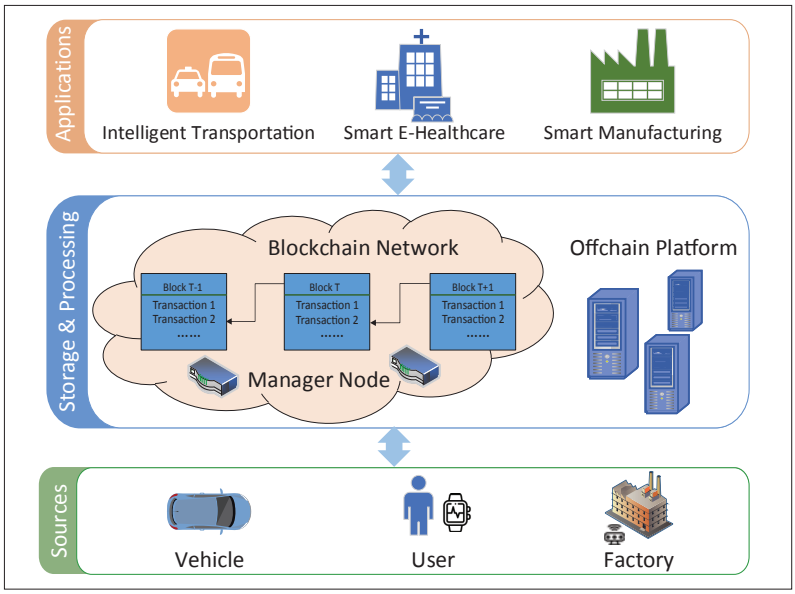

FIGURE 3. An illustration of a Blockchain-based data management architecture.

The blockchain architecture has many desired features including distribution, transparency, immutability, traceability, programmability, and automated verification. These features bring clear advantages for DM in NGWN.

Distribution and Transparency: When applying the blockchain architecture to DM, the conventional single point of trust can be avoided. More data stakeholders in NGWN are able to participate in data collection, storage, and processing through different consensus protocols in the consensus layer. In this way, DM becomes transparent across these stakeholders, and decentralized trust can be built among them. Honest stakeholders can be viewed as honest custodians to maintain the validity of DM, provided that the deployed consensus protocols are secure under reasonable assumptions.

Immutability and Traceability: By utilizing cryptographic techniques, such as Merkle hash tree, blockchain storage is immutable. It guarantees that life cycle events, including reading, writing, modification, and authorization, on the blockchain cannot be maliciously modified. Moreover, with digital signatures on life cycle events, data operations can be traced to their sources. Data provenance and digital forensics can also be adopted to detect malicious behavior and privacy breaches.

Programmability and Automation: The blockchain has two additional features: programmability and automation from the contract layer. Different DM procedures can be coded into executable programs and can be run in a decentralized manner on the blockchain. If DM procedures involve many data stakeholders, only one data stakeholder is required to invoke the deployed program when conditions or terms are met.

In the following, we briefly summarize existing literature on blockchain-based DM. A blockchain-based DM architecture is illustrated in Fig. 3, which consists of three components: data sources, data storage and processing, and applications. Data sources include a large number of end devices, including smart vehicles and sensors, with constrained storage and computing capabilities. Normally, they cannot afford the computational overhead of running consensus protocols and the increasing data storage overhead of maintaining the blockchain ledger. As a result, end devices are not directly connected to the blockchain network. Instead, they first connect to manager nodes [10], which are responsible for getting updates of transactions and sending/retrieving necessary data to/from end devices. To increase the throughput and reduce the transaction processing delay, the manager nodes can be further classified according to their roles in different functions, such as proposing, validation, and confirmation [11]. Note that the blockchain network can be partitioned into multiple network channels (ledgers) based on intended transactions and functions, such as user enrollment and data analysis [12]. Each channel is maintained by designated stakeholders (consortium) who can enforce fine-grained policies through deploying properly designed smart contracts. That is, the consortium blockchain can strike a balance between network robustness and efficiency for DM [13].

To mitigate the storage bottleneck of the blockchain, an off-chain data storage system is often integrated with the blockchain, where large-scale data are stored off blockchain, and only pivotal data are recorded on blockchain to verify correct executions of off-chain operations [14]. The off-chain storage system does not participate in consensus protocols in the blockchain, and can be viewed as an optional system to assist the blockchain in terms of data storage. In reality, off-chain storage systems may be deployed by different entities, such as clouds and fog nodes. Although off-chain storage enables users to revoke their consents on data usage and delete data, the on-chain data modification and deletion are still challenging [15] due to the immutability property of the blockchain.

In summary, blockchain is a promising architecture for DM in NGWN to achieve a wide range of security functionalities, including identity authentication, access control, provenance tracking, and record logging [16]. However, due to the transparency of blockchain, it is not straightforward to achieve blockchain-based privacy-preserving DM. Note that many important privacy protection properties, such as anonymity and confidentiality, are not considered in the three layers of the blockchain. The privacy issues include how to protect anonymous nodes in the blockchain network, how to hide users' identities among transactions, how to protect data confidentiality of on-chain data, and so on. To bridge this gap, we next discuss the state-of-the-art privacy-preserving techniques and DM solutions with privacy regulation compliance.

Privacy-Preserving Techniques for Data Management

This section focuses on four major stages of DM: data collection, data storage, data sharing, and data computation. We summarize existing privacy-preserving techniques throughout these stages, as shown in Table 1. These privacy-preserving techniques include cryptographic techniques and non-cryptographic techniques, which can

be adopted by users, network operators, and service providers to protect data privacy from not only external adversaries but also internal attackers.

Data Collection

Data collection can have two major components: data uploading at the user side and data transmission in NGWN.

Data Uploading: Anonymization is a widely recognized privacy-preserving method, which enables users to anonymize their identity and data during data uploading. Two main techniques can be applied to achieve anonymization: pseudonymization [17] and group/ring signature [18]. Pseudonymization-based anonymization methods, although more efficient in terms of computational cost, achieve weaker anonymity than group/ring-signature-based anonymization methods. An improper pseudonym change strategy has a great chance to cause serious privacy leakage. A straightforward way is to use a fresh one-time pseudonym per uploading to overcome the drawback at the huge cost of data storage and communication at the user side, since users need to update their pseudonyms frequently. In contrast, group/ring-signature-based anonymization methods [38] provide more robust privacy protection with lower storage and communication overhead at the cost of computation efficiency. Specifically, heavy cryptographic operations are performed at the user side, and each revocation of an existing anonymous identity credential belonging to one user can affect other users. As there can be a large number of end devices with limited capabilities in DM, it is necessary to have an anonymization solution that strikes a balance between privacy protection and efficiency. Different from anonymization, local data obfuscation is a lightweight non-cryptographic privacy-preserving approach for users to mask their data before uploading. A typical technique for local data obfuscation is local differential privacy [20], which does not rely on any trusted party and allows users to encode and perturb their data using Laplacian or Gaussian noise before data submission. Many variants of the local differential privacy, such as geo-indistinguishability [21], have also been proposed with different focuses. Additionally, taint analysis [22] is another non-cryptographic method that can assist users in detecting privacy leakage at the system level. By tracking the information flow, sensitive user inputs can be identified based on static and dynamic analysis. AI-based models have been applied for the taint analysis to automatically discover the information flow and predict potential privacy leakage. A challenge of this technique is to configure particular classifiers for identification accuracy.

Data Transmission: Encryption is a general cryptographic approach to protect data content privacy during data transmission. Generally, public key encryption techniques are utilized by two parties for negotiating a short-term symmetric key, and they can then use symmetric key encryption techniques with the negotiated key for private communications. For data transmission in DM, it is a challenging task to effectively manage multiple keys that belong to different devices, owners, and groups [23]. A centralized solution based on a traditional key server may suffer from many vulnerabilities, such as a single point of failure. Therefore, it is desirable to have a hierarchical and decentralized key management mechanism. From another perspective, privacy-preserving communication techniques such as mix-networks and onion routing offer routing path with privacy for users [24]. By shuffling or hiding the routing paths, adversaries cannot distinguish networking packet sources and destinations, as long as one of the routing nodes is not compromised. However, real-world implementations in NGWN may face many difficulties since the anonymous routing techniques can introduce more computation and communication overheads.

Stages	Functions	Techniques
Data collection	Data uploading [17–22]	Pseudonymization; group/ring signature; local differential privacy; AI-assisted taint analysis
	Data transmission [23, 24]	Public/symmetric key encryption; mix-networks; onion routing
Data storage	Data retrieval [25, 26]	Private information retrieval; oblivious RAM; searchable encryption
	Data auditing [27, 28]	Homomorphic authenticator
Data sharing	Data publishing [29–31]	Anonymity set; differential privacy
	Data access control [32, 33]	Symmetric key encryption; proxy re-encryption; attribute-based encryption
Data computation	Outsourced data computation [34]	Homomorphic encryption
	Collaborative data computation [35–37]	Federated learning; trusted execution environment; secure multi-party computation

TABLE 1. Summary of privacy-preserving techniques for data management.

Data Storage

We focus on two major research issues in data storage: data retrieval and data auditing.

Data Retrieval: To conceal the access pattern of personal data, privacy-preserving techniques such as private information retrieval and oblivious RAM have been proposed [25]. These techniques utilize oblivious transfer and shuffle techniques, such that users can retrieve an item from a database without revealing the item. When applying the above techniques to data storage in DM, the main goal is to reduce the computational complexity and communication rounds among data stakeholders. Moreover, privacy-preserving techniques such as searchable encryption (SE) [26] have been proposed to protect the search content and search patterns. By combining these techniques, stakeholders can outsource and store data into a remote database, and retrieve data in a privacy-preserving manner. That is, the data content is retrieved without leaking search keywords or indexes to the remote database. For various data types in DM, a versatile data indexing mechanism with adaptable privacy protections is needed.

Data Auditing: The most common method of achieving privacy-preserving data auditing is provable data possession (PDP) with homomorphic cryptographic authenticators [27]. Based on this technique, a third-party auditor can help users

Data computation involves two main areas: outsourced data computation and collaborative data computation. The former focuses on offloading heavy computational tasks to powerful servers without leaking a task requester's data inputs. The latter deals with cooperative computation tasks with multiple participants without exposing each participant's data input.

verify the integrity of their outsourced data in the remote database by checking homomorphic signatures generated from the data without knowing the data content. Even if the auditor is not always trustworthy, the property of public verification can still be guaranteed [28]. Nevertheless, when data auditing requirements become complicated in DM, it is more difficult to achieve desirable privacy guarantees for user data. A practical and lightweight data auditing scheme for DM should achieve privacy preservation, support dynamic data updating, enable batch auditing, and achieve auditing for multiple replicas.

Data Sharing

Data sharing mainly involves two procedures: data publishing and data access control.

Data Publishing: Data masking is a lightweight non-cryptographic method that can achieve data publishing with privacy preservation to some extent. Different principles have been proposed to achieve data masking, including *k*-anonymity, *l*-diversity, and *t*-closeness. The basic idea of these techniques is to conceal personal identifiable information (PII) and generate a large equivalence class to reduce the risks of privacy exposure [29]. Differential privacy can be introduced to resolve the issue in data publishing to generate high-utility synthetic data, which is suitable for high-dimension data without sacrificing the cost. [30, 31]. The research challenges when applying these techniques to DM is how to build a data generative model that fully complies with the privacy requirements, since different datasets may have different privacy and utility requirements,

Data Access Control (DAC): File-based DAC and policy-based DAC are two kinds of DAC mechanisms. To achieve file-based DAC, privacy-preserving techniques such as symmetric key encryption and proxy re-encryption can be applied [32]. Based on symmetric key encryption, each file is encrypted with a unique symmetric key. If a user is authorized to access the file, the user will obtain a shared symmetric key from the data owner. Since this technique is key-based, when the number of files increases, the key distribution cost also increases. To reduce the cost, proxy re-encryption has been proposed, which enables a user to encrypt files using a public key before uploading them to a remote data sharing center. A proxy re-encryption key can be generated based on a user's private key and a receiver's public key to transform the ciphertext such that the receiver can decrypt it. Policy-based DAC provides a more flexible data sharing approach compared to file-based DAC. An example of policy-based DAC is attribute-based encryption (ABE), which allows a user to encrypt their data following specific policies. By doing so, only receivers who satisfy the policies can decrypt the ciphertext to recover the shared data [33]. However, the revocation of attribute-based credentials becomes a challenging task as there are a large number of participants in NGWN.

Data Computation

Data computation involves two main areas: outsourced data computation and collaborative data computation. The former focuses on offloading heavy computational tasks to powerful servers without leaking a task requester's data input. The latter deals with cooperative computation tasks with multiple participants without exposing each participant's data input.

Outsourced Data Computation: Homomorphic encryption is a traditional cryptographic technique for achieving privacy preservation in outsourced data computation [34]. The data are encrypted before being outsourced to untrusted servers that perform computations directly on the ciphertext. This approach has two widely accepted designs: partially homomorphic encryption (PHE) and fully homomorphic encryption (FHE). PHE supports specified computations and is more efficient than FHE, while FHE can support arbitrary computations at the cost of time-consuming bootstrapping.

Collaborative Data Computation: We introduce three main techniques as follows: federated learning, trusted execution environment (TEE), and secure multi-party computation (SMC). In federated learning, participants can contribute their training parameters rather than their data with personally identifiable information (PII) for cooperative data computation, which is especially suitable for collaborative machine learning on resource-limited mobile devices [35]. TEE implements algorithms with sensitive data input in a secure enclave such that external attackers cannot access the enclave to break the data privacy [36]. It requires a trusted entity to attest to the code integrity before loading the code to the enclave. SMC is built on the oblivious transfer and garble circuit [37], where several parties can compute arbitrary functions without exposing individual input. However, SMC may incur a high communication overhead. For resource-restrained devices in NGWN, it is desired to utilize the SMC for collaborative data computations while ensuring low communication and computation overheads.

Existing privacy-preserving techniques have a wide range of functionalities for DM. At the same time, there are emerging challenges to utilize the techniques for DM in NGWN, as discussed later.

Data Management under Privacy Regulation

In this section, we discuss the recent privacy regulation (i.e., GDPR), its impacts on DM in NGWN, and existing literature on blockchain-based DM under GDPR.

Privacy Regulation: General Requirements and Impacts

GDPR defines legal requirements for data processing related to any "identifiable natural person" [5]. GDPR grants individual users two main categories of rights over their personal data:

- The right to be informed: Users can require information about the purpose of data processing, the period of data storage, and the existence of data exchange.

	System model	Trust assumption	GDPR compliance	Implementation
[40]	Cloud	N/A	Consent validation	N/A
[41]	Cloud	Honest-but-curious RS and malicious SP	Right of access/restricted processing Right to be informed/forgotten	Hyperledger Fabric
[42]	Smart city	Trusted membership service	Consent-based data processing Right to be informed/forgotten	Hyperledger Fabric
[6]	Cloud	Trusted log generator	Compliance monitoring	Ethereum

TABLE 2. Summary of blockchain-based DM under GDPR.

- The right to control: At any point of the data life cycle, users can access their data, restrict/object to any data processing, and require that delete their data be deleted.

Therefore, explicit terms about user data management must be specified and user consent must be obtained before any data operation is performed.

Since GDPR took effect in 2018, many application providers have been supplying consent notices before collecting user data. For DM in NGWN, as data exchanges among different data stakeholders are strictly regulated, traditional business models relying on collaboratively discovering knowledge from user data are affected.

GDPR-Compliant Data Management

According to Article 26 of GDPR, DM in NGWN involving multiple controllers (data stakeholders) should be conducted in a collaborative and transparent manner. As data stakeholders in NGWN usually come from different trust domains, blockchain can offer a promising solution for building a DM platform under GDPR [3, 39]. First, the blockchain can help data stakeholders decide data usage agreements to provide users with trustworthy access of data processing information. Second, smart contract techniques enable data stakeholders to securely update the data usage status to grant users applicable control of their data. Third, the storage immutability of blockchain ensures reliable logs of critical data life cycle events to monitor privacy breaches and pursue joint accountability on misbehaving data stakeholders.

Privacy-preserving techniques can be applied in blockchain-based DM. First, anonymous identity management techniques can enhance user identity privacy in the data uploading phase, while traditional data encryption techniques can help ensure data confidentiality during transmission. Second, secure data retrieving and auditing techniques can achieve efficient on-chain data search and integrity check. Third, various access control techniques can be adopted for consent-based data sharing on the blockchain. Finally, secure data computation techniques can help data stakeholders to collaboratively discover data knowledge without exposing user data privacy.

A summary of state-of-the-art works on blockchain-based GDPR-compliant solutions is given in Table 2 in terms of system model, trust assumption, GDPR compliance, and implementation. The early research efforts mainly focused on adopting the blockchain as an add-on component to regulate existing cloud-based DM platforms [40, 41]. In a conceptual framework [40], users can manage the storage and trading of their data on application providers (e.g., cloud servers) with consent-based access control via smart contract techniques. Subsequently, the roles of application providers can be further divided into a service provider (SP) for data collection and a resource server (RS) for data storage [41]. Integrated with data encryption and identity authentication techniques, fine-grained data access control can be achieved. In addition to consent-based data access control, a blockchain platform can be utilized to record data life cycle events performed by the cloud [6]. By designing a mechanism to translate the GDPR terms to smart contracts, logged data life cycle events on the cloud can be automatically checked for GDPR compliance. It is also promising to utilize blockchain and construct a DM platform [42] for a wide range of data sharing applications in the smart city in terms of health data, smart car data, smart meter data, surveillance data, and financial transactions. Data sharing domains can be modeled as "organizations" in the Hyperledger Fabric, where business processes are developed as "chaincode" and a certificate authority (CA) is implemented for identity management.

Research Challenges and Potential Solutions

As blockchain can serve as a promising architecture for DM in NGWN, there are many interesting ideas in the existing literature for blockchain-based DM with privacy-preserving designs. However, many research challenges need to be addressed for blockchain-based DM under GDPR.

Versatile Blockchain Architecture: Trust degrees among stakeholders and regulation requirements for different use cases in NGWN may change dynamically. A versatile blockchain architecture that can be tailored for different use cases is required, based on flexible consensus protocols, cross-chain operations, distributed membership management, and data provenance. Current consensus protocols cannot easily balance security guarantees with blockchain scalability, considering the large number of resource-limited devices in NGWN. Therefore, a new switching and scaling mechanism should be established to improve consensus protocols in an adaptable way. Moreover, cross-chain operations are necessary for DM since many industrial applications require functions like data sharing through transactions. Cryptographic techniques and non-cryptographic techniques can be adopted to provide interoperability between different blockchains. In addition, distributed membership management and data provenance through cryptographic accumulator and TEE should be considered to improve the security of blockchain, especially for the consortium blockchain.

As blockchain can serve as a promising architecture for DM in NGWN, there are many interesting ideas in the existing literature for blockchain-based DM with privacy-preserving designs. However, many research challenges need to be addressed for blockchain-based DM under GDPR.

Case-Driven Privacy Protection: Privacy protection is required for every stage of DM in NGWN. Many solutions have been proposed using different techniques with various properties. When applying them to specific use cases in NGWN, it is challenging to integrate them into a unified platform under the same trust assumptions. Thus, a hybrid solution for privacy-preserving DM is essential, where a trust model should be clearly defined according to various entities' roles and attributes. Also, suitable privacy-preserving techniques should be chosen and deployed as modules to address particular privacy requirements such that configurable privacy protection can be achieved to resist different kinds of attacks.

On/Off Chain Computation Model: On-chain computation and storage resources are expensive since every blockchain node needs to store all of the blockchain storage and update blockchain state when new transactions are added. This can result in huge on-chain overhead, especially when a consensus protocol with a high security level is implemented. Hence, it is critical to design an on/off chain computation model, where data operations are performed off-chain and verified on-chain efficiently [43]. Besides using hash functions for data integrity checking, it is desired to have more functional on/off-chain models that support complex computations.

On/Off-Chain Privacy Model: The on-chain data access is open to the public in a permissionless blockchain or restricted to specific nodes in a permissioned blockchain. As a result, for each data use case in NGWN, it is essential to have an on/off-chain privacy model that determines what specific data operations should be revealed to the public or individuals. For example, in a data sharing case, data providers and consumers should have access to the shared data in an off-chain manner. The blockchain only knows whether the data sharing follows the GDPR requirements [41]. Moreover, the trust levels of blockchain participants and data sensitivity can change dynamically. Therefore, it is essential to tailor the designs of privacy-preserving techniques for DM in NGWN with delegatable and fine-grained operation verifications, time-embedded cryptography primitives, and updatable and verifiable secret sharing.

Trusted Blockchain Input: It is usually required to have a trusted component in the blockchain-based DM, such as a trusted off-chain storage manager, to correctly upload data life cycle events to the blockchain storage. For DM in NGWN, weaker trust assumptions are more practical because data stakeholders may not always honestly interact with the blockchain. In this case, verifiable computation techniques, such as TEE and succinct non-interactive argument (SNARG) [14], can be utilized to ensure trusted blockchain input. In the meantime, data provenance based on blockchain storage can be used to analyze causal relationships between data life cycle events to detect dishonest blockchain input.

Conclusion and Future Directions

In this article, we have investigated DM for NGWN. From the perspectives of architecture requirements, privacy-preserving techniques, and privacy regulation compliance, we have conducted a comprehensive survey on the existing DM solutions and highlighted the research challenges.

For future research, more efforts should be directed to the designs, implementations, and evaluations of blockchain-based DM with three essential requirements: First, the blockchain-based DM should have a flexible architecture to satisfy various security and scalability requirements in NGWN. Second, the blockchain-based DM should support modular designs from privacy-preserving techniques to adapt to privacy regulation requirements under different use cases. Third, on/off-chain privacy and computation models for DM should be developed to strike a balance between privacy protection levels and processing efficiency.

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Verifiable computation techniques, such as TEE and succinct non-interactive argument, can be utilized to ensure trusted blockchain input. In the meantime, data provenance based on blockchain storage can analyze causal relationships between data lifecycle events to detect dishonest blockchain input.

Biographies

Xuemin (Sherman) Shen [M'97, SM'02, F'09] is currently a University Professor with the Department of Electrical and Computer Engineering, University of Waterloo, Canada. His research focuses on network resource management, wireless network security, social networks, 5G and beyond, and vehicular ad hoc networks. He is a Canadian Academy of Engineering Fellow, a Royal Society of Canada Fellow, and a Chinese Academy of Engineering Foreign Fellow. He received the R.A. Fessenden Award in 2019 from IEEE, Canada; the James Evans Avant Garde Award in 2018 from the IEEE Vehicular Technology Society; and the Joseph LoCicero Award in 2015 and Education Award in 2017 from the IEEE Communications Society.

Cheng Huang [M'20] received his B.Eng and M.Eng in information security from Xidian University, China, in 2013 and 2016, respectively, and was a project officer with the INFINITUS laboratory at the School of Electrical and Electronic Engineering, Nanyang Technological University until July 2016. He received his Ph.D. degree in electrical and computer engineering from the University of Waterloo in 2020. His research interests are in the areas of applied cryptography, cyber security, and privacy in the mobile network.

Dongxiao Liu [M'20] is a postdoctoral research fellow with the Department of Electrical and Computer Engineering, University of Waterloo. He received his Ph.D. degree from the Department of Electrical and Computer Engineering, University of Waterloo in 2020. His research interests include blockchain and mobile networks.

Liang Xue is working toward a Ph.D. degree with the Department of Electrical and Computer Engineering, University of Waterloo. She received her B.S. degree in information security and M.S. degree in computer engineering from the School of Computer Science and Engineering, University of Electronic Science and Technology of China in 2015 and 2018, respectively. Her research interests include applied cryptography, cloud computing, and blockchain.

Weihua Zhuang [M'93, SM'01, F'08] has been with the Department of Electrical and Computer Engineering, University of Waterloo since 1993, where she is currently a professor and a Tier I Canada Research Chair in Wireless Communication Networks. She is a Fellow of the Royal Society of Canada, the Canadian Academy of Engineering, and the Engineering Institute of Canada. She is also an elected member of the Board of Governors and VP-Publications of the IEEE Vehicular Technology Society. She was a recipient of the 2017 Technical Recognition Award from the IEEE Communications Society Ad Hoc & Sensor Networks Technical Committee.

Rob Sun is currently a principal engineer with Huawei Technologies Canada Co. Ltd. His work primarily focuses on the advancement of NG wireless, including 5G/6G and WiFi/IoT security architecture and standardization. He was also Vice Chair of the IEEE Privacy Management Protection Task Group, which was to set out the best practices for protecting personal privacy information, and support efficient, adaptable, and innovative approaches for privacy governance. He was regarded as one of the core contributors to the standardization of a series of NG WiFi security protocols and certifications, including the most recent WiFi WPA3 protocol suites. He has also co-authored a few books on wireless security technologies.

Bidi Ying, Ph.D., is currently working at Huawei Technologies Canada Co., Ltd. as a senior network architecture engineer. Her main research is about security and privacy in wireless networks. Before that, she worked at the University of Ottawa. During the past 15 years, she has published more than 200 papers in top conferences and reputable journals.