


# On the Dependability of 6G Networks

Ijaz Ahmad <sup>\*</sup>, Felipe Rodriguez, Jyrki Huusko and Kari Seppänen 

VTT Technical Research Center of Finland, FI-02044 Espoo, Finland

<sup>\*</sup> Correspondence: [ijaz.ahmad@vtt.fi](mailto:ijaz.ahmad@vtt.fi)

**Abstract:** Sixth-generation communication networks must be highly dependable due to the foreseen connectivity of critical infrastructures through them. Dependability is a compound metric of four well-known concepts—reliability, availability, safety, and security. Each of these concepts have unique consequences for the success of 6G technologies and applications. Using these concepts, we explore the dependability of 6G networks in this article. Due to the vital role of machine learning in 6G, the dependability of federated learning, as a distributed machine learning technique, has been studied. Since mission-critical applications (MCAs) are highly sensitive in nature, needing highly dependable connectivity, the dependability of MCAs in 6G is explored. Henceforth, this article provides important research directions to promote further research in strengthening the dependability of 6G networks.

**Keywords:** 6G; dependability; security; reliability; availability; safety; communication networks

## 1. Introduction

Fifth-generation wireless networks brought innovative technological concepts into the wireless domain that closed the gap between traditional IT domains and communication networks. For example, cloudification and softwarization of networking technologies enabled deploying new use cases and applications in wireless networks. Technologies from the physical layer, such as massive multi-input multi-output (MIMO), to the application layer, such as machine learning (ML) technologies, have increased networks' capacities and capabilities. However, 5G cannot meet the requirements of emerging services such as the Internet of Everything (IoE), due to the inherent limitations of 5G systems [1]. Sixth-generation communications networks will take a huge leap beyond 5G in order to meet the needs of future services and societies, which will be centered around data centric, intelligent, and automated processes [2]. Novel disruptive technologies in the domains of terahertz and optical communications, cell-less coverage through integrated terrestrial-satellite access technologies [3], distributed end-user terminal-based artificial intelligence (AI) [4,5], and distributed ledger technologies (DLTs) [6], to name a few, will converge to fulfill the needs of emerging applications and use cases [7].

Furthermore, 6G is expected to ignite a human transformation, thanks to improved context-aware devices with new human-machine interfaces provided by end-devices that are no longer mere data collectors, but multiple synchronized entities working in unison. This will dramatically improve the way we interact with both the physical and digital worlds. Such services will have stringent quality of service (QoS) requirements in terms of bandwidth, reliability, and latency that will be challenging for existing 5G networks to provide. For example, ubiquitous and universal computing with resources distributed locally and in the cloud, knowledge systems that store and convert data into actions, and efficient sensing for controlling the physical world cannot be provided in 5G, and thus, focus is put on 6G research. Sixth-generation networks are also envisioned to provide massive-scale connectivity, 3D networking, real-time immersion through extended reality (XR), and haptic applications [8].

To stand on the envisioned promises, 6G must be highly distributed to meet the needs of latency, reliability, and availability of critical services, such as industrial au-



**Citation:** Ahmad, I.; Rodriguez, F.; Huusko, J.; Seppänen, K. On the Dependability of 6G Networks. *Electronics* **2023**, *12*, 1472. <https://doi.org/10.3390/electronics12061472>

Academic Editors: Ivan Cvitić, Dragan Peraković, Anca Delia Jurcut and Goran Marković

Received: 27 January 2023

Revised: 16 March 2023

Accepted: 17 March 2023

Published: 20 March 2023



**Copyright:** © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

tomation systems, UAVs, and autonomous systems. Distributed clouds—edge, fog, and cloudlets [9]—will play a crucial role in providing the necessary computing and storage resources for distributed 6G. Softwarization of network functions and services will enable distributing important services to different network perimeters. Similarly, distributed AI in the distributed network will overcome challenges related to latency, reliability, data criticality, and privacy in 6G [10,11]. However, the distributed nature of the network will also create several challenges, mainly related to dependability. Therefore, in this article we discuss the dependability of 6G. Dependability, as discussed in detail in Section 3, ensures the trusted delivery of services. Elaborate discussion on dependability and its concepts is presented in [12], and thus we avoid writing in detail about dependability itself. In this article, we discuss the dependability of 6G from the systems engineering perspective, where the focus is laid on four well-known concepts: reliability, availability, security, and safety.

Reliability is the probability of a system working correctly for a certain period of time. As 6G networks will be highly distributed, the main concern regarding reliability is effectively coordination of the computing nodes. In order to achieve this, successful communication protocols between those computing nodes are needed, along with a reliable underlying network capable of supporting the amount of traffic generated by storing and retrieving data [13]. Availability refers to the probability of a system working properly at any given time. Distributed AI solutions for 6G networks are an attractive option for improving learning time while reducing resource consumption, and thereby improving the availability of AI-based systems and services. Form factor is an important variable, since it limits the resources, including energy, available for communication with external, distributed solutions. Security refers to capacity of a system for protecting itself by promptly identifying threats, and taking actions that effectively protect the services deployed on the system and data exchanged among the components and users. In the case of 6G network services, distributed AI/ML algorithms are needed to train models locally for threat identification and mitigation, in order to preserve the end user information. Finally, safety refers to the ability of a system to avoid harming human life, the environment, or private property. Since 6G networks will leverage use cases where human life is at the stake such as autonomous driving, it is in our interest to analyze the role of AI/ML in such situations.

In this work, we study the dependability of 6G networks in four dimensions, i.e., reliability, availability, safety, and security. We also analyze how the distributed nature of 6G networks negatively affects their dependability. Furthermore, we dive into the roles of distributed AI techniques and distributed mission-critical applications (MCAs) that are currently used in the intelligentization of the networks. We bring forth important challenges with potential solutions and shed light on interesting future research directions. Henceforth, this article is organized as follows: Section 2 highlights the related work and contributions of this article. Section 3 briefly discusses the concept of dependability. Section 4 discusses dependability in 6G networks. Section 5 briefly introduces the AI techniques expected to be deployed on 6G edges, and their effects on dependability. Section 6 provides insights into the relation between dependability of MCAs in 6G. Interesting future research directions are summarized in Section 7, and the article is concluded in Section 8.

## 2. Related Work and Our Contributions

In this section, we describe the related work and our contributions.

### 2.1. Related Work

Dependability is extremely important for future 6G communications, mainly due to the integration of critical infrastructures through wireless networks. There exists research that focus on each individual topic, such as reliability, availability, safety, and security. However, dependability as whole has received little research attention. There also exist research on specific topics, such as dependability of industrial IoT [14], where the focus is on real-time and reliability requirements of industrial IoT networks. Similarly, the authors

of [15] discuss the dependability of software-defined networks. The article argues the need for secure and dependable SDNs by-design by first highlighting the threat vectors that can be used by adversaries. Then, the article sketches the design of a secure and dependable network architecture, mainly focusing on the control platform. A survey on heterogeneous dependable wireless networks, focusing on industry, is presented in [16]. The article elaborates on the heterogeneous nature of the next generation factories, where diverse technologies are interconnected through a diverse set of wired and wireless connectivity technologies. However, the main focus is on industrial systems, where dependability in terms of availability and latency of existing technologies is critically discussed.

The related work on dependability can be divided based on the four categories discussed in this article, i.e. reliability, availability, safety, and security. Articles, surveys, and review articles can be found discussing each of these four aspects in detail. For instance, the authors of [17] discussed deep learning-based techniques that can increase reliability of 6G networks. A survey on deep learning techniques for improving reliability in 6G is presented in [18]. UAVs can also be used to increase the reliability of 6G networks, as surveyed in [19]. Even though all the dimensions of dependability are highly dependent, reliability and availability are highly intertwined. Increasing the reliability of communication networks increases availability. Increasing the reliability and availability of 6G networks, therefore, is discussed in [20], where the focus is mainly on the IoT. The safety feature of dependability is mainly discussed from use-case points of view, and general discussion on theme of safety in 6G networks is lacking. For example, huge research efforts are dedicated to safety in autonomous vehicles and UAVs [21]. Security in 5G and beyond is discussed in [22], in which a detailed description of the security landscape of 5G with potential research direction in 6G is presented. Security and trust in 6G are also elaborated in [23]. The authors discuss the main dimensions of security and trust in 6G, ranging from the physical layer up to the application layer.

The main lesson learned from the existing research is that most articles are focused on a specific dimensions of dependability.

## 2.2. Contributions of the Paper

The main contributions of this article revolve around:

- We analyze the role of dependability in 6G networks from a system-wide point of view, studying each of the four components of dependability separately.
- We analyze how the omnipresence and distributed nature of AI/ML affects the dependability of 6G systems.
- We study the importance of dependability in MCAs, analyzing every aspect of dependability separately.
- We identify future research directions that are summarized in Table 1 and will help to increase the dependability of future 6G networks.

For smooth readability, the most important acronyms are defined in Abbreviations. In the following section, we discuss the background and principles of dependability.

**Table 1.** Existing challenges and potential future research directions.

Dependability	Challenge	Potential Future Research Directions
Reliability	Distributed control and management will increase the complexity of the overall system which can lead to reliability challenges.	Dependable 6G would require a hierarchical architecture that provide logical centralized view of the overall network including the architecture and infrastructure elements, and loosely coupled distributed control elements, all synchronized through a global view can simplify the overall system.

Table 1. Cont.

Dependability	Challenge	Potential Future Research Directions
Availability	Due to the distributed control, availability can be increased in principle, however, availability can be compromised through weaknesses in security, reliability and safety.	The architecture should be modular and distributed as it is, and designed such that the effects of cascading failures are avoided, where availability of one module or component does not compromise the availability of another.
Safety	Safety is a rarely researched topic from technical perspectives and is intertwined with security.	The main work needed in increasing safety of future communications networks is defining safety in technical terms and aligning safety research with the rest, similar to security-by-design, safety-by-design must be brought into discussions and research.
Security	Security in 6G is extremely complicated in terms of new technologies, modular distributed design, and the increasingly vanishing physical-cyber borders leading to highly complex network architectures.	First, it will be important to know early whether to build 6G security on top of the 5G standards or rethink according to the new disruptive technologies from application to physical layers. How to design security systems for the loosely coupled, highly distributed, and inter-dependent systems that are synchronized on one hand and avoid the risks related to cascading failures on the other hand, will be extremely important. Furthermore, AI related risks and challenges including its sustainability will exacerbate in 6G and will require serious research efforts.

### 3. Dependability

Dependability is the ability of a system to deliver a service that can justifiably be trusted; in other words, it should avoid frequent and severe service failures [24]. Though crucial in importance, dependability is often overlooked in favor of other research directions. Priority has been given to coordinating computing activities between distributed nodes in order to achieve higher performance, or security mechanisms that help in protecting users and their data. As previously mentioned, dependability is a compound metric and can be discussed through four important indicators: reliability, availability, safety, and security. Although performance and security are important, and as such most of the works focus on them, the other three requirements of dependable systems should not be underestimated [25,26]. Moreover, there are many facets of dependability, for instance, confidentiality and integrity [27]. However, some of the concepts converge into the four aspects discussed throughout this article. Therefore, for brevity we limit the discussion to the topics of reliability, availability, safety, and security, as described below.

#### 3.1. Reliability

The complexity of distributed edge networks means that achieving reliability in such an environment is not an easy task. With the increasing number of MCAs solutions on the market, requirements for reliable systems are indispensable, and furthermore, still a challenge to achieve. Rapid changes in computing environments also bring challenges to reliability, for example, asynchronism, heterogeneity of software/hardware, scalability, and fault tolerance, to mention some. In [28], the authors briefly explored reliability issues in edge AI systems and proposed an architecture that meet latency and reliability requirements for many MCAs. It is identified that computation on edge systems occur in three different layers: bottom (end devices), middle (servers), and top (centralized cloud). In order to achieve good communication and a fast response, all three layers must be properly synchronized, like the storing and data access for processing [13].

#### 3.2. Availability

Availability is realized once reliability has been achieved. Reliability is the probability that the system is working, and availability is the probability of it working at a given time. Availability ensures that no denial of authorized access to the system occurs [29]. The advantage of distributed systems is that additional nodes and communication paths

help hiding any failure that might exist. Current research trends in edge computing aim at improving system availability by carefully planning task and data offloading from end devices towards edge servers with frameworks that are even capable of performing the offloading based on network statistics and the edge servers' computation capabilities. Another characteristic helping availability is the reassignment of tasks from failing nodes, although common node failures are still a problem, since a task that crashes a node can be moved to another node and causes the same type of crash. Since availability and reliability work together, it is important to notice they can also work at cross purposes; with this in mind, both concepts must be weighted against one another, as different systems might require a different degree of each.

### 3.3. Safety

Safety is critical for MCAs, especially in use cases where human lives are at danger, such as autonomous driving and telesurgery. The IEC 60601 [29], which is a technical standard for the safety and performance of the medical electrical equipment, defines safety as the avoidance of any hazards due to the operation of a device under normal or single-fault conditions. However, this definition can be broadened to cover non-medical domains, thereby including faulty conditions such as wrong lane selection in autonomous driving, or task offloading failure affecting the information given to the end user, or creating distractions in an augmented reality application. The current trend in communication networks is to simplify safety through the development of bug-free software or through an AI-based optimization problem. It is necessary to study the interaction between the composing cyberphysical systems (CPS) and the environment of each use case [30]. In [31,32], telesurgery safety considerations from the medical point of view are given. It also mentions their experience with different surgical robots and elaborates on some comparisons.

### 3.4. Security

Security is one of the main issues in communication networks, as both nodes and the whole network are attacked by malicious users [22,33]. The distributed and data-driven nature of future 6G communication networks and its use cases mean more data, and of course, a wider attack surface. The applications of AI or ML in communications networks are increasing at a higher pace due to apparent reasons [34]; however, AI and ML also bring their own security challenges in communications networks, as elaborated in [35,36]. The most important part is to identify the required level of security for a certain use case and adopt the principles of the security-by-design approach. These concepts are quite important due to the diverse nature of 6G MCAs. Furthermore, the rise in the number of capable attackers targeting communication networks call for stringent security requirements. In [37], the authors explore the application of blockchain technology alongside ML in order to protect vehicular networks from cyber attacks. Similarly, in [38], the authors used a smart contract architecture in heterogeneous vehicular networks for collaboratively performing tasks between moving vehicles and parked vehicles. The smart transactions consider the characteristics of both the network and the attack models for improving security. Furthermore, physical-layer security techniques can be used to provide security with drastic changes to the network architecture [23,39].

## 4. 6G and Dependability

### 4.1. Brief Introduction to 6G Networks

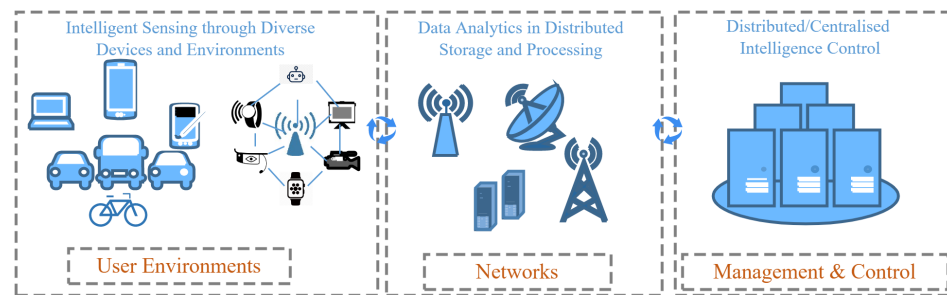
The rapid development of multimedia applications for use cases such as high-fidelity holograms, tactile Internet, and the support of MCAs require a higher bandwidth, lower latency, and higher reliability than that offered by the current 5G communication networks [40,41]. Therefore, 6G aims to fulfill these requirements through base-station densification (mmWave and terahertz tiny cells, temporary hotspots) with other means for distribution of network functions, such as extended edge computing, and exploration of higher frequencies above 300 GHz, as discussed in [1]. The resulting 6G networks, thus,

will be expected to provide more than just communications, i.e., to interconnect communication, computing, and sensing technologies with the physical, biological, and cyber worlds, thereby acting as distributed neural networks that will enable intelligence of everything. Sixth-generation networks will transform the way we communicate, from connected people and devices to connected intelligence. This means bringing intelligence closer to every person, home, or business, for example, in the form of edge intelligence. Therefore, 6G networks are bound to be large-scale, use heterogeneous access with cell-free or cell-less coverage, and dynamic with heavily-distributed storage and computation capabilities [42].

The transition from 5G to 6G requires changes not only in bandwidth, but from the physical to the application layer in order to meet the new requirements of emerging services, such as the Internet of Everything (IoE) [43]. Furthermore, 6G networks are expected to achieve data rates in the range of terabits per second, thanks to the developments in terahertz communications; and improvements in massive MIMO, beamforming, and novel coding schemes. A successful combination of these next-generation wireless networks with cloud, edge, and fog platforms is vital in order to realize increased network intelligence. To meet the requirements of latency and privacy, bringing cloud platforms closer to the sources of data, for instance, in the far edge, will be inevitable. Edge intelligence [28,44] thus opens up new horizons for achieving and exploiting the full potential of 6G networks.

Since the first generation (1G), the complexity of communication networks have increased while expanding both horizontally and vertically, thereby rendering them difficult to manage. Furthermore, along with complexity, the security threat landscape has also increased constantly [22]. Edge computing can play an important role in addressing both of these challenges, i.e., complexity and security. By devolving control into multiple control units, compared to centralized ones, security through redundancy can be increased as a general phenomenon. For instance, the chances of single points of failure, and of a single target for denial of service (DoS) and resource exhaustion attacks, are highly complicated in such distributed environments. Furthermore, edge computing plays a vital role in 6G communication networks, as it provides the computing the resources necessary for carrying out management and analysis close to end-users' devices [45].

Fast and focused data processing through edge computing is the cornerstone of applications in 6G, for example, in vehicle-to-everything communications [46]. In-depth data analysis could be carried out by the centralized cloud at the expense of delays [47]. Figure 1 shows a simplified architecture of an AI-based 6G network, which is divided into three parts: user environment, networks, and management and control. In the management and control, functions such as parameter optimization, resource management, and task scheduling are carried out. In the network part, some of the tasks performed are data filtering, knowledge discovery, and feature extraction for data analytics, besides the usual network layers' work. Finally, in the user's environment, all the sensing, monitoring, and data collection occurs. The increase in data volumes being processed at the edge of the network represents a difficulty in properly identifying useful data for a primary analysis, prior to passing them to the centralized cloud. These requirements have paved the way to the intelligentization of the edge computing, referred to now as edge intelligence or EdgeAI [48], transforming it into a AI-based platform capable of offering intelligent services [49]. In order to achieve this, research has departed from the centralized cloud-based approach, sparking an interest in distributed, low-latency, and reliable AI at the edge [50,51].



**Figure 1.** An abstract representation of enabling intelligence in 6G networks.

EdgeAI is drawing an increasing attention, and its development is closely aligned with that of reliability in communications and end-device constraints. This allows the deployment of a network whose operation resembles that of a distributed computer, which is deployed between the centralized cloud and end users. This distributed nature of EdgeAI can have huge impacts on dependability of 6G networks, as discussed below.

#### 4.2. Dependability in 6G Networks

In this part, we analyze the dependability of future 6G networks from the perspective of their distributed and data-driven nature. Concepts such as EdgeAI help reduce latency between the end-devices and edge servers. However, at the same time, they might be points of failure and interesting targets for security attacks, if its weaknesses are not properly addressed before deployment. Below we discuss the dependability of 6G networks in the four dimensions, i.e., reliability, availability, safety, and security from the perspectives of EdgeAI.

##### 4.2.1. Reliability

Sixth-generation networks are expected to offer extremely high reliability. EdgeAI supports the vision of 6G through offering more computational power near users or services while reducing overall latency. Reliability requires checking the necessary requirements instead of assuming that these are fulfilled and constantly monitoring the network [52]. Although in terms of performance, EdgeAI supposes a step forward, its distributed nature, combined with the high number of servers required, might well introduce other issues. First, we have asynchronism. As the number of edge servers rises, they are also expected to be capable of working in unison; this means being synchronized. Synchronization is improved when servers are aware of the status of neighboring servers; in other words, the exchange of information, such as available memory or processing power, is shared in a timely manner.

Another issue is the heterogeneity of software and hardware at the nodes. Although it brings benefits in the long run, the adoption of heterogeneous solutions might also pose challenges. As an example, heterogeneous EdgeAI servers might have different power consumption and performance levels due to non-identical CPU architectures. In the same manner, distinct feature support could hinder synchronism. Scalability could also be a problem for networks, as it increases the complexity of management, and it might also create issues with synchronism. As 6G networks will be highly scalable, fault tolerance is also important in order to ensure reliability. As a system scales to be hundreds of nodes in size, a fault tolerant system will enable the operations or services to continue at a reduced level, though not stopping completely.

##### 4.2.2. Availability

Availability is the assurance of access to services and resources by legitimate users, or the quality of being ready or present for immediate use [53]. As mentioned in Section 2, reliability and availability are both intertwined. As a combination of highly distributed systems, 6G networks will be capable of dissimulating failures at the edge servers by rapidly offloading the assigned processes towards a nearby server that possesses the

required resources. In the context of EdgeAI, if an edge server fails, then its tasks are offloaded towards a neighboring edge. This is where synchronism plays a major role, and in order to achieve this, servers must be aware of the status of each other. Furthermore, predictive analysis of available resources in neighboring edge nodes will be important. Such analysis will enable performing normal routine tasks, along with the system being able to offload tasks to neighboring nodes in cases of failures, as discussed in [36]. This process will be time consuming, but the system is perceived by the user as still functioning, even with the increase in delay that task offloading represents. Similarly, load-balancing techniques that can effectively distribute tasks among available resources can also increase the availability of critical resources [54]. Although highly related, it must be noted that a system with high availability is not necessarily reliable, thereby ensuring the expected high reliability of 6G networks does not guarantee meeting the availability criteria.

#### 4.2.3. Safety

Safety and security, looking intertwined, are highly complicated in terms of defining their roles in communications networks. Safety, also defined similarly in [55], is a system's characteristic of preventing losses due to unintentional actions by normal, non-harmful actors. Security, on the other hand, relates to deliberate actions (mostly harmful) by deliberate actors. Safety in 6G communications networks can be achieved by taking several measures that are also related to security, which are discussed in the following security part. Aside from foolproof security, safety can be achieved by improving monitoring and response systems, increasing multiplicity or redundancy, and distributing important control functions throughout the network. EdgeAI thus plays a very important role in providing opportunity for redundant resources and distributing important network control functions. The concept of devolving control functions, with the help of miniaturizing edge to the extreme, as discussed in [56], can improve safety in terms of minimizing the impact of failures and delimiting the consequences. The same is true for communications links, using multiple access technologies to avoid blackout due to failure in one. Satellite communications [57,58] present interesting solutions to be coupled with terrestrial networks for enabling safe operation in times of failures, as a redundant communication infrastructure. The key point in improving safety in 6G is enabling the system to function in the wake of uncertainty, failures in different perimeters and surroundings, and security vulnerabilities and attacks, which are discussed below.

#### 4.2.4. Security

As one of the main concerns regarding modern networks, security in 6G is of paramount importance. Novel technologies in 6G networks will also introduce new security concerns. In this regard, we could mention teraHertz (THz) technology, which is believed to hinder the ability of malicious users to perform eavesdropping; however, recent research has shown it is still possible, although difficult, to intercept the signals, even when transmitted with narrow beams [59]. Quantum communications are also expected to make a significant contribution in 6G networks, mainly from the perspectives of communications security, such as quantum and post quantum cryptography [60]. Nevertheless, the technology is still at its infancy, and although many advances have been made in the quantum cryptography field, there are still issues regarding operation errors in long distance communications. Furthermore, quantum computing can raise significant challenges to existing cryptographic security protocols [61].

Visible light communication (VLC) can improve wireless communications, as it offers a high bandwidth and is immune to electromagnetic interference. Moreover, VLC faces threats coming from attackers that are capable of positioning themselves within line-of-sight of the target. Physical security is also important, as the nodes of a highly distributed network can be easily targeted by malicious users and damaged as part of a cyberattack [56]. EdgeAI can help provide timely monitoring and response procedures, such as intrusion detection and prevention systems (IDS/IPS), deployed in the vicinity of where the threat



originates [22]. Moreover, ML techniques [34] such as federated learning (FL) that enable the applications of AI in a distributed manner, as in the case of EdgeAI, can enable predict and deploy security procedures before a security attack or incident happens. Therefore, in the following section, we discuss the application of FL in 6G networks.

## 5. Machine Learning, Dependability, and 6G

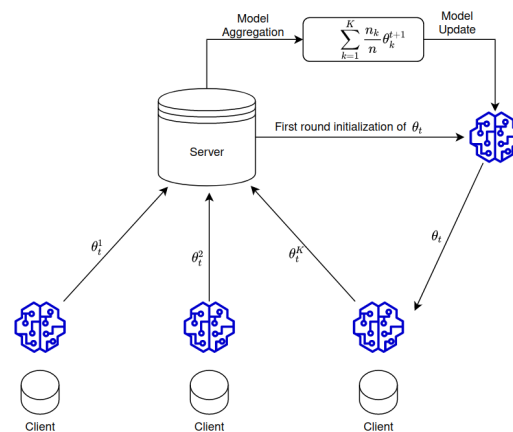
AI and its major branch, ML, will shape 6G networks [34,42]. Due to its tight QoS requirements, future 6G networks will possess such a complex architecture that performing legacy network operations will be deemed unsound. For this, ML techniques are emerging as a response to achieve truly intelligent orchestration and network management [62]. The dynamic nature of communication networks provides data for ML-enabled spectrum management and channel estimation, which are the basis of ultra-broadband techniques. Additionally, ML is being used to improve security, resource allocation, mobility management, and low-latency services in MCAs [34]. In particular, ML techniques such as deep learning have proved to be extremely efficient in preventing serious security attacks, such as distributed DoS attacks [63]. Distributed ML will be highly important in 6G due to the emerging needs of distributed processing at the edges of the network [64]. FL is currently among the most used distributed ML techniques in communication networks [44,65] and is highly important for 6G due to its ability to be used in a distributed manner, much like the foreseen distributed control nature of 6G networks.

### 5.1. Background in Brief

FL [66] was conceived by Google researchers back in 2016. Since then, it has experienced wide adoption in both industry and academia. The idea behind FL is to move the training towards the end devices while federating local models and learning, to build a privacy-preserving ML framework by keeping all raw data on devices and aggregating local model updates, while also reducing the communications overhead. The FL process is conformed by several communication rounds between a server and the clients, performed in the following fashion [4,67]:

- A number of clients is selected by the server based on certain conditions, such as being idle or its bandwidth limitation, to download the model parameters and use them to initialize their local model.
- Using their local data, each device trains and optimizes the downloaded model. This is done by using stochastic gradient descent, a determined number of minibatch steps, and several epochs in order to increase the update quality and reduce the communications cost.
- When the training is done, clients send their updates towards the server. It is important to notice that some clients might drop out due to connectivity issues, lack of processing power, etc. Nevertheless, the round continues with the received updates. If there are too many dropped out clients, the current round is abandoned.
- The server receives the updates, weights them based on their training set sizes, and finally, aggregates them. A new model is built on the server, and the next round begins.

Figure 2 shows a simplified flowchart of the previously explained FL process.  $\theta$  represents the global model parameters,  $n_k$  corresponds to the data size of the client  $k$ ,  $K$  is the total number of clients, and  $t$  is the communication round.



**Figure 2.** Simplified FL model presentation.

### 5.2. Dependability of Federated Learning

As one of the most popular ML techniques, FL has been used, and its processes are adopted to a wide range of use cases ranging from resource optimization to task offloading, and from the physical layer to the application layer. In this subsection, we analyze the dependability of FL with regard to its process, focusing on its algorithm rather than its applications in certain use cases.

#### 5.2.1. Reliability

ML techniques rely heavily on data. Data quality is fundamental for achieving high accuracy during the learning task. Client selection is a critical issue in FL, as clients are the ones updating the local models previous to the global aggregation, it is fundamental to properly select the clients that train the models using the highest quality of data. Most of the FL systems select their clients in a random manner, or based on resource conditions. Such selection of course might affect the global performance, as non-trustable nodes can also be selected. Moreover, the complexity of conceiving client selection in a communications network due to its dynamic nature also hinders their reliability. Even further, as it is difficult for the centralized entity that performs the selection to actually monitor a large-scale behavior, the selected untrustable clients are unlikely to be removed. Moreover, since the FL process consists of several rounds, previously selected untrusted clients might also be selected for future rounds. This can further damage the learning accuracy. Similarly, security vulnerabilities and lapses can also affect reliability.

#### 5.2.2. Availability

A lack of, or improper, criteria when selecting the clients for local training does not only affect reliability, but availability also. Untrusted clients using low quality data for training hinders the whole learning process and may severely affect predictions. In this manner, a FL framework whose accuracy is not as desired cannot be deployed, nor can services trust it, thereby rendering it unavailable. Availability in FL systems is complex to achieve due to the distributed nature of the model training, and the centralization of global model aggregation; in other words, it is not possible to hide a “faulty” or badly trained model when several untrusted clients have performed training with corrupted data. Moreover, this centralization of the aggregation process renders a FL framework vulnerable to weak aggregation algorithms, which are incapable of discerning high-quality trained models from those coming from suspicious clients. Availability is also hindered by security issues discussed in Section 4.

#### 5.2.3. Safety

Damage done by the selection of untrusted clients goes further than that of a faulty or badly trained model. Since learning is crucial for many use cases, untrusted clients might

hinder the prediction capacity of a system. This can cause safety-related issues for users. We can consider an autonomous vehicle with an positioning model based on FL, which is trained collectively with other autonomous vehicles. If a malicious vehicle is allowed to send its trained model for aggregation, this could affect the driving decisions of other vehicles, putting the passengers' lives at risk. The problem is only exacerbated by the centralization issue raised in the previous subsection, where weak aggregation algorithms do not help discriminating good from bad trained models.

#### 5.2.4. Security

Security is an important challenge in ML [35]. Even when FL improves user data privacy, security is still a main concern. An untrusted client that is selected to participate in a FL round could perform attacks, such as maliciously using unreliable data or injecting false data. Additionally, a malicious client could also launch attacks alongside other malicious users aimed at increasing misclassification. False-data injection refers to clients purposely adding wrong data to the training sets. On the other hand, workers might unintentionally provide low-quality raw data due to constraints in energy or high-speed mobility. Another security threat is related to the centralized model aggregation and the server where this function is located. In case a malicious user gains access to it, then the whole learning process will be hindered in the best case. In the worst case scenario, availability would be severely compromised. A communications channel vulnerability also affects FL frameworks, as the learning process consists of several rounds. An unencrypted channel will render the locally trained model vulnerable for attackers to perform reconstruction attacks.

## 6. Dependability for MCAs in 6G

One of the primary focus of 6G networks is MCAs. These applications usually require dependable services in terms of latency and error rates, and due to their nature, this must be equivalent to wired networks. The requirements of MCAs are closely related to those of Ultra-Reliable Low-Latency Communications (URLLC) with a target latency of 0.1 ms and a block error rate (BLER) of  $10^{-9}$ . Although these KPI values are not applicable to all use cases, they do have practical relevance in a couple of them. As examples, we could mention autonomous driving, remote surgery, and augmented reality [68]. Needless to say, MCAs also mandate high-security communications and resource efficiency. Current 5G networks' approaches for meeting the requirements of MCAs based on tweaking the system design is not scalable, nor efficient. Future 6G networks need to make use of application-domain information in order to predict actual resource requirements. Furthermore, 6G networks need to introduce new parameters that will not only help with characterizing resource needs but will also ease dependability analysis [17].

Due to its performance, edge computing is gaining traction as a viable solution for meeting the requirements of MCAs. The drivers behind the adoption of edge computing in MCAs use cases are the amount of data being transferred between end devices and edge servers, and time taken for data processing at the edge server. Due to the proximity of the edge server to the source of data, the network requirements mentioned at the beginning of this subsection could be met, even in the scenario of a massive amount of data. Furthermore, edge intelligentization eases meeting these requirements, as it is capable of offering micro-interaction with end devices, bringing management much closer to them, thereby reducing the communications overhead due to data fetching and controlling [34].

### 6.1. MCA Use Cases

This section will focus on briefly introducing and surveying three specific use cases that are in high demand for automated solutions: telesurgery, autonomous driving, and augmented reality. Considering an emergent surgical system, telesurgery is the use of wireless networking and robotics, which allows surgeons to operate on patients located far away. Among its benefits, we can mention the capacity to offer surgery in underserved remote

locations and enabling collaboration between surgeons from different medical centers. The most important requirement for telesurgery systems is latency. In [69], the authors determined the ideal latency for telesurgery systems to be 100 ms or less, while presenting a feasibility study for trans-sphenoidal resection of a pituitary tumor, where latency of 10 ms was achieved.

The work in [70] presents a drone-assisted telesurgery system that makes use of blockchain and 6G networks to become trusted and ultra-responsive. The authors favored an analysis of performance for the AI techniques used to classify diseases, and a cost analysis for the blockchain; dependability was not studied in this case. In [71], the authors introduced a 6G blockchain-based scheme for telesurgery that aims at being intelligent and efficient from the latency, throughput, and storage points of view. Although dependability is not directly mentioned, the authors did study the security and safety of the framework, and the reliability of the underlying 6G network. No availability analysis was performed. The importance of security, a dimension of dependability, in remote healthcare enabled by existing and future communication networks, such as 5G and future 6G, was thoroughly studied in [72]. The authors conclude that without proper security in place, remote healthcare will be detrimental rather than beneficial. This makes the dependability of communications networks highly important for such a critical use case. Dependability must not be considered as an add-on, but used as a benchmark from the basic initial design stage, which should be revisited during the working stages and must be continuously improved.

Autonomous driving technology refers to self-driving cars which are capable of sensing the environment and safely moving without human intervention [46]. Self-driving cars' set-ups are quite complex, usually comprising cameras, laser scanners, radars, laser beams, and an inertial measurement unit. Furthermore, autonomous driving represents the convergence of intelligent wireless sensing, communication, computing, and caching [46,73]. In this work we focus on EdgeAI, which represents the computation and communication parts of this use case. EdgeAI allows self-driving cars to accurately sense their surroundings and timely react using techniques for data offloading from the vehicles to the edge servers. In [74], the authors introduced a framework for EdgeAI-powered autonomous driving that achieves near-real-time task offloading while preserving privacy, and reducing communication delay. Additionally, reliability was explored as the inference accuracy. Security was enhanced through local training, and safety was analyzed as a crucial element that depends on the offloading and inferring time window and feasible sensing.

The work in [75] satisfies the QoS requirements of future vehicular networks through the use of idle resources from parked cars. The authors also successfully simulated user density as a way to predict resource availability and demonstrated a reduction in deployment costs. However, the paper does not discuss dependability or any of its components. Other techniques, such as game theoretic approaches, can be used in improving security, where contradictions in interest, among actors, exist, as discussed in [76,77]. The works in [78–81] investigate the improvement of dependability in vehicular networks; however, none of them clearly defines nor exposes all the factors that affect dependability.

Finally, we have augmented reality, which is the enhancement of objects through computer-generated information. Augmented reality applications are fast becoming attractive in mobile or smart wearable devices, especially because of their ability to enhance the visualization of the environment. The authors of [82] researched task offloading in mobile augmented reality applications and used 6G network characteristics in their simulations. Due to latency being one of the major concerns in augmented reality applications, the authors focused on transmission and application latency during their experimental analysis. However, neither dependability, nor any of its components, were taken into account. In [83], a metrology-oriented, automatic system based on augmented reality, was designed in order to help surgeons during operations. The authors aimed at achieving transmission dependability, which was verified based on the accuracy and latency of the system. Nevertheless, no description of dependability or its components was provided. Additionally, the work focuses mainly on reliability. The work in [84] aimed at increasing

the reliability of augmented reality applications by lowering the probabilities of communication and computation errors, and timeouts. Latency and accuracy are balanced through an optimization problem that minimizes failure probability. The other concepts associated with dependability were not explored. Other works, such as [85,86], also explored certain aspects of dependability.

## 6.2. Dependability Analysis of 6G MCAs

Based on the information from the previous section, MCAs are expected to be extremely dependable. This is not only due to their stringent network requirements, but also due to their use cases. Lack of dependability in MCAs could badly harm operations at a production factory or potentially place human lives at risk in telesurgery, for instance. Below, we discuss the dependability of MCAs from the perspectives of the four dimensions.

### 6.2.1. Reliability

The reliability of an MCA is directly related to how well it complies with the stringent requirements in terms of latency and errors. From one point of view, these requirements are met with the help of capable underlying networks. However, reliability is also affected by the architecture chosen for a given MCA, since it will determine the overall behavior and qualities of such an application. From the 6G perspective, the importance given to software architecture is nowhere near that of the underlying network. Of course, a capable network greatly benefits an application's performance, but a proper architecture further improves these benefits. Focus should also be given to use case-specific hardware, as an MCA will depend on their quality and trustability, as many use cases revolve around their use—for example, telesurgery.

### 6.2.2. Availability

Bad architecture and low-quality hardware can also affect the availability of MCAs. As many use cases, such as telesurgery and autonomous driving, depend on external hardware (such as sensors and CPS components), it is important to ensure that these are trustable and will not hinder the execution of the MCA. Moreover, a proper architecture in the form of resource localization would ensure the MCA is capable of deploying high capacity node replacements, thereby offering adequate scalability. Depending on the use case, some MCAs might use EdgeAI approaches for improving their bandwidth and latency requirements. Proper resource and task allocation are needed in order to take advantage of these scenarios.

### 6.2.3. Safety

The reliability and availability of MCAs each have a direct relationship with safety, especially in use cases that involve direct human contact. Since MCAs are usually the backbones of their respective use cases, the consequences of their failures can go from vast economical losses to putting human lives at danger. For example, in an autonomous driving scenario, if the vehicle is not capable of properly performing computations that help it determine whether or not to change lanes, the risk of an accident, and as an extension, human losses, is high. Therefore, MCAs need to re-focus, becoming more autonomous, so human operators are less involved and thus less prone to being affected in cases of faulty behavior. Additionally, a distributed architecture would benefit MCAs, since it increases their availability and reliability, making it easier to update or make changes to the application.

### 6.2.4. Security

MCAs are constantly targeted by malicious attackers, either due to the importance of the data they handle, or because of their key role in some industrial or medical use cases. If not properly secured, attackers targeting a remote surgery system could execute commands that hinder the performances of the controlled devices, severely threatening

human lives. Moreover, other scenarios, such as autonomous driving, are also susceptible to malicious attacks that could hinder many of the systems running on the vehicle, from communication devices to sensors and other integral parts of its systems. Although security aspects rely mostly on the underlying communication network, it is also worth noting that MCAs could provide some security aspects, such as controlling inter-element communications or defining which element can access what information in the system.

## 7. Future Research Directions

Sixth-generation networks will be highly distributed in nature. Network control will be shifted to far edge nodes, such as micro-edge [56], which may arise with new terminologies and technologies. Since centralized control will not be suitable for latency critical services, distribution of network management and control functions will be inevitable. However, such distribution will complicate the dependability of future networks. The challenges to dependability will be from many dimensions. For example, reliable network function or service transfer from a centralized cloud infrastructure to far edge or user node will be challenging and require more research in terms of resource discovery, alongside reliable functioning or service transfer. The distributed control, apparently, can increase the availability. However, such control functions can also be targeted by security attacks, such as DoS attacks and resource exhaustion attacks, to block access to legitimate users. The success of such attacks usually depends on the availability of resources at the receiving end(s). Hence, distributing network control functions into small units may decrease the overall dependability.

The resilience of the networks also must increase, which will require proper resilience strategies. Network resilience means that a network operates in the presence of difference challenges, such as security attacks, operational mistakes, configuration errors, and equipment failures [87]. This will require network mechanisms that are capable of protecting the network from failures through flexible means of configurations, cooperative techniques that enable network devices and segments to provide alternative routes, and efficient anomaly detection and traffic-shaping techniques. The notion of network abstraction and the simplicity of control put forward by the concepts of software defined networking (SDN) [88] can really help in this context, for instance, in the run-time mobility of traffic [89], traffic management [90], or load balancing among congested nodes [91]. Whether the technologies of SDN will prevail in 6G or not, research will show, however, the concepts and philosophy of SDN can surely help with increasing the dependability of 6G networks, and thus must be researched further.

Safety and security are highly intertwined. For example, if equipment is not physically safe, it cannot be considered to be secure. Similarly, if a device can be compromised through cyber attacks, its physical security can be meaningless in most use cases. Safety must be researched from the technical perspectives to obtain key performance indicators for safety, much like security. We do have security-by-design, but safety-by-design is rarely discussed. The security in 6G is highly complicated. New technologies are emerging, and it is possible that security requirements of different technology do not match, for instance, in the debate of privacy vs. accountability. Furthermore, the more the network control becomes distributed and modular, the more complicated the security of the whole ecosystem comprising diverse services, users, and even network functions, will become. Dependability, therefore, will be highly complicated to comprehend and must be researched from this perspective. One of the key questions in this regard will be to take an evolutionary incremental approach, based on existing 5G standards or a revolutionary approach, and start thinking of redesigning from scratch.

In 6G, AI will be used on a much higher scale than 5G; thus, the real threats that AI can pose will be more visible. Furthermore, existing AI systems use huge amounts of resources [92], ranging from energy and computing to bandwidth and spectrum. Therefore, research is needed on sustainable AI-based security approaches for AI-based security threats in 6G. One way ahead for ensuring dependable 6G networks is to maintain simplicity

in design with global visibility of network resources and their use, enabling programmable deployment of services, including security functions in a reliable, safe, and secure manner. The main challenges that need further research in this direction are also summarized in Table 1, along with possible research directions.

## 8. Conclusions

Sixth-generation communication networks will connect critical infrastructures. Therefore, the dependability of 6G communication networks is extremely important. Since 6G exacerbates the merging of the physical and digital worlds beyond the current traditional cyber-physical systems, dependability in terms of reliability, availability, safety, and security needed a thorough investigation. Therefore, in this article we have shed light on the dependability of 6G networks, first to highlight its importance and relevance in 6G, and then to bring forward existing challenges and potential solutions. The main challenges that persist in all dimensions of dependability arise from the distributed nature of 6G. The solutions, thus, must also be targeted at distributed network architectures. Therefore, edge computing, FL, and movable softwarized network functions, to name a few directions, related to reliability, availability, safety, and security, need to be researched. In summary, this article opens up interesting research questions and highlights research gaps to improve the dependability of 6G networks and systems.

**Author Contributions:** All the authors participated in conceptualization. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work was supported in part by the VTT Technical Research Centre of Finland and in part by the Business Finland through the SUNSET-6G and the AI-NET-ANTILLAS projects.

**Conflicts of Interest:** The authors declare no conflict of interest.

## Abbreviations

List of most common abbreviations:

Acronym	Full Term(s)
3D	Three Dimension
5G	Fifth Generation
6G	Sixth Generation
AI	Artificial Intelligence
AR	Augmented Reality
CPS	Cyber-Physical System
D2D	Device to Device
DLT	Distributed Ledger Technology
DoS	Denial of Service
DPI	Deep Packet Inspection
eMMB	enhanced Mobile Broadband
FL	Federated Learning
ICT	Information and Communication Technologies
IDS	Intrusion Detection System
IoT	Internet of Things
IPS	Intrusion Prevention System
IT	Information Technology
MCA	Mission-Critical Application
MEC	Multi-access Edge Computing
MIMO	Multi-Input Multi-Output
mIoT	massive IoT
ML	Machine Learning
NFV	Network Function Virtualization
QoS	Quality of Service

RAN	Radio Access Network
SDN	Software Defined Networking
VLC	Visible Light Communication
VNF	Virtual Network Function
VR	Virtual Reality
WSN	Wireless Sensor Networks
XR	Extended Reality

## References

1. Saad, W.; Bennis, M.; Chen, M. A Vision of 6G Wireless Systems: Applications, Trends, Technologies, and Open Research Problems. *IEEE Netw.* **2020**, *34*, 134–142. [\[CrossRef\]](#)
2. Giordani, M.; Polese, M.; Mezzavilla, M.; Rangan, S.; Zorzi, M. Toward 6G Networks: Use Cases and Technologies. *IEEE Commun. Mag.* **2020**, *58*, 55–61. [\[CrossRef\]](#)
3. Ahmad, I.; Suomalainen, J.; Porambage, P.; Gurtov, A.; Huusko, J.; Höyhty, M. Security of Satellite-Terrestrial Communications: Challenges and Potential Solutions. *IEEE Access* **2022**, *10*, 96038–96052. [\[CrossRef\]](#)
4. AbdulRahman, S.; Tout, H.; Ould-Slimane, H.; Mourad, A.; Talhi, C.; Guizani, M. A survey on federated learning: The journey from centralized to distributed on-site learning and beyond. *IEEE Internet Things J.* **2021**, *8*, 5476–5497. [\[CrossRef\]](#)
5. Peltonen, E.; Bennis, M.; Capobianco, M.; Debbah, M.; Ding, A.; Gil-Castiñeira, F.; Jurmu, M.; Karvonen, T.; Kelanti, M.; Kliks, A.; et al. 6G white paper on edge intelligence. *arXiv* **2020**, arXiv:2004.14850.
6. Sekaran, R.; Patan, R.; Raveendran, A.; Al-Turjman, F.; Ramachandran, M.; Mostarda, L. Survival Study on Blockchain Based 6G-Enabled Mobile Edge Computation for IoT Automation. *IEEE Access* **2020**, *8*, 143453–143463. [\[CrossRef\]](#)
7. Nawaz, S.J.; Sharma, S.K.; Mansoor, B.; Patwary, M.N.; Khan, N.M. Non-Coherent and Backscatter Communications: Enabling Ultra-Massive Connectivity in 6G Wireless Networks. *IEEE Access* **2021**, *9*, 38144–38186. [\[CrossRef\]](#)
8. Bariah, L.; Mohjazi, L.; Muhaidat, S.; Sofotasios, P.C.; Kurt, G.K.; Yanikomeroglu, H.; Dobre, O.A. A Prospective Look: Key Enabling Technologies, Applications and Open Research Topics in 6G Networks. *IEEE Access* **2020**, *8*, 174792–174820. [\[CrossRef\]](#)
9. Ren, J.; Zhang, D.; He, S.; Zhang, Y.; Li, T. A Survey on End-Edge-Cloud Orchestrated Network Computing Paradigms: Transparent Computing, Mobile Edge Computing, Fog Computing, and Cloudlet. *ACM Comput. Surv.* **2019**, *52*. [\[CrossRef\]](#)
10. Hashima, S.; Fadlullah, Z.M.; Fouda, M.M.; Mohamed, E.M.; Hatano, K.; ElHalawany, B.M.; Guizani, M. On Softwarization of Intelligence in 6G Networks for Ultra-Fast Optimal Policy Selection: Challenges and Opportunities. *IEEE Netw.* **2022**, 1–9. [\[CrossRef\]](#)
11. Letaief, K.B.; Shi, Y.; Lu, J.; Lu, J. Edge Artificial Intelligence for 6G: Vision, Enabling Technologies, and Applications. *IEEE J. Sel. Areas Commun.* **2022**, *40*, 5–36. [\[CrossRef\]](#)
12. Avizienis, A.; Laprie, J.C.; Randell, B. *Fundamental Concepts of Dependability*; Department of Computing Science Technical Report Series; University of Newcastle upon Tyne: Newcastle upon Tyne, UK, 2001.
13. Ahmed, W.; Wu, Y.W. A survey on reliability in distributed systems. *J. Comput. Syst. Sci.* **2013**, *79*, 1243–1255. [\[CrossRef\]](#)
14. Foukalas, F.; Pop, P.; Theoleyre, F.; Boano, C.A.; Buratti, C. Dependable Wireless Industrial IoT Networks: Recent Advances and Open Challenges. In Proceedings of the 2019 IEEE European Test Symposium (ETS), Baden, Germany, 27–31 May 2019; pp. 1–10. [\[CrossRef\]](#)
15. Kreutz, D.; Ramos, F.M.; Verissimo, P. Towards Secure and Dependable Software-Defined Networks. In Proceedings of the Second ACM SIGCOMM Workshop on Hot Topics in Software Defined Networking (HotSDN '13), Hong Kong, China, 16 August 2013; pp. 55–60. [\[CrossRef\]](#)
16. Scanzio, S.; Wisniewski, L.; Gaj, P. Heterogeneous and dependable networks in industry—A survey. *Comput. Ind.* **2021**, *125*, 103388. [\[CrossRef\]](#)
17. She, C.; Dong, R.; Gu, Z.; Hou, Z.; Li, Y.; Hardjawana, W.; Yang, C.; Song, L.; Vucetic, B. Deep Learning for Ultra-Reliable and Low-Latency Communications in 6G Networks. *IEEE Netw.* **2020**, *34*, 219–225. [\[CrossRef\]](#)
18. Salh, A.; Audah, L.; Shah, N.S.M.; Alhammedi, A.; Abdullah, Q.; Kim, Y.H.; Al-Gailani, S.A.; Hamzah, S.A.; Esmail, B.A.F.; Almohammed, A.A. A Survey on Deep Learning for Ultra-Reliable and Low-Latency Communications Challenges on 6G Wireless Systems. *IEEE Access* **2021**, *9*, 55098–55131. [\[CrossRef\]](#)
19. Masaracchia, A.; Li, Y.; Nguyen, K.K.; Yin, C.; Khosravirad, S.R.; Costa, D.B.D.; Duong, T.Q. UAV-Enabled Ultra-Reliable Low-Latency Communications for 6G: A Comprehensive Survey. *IEEE Access* **2021**, *9*, 137338–137352. [\[CrossRef\]](#)
20. Gupta, A.; Fernando, X.; Das, O. Reliability and Availability Modeling Techniques in 6G IoT Networks: A Taxonomy and Survey. In Proceedings of the 2021 International Wireless Communications and Mobile Computing (IWCMC), Harbin City, China, 28 June–2 July 2021; pp. 586–591. [\[CrossRef\]](#)
21. Li, S.; Cheng, X.; Huang, X.; Otaibi, S.A.; Wang, H. Cooperative Conflict Detection and Resolution and Safety Assessment for 6G Enabled Unmanned Aerial Vehicles. *IEEE Trans. Intell. Transp. Syst.* **2022**, *24*, 2183–2198. [\[CrossRef\]](#)
22. Ahmad, I.; Shahabuddin, S.; Kumar, T.; Okwuibe, J.; Gurtov, A.; Ylianttila, M. Security for 5G and beyond. *IEEE Commun. Surv. Tutor.* **2019**, *21*, 3682–3722. [\[CrossRef\]](#)



23. Ylianttila, M.; Kantola, R.; Gurtov, A.; Mucchi, L.; Oppermann, I.; Yan, Z.; Nguyen, T.H.; Liu, F.; Hewa, T.; Liyanage, M.; et al. 6G white paper: Research challenges for trust, security and privacy. *arXiv* **2020**, arXiv:2004.11665.
24. Avizienis, A.; Laprie, J.C.; Randell, B.; Landwehr, C. Basic concepts and taxonomy of dependable and secure computing. *IEEE Trans. Dependable Secur. Comput.* **2004**, *1*, 11–33. [[CrossRef](#)]
25. Heimann, D.I.; Mittal, N.; Trivedi, K.S. Dependability modeling for computer systems. In Proceedings of the Annual Reliability and Maintainability Symposium, Orlando, FL, USA, 29–31 January 1991; pp. 120–128.
26. Chen, D.; Garg, S.; Kintala, C.M.; Trivedi, K.S. Dependability Enhancement for IEEE 802.11 Wireless LAN with Redundancy Techniques. In Proceedings of the Dependable Systems and Networks, San Francisco, CA, USA, 22–25 June 2003; pp. 521–528.
27. Laprie, J.C. Dependable computing: Concepts, limits, challenges. In Proceedings of the Special issue of the 25th International Symposium on Fault-Tolerant Computing, Pasadena, CA, USA, 27–30 June 1995; pp. 42–54.
28. Gupta, R.; Reebadiya, D.; Tanwar, S. 6G-enabled Edge Intelligence for Ultra -Reliable Low Latency Applications: Vision and Mission. *Comput. Stand. Interfaces* **2021**, *77*, 103521. [[CrossRef](#)]
29. Ahmad, I.; Namal, S.; Ylianttila, M.; Gurtov, A. Security in Software Defined Networks: A Survey. *IEEE Commun. Surv. Tutorials* **2015**, *17*, 2317–2346 [[CrossRef](#)]
30. Banerjee, A.; Venkatasubramanian, K.K.; Mukherjee, T.; Gupta, S.K.S. Ensuring Safety, Security, and Sustainability of Mission-Critical Cyber-Physical Systems. *Proc. IEEE* **2012**, *100*, 283–299. [[CrossRef](#)]
31. Raytis, J.L.; Yuh, B.E.; Lau, C.S.; Fong, Y.; Lew, M.W. Anesthetic Implications of Robotically Assisted Surgery with the Da Vinci Xi Surgical Robot. *Open J. Anesthesiol.* **2016**, *6*, 115–118. [[CrossRef](#)]
32. Rim, L.J. Anesthetic considerations for robotic surgery. *Korean J. Anesth.* **2014**, *66*, 3–11. [[CrossRef](#)]
33. Ahmad, I.; Kumar, T.; Liyanage, M.; Okwuibe, J.; Ylianttila, M.; Gurtov, A. Overview of 5G security challenges and solutions. *IEEE Commun. Stand. Mag.* **2018**, *2*, 36–43. [[CrossRef](#)]
34. Ahmad, I.; Shahabuddin, S.; Malik, H.; Harjula, E.; Leppänen, T.; Lovén, L.; Anttonen, A.; Sodhro, A.H.; Mahtab Alam, M.; Juntti, M.; et al. Machine Learning Meets Communication Networks: Current Trends and Future Challenges. *IEEE Access* **2020**, *8*, 223418–223460. [[CrossRef](#)]
35. Suomalainen, J.; Juhola, A.; Shahabuddin, S.; Mämmelä, A.; Ahmad, I. Machine learning threatens 5G security. *IEEE Access* **2020**, *8*, 190822–190842. [[CrossRef](#)]
36. Ahmad, I.; Shahabuddin, S.; Sauter, T.; Harjula, E.; Kumar, T.; Meisel, M.; Juntti, M.; Ylianttila, M. The Challenges of Artificial Intelligence in Wireless Networks for the Internet of Things: Exploring Opportunities for Growth. *IEEE Ind. Electron. Mag.* **2020**, *15*, 16–29. [[CrossRef](#)]
37. Dibaei, M.; Zheng, X.; Xia, Y.; Xu, X.; Jolfaei, A.; Bashir, A.K.; Tariq, U.; Yu, D.; Vasilakos, A.V. Investigating the Prospect of Leveraging Blockchain and Machine Learning to Secure Vehicular Networks: A Survey. *IEEE Trans. Intell. Transp. Syst.* **2021**, *23*, 683–700. [[CrossRef](#)]
38. Hui, Y.; Cheng, N.; Su, Z.; Huang, Y.; Zhao, P.; Luan, T.H.; Li, C. Secure and Personalized Edge Computing Services in 6G Heterogeneous Vehicular Networks. *IEEE Internet Things J.* **2021**, *9*, 5920–5931. [[CrossRef](#)]
39. Singh, R.; Ahmad, I.; Huusko, J. The Role of Physical Layer Security in Satellite-Based Networks. *arXiv* **2023**, arXiv:2302.07375.
40. Zhang, Z.; Xiao, Y.; Ma, Z.; Xiao, M.; Ding, Z.; Lei, X.; Karagiannidis, G.K.; Fan, P. 6G Wireless Networks: Vision, Requirements, Architecture, and Key Technologies. *IEEE Veh. Technol. Mag.* **2019**, *14*, 28–41. [[CrossRef](#)]
41. David, K.; Berndt, H. 6G Vision and Requirements: Is There Any Need for Beyond 5G? *IEEE Veh. Technol. Mag.* **2018**, *13*, 72–80. [[CrossRef](#)]
42. Tariq, F.; Khandaker, M.R.A.; Wong, K.K.; Imran, M.A.; Bennis, M.; Debbah, M. A Speculative Study on 6G. *IEEE Wirel. Commun.* **2020**, *27*, 118–125. [[CrossRef](#)]
43. Nezami, Z.; Zamanifar, K. Internet of ThingsInternet of Everything: Structure and Ingredients. *IEEE Potentials* **2019**, *38*, 12–17. [[CrossRef](#)]
44. Wang, X.; Han, Y.; Wang, C.; Zhao, Q.; Chen, X.; Chen, M. In-Edge AI: Intelligentizing Mobile Edge Computing, Caching and Communication by Federated Learning. *IEEE Netw.* **2019**, *33*, 156–165. [[CrossRef](#)]
45. Pham, Q.V.; Fang, F.; Ha, V.N.; Piran, M.J.; Le, M.; Le, L.B.; Hwang, W.J.; Ding, Z. A Survey of Multi-Access Edge Computing in 5G and Beyond: Fundamentals, Technology Integration, and State-of-the-Art. *IEEE Access* **2020**, *8*, 116974–117017. [[CrossRef](#)]
46. Osorio, D.P.M.; Ahmad, I.; Sánchez, J.D.V.; Gurtov, A.; Scholliers, J.; Kuttila, M.; Porombage, P. Towards 6G-enabled Internet of Vehicles: Security and Privacy. *IEEE Open J. Commun. Soc.* **2022**, *3*, 82–105. [[CrossRef](#)]
47. Okwuibe, J.; Haavisto, J.; Kovacevic, I.; Harjula, E.; Ahmad, I.; Islam, J.; Ylianttila, M. SDN-Enabled Resource Orchestration for Industrial IoT in Collaborative Edge-Cloud Networks. *IEEE Access* **2021**, *9*, 115839–115854. [[CrossRef](#)]
48. Zhou, Z.; Chen, X.; Li, E.; Zeng, L.; Luo, K.; Zhang, J. Edge Intelligence: Paving the Last Mile of Artificial Intelligence with Edge Computing. *Proc. IEEE* **2019**, *107*, 1738–1762. [[CrossRef](#)]
49. Deng, S.; Zhao, H.; Fang, W.; Yin, J.; Dustdar, S.; Zomaya, A.Y. Edge Intelligence: The Confluence of Edge Computing and Artificial Intelligence. *IEEE Internet Things J.* **2020**, *7*, 7457–7469. [[CrossRef](#)]
50. Li, C.; Guo, W.; Sun, S.C.; Al-Rubaye, S.; Tsourdos, A. Trustworthy Deep Learning in 6G-Enabled Mass Autonomy: From Concept to Quality-of-Trust Key Performance Indicators. *IEEE Veh. Technol. Mag.* **2020**, *15*, 112–121. [[CrossRef](#)]
51. Harjula, E.; Karhula, P.; Islam, J.; Leppänen, T.; Manzoor, A.; Liyanage, M.; Chauhan, J.; Kumar, T.; Ahmad, I.; Ylianttila, M. Decentralized IoT edge nanoservice architecture for future gadget-free computing. *IEEE Access* **2019**, *7*, 119856–119872. [[CrossRef](#)]

52. Herlich, M.; Maier, C. Measuring and Monitoring Reliability of Wireless Networks. *IEEE Commun. Mag.* **2021**, *59*, 76–81. [[CrossRef](#)]
53. Bhagwan, R.; Savage, S.; Voelker, G.M. Understanding availability. In Proceedings of the International Workshop on Peer-to-Peer Systems, Berkeley, CA, USA, 21–22 February 2003; Springer: Berlin/Heidelberg, Germany; pp. 256–267.
54. Ahmad, I.; Karunaratna, S.N.; Ylianttila, M.; Gurtov, A. Load balancing in software defined mobile networks. In *Software Defined Mobile Networks (SDMN): Beyond LTE Network Architecture*; Wiley: Hoboken, NJ, USA, 2015; pp. 225–245.
55. Young, W.; Leveson, N.G. An integrated approach to safety and security based on systems theory. *Commun. ACM* **2014**, *57*, 31–35. [[CrossRef](#)]
56. Ahmad, I.; Lembo, S.; Rodriguez, F.; Mehnert, S.; Vehkaperä, M. Security of Micro MEC in 6G: A Brief Overview. In Proceedings of the 2022 IEEE 19th Annual Consumer Communications Networking Conference (CCNC), Las Vegas, NV, USA, 8–11 January 2022; pp. 332–337. [[CrossRef](#)]
57. Kodheli, O.; Lagunas, E.; Maturo, N.; Sharma, S.K.; Shankar, B.; Montoya, J.F.M.; Duncan, J.C.M.; Spano, D.; Chatzinotas, S.; Kisseleff, S.; et al. Satellite Communications in the New Space Era: A Survey and Future Challenges. *IEEE Commun. Surv. Tutor.* **2021**, *23*, 70–109. [[CrossRef](#)]
58. 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](#)]
59. Ma, J.; Shrestha, R.; Adelberg, J.; Yeh, C.Y.; Hossain, Z.; Knightly, E.; Jornet, J.M.; Mittleman, D.M. Security and eavesdropping in terahertz wireless links. *Nature* **2018**, *563*, 89–93. [[CrossRef](#)] [[PubMed](#)]
60. Song, F. A note on quantum security for post-quantum cryptography. In Proceedings of the International Workshop on Post-Quantum Cryptography, Waterloo, ON, Canada, 23 September 2014; pp. 246–265.
61. Omolara, A.E.; Alabdulatif, A.; Abiodun, O.I.; Alawida, M.; Alabdulatif, A.; Alshoura, W.H.; Arshad, H. The internet of things security: A survey encompassing unexplored areas and new insights. *Comput. Secur.* **2022**, *112*, 102494. [[CrossRef](#)]
62. Khan, L.U.; Pandey, S.R.; Tran, N.H.; Saad, W.; Han, Z.; Nguyen, M.N.H.; Hong, C.S. Federated Learning for Edge Networks: Resource Optimization and Incentive Mechanism. *IEEE Commun. Mag.* **2020**, *58*, 88–93. [[CrossRef](#)]
63. Mittal, M.; Kumar, K.; Behal, S. Deep learning approaches for detecting DDoS attacks: A systematic review. *Soft Comput.* **2022**, 1–37. [[CrossRef](#)]
64. Mwase, C.; Jin, Y.; Westerlund, T.; Tenhunen, H.; Zou, Z. Communication-efficient distributed AI strategies for the IoT edge. *Future Gener. Comput. Syst.* **2022**, *131*, 292–308. [[CrossRef](#)]
65. Liu, Y.; Yuan, X.; Xiong, Z.; Kang, J.; Wang, X.; Niyato, D. Federated learning for 6G communications: Challenges, methods, and future directions. *China Commun.* **2020**, *17*, 105–118. [[CrossRef](#)]
66. Kairouz, P.; McMahan, H.B.; Avent, B.; Bellet, A.; Bennis, M.; Bhagoji, A.N.; Bonawitz, K.; Charles, Z.; Cormode, G.; Cummings, R.; et al. Advances and open problems in federated learning. *Found. Trends® Mach. Learn.* **2021**, *14*, 1–210. [[CrossRef](#)]
67. Lim, W.Y.B.; Luong, N.C.; Hoang, D.T.; Jiao, Y.; Liang, Y.C.; Yang, Q.; Niyato, D.; Miao, C. Federated Learning in Mobile Edge Networks: A Comprehensive Survey. *IEEE Commun. Surv. Tutor.* **2020**, *22*, 2031–2063. [[CrossRef](#)]
68. Mahmood, N.H.; Böcker, S.; Munari, A.; Clazzer, F.; Moerman, I.; Mikhaylov, K.; López, O.L.A.; Park, O.; Mercier, E.; Bartz, H.; et al. White Paper on Critical and Massive Machine Type Communication Towards 6G. *arXiv* **2020**, arXiv:2004.14146.
69. Wirz, R.; Torres, L.G.; Swaney, P.J.; Gilbert, H.; Alterovitz, R.; Webster, R.J.; Weaver, K.D.; Russell, P.T. An experimental feasibility study on robotic endonasal telesurgery. *Neurosurgery* **2015**, *76*, 479. [[CrossRef](#)]
70. Gupta, R.; Shukla, A.; Tanwar, S. BATS: A Blockchain and AI-empowered Drone-assisted Telesurgery System towards 6G. *IEEE Trans. Netw. Sci. Eng.* **2020**, *8*, 2958–2967. [[CrossRef](#)]
71. Gupta, R.; Thakker, U.; Tanwar, S.; Obaidat, M.S.; Hsiao, K.F. BITS: A Blockchain-driven Intelligent Scheme for Telesurgery System. In Proceedings of the 2020 International Conference on Computer, Information and Telecommunication Systems (CITS), Hangzhou, China, 5–7 October 2020; pp. 1–5. [[CrossRef](#)]
72. Ahmad, I.; Asghar, Z.; Kumar, T.; Li, G.; Manzoor, A.; Mikhaylov, K.; Shah, S.A.; Höyhty, M.; Reponen, J.; Huusko, J.; et al. Emerging Technologies for Next Generation Remote Health Care and Assisted Living. *IEEE Access* **2022**, *10*, 56094–56132. [[CrossRef](#)]
73. Chowdhury, M.Z.; Shahjalal, M.; Ahmed, S.; Jang, Y.M. 6G Wireless Communication Systems: Applications, Requirements, Technologies, Challenges, and Research Directions. *IEEE Open J. Commun. Soc.* **2020**, *1*, 957–975. [[CrossRef](#)]
74. Yang, B.; Cao, X.; Xiong, K.; Yuen, C.; Guan, Y.L.; Leng, S.; Qian, L.; Han, Z. Edge Intelligence for Autonomous Driving in 6G Wireless System: Design Challenges and Solutions. *IEEE Wirel. Commun.* **2021**, *28*, 40–47. [[CrossRef](#)]
75. Qi, W.; Li, Q.; Song, Q.; Guo, L.; Jamalipour, A. Extensive Edge Intelligence for Future Vehicular Networks in 6G. *IEEE Wirel. Commun.* **2021**, *28*, 128–135. [[CrossRef](#)]
76. Abdalzaher, M.S.; Seddik, K.; Elsabrouty, M.; Muta, O.; Furukawa, H.; Abdel-Rahman, A. Game Theory Meets Wireless Sensor Networks Security Requirements and Threats Mitigation: A Survey. *Sensors* **2016**, *16*, 1003. [[CrossRef](#)]
77. Abdalzaher, M.S.; Muta, O. A Game-Theoretic Approach for Enhancing Security and Data Trustworthiness in IoT Applications. *IEEE Internet Things J.* **2020**, *7*, 11250–11261. [[CrossRef](#)]
78. Almeida, J.; Rufino, J.; Alam, M.; Ferreira, J. A Survey on Fault Tolerance Techniques for Wireless Vehicular Networks. *Electronics* **2019**, *8*, 1358. [[CrossRef](#)]

79. Zhou, Z.; Yu, H.; Xu, C.; Zhang, Y.; Mumtaz, S.; Rodriguez, J. Dependable Content Distribution in D2D-Based Cooperative Vehicular Networks: A Big Data-Integrated Coalition Game Approach. *IEEE Trans. Intell. Transp. Syst.* **2018**, *19*, 953–964. [[CrossRef](#)]
80. Boukerche, A.; Kantarci, B.; Kaptan, C. Towards ensuring the reliability and dependability of vehicular crowd-sensing data in GPS-less location tracking. *Pervasive Mob. Comput.* **2020**, *68*, 101248. [[CrossRef](#)]
81. Olowononi, F.O.; Rawat, D.B.; Liu, C. Dependable Adaptive Mobility in Vehicular Networks for Resilient Mobile Cyber Physical Systems. In Proceedings of the 2020 IEEE International Conference on Communications Workshops (ICC Workshops), Dublin, Ireland, 7–11 June 2020; pp. 1–6. [[CrossRef](#)]
82. Chakrabarti, K. Deep learning based offloading for mobile augmented reality application in 6G. *Comput. Electr. Eng.* **2021**, *95*, 107381. [[CrossRef](#)]
83. Arpaia, P.; De Benedetto, E.; Dodaro, C.A.; Duraccio, L.; Servillo, G. Metrology-Based Design of a Wearable Augmented Reality System for Monitoring Patient's Vitals in Real Time. *IEEE Sensors J.* **2021**, *21*, 11176–11183. [[CrossRef](#)]
84. Liu, J.; Zhang, Q. Code-Partitioning Offloading Schemes in Mobile Edge Computing for Augmented Reality. *IEEE Access* **2019**, *7*, 11222–11236. [[CrossRef](#)]
85. Zhang, X.; Slavin, R.; Wang, X.; Niu, J. Privacy Assurance for Android Augmented Reality Apps. In Proceedings of the 2019 IEEE 24th Pacific Rim International Symposium on Dependable Computing (PRDC), Kyoto, Japan, 1–3 December 2019; pp. 114–1141. [[CrossRef](#)]
86. Bahaee, S.S.; Gallina, B.; Laumann, K.; Skogstad, M.R. Effect of Augmented Reality on Faults Leading to Human Failures in Socio-technical Systems. In Proceedings of the 2019 4th International Conference on System Reliability and Safety (ICSRS), Rome, Italy, 20–22 November 2019; pp. 236–245. [[CrossRef](#)]
87. Sterbenz, J.P.; Hutchison, D.; Çetinkaya, E.K.; Jabbar, A.; Rohrer, J.P.; Schöller, M.; Smith, P. Resilience and survivability in communication networks: Strategies, principles, and survey of disciplines. *Comput. Netw.* **2010**, *54*, 1245–1265. [[CrossRef](#)]
88. Nunes, B.A.A.; Mendonca, M.; Nguyen, X.N.; Obraczka, K.; Turletti, T. A survey of software-defined networking: Past, present, and future of programmable networks. *IEEE Commun. Surv. Tutor.* **2014**, *16*, 1617–1634. [[CrossRef](#)]
89. Namal, S.; Ahmad, I.; Gurtov, A.; Ylianttila, M. Enabling secure mobility with OpenFlow. In Proceedings of the 2013 IEEE SDN for Future Networks and Services (SDN4FNS), Trento, Italy, 11–13 November 2013; pp. 1–5.
90. Ahmad, I.; Liyanage, M.; Namal, S.; Ylianttila, M.; Gurtov, A.; Eckert, M.; Bauschert, T.; Faigl, Z.; Bokor, L.; Saygun, E.; et al. New concepts for traffic, resource and mobility management in software-defined mobile networks. In Proceedings of the 2016 12th Annual Conference on Wireless On-Demand Network Systems and Services (WONS), Cortina d'Ampezzo, Italy, 20–22 January 2016; pp. 1–8.
91. Namal, S.; Ahmad, I.; Gurtov, A.; Ylianttila, M. SDN based inter-technology load balancing leveraged by flow admission control. In Proceedings of the 2013 IEEE SDN for Future Networks and Services (SDN4FNS), Trento, Italy, 11–13 November 2013; pp. 1–5.
92. García-Martín, E.; Rodrigues, C.F.; Riley, G.; Grahm, H. Estimation of energy consumption in machine learning. *J. Parallel Distrib. Comput.* **2019**, *134*, 75–88. [[CrossRef](#)]

**Disclaimer/Publisher's Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.