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Review

Key Technologies for 6G-Enabled Smart Sustainable City

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Abstract: With the advancement of information and communication technologies (ICTs), the way we live and communicate with each other is changing rapidly. As urban environments continue to evolve, the smart sustainable city (SSC) has sparked considerable attention. We are hoping for a new era in which numerous devices and machines including vehicles, sensors, and robots are all connected to communicate, respond, and operate in real time. The next-generation communication system, the sixth generation (6G), is expected to play a crucial role in improving the efficiency of urban operations and services. In this paper, we first provide the recent trends and key features of standardization in the SSC. To make the future SSC, we highlight key candidate technologies of 6G such as non-terrestrial networks, advanced mobile edge computing, vision-aided wireless communication, artificial intelligence (AI)-based wireless communication, and integrated sensing and communication. We put forth the main technical challenges given to each prime technology along with the potential benefits to pave the way for 6G-enabled SSC. We further address how the potential benefits of prime technologies enable various urban practice cases for 6G-enabled SSC.

Keywords: smart sustainable city; 6G; non-terrestrial networks; vision-aided wireless communication; mobile edge computing; deep learning; integrated sensing and communication

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1. Introduction

Recently, we are now seeing that urban environments continue to evolve with the advancement of information and communication technologies (ICTs). Nowadays, many cities are getting smarter with the use of ICTs, making traditional services and infrastructure more efficient. The smart city market is expected to grow from the United States dollar (USD) 511.6 billion in 2022 to USD 1024.4 billion by 2027, at a compound annual growth rate (CAGR) of 14.9% [1]. One important expectation in the future generations is that sustainability will be more important in improving the quality of our lives along with the protection of our ecosystem [2]. The smart sustainable city (SSC) has sparked significant interest in continuously improving the quality of life and efficiency of urban operations and services [3–5]. Despite many technological promises, there are still many challenges in realizing an envisioned future SSC where humans and machines experience a hyper-connected society. In the hyper-connected society, it is expected that intelligent things such as urban air mobility (UAM), internet-of-things (IoT) sensors, and robots will be seamlessly connected in future wireless networks without limitations on the data rate, latency, and coverage.

Wireless communication is an important part of social infrastructure among various ICTs. Internet-enabled mobile services have become omnipresent in our daily lives. In general, mobile communication systems have evolved approximately 10 years since the first generation (1G) was introduced in the 1980s. Note that the fifth generation (5G) was commercialized in 2019 and 5G services are now active in more than 90 countries. It is worth noting that 5G is creating an ecosystem for business innovation that involves smart cities. With the advent of 5G technologies, both academia and industry are doing research activities for the sixth generation (6G) [6,7]. 6G networks are considered one of the prime candidates to enable SSC to facilitate the emergence of new applications and services [8,9]. In this paper, we introduce 6G key candidate technologies that could be key enablers to realize future SSC.

The primary goal of this paper is to provide an up-to-date overview of various aspects related to the 6G-enabled SSC. These include standardization features, key enabling technologies, and potential benefits along with future research directions. Through this paper, we hope that it can be an opportunity to outline a way forward to realize a hyper-connected society and to target specific goals to achieve it by 6G prime technologies in the near future. The main contributions of this paper are summarized as follows:

- We highlight key features of standardization for SSC from an ICT perspective. In this paper, we articulate the importance of ICT infrastructure and candidate ICT technologies for 6G-enabled SSC.
- We put forth the prime technologies that can boost the evolution of SSC. Upon this categorization, we account for the main technical challenges given to each prime technology along with the potential benefits to pave the way for 6G-enabled SSC.
- We shed light on urban practice cases for 6G-enabled SSC. We address how the potential benefits of prime technologies enable various scenarios and applications.

The remainder of this paper is organized as follows. In Section 2, we present the definition of a smart city and then provide the smart city policies of various countries. In Section 3, we present smart city standards based on ICTs. In Section 4, we provide a brief explanation of the evolution of mobile communication systems and then investigate the key technologies for a 6G-enabled SSC. In Section 5, we provide our concluding remarks.

2. Recent Trend of Smart Sustainable City

As greenhouse gas emissions increase globally, cities are currently responsible for more than 70% of global energy consumption and greenhouse gas emissions. Furthermore, due to continuous urbanization, it is expected that the urban population in 2021 (i.e., 56% of the total population) will reach 68% of the total population by 2050 [3]. However, urbanization leads to various problems, such as environmental pollution, inefficient resource utilization, traffic congestion, and social inequality. To overcome these challenges, it is necessary to develop a more advanced urban model capable of surpassing the limitations of current city infrastructure.

A smart sustainable city refers to an innovative city where ICTs are used primarily to improve the quality of life and efficiency of city operations and services, while ensuring the need for current and future generations in economic, social, environmental, and cultural terms [4]. Moving to the post-pandemic world, the way we live and communicate with each other has changed rapidly. It is noted that people all over the world use various form factor devices such as smartphones, smart watches, augmented reality (AR) glasses, and virtual reality (VR) headsets to join online meetings and connect with their family and friends. Consequently, it is necessary for current cities to get smarter by exploiting innovative technologies. The emergence of smart cities is growing and has attracted increasing interest from industry. As shown in Figure 1, the amount of revenue from global smart city projects is expected to grow from USD 43.7 billion in 2020 to USD 165.8 billion in 2028 [5].

Within the last decade, several countries have established many smart city policies. Smart city policies are implemented in various ways by countries, but the use of innovative technologies and the implementation of advanced services are commonly considered to address economic and environmental challenges in cities. In Table 1, we present some smart city policies from various countries.

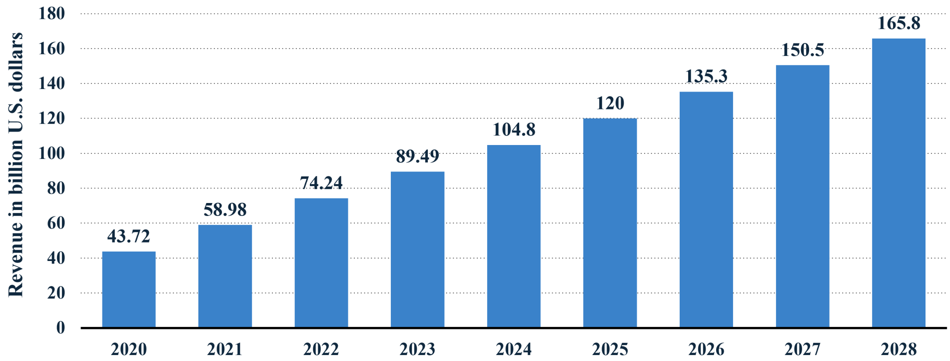

Figure 1. Projected revenue in the global smart city from 2020 to 2028.

Recently, the draft of the international mobile telecommunications (IMT)-2030 (6G) recommendation has been completed and six major usage scenarios have been defined [10]. Three of these usage scenarios are an advanced version of the IMT-2020 (5G) usage scenarios (i.e., enhanced mobile broadband (eMBB), massive machine-type communication (mMTC), ultra-reliable and low-latency communication (URLLC)) [11]. That is, immersive communication, massive communication, and hyper-reliable and low-latency communication (HRLLC). Three new usage scenarios include ubiquitous connectivity, AI and communication, and integrated sensing and communication. With the development of 6G communication systems, 6G candidate technologies such as non-terrestrial networks (NTN), artificial intelligence (AI), and integrated sensing and communication (ISAC) can be exploited in upcoming policies for SSC.

Table 1. Smart city policies in various countries.

Country	Contents
China	(2014) China's new urbanization strategy: Suggest the direction of smart city development via the application of ICTs (2016) 13th 5-year National informatization plan: set new smart city evaluation indicators and implementation goals (2021) Government work report: emphasize technology industry innovation, digital government construction, and industry intelligence
Europe	(2010) Energy 2020: Promote smart cities as one of the means to achieve the goals of reducing greenhouse gas emissions and expanding renewable energy (2013) Super city: Utilize high-tech services to solve regional problems and aim to make the city smart using ICT (2014–2020) Horizon 2020: Implement the smart cities and communities program for the establishment of a smart city infrastructure
Japan	(2016) Society 5.0: Establish a society that integrates physical space and cyberspace (2020) National strategic special zone system: Make the entire city designated as a super city by using advanced services
Republic of Korea	(2007–2013) U-City: Provide a comfortable and convenient environment by saving energy and reducing carbon emissions (2018–2022) Smart city innovation growth engine R&D: Aim to implement a data-based smart city innovation model for sustainable growth

Table 1. *Cont.*

Country	Contents
United States of America	(2015) Smart city initiative: Establish policies to solve various local problems and create new solutions for smart cities (2019) National spectrum Strategy: Plan to invest heavily in future technologies such as 5G, AI, advanced manufacturing, and quantum information science (2021) IoT strategy: Expand the approach by presenting an IoT framework based on the New York IoT strategy

3. Standardization of Smart Sustainable City

In this section, we explain the smart city standards from the ICT perspective and then briefly discuss representative standards of candidate ICT technologies for SSC.

3.1. ICT Standardization for Smart Sustainable City

The technical committee (TC) on smart cities, ISO/TC 268 [12], promotes standardization for smart cities, focusing on fostering sustainability within cities. Furthermore, ISO/IEC joint technical committee (JTC) 1 [13] has established working group (WG) 11 to investigate the standardization of ICT in smart cities. Within the ISO 37106 [14] standard, ISO/TC 268 has defined a smart operating model to implement a vision for a sustainable future. This model enables strategies and policies to operate more rapidly and reduce delivery risks. The new operation model focuses on citizen-centric and collaborative approaches, while the traditional city operation was inefficient and uncoordinated. In addition, this standard encompasses details of the delivery principles and risk management for the transition to a smart city operating model.

ISO/IEC JTC 1 WG 11 focuses on standardizing the platform for evaluating performance metrics in smart city data processing, especially from the ICT perspective. ISO/IEC 30146 [15] describes a set of evaluation indicators related to the adoption and use of smart city ICT, providing detailed information on measurement methods. This facilitates understanding smart city performance from an ICT perspective and enables the assessment of the city's ICT readiness. Within the standard, smart city ICT indicators are categorized into performance indicators and capability indicators. Performance indicators encompass citizen service, efficient governance, and livable environment, while capability indicators include smart facilities, information resources, and cybersecurity.

ITU-SG 20 [16] focuses on the standardization of key performance indicators (KPIs) to evaluate the use of ICT. Additionally, it focuses on standardizing IoT technologies for the establishment and operation of smart cities, aiming to address urban development challenges. ITU-T Y.4900/L.1600 [17] provides an overview of KPIs for SSC. These KPIs are categorized into six dimensions: (1) ICT, (2) environmental sustainability, (3) productivity, (4) quality of life, (5) equity and social inclusion, and (6) physical infrastructure, with each dimension comprising sub-dimensions. ITU-T Y.4901/L.1601 [18] covers how to evaluate the use of ICT and the utilization rate for each sub-dimension of the KPIs. Specifically, each sub-dimension incorporates the core indicator applicable to all cities, as well as the additional indicator that can be selected based on factors such as the city's economic strength, population, and geography. For example, Networks and access, a sub-dimension of the ICT dimension, includes the availability of wireless broadband subscriptions (core indicator) and the availability of WiFi in public areas (additional indicator) [18].

ITU-T Y.4904 [19] introduces the SSC maturity model (SSC-MM) to identify the development or progress level of a specific city in terms of smart sustainable development. To measure the achievement of sustainable development goals (SDG), there are five maturity levels categorized into three dimensions: (1) economic, (2) environmental, and (3) social. The main topics for each dimension are shown in Table 2, and the maturity levels of the ICT infrastructure topic in the economic dimension are shown in Table 3.

Table 2. Main topics of the three maturity dimensions.

Dimension	Main Topics
Economic	ICT infrastructure, Innovation, Employment, Trade (e-Commerce and export/import), Productivity, Physical infrastructure (water supply, electricity, health infrastructure, transport, road infrastructure, buildings and urban planning and public space), Public sector.
Environmental	Air quality, Water and sanitation, Noise, Environmental quality, Biodiversity, Energy.
Social	Education, Health, Safety (disaster relief, emergency, public safety and ICT), Housing, Culture, Social inclusion.

Table 3. Maturity levels of the ICT infrastructure.

Maturity Level	Contents
1	Have a clear roadmap or strategic plan for ICT-enabled SSC development.
2	Align SSC initiatives with the city's SSC strategy to support operations and activities for SSC development.
3	Deploy specific SSC initiatives and provide SSC services based on ICT infrastructures.
4	Integrate systems and data to provide SSC services (Advanced technologies such as IoT, cloud computing, and AI can be applied).
5	Improve the efficiency of the effectiveness to keep contributing to the long-term SSC vision of the city.

3.2. Standardization of Candidate ICT Technologies for Smart Sustainable City

For smart cities, ICT technologies such as AI, edge computing, and IoT are being employed in various sectors. To ensure seamless interoperability between ICT devices, the International Telecommunication Union Telecommunication Standardization Sector (ITU-T) is establishing standards that specify the requirements, frameworks, operations, and management systems for ICT technologies, enabling the development of advanced wireless networks. Table 4 presents the representative standards of the candidate ICT technologies for SSC.

Table 4. Candidate ICT technologies for SSC.

6G Technology	Main Contents
Cloud Computing	[ITU-T Y.3531] provides cloud computing requirements for machine learning as a service, which addresses requirements from use cases [20]; [ITU-T Y.3532] provides an overview of cloud-native applications and addresses functional requirements of platform as a service for cloud-native applications via various use cases [21].
Edge Computing	[ITU-T Y.3123] specifies the framework of edge computing capability exposure for IMT-2020 networks and beyond [22]; [ITU-T Y.3137] specifies the technical requirements for supporting application addressing in edge computing for future networks including IMT-2020, and also proposes new requirements towards fixed mobile convergence architecture for future networks [23].

Table 4. *Cont.*

6G Technology	Main Contents
Big Data	[ITU-T Y.3602] describes operations for big data provenance and provides the functional requirements for a big data service provider to manage big data provenance [24]; [ITU-T Y.3603] describes the general concept of metadata and its utilization in a big data ecosystem and provides requirements and a conceptual model of metadata for the data catalog [25].
IoT	[ITU-T Y.4210] specifies requirements for a universal communication module that is an important part of mobile IoT devices [26]; [ITU-T Y.4212] specifies the requirements and capabilities of network connectivity management in the IoT [27].
AI	[ITU-T M.3080] provides a framework of AI-enhanced telecom operation and management (AITOM) and describes the functional framework of AITOM to support telecom operation management [28]; [ITU-T M.3384] provides definitions, classifications, object selection, and an automatic evaluating mechanism for the evaluation of the intelligence levels of AITOM systems [29].

4. Key Candidate Technologies for Future SSC

The standardization features and policies for SSC presented in the previous sections pose various challenges in the development of 6G-enabled SSC. In this section, we provide a brief explanation on the evolution of mobile communication systems and then introduce the prime candidate technologies that could be key enablers in the realization of 6G-enabled SSC.

4.1. Evolution of Mobile Communication Systems

After the introduction of the first analog communication in the 1980s, a new generation of communication systems has been introduced almost every decade. The first generation refers to analog communication capable of only voice calls. The second generation (2G) refers to the digital communication era that allowed for data transmission, such as email and text messages. The third generation (3G) refers to the multimedia communication era that enabled various services such as video and digital music via mobile phones. In the fourth generation (4G), long-term evolution (LTE) provided maximum transmission speeds of up to 1 Gbps in the downlink. It is worth noting that LTE brings the popularization of smartphones and enables high-definition videos and network gaming even while on the move.

Recently, 5G was commercialized globally in 2019 [11]. The fifth generation can support transmission speeds of up to 20 Gbps, which is 20 times faster than 4G. It is well known that 5G has three key usage scenarios: eMBB, mMTC, and URLLC. Key features of 5G include the use of mmWave bands such as 28 GHz and network slicing, where each slice of a network can be employed for different purposes. Further, 5G imposes on the integration of mobile communication with vertical industries such as smart factories, connected vehicles, and smart cities.

Sixth-generation mobile communication is expected to be commercialized around 2030. Considering the trend of innovative technology adoption in mobile communication across several generations, it is anticipated that 6G will offer significantly enhanced performance and groundbreaking services compared to 5G. In June 2023, ITU-R WP 5D completed the draft of the new recommendation for IMT-2030 (6G) [10]. In the 6G vision, there are six usage scenarios in total. Among these, three usage scenarios are extended versions of the eMBB, mMTC, and URLLC, and also three new usage scenarios are introduced. These include (1) immersive communication, (2) massive communication, (3) hyper-reliable and low-latency communication (HRLLC), (4) ubiquitous connectivity, (5) integrated sensing and communication, and (6) AI and communication. To make these scenarios a reality, we need to support NTN as well as the terrestrial network (TN) for a wide range of coverage and mobility. In addition, by integrating sensing and AI with enhanced communication, the 6G network is expected to improve sensing accuracy, detection probability, and AI-related inference capabilities. This will boost productivity and enhance living standards in 6G-enabled SSC.

4.2. Prime Technologies for SSC

In this section, we put forth prime technologies that could be key enablers to realize 6G-enabled SSC. We highlight five prime technologies, namely, AI-based wireless communication, advanced mobile edge computing, non-terrestrial networks, vision-aided wireless communication, and integrated sensing and communication, as represented in Table 5. It is expected that the market sizes for five prime technologies will reach USD 1345.2 billion [30], USD 111.3 billion [31], USD 23.5 billion [32], USD 21.3 billion [33], and USD 4.2 billion [34], respectively, by around the year 2030. The relative importance of the five prime technologies can be assessed using the analytic hierarchy process (AHP) method [35–37]. This involved considering multiple criteria including market size, applicability, potential for growth, security, and user convenience for the comparison. Through the AHP method, we obtain the relative importance of core technologies in smart cities: (1) AI, (2) Advanced MEC, (3) NTN, (4) VAWC, and (5) ISAC, aligning with their market sizes. In the rest of this section, we discuss the key technical challenges, potential benefits, and urban practice cases for each prime technology. To this end, we have investigated much of the literature since 2017.

Table 5. Five prime technologies for 6G-enabled SSC.

Prime Technology	Key Features	Possible Contribution to Future SSC
AI-Based wireless communication	– Transmission performance improvement [38] – Overcoming outdated CSI [39] – Increasing energy efficiency [40]	– Effective electricity supply and management [41] – Weather prediction from historical data [41]
Advanced mobile edge computing	– Achieving low latency via decentralized structure [42] – High QoS achievement [43] – Overload mitigation [43]	– Real-time immersive service [42] – Enhanced privacy security [44]
Non-terrestrial networks	– Reducing coverage holes [45] – Frequency co-existence [46]	– RIS-aided zero-coverage hole networks [47] – UAM transportation service [46]
Vision-aided wireless communication	– Environmental awareness [48] – Energy conservation [49]	– UAV communication systems [50] – Traffic congestion mitigation [51]
Integrated sensing and communication	– High-resolution sensing [52] – Simultaneous imaging and localization [53]	– Enabling autonomous vehicles [53] – Traffic accident detection [54]

4.2.1. AI-based Wireless Communication

The architecture of future broadband communication systems is becoming more complex to support a variety of heterogeneous wireless services in the SSC. Furthermore, the large number of antennas and the high frequency band in next-generation broadband systems require reevaluating the transmission and reception frameworks in current cellular networks. To address technical challenges, various AI technologies, such as supervised learning, unsupervised learning, and reinforcement learning, are currently being employed in wireless communication systems [55,56]. AI-based communication systems are thought to be a promising candidate that can provide throughput enhancements for 6G networks and introduce new broadband services, distinct from conventional cellular networks.

In 6G networks, the role of MIMO technology is expected to become more prominent [38,57]. The large number of antennas makes channel state information (CSI) acquisition more complex in extremely large-scale MIMO systems at high frequencies. To address these technical challenges, the existing compressed sensing (CS) method based on sparsity-dependent assumptions needs to be reevaluated to fully exploit deep learning (DL) techniques. Consequently, DL-based CSI feedback methods, such as CsiNet (proposed in [58]), have attracted attention to improve its performance. In particular, CsiNet utilizes an encoder–decoder network structure to compress CSI and reduce the feedback overhead.

By applying AI techniques, as shown in Figure 2, the CSI acquisition architecture can be redesigned to dramatically improve channel estimation and prediction performance. Previous studies focus on the aim of enhancing wireless capabilities [59–63]. For example, channel estimation algorithms based on recurrent neural network (RNN) have been proposed to address the channel estimation problem in fast-changing channel environments, such as UAM and LEO wireless channels [64]. In addition, a DL-based satellite channel predictor, consisting of a long-term short memory (LSTM) unit, has been proposed to eliminate the negative effects of outdated CSI in LEO satellite massive MIMO systems [65].

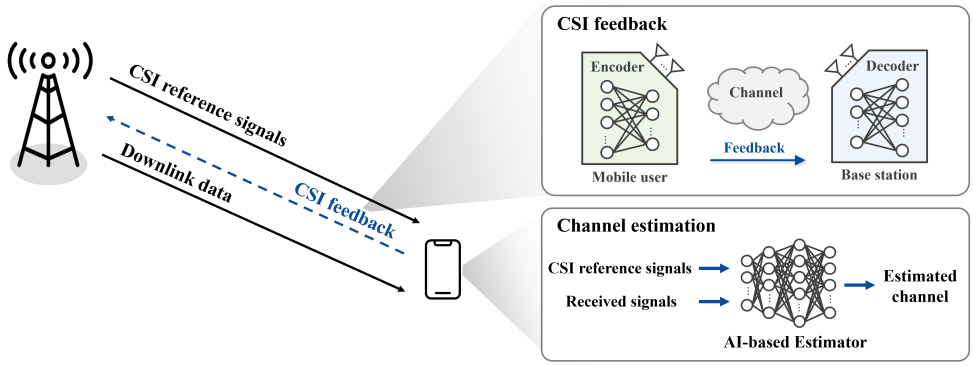

Figure 2. Illustration of AI-based channel estimation and CSI feedback.

However, in order to effectively enable AI-powered SSC, the following technical challenges must be addressed:

Training data: Acquiring sufficient training datasets is crucial because deep learning systems enhance channel estimation performance via dataset learning. However, in practical wireless communication scenarios, acquiring a large number of training samples is challenging due to the high cost of the time and frequency resources utilized for dataset training.

High-speed scenario: High-mobility scenarios in SSC pose challenges to 6G networks in effectively delivering new applications and services. For example, the base station must accurately reconstruct the CSI and even predict future CSI to mitigate channel aging issues. However, there is insufficient research on DL-based feedback and CSI prediction techniques that effectively address scenarios with fast channel changes. A DL-based feedback scheme should be carefully designed to ensure effective communication, even in highly mobile environments.

Generalization: In DL-based wireless communications, neural networks undergo training using CSI samples that adhere to a specific distribution of channel environments. However, the stability of channel environments is not guaranteed because UEs do not always remain in a fixed cell and frequently move to other cells. The communication systems, developed based on specific channel parameters, experience significant performance degradation when the channel changes rapidly. The DL-based CSI feedback architecture needs to be carefully designed to ensure flexibility in coping with various channel and network conditions.

Balancing complexity and performance: The high complexity and increased computational demands of DL-based communication systems make them unsuitable for UEs with limited computational power. Although neural network compression techniques can reduce complexity, this still poses challenges for small-scale devices with limited computational power, such as IoT sensors that are essential for building 6G smart cities. Addressing the tradeoff between performance and complexity is vital for enabling computationally cost-effective AI solutions in SSC.

Security and privacy: Security and privacy challenges in SSC networks necessitate reevaluating cybersecurity frameworks to provide wireless services with enhanced security, particularly when dealing with sensitive data [66]. For example, the exponential growth of widespread IoT connectivity has introduced vulnerabilities that result in an increase in malicious attacks [67]. To establish a secure SSC, it is crucial to tackle the security and privacy challenges associated with IoT devices in SSC networks.

To shed light on how AI-based wireless communication can be constructively exploited in SSC, we discuss its potential benefits in the following.

- *Improve transmission performance*: In the future 6G era, a multitude of UEs and machines will be connected to the internet through small devices equipped with AI, resulting in a hyper-connected society. The number of IoT terminals worldwide is increasing at a tremendous rate and is expected to grow even more in the future [68]. The rapid increase in IoT terminals can lead to the problem of increasing the amount of feedback. The CSI feedback method based on DL is considered a viable solution to effectively deal with the overhead problem caused by this rapid increase in feedback.
- *Low compression ratio and reduced time complexity*: One of the problems with traditional CS methods is their dependence on channel sparsity. To overcome this problem, DL can be used to take advantage of huge amounts of training samples and train multi-layer neural networks. One of the structures used to do this is an autoencoder. An autoencoder consists of an encoder, that leverages training data to compress the original channel matrix into a codeword, and a decoder, that learns the inverse transformation from the codeword to the original channel form. High-compression ratios and reduced time complexity can be achieved using these autoencoder structures.
- *High throughput and efficiency*: It is necessary to address the outdated CSI problem between the LEO satellite and UT to enable future transportation methods in SSC, such as UAM. A possible solution to predict CSI from channel estimates is to exploit the DL-based time series prediction model [69]. Furthermore, a DL-based CS algorithm for sparsity detection in the Doppler region was introduced to improve the channel estimation efficiency in high-speed mobile communication scenarios [39]. AI-based channel estimation and prediction algorithms can contribute to future-proofing transportation in SSC by tackling outdated CSIs and optimizing pilot use in high-speed communication scenarios. On top of the outdated CSI issue, the throughput of IoT needs to be improved. The authors in [70] proposed the generated data packet-based throughput maximization (GDPTM) algorithm and the deep deterministic policy gradient (DDPG)-based multi-node resource allocation (DMRA) algorithm to achieve improved throughput and extend the lifetime of IoT nodes. The authors in [71] proposed a two-layer algorithm to set energy causality constraints and address the throughput maximization problem for various scenarios of wireless powered communication networks (WPCN).
- *Energy efficiency*: The utilization of AI brings notable advantages in enhancing energy efficiency in SSC [72]. For example, in hospitals and schools, AI technology can leverage sensor systems in smart buildings to reduce energy costs while improving the safety and security of citizens. In [40], it is shown that energy efficiency can be improved via AI-based modules. Management of these AI modules can contribute to increasing the energy efficiency and sustainability of SSCs.

Beyond wireless transmission and reception technologies, AI can be applied to smart surveillance cameras across various domains [73,74]. Firstly, smart building systems can utilize DCNN to assess damage to building structures, as discussed in [75], and pedestrians can be classified from input images based on the CNN method discussed in [76]. Secondly, AI and IoT technologies are employed to implement efficient and convenient healthcare systems. For example, the authors in [77] proposes a GUI that oversees an individual's healthcare using an AI technology called XAI, which is used to explain AI models and their predictions. Lastly, smart energy systems exploit AI technology to manage the excessive use of energy in modern society. For example, the authors in [78] proposed an artificial intelligence-based home energy management system (AI-HEMS) to achieve energy savings through a predictive mechanism. With such diverse applications, AI is expected to provide more innovative and new services in SSCs in the future.

4.2.2. Advanced Mobile Edge Computing

With the advancement of IoT technology and machine-type communications, the number of connected devices is growing exponentially. In SSC, the internet of everything (IoE) services will emerge with the aim of improving the quality of life in urban spaces [79]. Future applications, such as extended reality (XR) and mobile holograms, will require the capabilities of extensive computations to deliver a large volume of data. When there are thin and light mobile devices, it would be challenging to satisfy the high computational requirements. Traditional centralized cloud computing can be applied to overcome the limitation of computing power in mobile devices, but there are many drawbacks, such as high latency, low spectral efficiency, and overload [80].

To overcome these drawbacks, mobile edge computing can be exploited to process high computational tasks on edge computing servers adjacent to user devices [81], as shown in Figure 3. Recently, advanced mobile edge computing, called split computing, has been introduced. With split computing, computing loads can be properly distributed among various network entities such as mobile devices, edge computing servers, and cloud data centers. For example, when the same amount of computational task is given, low-end devices, such as smart watches, offload heavy computation tasks to computation resources available in the network, while high-end mobile devices are capable of performing the necessary computation by themselves. This approach allows for the optimization of computing task efficiency by appropriately leveraging edge servers in terms of computing and storage. This optimization is achieved via collaborative scheduling of computing tasks and resource allocation [82,83].

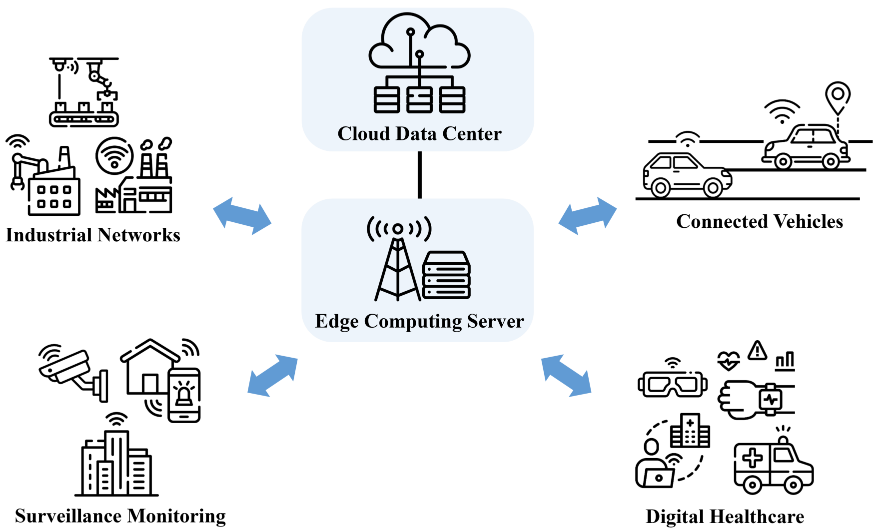

Figure 3. Various advanced MEC use cases on SSC.

In the following, we discuss the key challenges in applying advanced mobile computing for 6G-enabled SSC.

Diverse security requirements: Due to the limited resources of the edge nodes and their lack of intelligence against attacks, UEs connected to edge nodes are more vulnerable to attacks compared to centralized networks [84]. In addition, security requirements vary depending on the devices and applications used within the edge network. Lightweight security is required for applications with only a few functions, while robust security is required for applications that are sensitive to privacy issues or delays. Therefore, it is difficult to apply traditional security mechanisms to advanced mobile edge computing networks, which require access technologies and security mechanisms based on diverse security requirements [85].

Privacy leakage: To ensure secure transmissions, information should not be disclosed to parties other than the intended recipients. In this sense, the hierarchical and heterogeneous characteristics of MEC networks pose a significant privacy threat [86]. Unauthorized access to MEC nodes, for example, has the potential to compromise both privacy and network information [87]. Although the MEC architecture partitions information and access to mitigate privacy leakage, there is still a potential for privacy information leakage, including client status details, traffic statistics, and local network conditions, at the edge network [88]. Therefore, robust security and privacy measures should be implemented to counter the problem of privacy leakage in edge nodes and networks.

Mobility and resource allocation: Note that the mobility of UE causes frequent disconnections from the edge network, which degrades the quality of service (QoS) [84]. UEs can use different network access technologies, and managing the tradeoff between energy consumption and system performance is important. Hence, efficient resource allocation via computation offloading and dynamic task partitioning is crucial, taking into account the mobility of UEs connected to edge nodes [89]. It is imperative to develop a system management architecture that enables the seamless handover of services based on the mobility of UEs.

Uncompromising quality of service: The selection of the edge node to compute contributes to measuring QoS. The primary objective of advanced mobile edge computing is to perform the computing anywhere near the collected data. To evaluate network performance, latency is a vital QoS metric which is not only determined by computation time. The computation of the workload should be performed at a closer layer. In addition, this layer must have enough computation capability to perform the calculations at the edge network.

In the following, we elaborate on the potential benefits of leveraging advanced mobile edge computing for 6G-enabled SSC.

- *Real-time interaction*: By placing edge computing servers near UEs, it enables the efficient utilization of resources and data distribution according to the UE's computing capability. This approach offers high-speed communication compared to traditional centralized computing and can reduce the latency between servers and devices to 10 ms or less. Consequently, it ensures low latency and high QoS for delay-sensitive applications and real-time immersive services [43].
- *Enhanced data security*: In traditional centralized cloud computing, all information is concentrated in a centralized data center, which can be exposed to hacking and cybercrimes. In contrast, advanced mobile edge computing has a decentralized structure and can provide more robust data security. Further, in IoT-based SSC environments, an appropriate privacy rule for each IoT device at the network edge can be provided in real time based on the ontology model containing privacy information [44], providing more robust and efficient data security.
- *Overload reduction*: Traditional centralized cloud computing tends to concentrate all computational and data processing requests in a central data center, resulting in high bandwidth demands and overload. In contrast, advanced mobile edge computing enables local processing since UE's requests can be processed on edge servers, reducing the need for large data transfers to central data centers and the amount of

network traffic [43]. This reduces bandwidth demands and then mitigates bottlenecks, improving the network performance by alleviating the overload.

- *Preventing repetitive traffic*: In conventional telecommunication networks, backhaul links often experience congestion caused by repetitive traffic requests for the same content. The caching technique offers a solution to alleviate congestion by storing frequently requested content in various locations on the network, ensuring low-latency access. Edge computing systems, integrated with the caching technique, can effectively deliver resource-intensive smart services, encompassing smart transportation, smart tourism, and smart industry [90]. Furthermore, intelligent edge caching based on machine learning and optimization is expected to significantly reduce the latency of real-time applications [42].

MEC networks can contribute to the delivery of a variety of SSC services. Firstly, healthcare systems, assisted by edge computing architectures, can provide more personalized and expedited healthcare services. The data processing architecture between healthcare-related devices (such as smartwatches) and edge nodes must be reevaluated to satisfy the ultra-low latency, energy efficiency, and high levels of security conditions required for mission-critical healthcare applications [91]. Secondly, the two-tier edge computing-based traffic management model can enhance the accuracy and efficiency of traffic detection processes [92]. Large volumes of monitoring data collected for traffic congestion and accident detection can be partitioned and processed at edge nodes located near the detection cameras. This eliminates the need to forward the data all the way to the traffic management center for processing. In addition, it enables more effective urban traffic management by adjusting additional lanes and regulating the movement of autonomous vehicles.

4.2.3. Non-Terrestrial Networks for Zero-Coverage Networks

It is envisaged that UAM is one of the main transportation within the 6G-enabled SSC. To support aerial devices and provide greater coverage than currently deployed 5G systems, 6G wireless networks should be designed to support both NTN and terrestrial networks (TN) [7]. NTN has sparked significant global interest since it can provide high-speed Internet services even in rural, ocean, sea, and mountain areas [45]. Based on flying altitude and coverage area, NTN devices can be categorized into UAM, low-earth orbit (LEO) satellites, medium-earth orbit (MEO) satellites, and geostationary orbit (GEO) satellites (see Figure 4). LEO satellites get closer to Earth's surface to ensure faster response times compared to GEO satellites. Specifically, the round-trip delay (RTD) of a GEO satellite is around 500 ms, while that of a LEO satellite is less than 100 ms.

As the orbit of LEO satellites gets closer to Earth, the size of their footprint decreases, resulting in more limited coverage. For example, at an altitude of 550 km, the beam coverage reaches approximately 0.2% of the entire region [46]. Achieving global coverage would necessitate deploying a mega-constellation comprising a large number of LEO satellites. NTN technologies are expected to offer seamless connectivity for 6G-enabled SSC.

To achieve a fully connected SSC in a cost-effective manner, the following issues need to be addressed.

Channel realization due to high-mobility NTN devices: Most NTN devices move at high speeds from the perspective of ground devices [45]. The mobility of NTN devices induces a significant Doppler shift in wireless channels. The fast-changing wireless channels pose a critical challenge that must be addressed to ensure seamless radio connections in NTN networks. The wireless channel models should be reevaluated to capture diverse channel characteristics and time-varying properties in NTN networks.

Frequent handover in 3D coverage: High-speed movement of NTN devices causes a very short visible period. For example, the maximum visible time of LEO satellites is up to 25 min to a ground terminal. Due to the continual movement of the NTN coverage area, frequent handover will be required even for the fixed ground terminal. Also, the cell size can be varied depending on the elevation angle of the NTN devices. Thus, conventional handover techniques for terrestrial networks become incongruous in the new era of aerial and space networks.

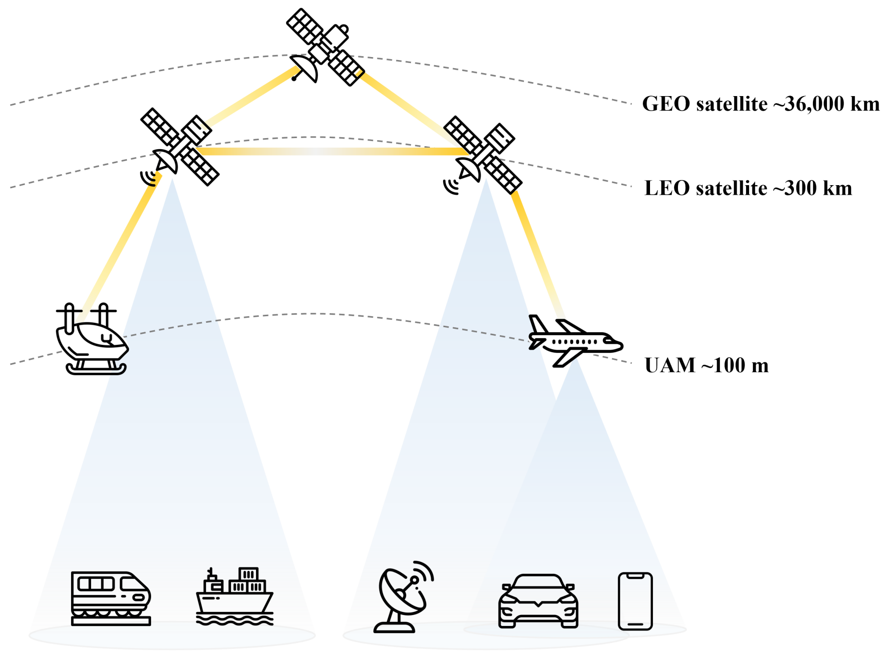

Figure 4. Candidate NTN terminals on SSC.

Integrated TN and NTN architecture: When satellites are closer to earth, the coverage of the satellites becomes smaller. Therefore, LEO satellites should work together to provide sufficient coverage to a designated area, which requires a complicated protocol and backhaul connection. A multi-layered architecture that integrates the satellite network, the airborne network, and the terrestrial network can provide better coverage and performance over the satellite network only [93]. This is because the airborne network can bridge the LEO/GEO satellite systems to the ground terminals. To obtain this full benefit of the multi-layered architecture, efficient protocols including network mobility management and resource allocation should be developed.

Weak LOS environments: Although the channels of NTN devices are dominated by line-of-sight (LOS) components in most aerial spaces, non-LOS components also occur near the ground in the channel model for NTN devices. Note that LOS probability depends on several factors such as the environmental information and elevation angle. For example, for an elevation angle of 10°, the LOS probability is lower in urban areas (24.6%), while the LOS probability is higher in suburban and rural areas (78.2%) [94]. Specifically, in weak LOS environments (i.e., urban areas), blockage can hinder the direct link between NTN devices and ground users. To remedy this problem, UAM can be exploited as the relay node. Also, a reconfigurable intelligent surface (RIS)-based beamforming can be applied to ensure the directivity of communication links [47,95].

To shed light on how NTN can be constructively exploited in SSC, we discuss its potential benefits in the following.

- *Relieving spectrum scarcity*: As the number of LEO satellites is rapidly increasing, and while frequency resources are becoming limited, the coexistence of GEO and LEO satellites has been studied to enable aggressive frequency reuse. Frequency co-existence between NTN devices is expected to be a promising approach to alleviating spectrum scarcity. The deployment of NTN should consider interference from the 3D network with the altitude of the NTN devices. As the altitude of the NTN devices increases, the beam width can be wider, thus intensifying inter-beam interference. To manage interference caused by the coexistence of NTN devices, advanced multiple access techniques such as non-orthogonal multiple access (NOMA) [96] or rate-splitting multiple access (RSMA) can be applied [97,98].

- *Power efficient and cost-effective deployment*: Note that LEO satellites have a lower power budget compared to GEO satellites. Transparent LEO satellites can be employed for an efficient power assumption. To fully achieve low-latency, regenerative LEO satellites using the inter-satellite links (ISL) should be exploited. Due to on-board processing in regenerative satellites, effective power management of LEO satellites is critical to ensure their optimal performance. The RIS can be combined with LEO satellite communication systems to ensure ubiquitous connectivity by addressing coverage holes [99]. Note that RISs consume much less power than conventional relay terminals, since RISs do not operate complicated signal processing. In addition, RISs can be easily mounted on NTN devices such as LEOs and UAMs.
- *Low latency over the globe*: While a round-trip delay (RTD) of a GEO satellite exceeds 250 ms, the RTD of a LEO satellite at an altitude of 600 km is less than 30 ms [94]. Thus, non-GEO devices can guarantee a faster response time compared to GEO. However, due to the low orbits of the non-GEO satellites, the beam coverage of the non-GEO satellites decreases. Thus, it requires the deployment of a mega-constellation including a large number of non-GEO satellites for global coverage while ensuring a delay as short as a few tens of milliseconds.

Recently, integrating satellite and terrestrial networks (ISTN) has sparked a significant interest due to its capability to increase coverage, reliability, and spectrum efficiency [100]. In 6G-enabled SSC, terrestrial infrastructures can be exploited as relay nodes to ensure reliable communication links. Due to obstructions on the ground, there may exist coverage holes that non-GEO satellites cannot cover. Even in the absence of an LOS link, employing RIS on non-GEO satellites or UAM can enable communication with information transmission. In particular, UAMs with RIS, taking advantage of their mobility, can provide a higher probability of LOS in channels between RIS and users. In addition, to alleviate the spectrum scarcity, NTN devices and terrestrial infrastructures need to exploit the same spectrum resources.

4.2.4. Vision-Aided Wireless Communication

Recently, vision-aided wireless communication (VAWC) has received much attention as a key enabling technology in realizing 6G-enabled SSC due to its capability to manipulate beamforming using visual and radio information collected by cameras in mmWave and THz bands [101], as shown in Figure 5. VAWC uses machine learning techniques to analyze the data collected by cameras. The aim of VAWC is to understand both the invisible and visible situations of mobile users and to predict their future locations [102]. One major bottleneck of exploiting the mmWave and THz bands is that these higher frequency bands tend to be vulnerable to blockage due to their high directivity and severe path loss. Due to its ability to mitigate intermittent blockage, VAWC can be considered a prime technology for achieving seamless connectivity in non-stationary scenarios where user equipment (UE) moves rapidly and the variation in path angle and time delay is not negligible.

Environmental awareness technologies are crucial to supporting emerging services such as UAM, smart factories, and smart farms. Since emerging services would demand not only high data rates but also low latency and high-precision positioning capabilities [48], VAWC can play a pivotal role in the development of SSC applications by identifying the location of obstacles from acquired image information [48]. To fully enjoy the benefits of VAWC in various smart city domains such as telemedicine and autonomous driving, we need to address the following challenges.

Building datasets: To utilize VAWC, an extensive collection of visual data sets is necessary to show a comprehensive, balanced, and diverse representation. Building such a dataset demands substantial time and financial resources, ensuring that the data represents all potential environmental scenarios. Consequently, building satisfactory datasets in VAWC remains a major challenge [103].

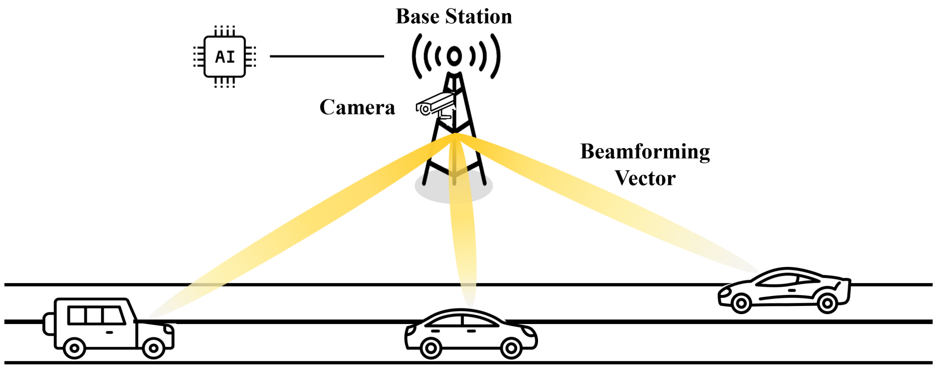

Figure 5. Illustration of vision-aided wireless communication.

Selection of deep learning techniques: The utilization of various deep learning techniques in VAWC, such as encoder–decoder architectures, generative adversarial neural networks (GANs), and transformers, has proven to be effective. For example, encoder–decoder architectures have been widely used in semantic segmentation and sequence-to-sequence tasks. In addition, transformers using attention mechanisms are robust in processing unordered data [104]. It is worth noting that identifying efficient DL techniques to address specific environments with visual data remains a major challenge.

Training for environmental compatibility: One of the important challenges in VAWC is to ensure environmental compatibility in different wireless environments [48]. To this end, the training of various datasets collected from different environments is necessary, but this process requires substantial time and effort. As a potential solution, transfer learning can be considered [105]. This approach involves adapting a pre-trained VAWC model trained on common visual characteristics, by utilizing a small amount of target environment data to create a VAWC model adaptable to the new environment.

Privacy issue: VAWC systems can collect a wide range of personal identification information during the process of visual information collection. The development of VAWC should be approached with consideration for network security and privacy issues, as it extensively observes the daily activities of mobile users [106]. Addressing privacy concerns in VAWC poses a significant challenge, requiring mechanisms to assess data security risks and ensure privacy.

In the following, we discuss the potential benefits of using VAWC in SSC.

- *Maximizing beamforming gain*: Unlike conventional codebook-based beam management, VAWC can effectively improve the beamforming accuracy by using the UE's angle information obtained via RGB images at base stations. In [101], it is shown that the orientation error of DL-based object detection is below 0.5 degrees, which can be used to maximize the beamforming gain using VAWC. Moreover, with the advancement of sensing technologies, positioning errors are expected to be further reduced in higher frequency bands.
- *Latency reduction*: Leveraging location information extracted from collected RGB images enables the replacement of transmission latency with the processing latency of DL techniques. This is because the handshake operation for conventional beam refinement is no longer needed. Considering that the minimum latency of 5G beam management is around 20 ms, VAWC-based beam management achieves approximately 4 ms faster speeds [49]. Therefore, we conjecture that VAWC emerges as a promising technology to support HRLLC.
- *Environment-aware operation*: VAWC can utilize acquired visual information to identify components of the radio environment, such as the exact location of users and obstacles. Visual data from NTN devices can be used to analyze user distribution, which facilitates the planning of the power budget for optimal energy efficiency [103]. Further, visualization information can be used to perform intelligent functions such as predicting beam blockages and managing mobility.

- *Improve service availability:* The VAWC systems enhance the availability of mobile services by efficiently optimizing the utilization of wireless resources because they can collect a substantial amount of visual data required for real-time monitoring of surrounding environments [107]. For example, power-limited IoT devices can deliver seamless mobile services by optimizing energy consumption via the transmission power prediction process. In addition, deep learning techniques that use visual information can be employed to predict LOS blockage situations to secure uninterrupted radio connections in fast handover scenarios.

VAWC can offer a diverse range of services for SSC. For example, visual data obtained from cameras can establish connections with nearby terminals and vehicles by effectively understanding traffic conditions [51]. Assuming an LOS channel scenario, BS can facilitate fast and reliable transmission and reception for mobile users by predicting vehicles and pedestrians that may interfere with wireless connections. Furthermore, real-time visual information can be leveraged to predict future traffic conditions or detect accidents in changing road conditions. This information can be incorporated into future traffic schedules to mitigate traffic congestion.

In UAV communication systems, VAWC technology pursues the optimal wireless solutions by enabling accurate positioning between the UAV and the receiver. For instance, flight path planning and power allocation utilizing visual information, collected via cameras mounted on UAVs, enable the optimal design of UAV communication systems [50]. Moreover, when multiple UAVs are employed, visual information from ground base stations and UAVs can be leveraged to establish wider service coverage and reliable wireless connections.

4.2.5. Integrated Sensing and Communication

Progress in IoT services, including AI, smart cities, and autonomous driving, relies on the advanced sensing, communication, and computation capabilities in next-generation wireless networks. The growing need for an integrated sensing and communication system arises from its potential to improve both functionalities and minimize the use of wireless resources via full cooperation. Moreover, integrated systems can boost efficiency in system design by sharing hardware components [108,109].

The high-resolution sensing, imaging, and environmental reconstruction capabilities of ISAC systems are crucial for facilitating diverse applications in smart cities. These capabilities have a significant impact on key areas like environmental monitoring, traffic management, energy efficiency, and the implementation of improved safety and security measures [54,110]. In accordance with the smart city paradigm, the strategic utilization of wireless resources aims to optimize network efficiency, reduce energy consumption, and promote the adoption of sustainable practices.The application of the ISAC system is depicted in Figure 6.

While managing interferences between communication and sensing functionalities is a key challenge for ISAC systems, recent research has shown that the RSMA technique can effectively achieve flexible and robust interference management between communication and sensing, as well as among communication users [111]. In addition, the following technical challenges should be addressed to exploit the full benefits of ISAC in SSC.

Joint waveform design: The waveform design approach must involve consideration of all the communication and sensing requirements essential to support ISAC. The main goal of communication is to maximize spectral efficiency, whereas sensing aims to enhance estimation resolution or accuracy. In ISAC systems, it is desirable to share a single set of common transmission waveforms for both communication and target sensing. Therefore, a joint waveform design framework needs to be developed to improve the network throughput and estimation performance.

Doppler effect: ISAC has been widely employed in LEO satellite communication systems. The high velocity of LEO satellites (approximately 7.6 km/s at an altitude of 600 km) induces a substantial Doppler shift in radio links between ground terminals and

NTN devices. A possible solution to the Doppler issue is to leverage machine learning techniques for accurate channel estimation and compensation of frequency-selective and time-varying channel effects. It is essential to mitigate the Doppler effects by carefully selecting sensing parameters and estimating communication channels [112].

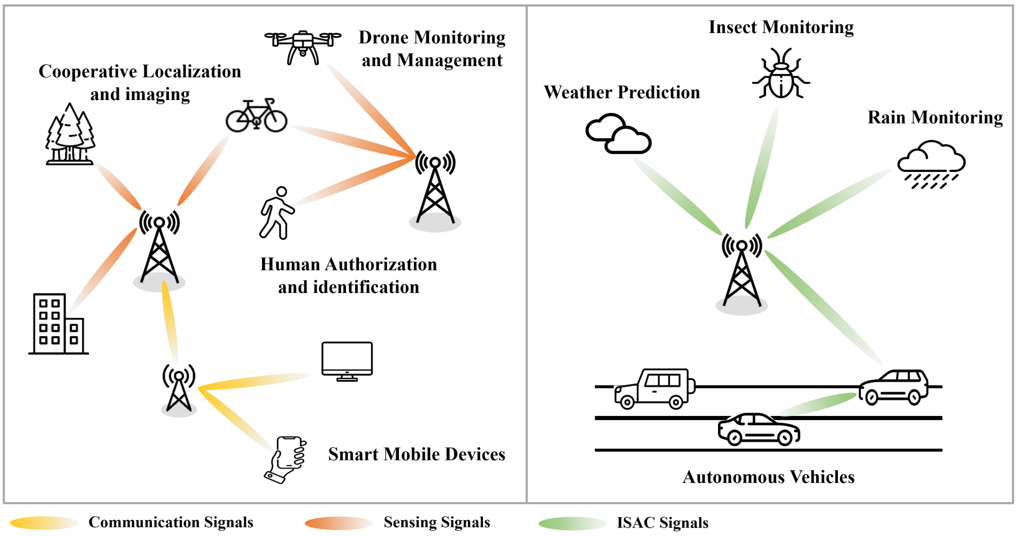

Figure 6. Application of ISAC on 6G-enabled SSC use cases.

Personal data breach: Next-generation communication systems will be designed to offer a variety of IoT-enabled broadband services. As the number of connected devices increases, ensuring the security of SSC networks becomes increasingly crucial. For example, the openness of wireless sensing allows attackers to eavesdrop on the CSI of the target, potentially leading to a breach of the user's personal information and disruption of legitimate communication [113]. The security-related transmission/reception schemes in ISAC systems have not yet been extensively studied.

Fixed bandwidth: ISAC systems perform detection and communication functions in the same frequency band by sharing common hardware. The 3rd Generation Partnership Project (3GPP) has defined two frequency ranges for new wireless technologies: one supporting up to 100 MHz and the other allowing for a maximum of 400 MHz. Although this resolution is sufficient for typical detection tasks (range resolutions of 1.5 m and 0.375 m), it falls short when higher precision and location information are required, as in the case of autonomous vehicles. Developing signal processing techniques that can enhance detection performance and range resolution becomes crucial when the available frequency bandwidth is limited [114].

In the following, we discuss the potential benefits of ISAC when applying ISAC in SSC.

- *Ultra-wideband communication*: Millimeter wave is considered a key technology for future 6G networks. ISAC systems are particularly suited to high-resolution sensing tasks when operating in the millimeter wave band. This can be utilized effectively in 3D imaging and applications with millimeter-level resolution. mmWave can be used to help autonomous vehicles accurately sense and react to their surroundings, while 3D imaging allows vehicles to understand obstacles around them or interactions with other vehicles in real-time. It is also expected to be utilized in security systems and medical applications [52].
- *High accuracy and localization*: In future super-intelligent societies, location determination methods, such as collaborative mapping techniques, play a crucial role in training robots to emulate human-like senses. ISAC enables the localization and tracking of various objects such as vehicles and drones. High-precision relative localization becomes crucial when two or more entities approach each other or move cooperatively. The

advanced accuracy and localization capabilities of ISAC can contribute to innovation in autonomous technologies such as robots and drones [53].

- *Gesture and activity recognition*: Human gestures play a crucial role as an interface for interacting with IoT and mobile devices. The ISAC networks, utilizing a broad bandwidth, offer enhanced resolution and accuracy in capturing gestures, thereby enabling a diverse range of applications that leverage gesture-capturing techniques. Furthermore, the ISAC-based technology for gesture and activity recognition is well suited for smart city scenarios, especially in minimizing the exposure of personal information when compared to camera-based activity recognition technology. For example, smart hospitals may incorporate functions such as intrusion detection or respiratory sensing without relying on camera devices [115].
- *Augmented human senses*: The ISAC system is recognized as a leading candidate for driving innovation in SSC, attributed to its capability to recognize surrounding environments beyond human capabilities. The augmented sensing technology utilizes portable devices to sense the surrounding environment, emphasizing the integration of high-resolution imaging and communication capabilities to intelligently manage the SSC infrastructure. For example, augmented human sensing functions in ISAC systems could enhance key SSC functions, including environmental monitoring, traffic flow management, and the reinforcement of safety and security [52,54].

ISAC can be verified in real-world environments. Taking environmental monitoring as an example, it performs sensing by analyzing the path loss of mmWave links and observing changes in environmental characteristics such as moisture and insects. Cell networks with such sensing capabilities utilize communication systems to transmit collected data or receive commands. They contribute to the management and improvement of smart city infrastructure by detecting environmental factors like air pollution, noise levels, and temperature. Additionally, ISAC technology, applied to inter-vehicle communication within the city, concurrently achieves high-speed communication and precise vehicle localization. This enhances key functions such as secure access, simultaneous localization, and mapping, thereby elevating the efficiency and safety of smart city operations [116,117].

4.3. Discussion on Sustainability of 6G-Enabled SSC

In Agenda 2030, UN introduced the sustainable development goals (SDGs) to resolve many social issues such as climate change and education inequality [2]. Among all 17 SDGs, SDG 11, sustainable city and communities, will be highly related to 6G-enabled SSC. It is worth noting that the new urban agenda (NUA) was established to serve as an accelerator for SDG 11. The NUA emphasizes the sustainability of future urban planning and development in social, economic, environmental, and spatial sustainability [118]. In particular, the NUA aims to pursue the equal enjoyment of benefits from smart cities for all individuals. Note that spatial sustainability signifies the potential to improve the social, economic, and environmental value of urban spatial conditions. It involves guiding the physical form of urban environments to promote equitable access to jobs, housing, and social interactions.

A wide deployment of prime technologies for 6G-enabled SSC will play a pivotal role in resolving many social issues. For example, the combination of NTN and advanced mobile edge computing can achieve global coverage and enable remote learning, which could provide a means to reduce regional and social disparities. Sixth-generation-enabled SSC will play an important role in the achievement of UN's SDGs and vastly support the quality and opportunities of humans and everything.

5. Summary and Outlook

In this paper, we explored the main technical challenges and potential benefits of prime technologies essential for creating 6G-enabled smart sustainable cities. We have identified several key enabling technologies and their roles in improving the quality of life of humans and the efficiency of urban services. With these disruptive technologies, 6G-enabled SSC is envisioned to seamlessly connect intelligent things such as UAM, IoT sensors, robots, and mobile devices without limitations on the data rate, latency, and coverage. In Figure 7, we represent the overall 6G-enabled SSC architecture by highlighting the key enabling technologies. We anticipate that this will bring a truly hyper-connected society to achieve ubiquitous connectivity, sustainability, and enhanced security. Further, we have put forth urban practice cases for 6G-enabled SSC. We have addressed how the potential benefits of prime technologies enable various scenarios and applications. While we find these technologies to be quite promising and relevant for 6G-enabled SSC, in the future, we will explore more technologies, and our perspectives on the significance and effectiveness of various technologies will naturally change. An important future direction is to consider the concept of smart rural to achieve balanced development between rural areas because overcrowding in SSC leads to numerous and serious environmental issues, as well as disparities between urban and rural environments.

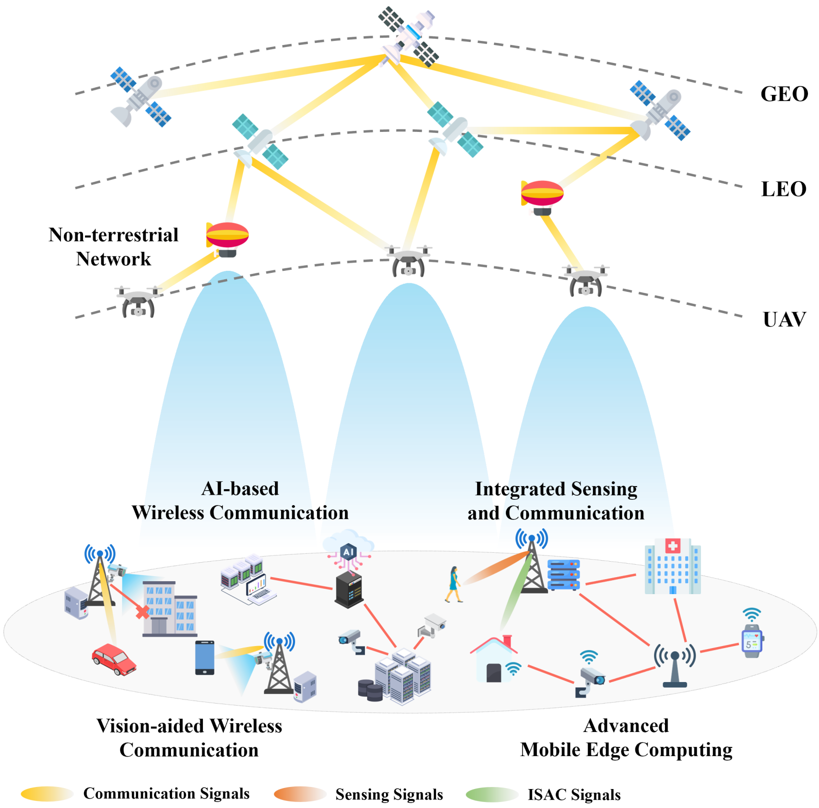

Figure 7. Overall 6G-enabled SSC architecture.

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Abbreviations

The following abbreviations are used in this manuscript:

5G	Fifth Generation
6G	Sixth Generation
AI	Artificial Intelligence
AR	Augmented Reality
CS	Compressed Sensing
DL	Deep Learning
eMBB	Enhanced Mobile Broadband
GAN	Generative Adversarial Network
GEO	Geostationary Orbit
HAPS	High-Altitude Platform Station
HRLLC	Hyper-Reliable and Low-Latency Communication
ICT	Information and Communication Technology
IoE	Internet of Everything
IoT	Internet of Things
IMT	International Mobile Telecommunications
ISAC	Integrated Sensing and Communication
ISL	Inter-Satellite Link
ITU-T	International Telecommunication Union Telecommunication standardization sector
JTC	Joint Technical Committee
KPI	Key Performance Indicator
LEO	Low Earth Orbit
LOS	Line of Sight
LSTM	Long Short-Term Memory
MEO	Medium Earth orbit
MIMO	Multiple-Input Multiple-Output
mMTC	Massive Machine-Type Communications
mmWave	Millimeter Wave
NOMA	Non-Orthogonal Multiple Access
NTN	Non-Terrestrial Networks
QoS	Quality of Service
RIS	Reconfigurable Intelligent Surface
RNN	Recurrent Neural Network
RSMA	Rate-Splitting Multiple Access
RTD	Round-Trip Delay
SCP	Satellite Channel Predictor
SDG	Sustainable Development Goals
SSC	Smart Sustainable City
SSC-MM	SSC Maturity Model
TC	Technical Committee
THz	Terahertz
TN	Terrestrial Network
UAM	Urban Air Mobility
UE	User Equipment
URLLC	Ultra-Reliable and Low Latency Communication
VAWC	Vision-aided Wireless Communication
VR	Virtual Reality
WG	Working Group
XR	Extended Reality

References

1. Research and Markets. Global Smart Cities Market. 2022. Available online: https://www.researchandmarkets.com/reports/5146372 (accessed on 27 December 2023).
2. UN. The Sustainable Development Goals Report. 2023. Available online: https://unstats.un.org/sdgs/report/2023/The-Sustainable-Development-Goals-Report-2023.pdf (accessed on 27 December 2023).
3. UN-Habitat. World Cities Report 2022: Envisaging the Future of Cities. 2022. Available online: https://unhabitat.org/sites/default/files/2022/06/wcr_2022.pdf (accessed on 30 November 2023).
4. ITU. ITU Smart Sustainable Cities. 2021. Available online: https://www.itu.int/en/ITU-T/ssc/united/Documents/Reports-on-SSC/ITU_smart_sustainable_cities_brochure.pdf?csf=1&e=yIueWP (accessed on 30 November 2023).
5. Statista. Projected Revenue Generated by Companies in the Global Smart City from 2020 to 2028. 2023. Available online: https://www.statista.com/statistics/1111626/worldwide-smart-city-market-revenue/ (accessed on 30 November 2023).
6. 6G Flagship. Key Drivers and Research Challenges for 6G Ubiquitous Wireless Intelligence. 2019. Available online: https://jultika.oulu.fi/files/isbn9789526223544.pdf (accessed on 30 November 2023).
7. Samsung Research. 6G White Paper: The Next Hyper-Connected Experience for All. 2020. Available online: https://research.samsung.com/ (accessed on 30 November 2023).
8. Docomo. White Paper 5G Evolution and 6G (Version 4.0). 2022. Available online: https://www.docomo.ne.jp/english/corporate/technology/whitepaper_6g/ (accessed on 30 November 2023).
9. Samsung Research. 6G Spectrum: Expanding the Frontier. 2022. Available online: https://cdn.codeground.org/nsr/downloads/researchareas/2022 (accessed on 30 November 2023).
10. ITU. IMT towards 2030 and Beyond. 2023. Available online: https://www.itu.int/en/ITU-R/study-groups/rsg5/rwp5d/imt-2030/Pages/default.aspx (accessed on 30 November 2023).
11. ITU. Recommendation ITU-R M.2083-0: IMT Vision—Framework and Overall Objectives of the Future Development of IMT for 2020 and Beyond. 2015. Available online: https://www.itu.int/dms_pubrec/itu-r/rec/m/R-REC-M.2083-0-201509-I!!PDF-E.pdf (accessed on 30 November 2023).
12. ISO. ISO/TC 268: Sustainable Cities and Communities. Available online: https://www.iso.org/committee/656906.html (accessed on 30 November 2023).
13. ISO/IEC. ISO/IEC JTC 1: Information Technology. Available online: https://www.iso.org/committee/45020.html#secretariat (accessed on 30 November 2023).
14. ISO. Recommendation ISO 37106: Sustainable Cities and Communities—Guidance on Establishing Smart City Operating Models for Sustainable Communities. 2021. Available online: https://www.iso.org/standard/82854.html (accessed on 30 November 2023).
15. ISO/IEC. Recommendation ISO/IEC 30146: Information Technology—Smart City ICT Indicators. 2019. Available online: https://www.iso.org/standard/70302.html (accessed on 30 November 2023).
16. ITU. ITU-T SG20: Internet of Things (IoT) and Smart Cities and Communities (SC&C). Available online: https://www.itu.int/en/ITU-T/studygroups/2022-2024/20/Pages/default.aspx (accessed on 30 November 2023).
17. ITU. Recommendation ITU-T Y.4900/L.1600: Overview of Key Performance Indicators in Smart Sustainable Cities. 2016. Available online: https://www.itu.int/rec/T-REC-L.1600-201606-I (accessed on 30 November 2023).
18. ITU. Recommendation ITU-T Y.4901/L.1601: Key Performance Indicators Related to the Use of Information and Communication Technology in Smart Sustainable Cities. 2016. Available online: https://www.itu.int/rec/T-REC-L.1601-201606-I (accessed on 30 November 2023).
19. ITU. Recommendation ITU-T Y.4904: Smart Sustainable Cities Maturity Model. 2019. Available online: https://www.itu.int/rec/T-REC-Y.4904-201912-I (accessed on 30 November 2023).
20. ITU-T. Recommendation ITU-T Y.3531: Cloud Computing—Functional Requirements for Machine Learning as a Service. 2020. Available online: https://www.itu.int/rec/T-REC-Y.3531-202009-I (accessed on 30 November 2023).
21. ITU-T. Recommendation ITU-T Y.3532: Cloud Computing—Functional Requirements of Platform as a Service for Cloud Native Applications. 2023. Available online: https://www.itu.int/rec/T-REC-Y.3532-202305-I (accessed on 30 November 2023).
22. ITU-T. Recommendation ITU-T Y.3123: Framework of Edge Computing Capability Exposure for IMT-2020 Networks and Beyond. 2023. Available online: https://www.itu.int/rec/T-REC-Y.3123-202305-I (accessed on 30 November 2023).
23. ITU-T. Recommendation ITU-T Y.3137: Technical Requirements for Supporting Application Addressing in Edge Computing for Future Networks Including IMT-2020. 2022. Available online: https://www.itu.int/rec/T-REC-Y.3137-202209-I (accessed on 30 November 2023).
24. ITU-T. Recommendation ITU-T Y.3602: Big Data—Functional Requirements for Data Provenance. 2022. Available online: https://www.itu.int/rec/T-REC-Y.3602-202209-I (accessed on 30 November 2023).
25. ITU-T. Recommendation ITU-T Y.3603: Big Data—Requirements and Conceptual Model of Metadata for Data Catalogue. 2023. Available online: https://www.itu.int/rec/T-REC-Y.3603-202305-I (accessed on 30 November 2023).
26. ITU-T. Recommendation ITU-T Y.4210: Requirements and Use Cases for Universal Communication Module of Mobile IoT Devices. 2020. Available online: https://www.itu.int/rec/T-REC-Y.4210-202008-I (accessed on 30 November 2023).
27. ITU-T. Recommendation ITU-T Y.4212: Requirements and Capabilities of Network Connectivity Management in the Internet of Things. 2021. Available online: https://www.itu.int/rec/T-REC-Y.4212-202111-I (accessed on 30 November 2023).

28. ITU-T. Recommendation ITU-T M.3080: Framework of Artificial Intelligence Enhanced Telecom Operation and Management (AITOM). 2021. Available online: https://www.itu.int/rec/T-REC-M.3080-202102-I (accessed on 30 November 2023).
29. ITU-T. Recommendation ITU-T M.3384: Intelligence Levels of Artificial Intelligence Enhanced Telecom Operation and Management. 2023. Available online: https://www.itu.int/rec/T-REC-M.3384-202304-I (accessed on 30 November 2023).
30. M&M. Artificial Intelligence (AI) Market. 2023. Available online: https://www.marketsandmarkets.com/Market-Reports/artificial-intelligence-market-74851580.html (accessed on 27 December 2023).
31. M&M. Edge Computing Market. 2023. Available online: https://www.marketsandmarkets.com/Market-Reports/edge-computing-market-133384090.html (accessed on 24 December 2023).
32. M&M. 5G NTN Market. 2023. Available online: https://www.marketsandmarkets.com/Market-Reports/5g-ntn-market-186116188.html (accessed on 27 December 2023).
33. Spherical Insights. Global Computer Vision Market. 2022. Available online: https://www.sphericalinsights.com/reports/computer-vision-market (accessed on 25 December 2023).
34. M&M. Wearable Sensors Market. 2023. Available online: https://www.marketsandmarkets.com/Market-Reports/wearable-sensor-market-158101489.html (accessed on 27 December 2023).
35. Simjanović, D.J.; Zdravković, N.; Vesić, N.O. On the factors of successful e-commerce platform design during and after COVID-19 pandemic Using extended fuzzy AHP method. *Axioms* **2022**, *11*, 105. [CrossRef]
36. Milošević, M.R.; Milošević, D.M.; Stanojević, A.D.; Stević, D.M.; Simjanović, D.J. Fuzzy and interval AHP approaches in sustainable management for the architectural heritage in smart cities. *Mathematics* **2021**, *9*, 304. [CrossRef]
37. Lozynska, O.; Chaikovskyi, V. Using the analytic hierarchy process for budget and cost control in IT projects. In Proceedings of the 2023 IEEE 18th International Conference on Computer Science and Information Technologies (CSIT), Lviv, Ukraine, 19–21 October 2023; pp. 1–4.
38. Mishra, P.; Ul Amin, M.; Singh, G. Deep learning based MIMO detection in 6G wireless communication system. In Proceedings of the 2023 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE), Dubai, United Arab Emirates, 9–10 March 2023; pp. 366–369.
39. Ye, L.; Hou, X.; Wang, Q. Deep learning based CS channel estimation in MIMO system. In Proceedings of the 2022 IEEE 8th International Conference on Computer and Communications (ICCC), Chengdu, China, 9–12 December 2022; pp. 31–35.
40. Rehman, A.U.; Tito, S.R.; Ahmed, D.; Nieuwoudt, P.; Lie, T.T.; Vallès, B. An artificial intelligence-driven smart home towards energy efficiency: An overview and conceptual model. In Proceedings of the 2020 FORTEI-International Conference on Electrical Engineering (FORTEI-ICEE), Bandung, Indonesia, 23–24 September 2020; pp. 47–52.
41. Navarathna, P.J.; Malagi, V.P. Artificial intelligence in smart city analysis. In Proceedings of the 2018 International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 13–14 December 2018; pp. 44–47.
42. Khan, L.U.; Yaqoob, I.; Tran, N.H.; Kazmi, S.M.A.; Dang, T.N.; Hong, C.S. Edge-computing-enabled smart cities: A comprehensive survey. *IEEE Internet Things J.* **2020**, *7*, 10200–10232. [CrossRef]
43. Hassan, N.; Yau, K.-L.A.; Wu, C.; Bernardino, J. Edge computing in 5G: A review. *IEEE Access* **2019**, *7*, 127276–127289. [CrossRef]
44. Gheisari, M.; Wang, G.; Chen, S. An edge computing-enhanced internet of things framework for privacy-preserving in smart city. *Comput. Electr. Eng.* **2020**, *81*, 106504. [CrossRef]
45. Giordani, M.; Zorzi, M. Non-terrestrial networks in the 6G era: Challenges and opportunities. *IEEE Netw.* **2021**, *35*, 244–251. [CrossRef]
46. Lee, H.; Lee, B.; Yang, H.; Kim, J.; Kim, S.; Shin, W.; Shim, B.; Poor, H.V. Towards 6G hyper-connectivity: Vision, challenges, and key enabling technologies. *J. Commn. Netw.* **2023**, *25*, 344–354. [CrossRef]
47. Chen, Y.; Wang, Y.; Zhang, J.; Zhang, P.; Hanzo, L. Reconfigurable intelligent surface (RIS)-aided vehicular networks: Their protocols, resource allocation, and performance. *IEEE Veh. Technol. Mag.* **2022**, *17*, 26–36. [CrossRef]
48. Kim, S.; Moon, J.; Kim, J.; Ahn, Y.; Kim, D.; Kim, S.; Shim, B. Role of computer vision in 6G wireless communications. *IEEE Wirel. Commun.* **22023**, *submitted*.
49. Ahn, Y.; Kim, J.; Kim, S.; Shim, K.; Kim, J.; Kim, S.; Shim, B. Towards intelligent millimeter and terahertz communication for 6G: Computer vision-aided beamforming. *IEEE Wirel. Commun.* **2023**, *30*, 179–186. [CrossRef]
50. Hua, Z.; Lu, Y.; Pan, G.; Gao, K.; da Costa, D.B.; Chen, S. Computer vision-aided mmWave UAV communication systems. *IEEE IoT-J.* **2023**, *10*, 12548–12561. [CrossRef]
51. Nishio, T.; Koda, Y.; Park, J.; Bennis, M.; Doppler, K. When wireless communications meet computer vision in beyond 5G. *IEEE Commun. Mag.* **2021**, *5*, 76–83. [CrossRef]
52. Pin Tan, D.K.; He, J.; Li, Y.; Bayesteh, A.; Chen, Y.; Zhu, P.; Tong, W. Integrated sensing and communication in 6G: Motivations, use cases, requirements, challenges and future directions. In Proceedings of the 2021 1st IEEE International Online Symposium on Joint Communication & Sensing (JC &S), Dresden, Germany, 23–24 February 2021; pp. 1–6.
53. Liu, F.; Cui, Y.; Masouros, C.; Xu, J.; Han, T.X.; Eldar, Y.C.; Buzzi, S. Integrated sensing and communications: Toward dual-functional wireless networks for 6G and beyond. *IEEE J. Sel. Areas Commun.* **2022**, *40*, 1728–1767. [CrossRef]
54. Bayesteh, A.; He, J.; Chen, Y.; Zhu, P.; Ma, J.; Shaban, A.W.; Yu, Z.; Zhang, Y.; Zhou, Z.; Wang, G. Integrated sensing and communication (ISAC)—From concept to practice. *Commun. Huawei Res.* **2022**, *2*, 4–25.
55. Jiao, J.; Sun, X.; Fang, L.; Lyu, J. An overview of wireless communication technology using deep learning. *China Commun.* **2021**, *18*, 1–36. [CrossRef]

56. Nithya, T.; Kumar, V.N.; Gayathri, S.; Deepa, S.; Varun, C.M.; Subramanian, R.S. A comprehensive survey of machine learning: Advancements, applications, and challenges. In Proceedings of the 2023 Second International Conference on Augmented Intelligence and Sustainable Systems (ICAISS), Trichy, India, 24–26 November 2023; pp. 354–361.
57. Pereira de Figueiredo, F.A. An overview of massive MIMO for 5G and 6G. *IEEE Lat. Am. Trans.* **2022**, *20*, 931–940. [CrossRef]
58. Wen, C.-K.; Shih, W.-T.; Jin, S. Deep learning for massive MIMO CSI feedback. *IEEE Wirel. Commun. Lett.* **2018**, *7*, 748–751. [CrossRef]
59. Guo, J.; Wen, C.-K.; Jin, S.; Li, G.Y. Overview of deep learning-based CSI feedback in massive MIMO systems. *IEEE Trans. Commun.* **2022**, *70*, 8017–8045. [CrossRef]
60. Wang, T.; Wen, C.-K.; Jin, S.; Li, G.Y. Deep learning-based CSI feedback approach for time-varying massive MIMO channels. *IEEE Wirel. Commun. Lett.* **2019**, *8*, 416–419. [CrossRef]
61. Chun, C.-J.; Kang, J.-M.; Kim, I.-M. Deep learning-based channel estimation for massive MIMO systems. *IEEE Wirel. Commun. Lett.* **2019**, *8*, 1228–1231. [CrossRef]
62. Le, H.A.; Van Chien, T.; Nguyen, T.H.; Choo, H.; Nguyen, V.D. Machine learning-based 5G-and-beyond channel estimation for MIMO-OFDM communication systems. *Sensors* **2021**, *21*, 4861. [CrossRef] [PubMed]
63. Jiang, Y.; Lin, W.; Zhao, W.; Wang, C. AcsiNet: Attention-based deep learning network for CSI prediction in FDD MIMO systems. *IEEE Wirel. Commun. Lett.* **2023**, *12*, 471–475. [CrossRef]
64. Liao, Y.; Hua, Y.; Cai, Y. Deep learning based channel estimation algorithm for fast time-varying MIMO-OFDM systems. *IEEE Commun. Lett.* **2020**, *24*, 572–576. [CrossRef]
65. Zhang, Y.; Wu, Y.; Liu, A.; Xia, X.; Pan, T.; Liu, X. Deep learning-based channel prediction for LEO satellite massive MIMO communication system. *IEEE Wirel. Commun. Lett.* **2021**, *10*, 1835–1839. [CrossRef]
66. Sharma, V.; Kumar, S. Role of artificial intelligence (AI) to enhance the security and privacy of data in smart cities. In Proceedings of the 2023 3rd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 12–13 May 2023; pp. 596–599.
67. Ilyas, M. IoT applications in smart cities. In Proceedings of the 2021 International Conference on Electronic Communications, Internet of Things and Big Data (ICEIB), Yilan, Taiwan, 10–12 December 2021; pp. 44–47.
68. Kamruzzaman, M.M.; Hossin, M.A.; Alruwaili, O.; Alanazi, S.; Alruwaili, M.; Alshammari, N.; Alaerjan, A.; Zaman, R. IoT-oriented 6G wireless network system for smart cities. *Comput. Intell. Neurosci.* **2022**, *2022*, 1874436. [CrossRef] [PubMed]
69. Tekgul, E.; Chen, J.; Tan, J.; Vook, F.; Özen, S.; Jajoo, A. Deep learning-based channel state information prediction with incomplete history. In Proceedings of the 2022 IEEE Wireless Communications and Networking Conference (WCNC), Austin, TX, USA, 10–13 April 2022; pp. 447–452.
70. Zheng, K.; Luo, R.; Wang, Z.; Liu, X.; Yao, Y. Short-term and long-term throughput maximization in mobile wireless-powered internet of things. *IEEE Internet Things* **2023**, *1*, 1. [CrossRef]
71. Liu, X.; Xu, B.; Zheng, K.; Zheng, H. Throughput maximization of wireless-powered communication network with mobile access points. *IEEE Trans. Wirel. Commun.* **2023**, *22*, 4401–4415. [CrossRef]
72. Saini, J.S.; Arora, S.; Kamboj, S. Prediction of smart building and smart city resources using AI-techniques. In Proceedings of the 2023 2nd International Conference for Innovation in Technology (INOCON), Bangalore, India, 3–5 March 2023; pp. 1–5.
73. Mahamuni, C.V.; Sayyed, Z.; Mishra, A. Machine learning for smart cities: A survey. In Proceedings of the 2022 IEEE International Power and Renewable Energy Conference (IPRECON), Kollam, India, 16–18 December 2022; pp. 1–8.
74. Ashwini, B.P.; Savithramma, R.M.; Sumathi, R. Artificial intelligence in smart city applications: An overview. In Proceedings of the 2022 6th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 25–27 May 2022; pp. 986–993.
75. Yu, Y.; Wang, C.; Gu, X.; Li, J. A novel deep learning-based method for damage identification of smart building structures. *Struct. Health Monit.* **2019**, *18*, 143–163. [CrossRef]
76. Kim, B.; Yuvaraj, N.; Sri Preethaa, K.R.; Santhosh, R.; Sabari, A. Enhanced pedestrian detection using optimized deep convolution neural network for smart building surveillance. *Soft Comput.* **2020**, *24*, 17081–17092. [CrossRef]
77. Pawar, U.; O'Shea, D.; Rea, S.; O'Reilly, R. Explainable AI in healthcare. In Proceedings of the 2020 International Conference on Cyber Situational Awareness, Data Analytics and Assessment (CyberSA), Dublin, Ireland, 15–19 June 2020; pp. 1–2.
78. Kwon, K.; Lee, S.; Kim, S. AI-based home energy management system considering energy efficiency and resident satisfaction. *IEEE Internet Things J.* **2022**, *9*, 1608–1621. [CrossRef]
79. Liu, Y.; Peng, M.; Shou, G.; Chen, Y.; Chen, S. Toward edge intelligence: Multiaccess edge computing for 5G and internet of things. *IEEE Internet Things J.* **2020**, *7*, 6722–6747. [CrossRef]
80. Singh, P.; Kaur, A.; Aujla, G.S.; Batth, R.S.; Kanhere, S. DaaS: Dew computing as a service for intelligent intrusion detection in edge-of-things ecosystem. *IEEE Internet Things J.* **2021**, *8*, 12569–12577. [CrossRef]
81. Satyanarayanan, M. The emergence of edge computing. *Computer* **2017**, *50*, 30–39. [CrossRef]
82. Luo, Q.; Hu, S.; Li, C.; Li, G.; Shi, W. Resource scheduling in edge computing: A survey. *IEEE Commun. Surv. Tutor.* **2021**, *23*, 2131–2165. [CrossRef]
83. Chen, S.; Li, Q.; Zhou, M.; Abusorrah, A. Recent advances in collaborative scheduling of computing tasks in an edge computing paradigm. *Sensors* **2021**, *21*, 779. [CrossRef] [PubMed]

84. Carvalho, G.; Cabral, B.; Pereira, V.; Bernardino, J. Edge computing: Current trends, research challenges and future directions. *Computing* **2021**, *103*, 993–1023. [CrossRef]
85. Zeyu, H.; Geming, X.; Zhaohang, W.; Sen, Y. Survey on edge computing security. In Proceedings of the 2020 International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE), Fuzhou, China, 12–14 June 2020; pp. 96–105.
86. Porambage, P.; Okwuibe, J.; Liyanage, M.; Ylianttila, M.; Taleb, T. Survey on multi-access edge computing for internet of things realization. *IEEE Commun. Surv. Tutor.* **2018**, *20*, 2961–2991. [CrossRef]
87. Wang, X.; Garg, S.; Lin, H.; Kaddoum, G.; Hu, J.; Hossain, M.S. A secure data aggregation strategy in edge computing and blockchain-empowered internet of things. *IEEE Internet Things J.* **2022**, *9*, 14237–14246. [CrossRef]
88. Ali, B.; Gregory, M.A.; Li, S. Multi-access edge computing architecture, data security and privacy: A review. *IEEE Access* **2021**, *9*, 18706–18721. [CrossRef]
89. Yousefpour, A.; Fung, C.; Nguyen, T.; Kadiyala, K.; Jalali, F.; Niakanlahiji, A.; Kong, J.; Jue, J. All one needs to know about fog computing and related edge computing paradigms: A complete survey. *J. Syst. Archit.* **2019**, *98*, 289–330. [CrossRef]
90. Zhang, K.; Leng, S.; He, Y.; Maharjan, S.; Zhang, Y. Cooperative content caching in 5G networks with mobile edge computing. *IEEE Wirel. Commun.* **2018**, *25*, 80–87. [CrossRef]
91. Hartmann, M.; Hashmi, U.S.; Imran, A. Edge computing in smart health care systems: Review, challenges, and research directions. *Trans. Emerg. Telecommun. Technol.* **2022**, *33*, e3710. [CrossRef]
92. Liu, G.; Shi, H.; Kiani, A.; Khreishah, A.; Lee, J.; Ansari, N.; Liu, C.; Yousef, M.M. Smart traffic monitoring system using computer vision and edge computing. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 12027–12038. [CrossRef]
93. Guo, H.; Li, J.; Liu, J.; Tian, N.; Kato, N. A survey on space-air-ground-sea integrated network security in 6G. *IEEE Commun. Surv. Tutor.* **2022**, *24*, 53–87. [CrossRef]
94. *3GPP TR 38.811*; Study on New Radio (NR) to Support Non-Terrestrial Networks. 3GPP: Sophia Antipolis, France, 2020.
95. Wu, Q.; Zhang, R. Towards smart and reconfigurable environment: Intelligent reflecting surface aided wireless network. *IEEE Commun. Mag.* **2017**, *55*, 106–112. [CrossRef]
96. Shin, W.; Vaezi, M.; Lee, B.; Love, D.J.; Lee, J.; Poor, H.V. Non-orthogonal multiple access in multi-cell networks: Theory, performance, and practical challenges. *IEEE Commun. Mag.* **2017**, *55*, 176–183. [CrossRef]
97. Yin, L.; Clerckx, B. Rate-splitting multiple access for multigroup multicast and multibeam satellite systems. *IEEE Trans. Commun.* **2021**, *69*, 976–990. [CrossRef]
98. Clerckx, B.; Mao, Y.; Jorswieck, E.A.; Yuan, J.; Love, D.J.; Erkip, E.; Niyato, D. A primer on rate-splitting multiple access: Tutorial, myths, and frequently asked questions. *IEEE J. Sel. Areas Commun.* **2023**, *41*, 1265–1308. [CrossRef]
99. Li, H.; Mao, Y.; Dizdar, O.; Clerckx, B. Rate-splitting multiple access for 6G—Part III: Interplay with reconfigurable intelligent surfaces. *IEEE Commun. Lett.* **2022**, *26*, 2242–2246. [CrossRef]
100. Wang, D.; Giordani, M.; Alouini, M.-S.; Zorzi, M. The potential of multilayered hierarchical non-terrestrial networks for 6G: A comparative analysis among networking architectures. *IEEE Veh. Technol. Mag.* **2021**, *16*, 99–107. [CrossRef]
101. Ying, Z.; Yang, H.; Gao, J.; Zheng, K. A new vision-aided beam prediction scheme for mmWave wireless communications. In Proceedings of the 2020 IEEE 6th International Conference on Computer and Communications (ICCC), Chengdu, China, 11–14 December 2020; pp. 232–237.
102. Charan, G.; Alrabeiah, M.; Alkhateeb, A. Vision-aided dynamic blockage prediction for 6G wireless communication networks. In Proceedings of the 2021 IEEE International Conference on Communications Workshops (ICC Workshops), Montreal, QC, Canada, 14–23 June 2020; pp. 1–6.
103. Tian, Y.; Pan, G.; Alouini, M.S. Applying deep-learning-based computer vision to wireless communications: Methodologies, opportunities, and challenges. *IEEE Open J. Commun. Soc.* **2020**, *2*, 132–143. [CrossRef]
104. Vaswani, A.; Shazeer, N.; Parmar, N.; Uszkoreit, J.; Jones, L.; Gomez, A.N.; Kaiser, Ł.; Polosukhin, I. Attention is all you need. *Adv. Neural Inf. Process. Syst.* **2017**, *30*.
105. Yuan, Y.; Zheng, G.; Wong, K.K.; Ottersten, B.; Luo, Z.Q. Transfer learning and meta learning-based fast downlink beamforming adaptation. *IEEE Trans. Wirel. Commun.* **2021**, *20*, 1742–1755. [CrossRef]
106. Hua, Z.; Ke, Y.; Yang, Z.; Di, Z.; Pan, G.; Gao, K. Computer vision-aided mmWave communications for indoor medical healthcare. *Comput. Biol. Med.* **2023**, *169*, 107869. [CrossRef] [PubMed]
107. Xu, W.; Gao, F.; Zhang, Y.; Pan, C.; Liu, G. Multi-User matching and resource allocation in vision aided communications. *IEEE Trans. Commun.* **2023**, *71*, 4528–4543. [CrossRef]
108. Yin, L.; Mao, Y.; Dizdar, O.; Clerckx, B. Rate-splitting multiple access for 6G—Part II: Interplay with integrated sensing and communications. *IEEE Commun. Lett.* **2022**, *26*, 2237–2241. [CrossRef]
109. Li, X.; Gong, Y.; Huang, K.; Niu, Z. Over-the-Air integrated Sensing, communication, and computation in IoT networks. *IEEE Wirel. Commun.* **2023**, *30*, 32–38. [CrossRef]
110. Demirhan, U.; Alkhateeb, A. Integrated sensing and communication for 6G: Ten key machine learning roles. *IEEE Commun. Mag.* **2023**, *61*, 113–119. [CrossRef]
111. Rajput, K.; Wu, L.; Bhavani Shankar, M.R. Next-Generation IoT networks: Integrated sensing communication and computation. In Proceedings of the 2023 IEEE International Conference on Acoustics, Speech, and Signal Processing Workshops (ICASSPW), Rhodes Island, Greece, 4–10 June 2023; pp. 1–4.

112. Yin, L.; Liu, Z.; Bhavani Shankar, M.R.; Alaee-Kerahroodi, M.; Clerckx, B. Integrated sensing and communications enabled low earth orbit satellite systems. *arXiv* **2023**, arXiv:2304.00941.
113. Wang, J.; Varshney, N.; Gentile, C.; Blandino, S.; Chuang, J.; Golmie, N. Integrated sensing and communication: Enabling techniques, applications, tools and data sets, standardization, and future directions. *IEEE Internet Things J.* **2022**, *9*, 23416–23440. [CrossRef]
114. Lu, S.; Liu, F.; Li, Y.; Zhang, K.; Huang, H.; Zou, J.; Li, X.; Dong, Y.; Dong, F.; Zhu, J.; et al. Integrated sensing and communications: Recent advances and ten open challenges. *arXiv* **2023**, arXiv:2305.00179.
115. Liu, J.; Liu, H.; Chen, Y.; Wang, Y.; Wang, C. Wireless sensing for human activity: A survey. *IEEE Commun. Surv. Tutor.* **2020**, *22*, 1629–1645. [CrossRef]
116. Cui,Y.; Liu, F.; Jing, X.; Mu, J. Integrated sensing and communications for ubiquitous IoT: Applications, trends, and challenges. *IEEE Netw.* **2021**, *35*, 158–167. [CrossRef]
117. Li, X.; Liu, F.; Zhou, Z.; Zhu, G.; Wang, S.; Huang, K.; Gong, Y. Integrated sensing, communication, and computation over-the-air: MIMO beamforming design *IEEE Trans. Wirel. Commun.* **2023**, *22*, 5383–5398. [CrossRef]
118. UN Habitat 2020. The New Urban Agenda Illustrated. 2020. Available online: https://unhabitat.org/sites/default/files/2020/12/nua_handbook_14dec2020_2.pdf (accessed on 27 December 2023).