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Review

Edge AI and Blockchain for Smart Sustainable Cities: Promise and Potential

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Abstract: Modern cities worldwide are undergoing radical changes to foster a clean, sustainable and secure environment, install smart infrastructures, deliver intelligent services to residents, and facilitate access for vulnerable groups. The adoption of new technologies is at the heart of implementing many initiatives to address critical concerns in urban mobility, healthcare, water management, clean energy production and consumption, energy saving, housing, safety, and accessibility. Given the advancements in sensing and communication technologies over the past few decades, exploring the adoption of recent and innovative technologies is critical to addressing these concerns and making cities more innovative, sustainable, and safer. This article provides a broad understanding of the current urban challenges faced by smart cities. It highlights two new technological advances, edge artificial intelligence (edge AI) and Blockchain, and analyzes their transformative potential to make our cities smarter. In addition, it explores the multiple uses of edge AI and Blockchain technologies in the fields of smart mobility and smart energy and reviews relevant research efforts in these two critical areas of modern smart cities. It highlights the various algorithms to handle vehicle detection, counting, speed identification to address the problem of traffic congestion and the different use-cases of Blockchain in terms of trustworthy communications and trading between vehicles and smart energy trading. This review paper is expected to serve as a guideline for future research on adopting edge AI and Blockchain in other smart city domains.

Keywords: edge computing; edge intelligence; Blockchain; smart grids; smart mobility; smart energy

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1. Introduction

Many countries have created strategies to transform their cities into smart cities to exploit the opportunities arising from urbanization. Smart cities enable operational efficiencies, maximize environmental sustainability, and develop new services for citizens. For example, the United Arab Emirates has launched its initiative to transform its cities into smart cities. The UAE government has also outlined its overall Blockchain strategy for increased security, immutability, resilience, and transparency.

With the climate change issues that have surfaced in the last few years, cities and civil society are increasingly demanding a more sustainable future for their citizens and communities [1,2]. The long-term sustainability of cities requires new, innovative, and disruptive solutions and services that are good for people, the planet, and businesses [3]. Building sustainable cities and environments will not be possible without the right technologies to digitize all city and business processes and obtain and share insights from data [4].

The advancements in sensing and communication technologies, the proliferation of mobile devices, and the widespread use of social media networks have resulted in an exponential growth in the information generated and exchanged. The phenomenon of big data refers to this exponential growth in data volume. It is made up of a set of technologies and algorithms that allow processing massive amounts of data in real time to derive insights from it. The processed information and the resulting insights are made available to decision-makers. Therefore, the reliability of the data is of the utmost importance to permit their exchange and facilitate transactions between businesses.

Billions of edge devices are connected to the Internet and generate zettabytes of data. Extracting value from these massive volumes of data at the required speed of the applications remains the main problem to be solved [5]. For many applications, the processing power offered by cloud computing is often used to process data. However, sending data to cloud servers for processing reveals limitations due to increased communication delays and network bandwidth consumption. Therefore, using cloud computing is not the best solution for real-time and latency-sensitive applications [6–8]. There is a growing trend towards using edge and fog computing to process data and extract value for these latency-sensitive applications. The use of streaming data analytics, machine learning, and deep learning for data processing at the edge resulted in the emergence of a new interdisciplinary technology known as edge AI that enables distributed intelligence with edge devices [9,10]. Research on edge AI and commercial solutions of this new technology are still relatively new.

The execution of transactions generally depends on many intermediaries who authenticate the information exchanged to establish "trust" between the parties in the transaction. A typical example is banking, where banks are responsible for validating financial transactions, and building trust between the parties in the transaction [11]. The essence of trusted intermediaries, such as banks, notaries, lawyers, and the government, is to facilitate a transaction that does not force the parties to trust each other. In today's digital age, reliance on these trusted intermediaries is just the result of a fundamental "lack of faith."

The recent years have witnessed the emergence of Blockchain technology to address this issue of trust [12–14]. A blockchain creates a source of truth that allows peer-to-peer (P2P) transactions to get rid of the need for trusted intermediaries. Its distributed ledger securely stores transaction information across multiple computer systems on the blockchain. Each block in the chain contains information concerning several transactions. Each time a new transaction occurs between two peers on the blockchain network, the ledger of each participant appends a record of that transaction with a hash, which is an immutable cryptographic signature. A change in a block of a chain means tampering with the block. To corrupt a blockchain system, hackers would have to change every block in the chain, and in all versions of the chain distributed across the blockchain network [15].

Blockchain is poised to revolutionize the way businesses, as well as governments, conduct all types of transactions [16]. It will significantly impact everyone (logistics, industry, government, banking, real estate, health, education, and citizen services). Blockchain technology has the potential to improve government services, streamline government processes and provide secure yet efficient information sharing [17,18]. Moreover, by using Blockchain technology, governments can finally offer different services, eliminate bureaucracy and the lack of transparency, prevent tax evasion and reduce waste.

1.1. Contributions

Although edge computing and blockchain have been extensively studied in the literature, very few works survey the integration of edge AI and blockchain in smart cities. This article reviews recent research efforts on edge AI and blockchain for enabling intelligent and secure edge applications and networks in two fundamental areas of smart cities—smart mobility and smart energy. Beginning with an introduction to edge AI and blockchain, we then review research efforts to integrate these two emerging technologies, including training learning models at the edge, security, privacy, scalability, and model sharing. Mainly, we provide a survey on the use of edge AI in various applications in smart mobility, such as traffic monitoring and management in intelligent transport systems, and smart energy, such as optimized energy management in smart buildings, green energy management, and energy efficiency in smart cities. Furthermore, we review recent research efforts on the use of Blockchain in various applications in smart mobility, including distributed credential management, reputation systems, key and trust management, and smart energy, including distributed energy management and energy trading. Possible research challenges and future directions are also outlined. The key contributions of this article are highlighted as follows:

1. It provides an overview of edge AI and blockchain fundamentals.
2. It analyzes the opportunities brought by edge AI in smart mobility and smart energy.
3. It analyzes the opportunities brought by Blockchain in smart mobility and smart energy.
4. It reviews some efforts to integrate these two emerging technologies in the context of smart cities.
5. Finally, it outlines key open research issues and future directions toward the full realization of edge AI and Blockchain in smart cities.

For the reader's convenience, the studies discussed in this review are shown in Figure 1.

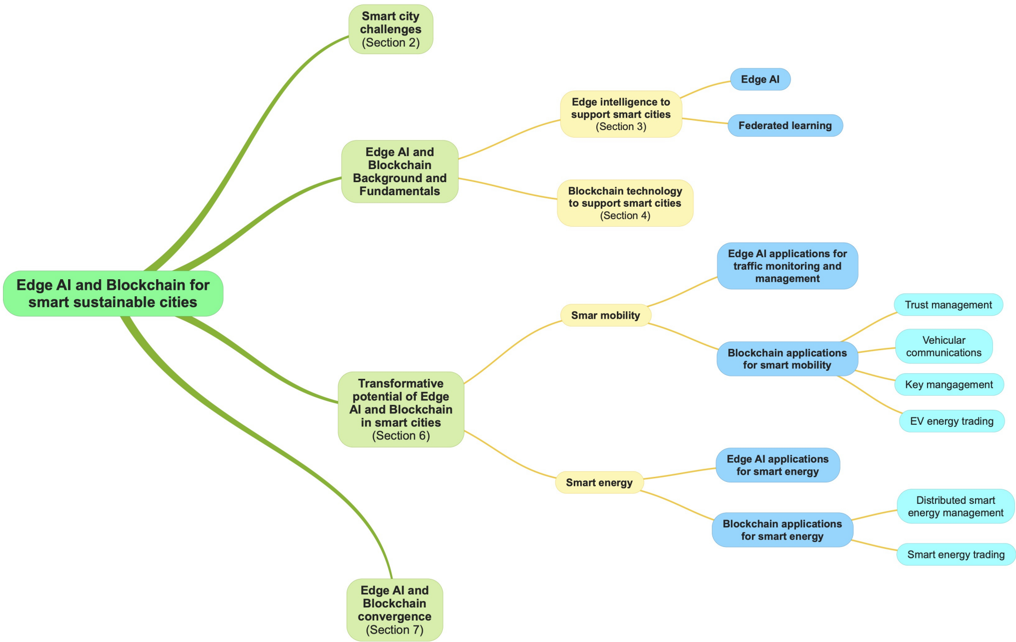

Figure 1. Classification of the studies of this review.

1.2. Structure of the Review

The remainder of this review is organized as follows: Section 2 unfolds the challenges facing smart cities. Sections 3 and 4 present the fundamentals of edge AI, federated learning, and Blockchain technology, and describe their potential to support smart city operations. The methodology used in this review is described in Section 5. Section 6 describes the transformative potential and applications of edge AI and Blockchain in two vital areas of smart cities, smart mobility and smart energy. Section 7 highlights some efforts showing the convergence of these two technologies. The open research issues and future directions are highlighted in Section 8. Finally, Section 9 concludes this review.

2. Smart City Systems and Key Challenges

As the world population grows, small and large cities are witnessing large migratory waves that pressure local governments and officials to deal with many social issues. These issues essentially concern ensuring a steady supply of water and electricity, providing appropriate healthcare services for all citizens, building and maintaining road infrastructure, providing adequate public transportation, ensuring security and safety throughout the city, and offering adequate education services [19].

The future of cities looks bright as many local governments start to build on smart city initiatives and embrace new digital technologies and innovations to tackle all of these issues, maximize the use of resources, provide a better quality of life for residents and a favorable investment climate for business [20,21]. For companies, smart city initiatives offer many innovation opportunities to develop new services and provide smart solutions for the cities. The vast amounts of data obtained by smart city systems and advancements in data stream processing, machine learning, and artificial intelligence enable entrepreneurs to develop new smart solutions and new business models [22]. Smart cities such as Dubai, Barcelona, Amsterdam, Singapore, New York, and Stockholm, to name a few, are enticing other cities to jump on the bandwagon [23].

Smart cities are complex entities that integrate various systems to support the human life cycle. These systems include smart healthcare, smart transportation, smart manufacturing, smart buildings, smart energy, and smart farming, among others.

2.1. Smart Healthcare

Smart healthcare is a set of technologies that are harnessed to actively manage healthcare data and respond to the needs of the medical ecosystem intelligently to increase longevity and improve the quality of life for citizens. These technologies include mobile devices, Internet of Things (IoT) devices, and mobile Internet, which enable dynamic access to information, connecting people, materials, and health-related institutions. Smart healthcare aims to foster interaction between all entities in health care, including hospitals, pharmacies, healthcare insurers, help them make informed decisions, ensure that participants have access to the services they need, and facilitate the rational allocation of resources [24,25].

2.2. Smart Transportation

With the emergence of intelligent transportation systems, the proliferation of IoT-based solutions, and advances in artificial intelligence, smart cities are entering a new era of a development called smart transportation. Smart city traffic management and smart transportation are revolutionizing the way cities approach mobility and emergency response while solving traffic problems by reducing congestion and the number of accidents on the streets and roads of cities [26,27]. Smart transportation relies on the deployment and use of sensors, advanced communication technologies, high-speed networks, and automation [28].

2.3. Smart Manufacturing

Smart manufacturing is a technology-driven approach for monitoring the production process using machines connected to the Internet. Its main goal is to present opportunities for automating operations using data analytics to boost manufacturing and energy efficiency, enhance labor security, and reduce environmental pollution levels [29]. Smart manufacturing deployments involve integrating IoT devices into manufacturing machinery to collect operational status and performance data. In addition, many technologies are being used to help enable smart manufacturing, including data streams processing, edge and fog computing, artificial intelligence, robotics, driverless vehicles, blockchain, and digital twins [30,31].

2.4. Smart Buildings

Smart buildings are buildings in the tertiary sector or residential buildings for which high-tech tools, such as sensors and sophisticated control systems, make it possible to adapt the settings according to the needs of the occupants [32]. The proliferation of new information and communication technologies now makes it possible to considerably improve our living environment by managing and controlling lighting, ventilation, and air conditioning, in short, the entire infrastructure of a modern building. The implementation of intelligent buildings brings more comfort and convenience to its residents, reduces energy consumption, and mitigates our negative impact on the environment.

2.5. Smart Energy Systems

Smart energy systems represent one of the most attractive smart city opportunities. Unlike smart grids, which primarily focus on the electricity sector, smart energy systems focus on the comprehensive integration of more sectors, including electricity, cooling, heating, buildings, manufacturing, and transportation. They aim to transform existing solutions into future renewable and sustainable energy solutions [33].

2.6. Smart Farming

Smart farming is an emerging concept in modern agriculture that refers to managing farms using digital technologies such as IoT, soil scanning, drones, robots, edge and cloud data management solutions, and AI [34,35]. It aims to increase the quantity and improve the quality of crops and agricultural products while optimizing the human labor required for production. When equipped with these technologies, farmers can remotely monitor crops and field conditions without going into the field. In addition, they will be able to make strategic decisions for their farms based on data collected from various devices.

Despite the promising and potential benefits that digital technologies bring to smart cities, there are many challenges in the way of a successful digital transformation [36]. These challenges mainly relate to the aging infrastructure, which hampers the development of many cities, security and privacy concerns with the proliferation of digital technologies, and social inclusion, which requires the design of solutions that address all categories of citizens and not only tech-savvy people. Addressing these challenges and concerns requires the use of new technologies and the development of new data-driven urban planning methods that challenge traditional models of urban development. The technology and innovative spirit of the new generation of entrepreneurs are the main catalysts for smart cities to be sustainable, safer, and more livable. These technologies and innovations are dramatically changing the way residents, businesses and government entities interact with each other for the benefit of all. Two promising technologies that are starting to make their way into several smart city projects are Blockchain and edge AI, which can potentially disrupt many of the areas above related to smart cities. They can make the various smart city operations and initiatives safer, transparent, efficient, smart, and resilient, resulting in more efficient and productive cities.

3. Edge AI and Federated Learning to Support Smart Cities

3.1. Edge AI Overview

Edge computing, sometimes referred to as IoT, is proliferating and is becoming an essential component in most business strategies over the last few years [5,37–39]. IoT devices, sensors, and smartphones transform many businesses from top to bottom. Furthermore, the emergence of artificial intelligence has been phenomenally stunning in its ability to impact the operations at the network edge. Increased computing power at the edge combined with the light deployment of machine learning and deep learning help make edge devices extremely smart [10,40]. Edge AI enables devices to deliver real-time insights and predictive analytics without sending data to remote cloud servers. Many businesses are now taking advantage of this by deploying intelligent solutions in production. With the various industrial IoT devices deployed in modern factories, manufacturers can be alerted with issues in their supply chain and proactively avoid unplanned downtime [41]. Additionally, a small device on a street radar can now instantly recognize a car that is speeding, the passengers in the vehicle, and whether the driver has a license or not [42].

Artificial intelligence (AI) with pre-trained models has the potential to empower smart cities by permitting decision-makers to make informed decisions, which will benefit both the city and citizens [43]. For instance, many smart city sectors will benefit from two typical vision-based image processing tasks, image classification and object detection, which arise in many edge-based AI applications [44–46].

AI continues to enter new segments with great promise at a high rate. Currently, digital industries such as finance, retail, advertising, and multimedia have been the sectors that have exploited AI the most. AI has created real value in these fields. However, the significant and vital problems in several other areas remain unresolved. The solution to the problems of cities concerning transport, energy and water supply, citizen security, healthcare, and many others is to replace or upgrade old and ineffective technologies.

New and AI-driven technologies have the potential to enable efficient transport systems, clean energy, and efficient health systems and industry [47]. A critical element in these areas is introducing and deploying intelligence "at the network edge" of high-speed and broadband networks. The edge is the bulk of our world at present. Bringing intelligence to the edge means that even the smallest devices deployed everywhere are capable of detecting, learning from, and reacting to their environments. AI enables, for example, devices on certain streets or public spaces in the city to make higher-level decisions, act autonomously, and report significant flaws or improvements to affected users or the cloud.

Edge AI means that AI algorithms are executed locally on a hardware edge device [48,49]. The AI device can process its local data and make decisions independently without requiring a connection to function correctly. The device must have sensors connected to a small microcontroller unit (MCU) to use edge AI. The MCU is loaded with specific machine learning models that have been pre-trained on certain typical scenarios that the device will encounter. The learning process can also be continuous, allowing the device to learn as soon as it faces new situations. The AI reaction can be a physical actuation on the device's immediate environment or a notification to a specific user or the cloud for further analysis and assistance.

Recently, special-purpose hardware has emerged to accelerate specific compute- or I/O-intensive operations at the edge. These edge hardware accelerators include Google's edge Tensor Processing Unit (TPU) [50,51], Nvidia's Jetson Nano and TX2 edge Graphical Processing Units (GPUs) [52,53], Intel's Movidius Vision Processing Unit (VPU) [54], and Apple's Neural Engine, which have emerged recently. They are explicitly designed for edge computing to support edge AI applications such as visual and speech analytics, face recognition, object detection, and deep learning inference.

Edge computing and edge AI encompass operations such as data collection, parsing, aggregation, and forwarding, as well as rich and advanced analytics that involve machine learning and event processing and actions at the edge. Edge AI will enable real-time operations, including data creation, decision making, and reaction time in milliseconds. These operations are essential for monitoring public spaces with crowds of people, self-driving cars, robots, monitoring machines in a factory, and many other areas. Edge AI will reduce data communication costs and power consumption as edge devices process data locally and transmit fewer data to the cloud, improving battery life, which is extremely important.

Smart cities are ideal for the use of edge computing and edge AI. Indeed, sensors and actuators can receive commands based on local decisions without waiting for decisions made in another distant place. Cities can use edge computing for video surveillance applications and getting up-to-date data concerning the conditions of roads, intersections, and buildings to take remedial actions before accidents occur. They also can use it for controlling lighting, energy and power management, water consumption, and many more. Municipalities and local governments can push the processing of urban IoT data streams from the cloud to the edge, reducing network traffic congestion and shortening end-to-end latency. By processing the data generated by edge devices locally, urban facilities can avoid the problem of streaming and storing large amounts of data in the cloud, which impact privacy and make them vulnerable.

3.2. Federated Learning at the Edge

Machine learning techniques typically rely on centrally managed training data, even when the training process is performed on a cluster of machines. This process often takes advantage of the characteristics of the overall training data set and the availability of validation data sets to adjust several parameters. However, centralizing data management for training is often not feasible or practical because of data privacy, confidentiality, and regulatory compliance.

Privacy regulatory frameworks require that data holders maintain the privacy of personal information and limit how to use the data. Examples of these frameworks include the European Union's General Data Protection Regulation (GDPR) [55] and the Health

Insurance Portability and Accountability Act 1996 (HIPAA) [56]. These restrictions make the management of central data repositories very expensive and a burden for data holders.

Federated learning (FL) is a learning approach that aims to solve the issues mentioned above of centralized training data management and data privacy. It allows collaboratively building a learning model without having to move the data beyond the firewalls of the participating organizations [57,58]. Instead, as shown in Figure 2, an initial AI model, hosted in a central server, is transferred to multiple organizations. Each organization trains the AI mode with its data to obtain new weight parameters sent back to the central server. The central server then uses any new weight settings from the participating organizations to create an updated single model. Several iterations of this process may be necessary to obtain an AI model good enough to be used in production. Several research efforts have evaluated the performance of models trained by FL. They have found that they achieve performance levels comparable to models trained on centrally hosted data sets and superior to models that only use isolated data from a single organization [59,60].

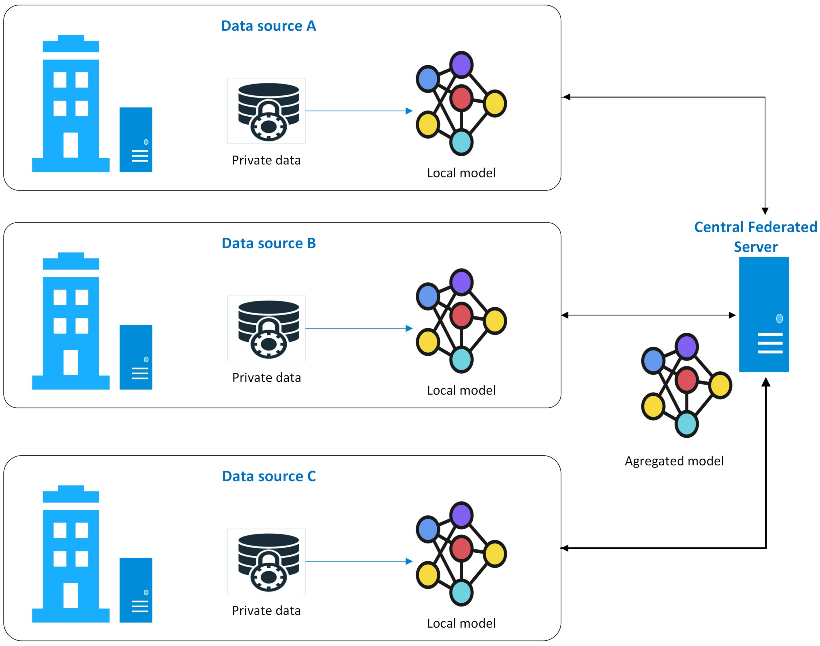

Figure 2. Federated learning architecture.

4. Blockchain to Support Smart Cities' Operations

4.1. Blockchain Overview

Blockchains are essentially shared databases that enable the participants, called nodes in a network, to confirm, reject, and view transactions. They facilitate recording transactions and tracking asset movements in a business network. Assets can be tangible, such as property, cars, land, or intangible, such as patents and copyrights. Transaction data are stored in a block-based structure, where blocks are linked to each other through a method known as cryptographic hashing. Combined with the distributed and decentralized nature of the blockchain ledger, this method makes each block of data virtually impossible to change once it is added to the chain. Therefore, the blockchain distributed ledger is cryptographically secure and immutable. It works in append-only mode and can only be updated by consensus or peer-to-peer agreement. Blockchain is often viewed as a specific subset of the larger universe of distributed ledger technology (DLT) [61]. The distributed ledger makes Blockchain technology resilient since the network does not have a single point of vulnerability. In addition, each block uniquely connects to previous blocks via a digital signature. Making a change to a record without disrupting earlier records in the chain is impossible, making the information tamper-proof. Allowing its participant to transfer assets over the Internet without a centralized third party is the essential innovation in Blockchain technology.

Blockchain technology emerged over the last few years as the underlying technology for Bitcoin. The consequences of the subprime crisis in 2008 reduced confidence in the existing financial system [62]. Satoshi Nakamoto wrote a white paper describing the "bitcoin protocol", which used a distributed ledger and consensus to compute algorithms in the same year. The protocol was authored to facilitate direct P2P transactions and disintermediate traditional financial intermediaries [63].

Since the birth of the Internet, many attempts to create virtual currencies have failed due to the double-spending problem. The current solution to eliminate the double-spending problem is introducing "trusted intermediaries" such as banks. Blockchain technology solves the double-spending problem without these trusted intermediaries, making it easier to securely move assets such as virtual currencies over the Internet. Other areas other than currencies could benefit from this concept, making Blockchain technology very promising.

As illustrated in Figure 3, the blockchain architecture allows participants in a business network, for example, to share an updated ledger using peer-to-peer replication each time a transaction occurs. Each participant acts as a publisher and subscriber and can receive or send transactions to other participants, and data are synchronized across the network. The blockchain network eliminates duplication of effort and reduces the need to use the services of intermediaries, making it economical and efficient. Using consensus models to validate transaction information also makes the network less vulnerable. Transactions are secure, authenticated, and verifiable.

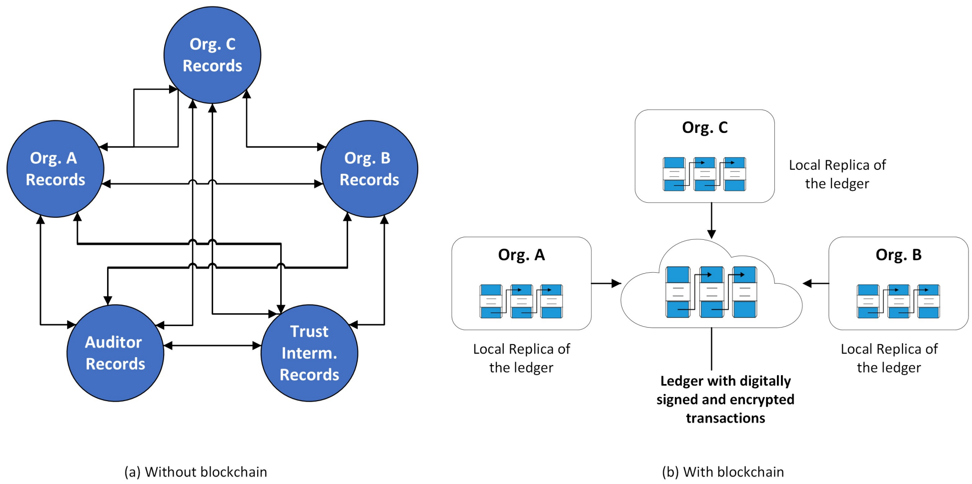

Figure 3. Network of business parties and intermediaries without and with Blockchain. (**a**) Transactions between Org. A, B, and C involve intermediaries. (**b**) Participants share an updated ledger using P2P replication each time a transaction occurs.

4.2. Blockchain Benefits

The blockchain network stores data in a tamper-proof form, and it permits valid users only to append data to the blockchain. Understanding the primary attributes, depicted in Figure 4, of Blockchain that make this technology unique is essential to comprehend its full potential.

- **Distributed shared ledger:** This is a distributed append-only system shared across the corporate or business network, making the system more resilient by eliminating the centralized database, which is a single point of failure.
- **Consensus:** A transaction is only committed and appended to the ledger when all validating parties consent to a network verified transaction.
- **Provenance:** The entire history of an asset is available over a blockchain.

- **Immutability:** Records are indelible and cannot be tampered with once committed to the shared ledger, thereby making all information trustworthy.
- **Finality:** Once a transaction is completed over a blockchain, it can never be reverted.
- **Smart contracts:** Code is built within a blockchain that computers/nodes execute based on a triggering event. Essentially, an "if this then that" statement can be auto-executed.

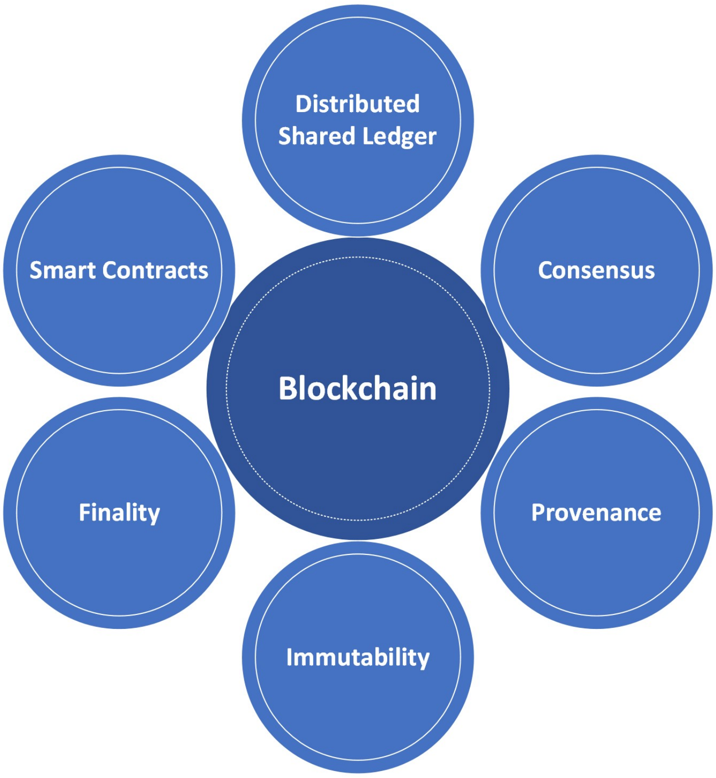

Figure 4. Blockchain benefits.

Blockchain has the potential to disrupt any form of transaction that requires information to be trusted. With the advent of Blockchain technology, all trusted intermediaries are the subject of disruption in one form or another, and Blockchain technology solves the problems associated with the way information-related transactions occur today. Blockchain creates a permanent and unalterable ledger of information by validating transactions through its distributed network of peers.

4.3. Types of Blockchain Networks

Blockchain networks are either public or private. A public blockchain network operates in a decentralized open environment with no restriction on the number of people joining the network, and the private blockchain network functions within limits defined by a control entity. The intrinsic technology of both networks remains the same; however, the dynamics and utility of closed and open networks are different. This difference plays out based on the incentives for nodes to remain a part of the network. The key idea is that in a public blockchain, the consensus mechanism rewards each participant for staying a part of the network, and in a private blockchain, the need for creating this incentive does not exist.

A genuinely transparent public registry's democratized nature may not be helpful to an organization or corporate network since the parties are known, and there is a level of understanding of the members who can participate in the network and transactions. The consensus is that while public blockchains work well for specific applications such as cryptocurrency (bitcoin) based transactions, the most important application of Blockchain technology as an enterprise solution would not be possible than with the increased regulatory control associated with a private Blockchain ecosystem.

Blockchain technology is still emerging, and therefore its different applications evolve continuously and iteratively. An ecosystem where multiple private blockchains interact with each other on a publicly distributed network may address the issue of public vs. private blockchain networks. In that shared ecosystem, public and private blockchains work in symbiosis in the same way private networks interact with the Internet.

Blockchain technology is being applied in numerous domains of smart cities, such as healthcare, power grid, transportation, supply chain management, education, manufacturing, the construction industry, and many others. Several works survey and describe the application of Blockchain in these areas [64–66].

4.4. Blockchain Suitability

Blockchain technology is only suitable when multiple parties share data and need a common information view. However, sharing data is not the only qualifying criteria for Blockchain to be a viable solution. The following situations make Blockchain a viable and efficient solution:

- A transaction depends on several intermediaries whose presence increases the transaction's time, cost, and complexity.
- Reducing delays and speeding up a transaction is incredibly advantageous for the business.
- Transactions created by the business participants depend on each other.
- Actions undertaken by multiple participants should be recorded and involved validated data updated.
- Building trust between the participants is necessary for the business.

To sum up, Blockchain technology is certainly not a solution to all transaction issues.

5. Methodology

This review paper uses a qualitative research approach to synthesize the relevant literature on the article's subject. Given the descriptive nature of the present study, the qualitative approach allows for reviewing and synthesizing a large amount of pertinent literature. A systematic review strategy was adopted without claiming to be exhaustive in pursuing this objective.

5.1. Search Criteria Formulation

The search criteria used were:

- C1: ("Edge AI" OR "edge intelligence") AND "Blockchain";
- C2: ("Edge AI" OR "edge intelligence") AND ("smart mobility" OR "smart transportation");
- C3: "Blockchain" AND ("smart mobility" OR "smart transportation");
- C4: ("Edge AI" OR "edge intelligence") AND "smart energy";
- C5: "Blockchain" AND "smart energy".

The purpose of this review paper is to answer the following research questions.

- RQ-1: What are the applications of edge AI and Blockchain regarding smart mobility and smart energy? This research question intends to identify the state-of-the-art research regarding the applications of edge AI and Blockchain technology in these two key areas of a smart city.
- RQ-2: What are the potential open research issues and future directions in edge AI and Blockchain implementation in these two vital areas of a smart city? This question aims to define the open questions and research directions for the wide adoption of edge AI and Blockchain to address the challenges in implementing smart mobility and smart energy. Consequently, answering this question encourages researchers to understand the current research findings and trends in edge intelligence and Blockchain.

5.2. Source Selection and Approach

The review included articles published between 2017 and 2021. A search for relevant research on the topic of this review was conducted using the following databases and search engines: (i) Scopus, (ii) ScienceDirect, and (iii) Google Scholar, which provide excellent coverage of the study topics. The search used the search criteria above and revolved around the terms "Edge AI" and "Blockchain" while including synonyms as additional terms such as "edge intelligence" and "distributed ledger" to increase the search results.

Most of the papers reviewed are journal articles, with some conference papers also included. Papers were selected based on the quality of the journal, relevance to the topic, and filtered by date of publication. Edge intelligence and Blockchain are still in their infancy and are evolving rapidly. Article selection was based on titles, keywords, abstracts, and conclusions relevant to the topic. References cited in this review paper published before 2017 mainly concern the background and literature review on smart city areas and challenges, edge computing, and Blockchain.

The initial search for the five search criteria (C1–C5) found 417 references from Scopus, 533 from ScienceDirect, and 931 from Google Scholar (review articles). However, the total number of papers was reduced to 150 after the title and abstract screening, excluding, and eliminating duplicates. Afterwards, the papers were classified into four main classes: background and fundamentals, edge AI and Blockchain convergence, applications of edge AI in smart mobility and smart energy, and applications of Blockchain in smart mobility and smart energy.

6. Transformative Potential of Edge AI and Blockchain in Smart Cities

Modern cities struggle to automate many of their processes and coordinate them with various stakeholders. Citizens expect their governments and smart city entities to respond quickly to their demands and needs while ensuring transparency, fairness, and accountability to the public. Success in these endeavors, especially in the digital age, requires that up-to-date data be collected and processed in near real-time. Much of the challenge is in the management and processing of data. Unfortunately, traditional centralized databases and data management tools are not enough to meet the new challenges that smart cities face. The data exchanged between the various city actors can be tampered with. The single point of failure of the standard database client-server model compromises data security, making transparency challenging to achieve when city databases are centralized. Additionally, using centralized databases results in slow and inefficient operations such as registering identifications (IDs) and electoral voting.

Smart cities and government entities can address the above issues by taking advantage of the recent advances in edge AI and using an innovative data management structure. This data structure uses distributed ledgers and cryptography. Furthermore, they can offer citizens smart on-demand services while ensuring data privacy and security, unprecedented transparency, fairness, and accountability [67,68]. Here, we discuss the potential of these two technologies in two crucial subsystems of a smart city, smart mobility, and smart energy management, and review relevant research works on their usage in these areas.

6.1. Smart Mobility

Modern cities suffer from major issues such as traffic congestion, emissions, and safety. Without innovative solutions, mobility problems will intensify due to the continued growth of the population, which leads to an increase in the number of vehicles on the roads, the kilometers traveled, and consequently the increase in emissions. In response, the mobility industry is developing a fascinating range of innovations designed for urban roads, such as intelligent traffic and parking management systems, mobility as a service, and carpooling solutions. "Smart transport" often refers to the use of new digital technologies and data-driven management techniques in transport systems to address the mobility problems [28,69]. The phenomenal technological developments in recent years, which have brought about significant changes in all aspects of our life, promise to improve transport in cities in all its forms. Smart transport, being a dream, is becoming more and more a reality. We are seeing more and more applications that integrate live data and feedback from multiple sources to gain a holistic and real-time view of the traffic status, helping stakeholders better manage road traffic and deliver quality services to road users. Other innovations that contribute to smart transport and mobility include:

- The development of new models of shared mobility;
- The development of more reliable and convenient public transport;
- The development of applications allowing to alert drivers of hazardous situations quickly;
- The development of navigation applications that allow drivers to find in real-time the best route possible;
- The ability to adjust road signals and speed limits in real-time based on current traffic conditions;
- The development of new concepts of electric, connected, and autonomous vehicles.

Because of the costly computations of traffic management systems, the improvement of the real-time processing of data is one of the best ways to optimize traffic management systems [27]. Traffic data are obtained from various sensors and IoT devices deployed on urban roads and vehicles by transportation systems. Intelligent transport systems are evolving towards intensive use of edge computing and edge AI technologies, especially for traffic management processes [70]. Gigabytes of sensory data are analyzed, filtered, and compressed locally before being transmitted through IoT edge gateways to multiple systems for later use. Edge processing for traffic management solutions allows one to save on storage, network expenses, and operating costs.

6.1.1. Edge AI for Traffic Monitoring and Management

Traffic management is an undeniable component of smart mobility, which combines different measures to preserve traffic capacity, reduce congestion at roads and intersections, and improve the safety and reliability of the overall road transport system. Modern traffic management systems are composed of advanced sensing and monitoring technologies, management tools, and a set of intelligent applications to achieve these goals. These technological solutions prepare smart cities for future cutting-edge technological developments, in particular the proliferation of autonomous vehicles, connected vehicles, and the large-scale deployment of Fifth Generation (5G) cellular networks and edge AI systems [71]. Several works investigated edge computing-based solutions for traffic management in smart cities. Barthélemy et al. [70] designed a visual sensor for monitoring the flow of bicycles, vehicles, and pedestrians traffic. Their complete edge-computing-based solution aims to deploy multiple visual sensors and collect data through a framework called Agnosticity. The visual sensor hardware uses the NVIDIA Jetson TX2 on-board computing platform to perform all computations onboard. Its software pairs YOLOv3 [72], a popular convolutional deep neural network, with Simple Online and Realtime Tracking (SORT) [73], a real-time tracking algorithm. The metadata are then extracted and transmitted using Ethernet or LoRaWAN protocols. The sensor provides a privacy-compliant tracking solution by transmitting only metadata instead of raw or processed images. Municipalities can combine the sensors with the existing Closed-circuit television (CCTV) infrastructure, and this integration helps optimize infrastructure usage and add value to the network by leveraging the vast video data collected. Besides, the Long Range Wide Area Network (LoRaWAN) protocol facilitates the deployment of additional cameras in areas where conventional internet connectivity is not available.

Dinh et al. [74] proposed an inexpensive and efficient edge-based system integrating object detection models to perform vehicle detection, tracking, and counting. They created a Video Detection Dataset (VDD) in Vietnam and then examined it on two different types of edge devices. They evaluated their proposed traffic counting system in a Coral Dev TPU Board and then a Jetson Nano GPU Board and implemented several models in the two boards. The MobileDet 320 × 320 SSD model implemented in the Coral Dev TPU Board for the vehicle detection context achieves an accuracy of 92.1%, and the proposed method achieves a maximum inference speed of around 26.8 Frames per second (FPS) on VDD.

Additionally, Kumar et al. [75] investigated how to detect and track vehicles effectively. Their proposed method detects tracks and extracts vehicle parameters for speed estimation using a single camera. They used the Automatic Number Plate Recognition (ANPR) system to select keyframes where a speed limit violation occurs. The average detection accuracy obtained is approximately 87.7%. The proposed approach uses cropping operations to minimize the scope of any detection of false positives on both sides of the road. The average detection accuracy obtained is 87.7%. The proposed approach tracks vehicles moving in one direction but fails to detect vehicles coming from opposite directions.

Likewise, Song et al. [76] proposed a vision-based vehicle detection and counting system for highways. The proposed method is not expensive, is highly stable, and does not require a significant investment in terms of monitoring equipment. They used a "Vehicle dataset" to train a YOLOv3 network to obtain the vehicle object detection model. Image segmentation and YOLOv3 allowed them to detect three types of vehicles: cars, buses, and trucks. A convolutional neural network and the Oriented FAST and Rotated BRIEF (ORB) algorithm [77] were used to extract the features of detected vehicles. The authors stated that vehicles' detection speed is fast, and its accuracy is high. Traffic footages taken by highway surveillance video cameras have good adaptability to the YOLOv3 network. Multi-object tracking uses the object box detected in vehicle detection using YOLOv3. The ORB algorithm uses the Features from the Accelerated Segment Test (FAST) to detect feature points, and the Harris operator performs corner detection.

In many cities, a segment of a public or private road can be used to load and unload goods at specific times or at any time. Parking signs and road markings are typically used to warn drivers of parking regulations. These areas are known as loading bays. Parking inspectors generally monitor these areas, and motorists found violating the rules can be fined. These restrictions on urban freight deliveries require establishing a loading bay system and dividing the last mile delivery into driving and walking segments. Loading bays are sometimes occupied, requiring rerouting delivery vehicles and searching for an alternative loading bay. The authors in [78] introduced a fuzzy clustering method to test different optimization approaches and make the system flexible enough to accommodate this problem. We believe that edge AI and computer vision can help address where and how many loading bays should be used to perform this transshipment and execute last-mile delivery most efficiently.

6.1.2. Blockchain for Smart Mobility

With the population growth of cities and the rapid increase in demand for smart transport and mobility solutions, there is an urgent need for innovative solutions that use existing infrastructure in cities and on external roads and highways between cities. Smart mobility technologies aim to provide many new applications and perspectives for efficient and safe movement on roads while reducing Carbon dioxide (CO_2) emissions and improving air quality [69]. Transportation systems management is a challenging endeavor in many modern cities [79].

Blockchain technology can improve information sharing between different stakeholders in cities, improve the robustness of the overall transport system and facilitate communication between vehicles, contact with road units, and transport traffic control centers. In addition, Blockchain in the transport sector also can reduce the processing time of transport-related transactions, approvals, and exchange of documents and speed up customs clearance. This section summarizes relevant work on Blockchain-based solutions for smart transportation and mobility. Figure 5 depicts the main areas where Blockchain has been used to contribute to the smart mobility goals, and Table 1 summarizes the focus area of each of the reviewed works and the Blockchain mechanisms they used.

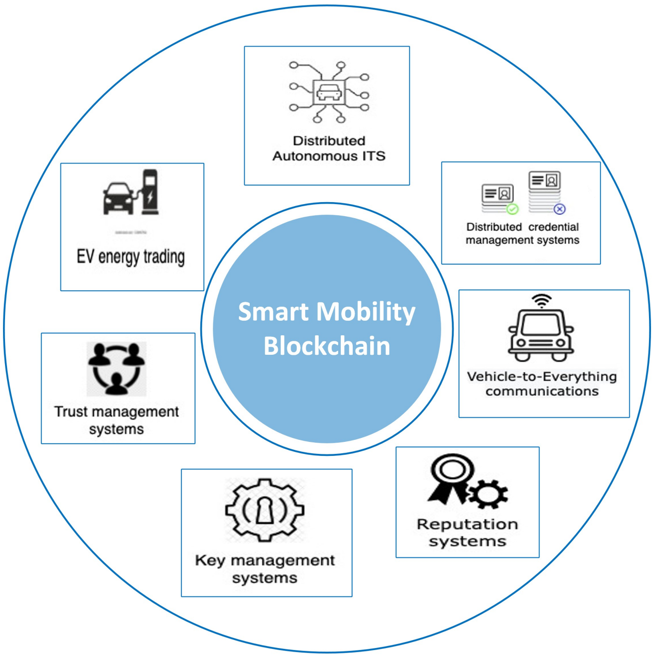

Figure 5. Blockchain for smart mobility.

Table 1. Summary of Blockchain-based smart mobility literature review.

Ref.	Focus	Blockchain Used Mechanisms
[80]	Blockchain as the operating system of smart cities, with transportation management as one of the main focus areas	Etherium-like Blockchain, smart contracts
[81]	Blockchain in vehicular communications, in particular, a system for revocation and accountability in a Security Credential Management System.	Distributed Ledger, hierarchical consensus
[82]	A blockchain-based vehicular network architecture in smart city.	Distributed blockchain vehicular network, Miner Vehicular Node, revocation authority, Block Node Controller
[83]	Reputation systems in vehicular networks based on Blockchain technology.	Vehicular blockchain, Miner Vehicle, Trusted Authority, distributed consensus
[84]	Blockchain-based key management scheme to transfer security keys between distributed security managers in heterogeneous Vehicular Communication Systems.	Blockchain structure without the third-party authorities, Transaction format, Mining, and Proof algorithm.
[85]	Blockchain-based decentralized Key Management Mechanism for VANET.	Vehicular blockchain network, Ethereum-based Smart contract, mining functions.
[86]	Decentralized Trust Management system in vehicular networks based on Blockchain technology.	Vehicular blockchain, Miner Vehicle, Trusted Authority, distributed consensus
[87]	Decentralized Trust Management system in vehicular networks based on Blockchain technology and the Tendermint consensus protocol.	Vehicular blockchain, Tendermint(consensus without mining), BFT based consensus.
[88]	A location privacy protection system based on trust management in Blockchain-based VANET.	Vehicular blockchain to record the trustworthiness of vehicles, PBFT consensus algorithm.
[89]	A Blockchain-based system combined with auctions to enable BEVs to trade energy using day-ahead and real-time trading markets.	Blockchain to record trading contracts, Smart contract.
[90]	Roaming charging process of electric vehicles and Blockchain technology to support user identity management and record energy transactions securely.	Distributed ledge to record energy transactions
[91]	Blockchain to mitigate trust Issues in Electric Vehicle Charging.	Hyperledger Fabric, smart contract.

Bagloee et al. [80] suggested that to reduce traffic congestion and achieve system equilibrium, traffic authorities may issue a limited number of mobility permits, distributed equally to all drivers, which may be tradable in an open market. Such a progressive scheme is now possible in light of the ever-increasing use of various kinds of sensors, cameras, RFIDs, radars, and lidars. Blockchain technology and smart contracts can be used as a valid, promising, and feasible solution for implementing the tradable part of this scheme. The authors also suggested that drivers and passengers use the Tradable Mobility Pass (TMP) equally to pay parking fees, public transport tickets, car registration fees, and highway tolls. An Ethereum-like blockchain and "smart contracts" can be used to program their mobility credits for trading in the open market and spending against the above payments and mileage. They can also be used to trade TMPs en-route by permitting vehicles to communicate with each other and place bids for faster routes at higher prices. Blockchain can also facilitate communication between connected vehicles and the road infrastructure by considering data exchange requests as transactions to be stored and retrieved from a blockchain database.

Additionally, Blockchain can provide safe, secure, and well-informed access to driving behavior information for driving license agencies and insurance companies, which typically know little about driving behavior. Insurance companies' predictions are based on claims history [92]. Access to data from connected vehicles can help them set insurance premiums commensurate with drivers' risk levels.

Blockchain in vehicular communications. Some works proposed Blockchain-based solutions to help create a secure, trusted, and distributed autonomous Intelligent Transportation System (ITS) capable of controlling and managing physical and digital assets. At the same time, most ITSs were centralized [93]. The authors in [81] described the design of a Blockchain-based decentralized alternative to existing security credential management systems, which aimed to get rid of the need of using the services of a centralized trusting authority.

Vehicle-to-Everything (V2E) communications are an essential component in any ITS. They help provide information on road accidents, road conditions, traffic jams, allowing road drivers to be aware of critical situations, thus enhancing transport safety. Sharma et al. [82] proposed a distributed transport management system that allows vehicles to share their resources and create a network where value-added services, such as automatic gas refill and ride-sharing, can be produced. Additionally, Yang et al. [83] proposed reputation systems in vehicular networks based on Blockchain technology.

Lei et al. [84] proposed a Blockchain-based key management scheme to transfer security keys between distributed security managers in heterogeneous Vehicular Communication Systems (VCS). The blockchain structure enables secure key transfer between participating network security managers and eliminates the need for a central manager or third-party authority.

Likewise, the authors in [85] proposed a decentralized key management mechanism for Vehicular Ad-hoc Networks (VANETs) with Blockchain to automatically register, update, and revoke the user's public key. They also described a lightweight mutual authentication and key agreement protocol based on the bivariate polynomial. Additionally, they analyzed the security of their proposed mechanism for managing distributed keys and have shown that it can prevent typical attacks, including insider attacks, public key tampering attacks, Denial-of-Service (DoS) attacks, and collusion attacks.

Additionally, Yang et al. [86] proposed a decentralized Blockchain-based trust management system in vehicular networks. Vehicles can query the trust values of neighboring vehicles and assess the credibility of received messages. The RSUs aggregate the confidence values based on evaluations generated by the messages' recipients. Using Blockchain, all RSUs contribute to maintaining a reliable database.

Similarly, Arora et al. [87] proposed a Blockchain-based trust management system for VANETs based on the Tendermint protocol to eliminate the possibility of malicious nodes entering the network and reduce power consumption. Vehicles assess the messages received from neighboring vehicles using the gradient boosting technique (GBT). Based on the assessment results, the message source vehicle generates the ratings, uploads them to RSUs, and calculates the trust offset value. All RSUs maintain the trust blockchain, and each RSU adds its blocks to the trust blockchain.

In another work, Luo et al. [88] proposed a location privacy protection system based on trust in Blockchain-based VANET. Their trust management approach uses Dirichlet distribution to allow requesters to cooperate only with vehicles they trust. In addition, they also developed the blockchain data structure to record the trustworthiness of vehicles on publicly accessible blocks promptly to allow any vehicle to access historical trust information of counterparties whenever necessary.

Blockchain for Electrical Vehicles. Battery Electric Vehicles (BEVs) are known for their low operating costs because they have fewer moving parts that require maintenance. In addition, they are very environmentally friendly as they do not use fossil fuels. Modern BEVs use rechargeable lithium-ion batteries, which have a longer life and retain energy very well with a self-discharge rate of only 5% per month. In many cities around the world, Charging Stations (CSs) are increasingly deployed in various geographic locations, residential garages, and public/private parking lots to meet the energy needs of BEVs, increasing the load on electrical distribution systems.

Intelligent car parking lots offer BEVs parking and recharging services during their parking time for a fee. Customers of these parking lots want fast charging services at low cost, while parking lot operators aim to maximize their profit. BEV owners increasingly tend to purchase power from other electric vehicles to reduce recharging costs and reliance on the primary electricity grid.

Huang et al. [89] proposed a Blockchain-based system to enable BEVs to trade energy using day-ahead and real-time trading markets. Users of BEVs submit their price offers to participate in a double auction. Then, the operator of the charging system performs intelligent matching of the different offers to reduce the impact on the power grid by programming the charging and discharging behavior of electric vehicles taking into account the satisfaction of EV users and the social benefits. The operator of the charging system uploads the trading contract to the blockchain once the trading results are cleared. Case studies have demonstrated the effectiveness of the proposed model. Ferreira et al. [90] studied the roaming charging process of electric vehicles and used Blockchain technologies to support user identity management and record energy transactions securely. They used off-chain cloud storage to record transaction details. Blockchain-based digital identity management avoids charging cards used as an authentication process in charging systems. It can achieve interoperability between different countries, allowing a roaming process of BEV charging. In [91], Gorenflo et al. described a methodology for the design of Blockchain-based systems. They have demonstrated its usefulness in creating a system for recharging electric vehicles in a decentralized network of recharging stations. The proposed system aims to solve the problem of trust between the different actors of the system, including customers, providers of electric vehicle charging services, and property owners. Trust problems arise from the potential for tampering with transaction data. The blockchain ledger in the proposed solution contains a record of every transaction and acts as an immutable audit trail.

6.2. Smart Energy

In recent years, the term "Smart Energy" has been used more and more to mean an approach that goes beyond the concept of "Smart Grid." While the smart grid concept mainly focuses on the electricity sector, smart energy embodies a holistic approach that includes many sectors (electricity, heating, cooling, buildings, industry, and transport). It allows the development of affordable solutions for transforming existing systems into future renewable and sustainable energy solutions [33]. Smart energy solutions typically use various disruptive technologies, including artificial intelligence, deep learning, Blockchain and distributed ledger technologies, distributed sensing and actuation technologies, and, recently, edge computing and federated learning technologies.

6.2.1. Edge AI for Smart Energy Management

Several research efforts are increasingly studying and developing smart energy solutions. Shah et al. [94] reviewed several research works that use different energy optimization techniques in smart buildings and rely on IoT solutions. Their study aimed to identify algorithms and methods for optimized energy use and edge and fog computing techniques used in smart home environments. From an initial batch of 3800 papers, they found only 56 articles relevant to their study. The detailed analysis of these papers revealed that many researchers had developed new optimization algorithms to optimize energy consumption in smart homes.

Zhang et al. [95] proposed an IoT-based green energy management system to improve the energy management of power grids in smart cities. With the implementation of IoT, smart cities can control energy through ubiquitous monitoring and secure communications. The proposed system uses deep reinforcement learning. The authors' results show that IoT sensors help detect energy consumption, predict energy demand in smart cities, and reduce costs. Aided by a systematic learning process, the energy management system can balance energy availability and demand by stably maintaining grid states.

Abdel-Basset et al. [96] proposed a smart edge computing framework to achieve efficient energy management in smart cities. They reviewed relevant work on data-driven load forecasting (LF) techniques used in real-life scenarios such as smart buildings to predict the day's energy demand in advance and make appropriate energy demands on smart grids. These short-term forecasts help to avoid energy shortages and promote fair consumption. They classified these techniques into two classes: statistical or machine learning-based techniques and deep learning-based techniques. They introduced a new deep learning architecture, called Energy-Net, to predict energy consumption by integrating the spatial and temporal learning capability. They validated the robustness of their proposed architecture through a comparative analysis of public datasets with recent cutting-edge approaches. According to the authors, the trained Energy-Net system is deployable on resource-limited edge devices to forecast potential energy needs sent as a request to the smart grid through cloud-fog servers. As a result, the smart grid supplies the demanded energy to different smart city sectors. Energy management is, therefore, performed efficiently.

The authors in [97] studied and proposed an energy management framework based on edge computing for a smart city. They developed an energy scheduling scheme based on deep reinforcement learning to deal with the intermittency and uncertainty of energy supplies and demands in cities for a long-term goal. They analyzed the efficiency of the energy scheduling scheme in the cases with and without edge servers, respectively. Their results demonstrate that the proposed model can achieve low energy costs while exhibiting lower delays than traditional schemes.

6.2.2. Blockchain for Smart Energy Management

Blockchain technology in the energy sector is up-and-coming. It can significantly reduce energy trading costs, increase process efficiency, and deliver customer cost benefits. It can establish direct interactions between all the actors involved, which guarantees the optimal use of existing production capacities while offering energy at the best price. The application of Blockchain in emerging smart energy systems in smart cities has recently received a great deal of attention. In addition to the BEV charging we mentioned, there is an increasing need for decentralized energy management, energy trading platforms development, and secure data and financial transactions between the different actors involved. This need arises from the proliferation of new devices, technologies, renewable energy resources, and electric vehicles. Additionally, there is a growing interest worldwide in using Blockchain technologies to create a secure and more resilient environment for the smart energy industry. Several research efforts investigated the opportunities, benefits, challenges, as well as drawbacks of Blockchain technologies in the context of smart energy [98–100].

This section reviews some efforts regarding the use of Blockchain in smart energy systems. We do not intend to provide a full survey. Andoni et al. [101] reviewed and ranked about 140 Blockchain-based projects in the energy sector. Additionally, the authors in [102] reviewed several research works regarding the applications of Blockchain technology in smart grids. They categorized them in decentralized energy management, energy trading, BEVs, financial transactions, cybersecurity, testbeds, environmental issues, and demand response (DR). A common aspect of most of the efforts is the usage of Blockchain to address decentralized energy management, energy trading, transparency, and its perceived benefits to system security. However, system security and user privacy are typically dependent on the type of blockchain used. Table 2 summarizes these efforts.

Table 2. Summary of Blockchain-based smart energy literature review.

Ref.	Focus	Blockchain Used Mechanisms
[98]	Distributed management of DR in smart grids	Smart contracts, consensus-based DR validation approach
[99]	Smart energy trading	Smart contracts
[100]	P2P energy and carbon trading	pay-to-public-key-hash with multiple signatures to secure transaction
[101]	Review of challenges of Blockchain technology in the energy sector	
[102]	Review of blockchain in future smart grids	
[103]	Review of blockchain applications in different areas of a smart city, including smart energy	
[104]	Automated energy DR, P2P energy trading	Smart contracts, noncooperative game for consumption strategy to reach consensus
[105]	Distributed energy system (short review)	Smart contracts, consensus
[106]	Federated power plants with P2P energy trading	
[107]	Distributed energy management in a multi-energy market enhanced with blockchain	Smart contracts, consensus
[108]	Distributed energy exchange	Smart contracts
[109]	Microgrid energy market, P2P energy trading	
[110]	Electricity Trading for Neighborhood Renewable Energy	P2P Blockchain network
[111]	Smart homes energy trading	Ethereum's smart contracts, consensus
[112]	P2P solar energy market	Auction mechanism in the smart contracts.
[113]	P2P Energy Trading	Ethereum-based blockchain, Smart contracts, Distributed consensus for verification and group management
[114]	Federated Learning-based P2P Energy Sharing assisted with Blockchain	smart contracts for energy demand prediction
[115]	Electrical energy transaction ecosystem between smart homes prosumers and consumers, P2P energy trading	Smart contracts (energy tags)
[116]	Review of applications of smart communities, including energy trading in ITS using blockchain.	Smart contracts, miners, consensus.

Decentralized Energy Management. The ever-growing deployment of renewable energy systems in smart grids highlights the need to develop distributed energy management systems and trigger fundamental changes in energy trading [117,118]. A large body of literature has investigated the usage of Blockchain technologies to ease decentralized energy management according to the P2P model used by Blockchain [103–106,119].

Real-time energy management has the potential to resolve the impact of various uncertainties in the energy market, provide instant energy balance and improve business returns. Wang et al. [107] proposed a bidding strategy for the energy market, with multiple participants, which uses an adaptive learning process that incorporates a reserve price adjustment and a mechanism of dynamic compensation. Participants perform bid adjustments based on adaptive learning leveraging real-time market information to increase transaction rate and maximize profits. Blockchain technology guarantees the transparent and efficient performance of the presented bidding strategy. A decentralized Blockchain application showed that the system could achieve real-time energy management and dynamic trading in practice.

Energy trading. Recent years have seen the high penetration of renewable energy systems in smart grids and homes. However, complex energy trading and complicated monitoring procedures are obstacles to developing renewable energies. Energy trading involves various actors, including residential consumers, renewable energy producers, BEVs, and energy storage, which can participate in a Blockchain-based market for energy trading with the roles of prosumer and consumer. Actors propose their energy costs due to their resources and capabilities, which leads to a competitive energy market. Therefore, the blockchain can facilitate energy trading and data transactions while guaranteeing transaction security, improving transparency, and easing financial transactions. The data flow between prosumers and consumers without human involvement [108].

A significant body of research has studied and proposed Blockchain-based networks to enable energy trading and related transactions. For example, the authors in [109,110] have studied renewable energy developments, including wind and solar power, in smart homes. They proposed to use Blockchain technology to trade energy between smart homes and increase their financial benefits.

Additionally, Kang et al. [111] investigated energy trading between smart homes using Blockchain technology. Smart homes store energy in energy storage, and consumer nodes equipped with miners monitor energy consumption. Therefore, if the stored energy is not sufficient to power the loads, the additional energy is purchased from the prosumer nodes by having Ethereum smart contracts manage the energy trade according to the following rules:

- Energy trading conditions should be specified to permit energy exchange between prosumers and consumers.
- Prosumers and consumers should determine price and exchange procedures beforehand, and the prosumers should complete the proof-of-work.
- If a consumer's stored energy falls below a certain level, her home miners should send energy trading requests to appropriate prosumers.
- Energy trading takes place when consumer requirements match prosumer conditions.

It is widely expected that the global demand for clean and stable energy sources will continue to increase over the coming decades. With the recent penetration of distributed resources into energy trading, communities can take advantage of cheaper electricity prices while supporting green energy locally. However, this poses new challenges mainly in the auction process to ensure individual rationality and economic efficiency, mitigated with the help of Blockchain technology. Lin et al. [112] studied the application of P2P energy trading and Blockchain technology in the development of photovoltaic (PV) units. They proposed a P2P energy trading model using a Discriminatory and Uniform k-Double Auction (k-DA). They verified the financial benefits of the proposed model through simulation.

The authors in [113] have exploited the opportunities offered by Blockchain in building the prosumer group in the context of P2P energy trading. They proposed a Blockchain-assisted adaptive model, named SynergyChain, to improve the scalability and decentralization of the prosumer aggregation mechanism in the context of P2P energy trading. The model showed that the coalition of multiple energy prosumers through aggregation outperformed the case in which individual prosumers participated in the energy market. They implemented a reinforcement learning module that decides whether the system should act as a group or independently. The complete analysis using the hourly energy consumption dataset showed a substantial improvement in system performance and scalability compared to centralized systems. Furthermore, their system worked better with the learning module, in terms of cost-effectiveness and performance, than without it. In another work [114], the authors proposed FederatedGrids, a platform that uses federated learning and Blockchain for P2P energy trading and sharing. It creates a collaborative environment that maintains a good balance between the participants of the different micro-grids. The blockchain helps to ensure trust and privacy between all participants. Smart contracts and federated learning allow the platform to predict future energy production and system load, thus allowing prosumers to make optimal decisions related to their energy sharing and exchange strategies.

Smart cities can significantly benefit from Blockchain capabilities to maximize energy efficiency and improve energy resource planning and management. Blockchain-based networks can directly connect multiple energy resources and household appliances, thereby providing users with high-quality, inexpensive, and efficient energy [115]. They can help regulate the distribution and transformation of energy in smart grids, bringing more transparency to energy transactions [116].

7. Edge AI and Blockchain Convergence

Several research efforts studied the convergence between Blockchain and edge computing without considering or giving details about the AI component at the edge [68,120–126]. However, as AI techniques further proliferate at the edge in various smart city systems (healthcare, transportation, power grid, etc.) and ensure huge benefits, they also introduce increased privacy and security threats. Therefore, robust security measures are needed to protect data and AI models at the edge. These measures include security features for data storage, encryption, data dissemination, and key/certificate management. As we discussed earlier, edge AI and Federated Learning are emerging technologies for building smart latency-sensitive services at the edge while protecting data privacy. On the other hand, Blockchain technology shows significant possibilities with its immutable, distributed, and auditable data recording for safeguarding against data breaches in a distributed environment.

The convergence between Blockchain and AI is attracting much interest in academia and industry to solve many challenging problems to manage effectively a few years ago. The characteristics of blockchain technology and its decentralized architecture, which we discussed in Section 4.1, can help build robust and secure AI applications. Blockchain attributes of immutability, provenance, consensus, and transparency enable secure sharing of AI training data and pre-trained AI models using a permanent and unalterable record of AI data and models. Secure sharing of AI data and models is associated with increased trust in AI models and the data they work with.

More and more research efforts study the convergence of edge AI and Blockchain. Table 3 summarizes those efforts. Jiang et al. [127] argued that conventional approaches for object detection that rely on classic and connectionist AI models are not adequate to support the large-scale deployment of the Visual Internet of Vehicles (V-IoV). On the other hand, edge intelligence, which integrates edge computing and AI, demonstrated a balance between efficiency and computational complexity. Edge AI involves training learning models and analyzing V-IoV data, reducing latency, improving time to action, and minimizing network bandwidth usage. Object detection tasks can be offloaded and executed on Roadside Units (RSUs) using the edge's storage and computing power capabilities. The authors proposed an edge AI framework for object detection in the V-IoV system and a You Only Look Once (YOLO)-based abductive learning algorithm for robust and interpretable AI. The abductive model combines symbolic and connectionist AI to learn from data. Additionally, Blockchain complements edge AI with security, privacy, reliability, scalability, and enables model sharing.

Lin et al. [128] consider that extracting knowledge, such as classification models, detection, and predictions from physical environments, from sensory data, could be achieved by introducing edge computing and edge AI into the Internet of Things. Since multiple nodes with heterogeneous Edge AI devices generate isolated knowledge, collaboration and data exchange between nodes are essential to building intelligent applications and services. The authors proposed a P2P knowledge marketplace to make knowledge tradable in edge AI-enabled IoT and a knowledge consortium blockchain for secure and efficient knowledge management and exchange in the market. The blockchain consortium includes a cryptographic knowledge coin, smart contracts, and a consensus mechanism as proof of trade.

Rahman et al. [129] addressed in their work the challenge of bringing intelligent and cognitive processing to the edge where the massive amount of IoT data are generated and processed by mobile edge computing (MEC) nodes. Key transactions are anonymized and securely recorded in the blockchain, where big data are securely stored in the decentralized off-chain solutions with an immutable ledger. Qiu et al. [130] proposed AI-Chain, a Blockchain-based edge intelligence for Beyond Fifth-Generation (B5G) networks. AI-Chain is an immutable and distributed record of local learning outcomes that can lay a new foundation for sharing information between edge nodes. Leveraging the portability of deep learning, each node at the edge trains neural network components and applies AI-Chain to share its learning results. This process dramatically reduces the wastage of computing power and improves the learning power of the edge node through the learning power of other edge nodes. Du et al. [131] reviewed the existing literature on Blockchain-enabled edge intelligence in the IoT domain, identified emerging trends, and suggested open issues for further research, including transaction rejection, selfish learning, and fork issues. Fork problems arise when edge nodes disagree on the same learning model and alternative chains (i.e., forked chains) emerge.

As a use case of the convergence of Blockchain and edge AI, we consider in the following some efforts in the context of smart mobility. IoV is an emerging technology that has the potential to alleviate traffic problems in smart cities. In an IoV network, the vehicles are equipped with modern communication and sensing technologies that allow the sharing and exchanging of data between the vehicles and the RSUs. The massive volume of data captured by vehicle sensors, including GPS and RADAR, favors data-driven AI models. Attacks against vehicles using polymorphic viruses cannot be easily recognized and predicted because their signatures continually change. The centralized ML paradigm is evolving towards a more decentralized and distributed learning framework, especially in a federated learning setup, to accommodate the increase in likely privacy and security issues.

Several works proposed federated learning-based solutions for the IoV [132–135]. Although federated learning provides incredible security to learning structures, it faces several other security issues as it operates based on a centralized aggregator. For model training, federated learning relies on local workers, who may be vulnerable to cyber intrusions. If a local model is attacked, it can mislead other models, and therefore the global update is erroneous. Because of the likelihood of such possible attacks in federated learning, Blockchain is used with federated learning to give a decentralized arrangement to control incentives and reliably ensure security and protection. Due to the promising capability of federated learning, especially for building an ITS, and the requirement to alleviate potential attacks, some Blockchain-enabled federated learning schemes for IoV have been proposed over the last few years.

The authors in [136] proposed a framework for knowledge sharing in IoV based on a hierarchical federated learning algorithm and a hierarchical blockchain. Vehicles and RSUs learn surrounding data through machine learning methods and share learning knowledge. The use of blockchain framework targets large-scale vehicle networks, and the hierarchical federated learning algorithm aims to meet the distributed model and privacy requirements of IoVs. They modeled knowledge sharing as a trading market process to drive sharing behaviors and formulated the trading process as a multi-leader, multi-player game. The authors stated that their simulation results showed that the proposed hierarchical algorithm improves sharing efficiency and learning quality and achieves approximately

10% more accuracy than conventional federated learning algorithms. RSUs reach optimal utility during the sharing process. Moreover, the blockchain-enabled framework effectively protects against malicious workers during the sharing process.

The authors in [137] proposed a blockchain-enabled federated learning framework to improve the performance and privacy of autonomous vehicles. The framework facilitates the efficient communication of autonomous vehicles, where on-board local learning modules exchange and verify their updates in a fully decentralized manner without any centralized coordination by leveraging the blockchain consensus mechanism. The framework extends the reach of its federation to untrustworthy public network vehicles via a validation process of local training modules. By offering rewards proportional to the usefulness of data sample sizes, the framework encourages vehicles with immense data samples to join the federated learning.

In the IoV, exchanging messages between vehicles is essential to ensure road safety, and broadcasting is generally used for emergencies. To solve the low probability of receiving broadcast messages in high-density and vehicle mobility scenarios, the authors of [138] proposed a blockchain-assisted federated learning solution for message broadcasting. Similar to the Proof-of-Work (PoW) consensus used in several blockchains, vehicles compete to become a relay (minor) node by processing the proposed Proof-of-Federated-Learning (PoFL) consensus embedded in the smart contract of the blockchain. The Stackelberg game further analyzes the business model to incentivize vehicles to be involved in federated learning and message delivery. The authors stated that their solution outperforms the same solution without blockchain, allowing more vehicles to upload their local models and yield a more accurate aggregated model in less time. It also outperforms other blockchain-based approaches by reducing the consensus time by 65.2%, improving the message delivery rate by at least 8.2%, and more effectively maintaining the privacy of neighboring vehicles.

Doku et al. [139] proposed a federated learning framework called iFLBC to bring artificial intelligence to edge nodes through a shared machine learning model powered by Blockchain technology. Their motivation is to filter relevant data from irrelevant data using a mechanism called Proof of Common Interest (PoCI). The relevant data of an edge node are used to train a model, which is then aggregated with models trained by other edge nodes to generate a shared model stored on the blockchain. Network members download the aggregated model to provide intelligent services to end-users.

Table 3. Summary of edge AI and Blockchain convergence literature review.

Ref.	Focus Area	Edge AI Use Case	Blockchain Use Case
[127]	Knowledge management and exchange in the Internet of Vehicles (IoV)	Object detection in and a YOLO-based abductive learning algorithm for robust and interpretable AI.	Security, privacy, reliability, scalability, and model sharing.
[128]	Making Knowledge Tradable in Edge-AI Enabled IoT.	Extracting knowledge, such as classification models, detection, and predictions from physical environments and sensory data at the edge. A P2P knowledge marketplace to make knowledge tradable in edge AI-enabled IoT	A knowledge consortium blockchain for secure and efficient knowledge management and exchange in the market. The blockchain consortium includes a cryptographic knowledge coin, smart contracts, and a consensus mechanism as proof of trade.
[129]	Blockchain and IoT-Based Cognitive Edge Framework for Sharing Economy Services in a Smart City	Bringing intelligent and cognitive processing to the edge where the massive amount of IoT data are generated and processed by mobile edge computing (MEC) nodes.	Key transactions are anonymized and securely recorded in the blockchain, where big data are securely stored in the decentralized off-chain solutions with an immutable ledger.

Table 3. *Cont.*

Ref.	Focus Area	Edge AI Use Case	Blockchain Use Case
[130]	Blockchain Energized Edge Intelligence for Beyond 5G Networks	AI-Chain, a Blockchain-based edge intelligence for B5G networks. Each node at the edge trains neural network components and applies AI-Chain to share its learning results.	An immutable and distributed record of local learning outcomes that lays the foundation for sharing information between edge nodes.
[139]	Edge Intelligence using a federated learning Blockchain network	iFLBC, a federated learning framework called to bring AI to edge nodes through a shared machine learning model. powered by Blockchain technology. The relevant data of an edge node is used to train a model, which is then aggregated with models trained by other edge nodes to generate a shared model.	The shared model is stored on the blockchain. Network members download the aggregated model to provide intelligent services to end-users.
[136]	Knowledge sharing in IoV	Hierarchical federated learning. Vehicles and RSUs learn surrounding data through machine learning methods and share learning knowledge. Aims to meet the distributed model and privacy requirements of IoVs.	Hierarchical blockchain. Knowledge sharing is modeled as a trading market process to drive sharing behaviors. The trading process is formulated as a multi-leader, multi-player game.
[137]	Federated Learning With Blockchain for Autonomous Vehicles.	Federated learning framework. The framework extends the reach of its federation to untrustworthy public network vehicles via a validation process of local training modules.	On-board local learning modules exchange and verify their updates in a fully decentralized manner without any centralized coordination by leveraging the blockchain consensus mechanism.
[138]	Messages dissemination in the IoV	Blockchain-assisted federated learning solution for message broadcasting. The Stackelberg game further analyzes the business model to incentivize vehicles to be involved in federated learning and message delivery.	Vehicles compete to become a relay (minor) node by processing the Proof-of-Federated-Learning (PoFL) consensus embedded in the smart contract of the blockchain.

8. Open Research Issues

The research initiatives reported above represent attempts to mitigate the challenges of implementing edge AI and Blockchain in two key areas of smart cities, smart mobility and smart energy. However, there remain unresolved challenges. This section examines four potential prospective research trends for future implementation.

- **Collaboration and data exchange.** As we described earlier, since multiple nodes with heterogeneous edge devices generate isolated knowledge, collaboration and data exchange between nodes are essential to building intelligent applications and services for smart mobility and smart energy. Storing, sharing, querying, and exchanging data training models require additional security and privacy measures. Blockchain technology helps meet these requirements. However, edge devices with limited storage may not be able to store the training model or the blockchain structure that grows as transaction blocks are added to the blockchain. Moreover, it is common for edge devices to store distributed ledger data that are not even useful for their transactions. Therefore, cutting-edge blockchain-specific equipment or platforms to support decentralized blockchain data storage are required.

- **Impact of edge connections on Blockchain-enabled smart mobility.** In a smart mobility scenario, edge devices on connected vehicles, for example, are often connected to other edge devices or cloud servers through unreliable wireless channels. As we discussed earlier, Blockchain can facilitate communication between connected vehicles and the road infrastructure by considering data exchange requests as transactions to be stored and retrieved from a blockchain database. Due to the inevitable network delays, a vehicle participating in the blockchain may not receive the most recent block. It may then create an alternative chain that branches off the main chain. This problem is known as the forking problem. It can also arise when edge nodes disagree on the same learning model and forked chains emerge. Such forking reduces throughput because only one chain survives, ultimately, while all other blocks in different chains are removed. Further research in this area is needed.
- **Prediction of future energy production and system load.** In P2P smart energy trading scenarios, the decentralization of prosumers brings many issues. Blockchain helps to ensure trust and privacy between all players in the energy market. Smart contracts and learning models at participating nodes should help predict future energy production and system load, allowing prosumers to make optimal decisions about sharing and pricing their energy. Further research on federated learning models for energy trading and pricing is needed.
- **Energy efficiency.** Incorporating AI in edge devices is challenging because of the power-hungry features of deep learning algorithms, such as convolutional neural networks (CNNs). Therefore, energy efficiency is a critical issue for edge AI applications. Some research efforts investigated the usage of reservoir computing as an alternative, which promises to provide good performance while exhibiting low-power characteristics [140]. Additionally, with the growing calls for the application of rigid environmental standards and the rapidly rising energy costs, smart cities increasingly take the energy efficiency issue more seriously. However, some Blockchain consensus mechanisms such as PoW (Proof of Work) are computationally expensive as blockchain nodes perform complex computations to mine the next block. PoW is not an energy-efficient approach and consumes a large amount of electricity due to computation redundancy. Researchers are developing alternative less computationally expensive consensus mechanisms for blockchain systems. Although highly promising, these consensus mechanisms are still in their infancy and suffer from scalability issues, and their security has not been rigorously investigated. Therefore, further research is needed concerning the design of energy-efficient edge AI applications and consensus mechanisms for blockchain systems.

9. Conclusions

Smart cities face several challenges due to population growth and migratory waves. This article examines the current and potential contributions of edge AI and Blockchain technology in coping with smart city challenges through the lens of sustainability in two main areas, which are smart mobility and smart energy. It contributes to the sustainability literature by identifying and bringing together recent research on edge AI and Blockchain, highlighting their positive impacts and potential implications on smart cities.

This review highlights the existing and potential convergence of edge AI and Blockchain. It shows that edge AI and Blockchain technology can help address the problem of traffic congestion and management by automating the detection, counting, and identification of vehicle speeds. Furthermore, these technologies can help establish trustworthy communications and energy trading between vehicles and reliable and secure distributed smart energy management. Finally, this article discusses potential research trends for future implementations of edge AI and Blockchain to provide innovative solutions in smart mobility and smart energy. It is expected that this review will serve as a guideline for future research on the adoption of edge AI and Blockchain in other areas of smart cities.

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