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PERSPECTIVE

Toward AI in 6G: Concepts, Techniques, and Standards

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ABSTRACT The rapid evolution of cellular networks, driven by the proliferation of mobile devices and the exponential growth of the Internet of Things (IoT), has significantly advanced wireless communication technologies. Fifth generation of wireless communications technology (5G) enhanced data rates, latency, and network capacity, resulting in the emergence of new applications. However, the sixth generation (6G) is foreseen to support a new set of use cases with diverse requirements. This paper explores the critical role of artificial intelligence (AI) in shaping the trajectory from 5G to 6G. We discuss AI applications in 5G for network planning, resource allocation, traffic management, and security, as well as propose infrastructure upgrades, like edge servers and enhanced network topologies, to support AI in 6G. Additionally, we outline a visionary perspective on AI's potential contributions to 6G, highlighting its role in enabling innovative

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services and applications. By providing this forward-looking perspective, this paper aims to stimulate discussion and guide the development of intelligent and autonomous 6G networks.

INDEX TERMS 5G, 6G, artificial intelligence, autonomous networks, intelligent networks, machine learning, network automation, network optimization, network planning, resource allocation, telecommunication.

I. INTRODUCTION

Over the past decade, the proliferation of mobile devices, the exponential growth of the Internet of Things (IoT), and the increasing demand for high-speed data transfer have driven the rapid evolution of cellular networks. The fifth-generation of wireless communication technology (5G) has brought several notable improvements in data rates, latency, network capacity, and consequently enabled a wide range of applications and use cases. The sixth-generation of wireless networks (6G) will continue to develop towards even higher frequency ranges, wider bandwidths, and massive antenna arrays [1]. However, as we move towards 6G, the ever-growing complexity and diversity of services and applications will pose new challenges that necessitate more agile, intelligent and robust strategies. There are numerous ongoing discussions in the industry about the true nature of 6G, its requirements, unique characteristics, and the added value it offers compared to 5G. The one thing that almost all involved industrial parties and academia collectively agree upon is that artificial intelligence (AI) and machine learning (ML) will play a determinant role in providing novel and sophisticated solutions to improve 6G wireless communication systems. AI and ML will offer further potential to optimize network performance, enhance user experience, and ultimately enable new services and complex applications like metaverse and digital twins [2], [3], [4], [5].

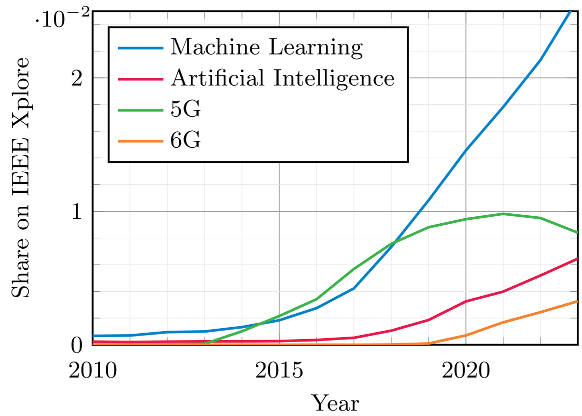

FIGURE 1. Number of search results on IEEE Xplore containing the keywords 'machine learning', 'artificial intelligence', '5G', and '6G' in the title, normalized to the total number of publications in each year.

This trend is also evident in FIGURE 1, which illustrates the number of publications on IEEE Xplore containing such specific keywords in their titles (normalized to the total number of publications each year). Of particular significance is the simultaneous rise of ML and 5G technologies, indicating that, the development of 6G stands to benefit from the accumulated insights and advancements in ML and AI over the past decade.

AI-enabled solutions and ML-based techniques in 5G networks have been initially explored in various domains, including user association, cell zooming, pilot assignment [6], base stations sleeping [7], network planning [8], resource allocation and power control [9], [10], [11], traffic management [12], [13], [14] and security [15]. Nevertheless, their full deployment in 5G networks has faced several crucial challenges, such as dependency on historical data (a.k.a. prior knowledge), computational complexity, and model interpretability [8].

The deployment of densely distributed edge servers with ample computing resources may enable localized model training and reduce latency [16]. Enhancing the network topology is also necessary to support the distribution of ML tasks, which demand a network architecture that can efficiently handle increased traffic while ensuring low-latency connections. On one hand, spectrum sharing methods and the integration of new spectrum bands will enhance the efficiency and capacity of wireless communication systems. On the other hand, the creation of new concepts like digital twins, that unify the experiences across physical, and digital realms, will also shape the system requirements and introduce novel technologies in 6G along with a new set of challenges. Similarly, emerging ML models like graph neural networks (GNNs) can offer notable advantages for 6G and respective applications, especially in IoT. GNNs are specifically designed to process and learn from graph-structured data in order to capture relationships between interconnected entities [17].

However, it is evident that the nature of the challenges that 6G faces is not unimodal and there is no set of unique solutions that universally address all the existing and emerging issues related to fully integrating AI at the core of 6G. As the research community and industry stakeholders simultaneously gear up for defining and developing 6G while effectively addressing emerging challenges, it is important to conduct critical analysis on the limitations and shortcomings of AI solutions in 5G networks in key domains and explore pragmatic approaches that can pave the way to more intelligent and autonomous networks while also targeting other important objectives such as making networks more efficient, lowering costs, improving sustainability, and increasing reliability in 6G. For example AI can have a significant impact on important societal values such as human dignity and self-determination, privacy and security in a stable democracy, as well as justice, solidarity and sustainability [18]. As this is a very extensive topic, this work will not go into more details but only provide some references as a starting point [19], [20].

This paper aims to bridge the gap between the current state of AI in 5G (including relevant use cases) and the transformative potential of AI in 6G. By analysing the limitations of existing research methodologies and the open challenges that hinder full-scale AI deployment, this paper proposes a set of enabling concepts and techniques that can pave the way for the realization of highly intelligent and (fully) autonomous 6G networks. Furthermore, it examines the ongoing standardization and regulatory efforts, and suggests potential revisions and new policies to address the unique requirements and challenges of AI in 6G.

A. DEFINITIONS IN THE CONTEXT OF THIS WORK

Artificial Intelligence (AI) in this paper refers to the capability of computer systems to perform tasks that typically require human intelligence. In the context of this paper for 5G and future 6G networks, we exclusively focus on ML, which is a subset of AI. ML enables computer systems to learn from data and improve their performance on specific tasks without being explicitly programmed. Throughout this paper, when we discuss AI, we are referring to the application of ML techniques to *automate*, *optimize*, and *enhance* different functions within 5G and future 6G network architectures. This includes using supervised learning algorithms [21] that learn patterns from labeled training data, unsupervised learning algorithms [22] that find structures in unlabeled data, and reinforcement learning algorithms [23] that aim to define optimized action-reward policies by interacting with dynamic environments.

Trustworthiness in this paper, refers to the ability of AI system to operate, *securely*, *transparently*, and as intended *without bias and causing unintentional or intentional harm*, following explainability principles defined below. Establishing comprehensive trustworthiness for AI in 6G networks necessitates defining standards across dimensions like transparency, cybersecurity, and resilience that specifically address the wireless networking domain.

Explainability in this paper is defined as the ability to provide human-understandable justifications and reasons for how AI systems make decisions or arrive at specific outputs. We believe that explainability provides the foundations for users and network operators to appropriately integrate AI in 6G. Constructing comprehensible explanations then becomes crucial for maintaining acceptance and enabling auditability.

B. OUTLINE

In Section II, we examine the current state of AI utilization in cellular communications. The various network application areas impacted by the utilization of ML methods are described in subsection II-A. Moreover, we discuss future use cases of AI in network infrastructure planning and management. In subsection II-B we identify some research limitations of AI methodologies. In subsection II-C, we attempt to list the open challenges and requirements that must be addressed for both AI and the network infrastructure.

In Section III, we delve deeper into potential roles and pragmatic integration of AI in 6G. In subsection III-A, we discuss the key enabling concepts and novel frameworks that will underpin the realization of 6G networks, harnessing the potential of AI techniques for intelligent and adaptive communication systems. In subsection III-B, we investigate the AI techniques that have emerged from recent advancements, with a focus on performance gain, increased efficiency, and enabling new capabilities that are crucial for realizing 6G use cases. In subsection III-C, we outline our vision for AI-enabled 6G. We discuss which AI algorithms will impact specific network components and how these AI-enabled components will contribute to improving sustainability, performance, adaptability, and trustworthiness requirements.

In Section IV, we examine ongoing efforts in AI-related topics by regulatory and standardization entities within the telecommunications industry. We also review existing policies and suggest potential revisions to address the requirements and challenges of 6G networks. We also look at existing policies and suggest potential revisions to fit requirements and issues of 6G networks.

Finally, in Section V we conclude by summarizing the work's key points, including AI's current role in 5G, proposed upgrades for 6G, and emerging AI techniques. We highlight the potential impact of AI on 6G requirements and network design, as well as the importance of ongoing standardization efforts and policy considerations for AI in telecommunications.

II. AI AND CELLULAR COMMUNICATIONS

While the integration of AI in 5G and future 6G networks offers significant potential benefits, it also necessitates a critical examination of the current state-of-the-art and the exploration of novel ideas to overcome existing limitations. Many of the initial attempts to introduce AI in 5G have relied on simplified assumptions or simulations that do not fully capture the complexities of real-world deployments. However, it is crucial to acknowledge the progress made in 5G AI integration, particularly in optimizing energy consumption across the network infrastructure, as extensively discussed in [24] and [25]. Moreover, the unique expected characteristics of 6G, such as dynamic network behaviors, diverse user interactions, and the importance of accounting for adaptability and trustworthiness, require fresh perspectives on AI integration. To this end, this section analyzes the existing research on AI in cellular communications, highlights the limitations and challenges that need to be addressed from different angles, and delves into specific areas where pragmatic perspectives are needed, including the limitations of relying solely on historical data, the need for explainable AI (XAI), the potential of AI for enabling new

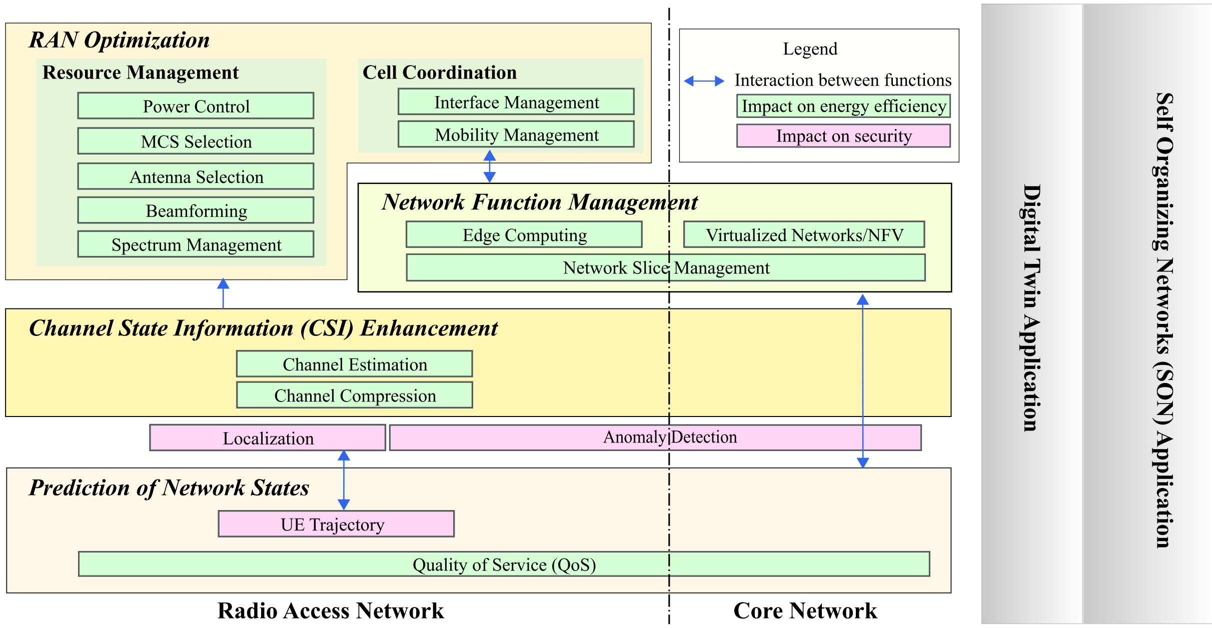

FIGURE 2. Potential applications of machine learning in mobile networks and their interconnections.

6G use cases, the challenges of integrating AI with edge computing, and the ethical considerations of AI in 6G.

A. NETWORK APPLICATIONS BENEFITING FROM AI

The integration of advanced AI technologies in 5G has unlocked a multitude of key capabilities and impacted various aspects of network operations and service delivery. From automated optimization of critical functions to predictive analytics for proactive network management, AI techniques have introduced new levels of intelligence, adaptability, and personalization into 5G networks. However, to achieve the objective of even more intelligent and autonomous networks in 6G, it is necessary to gain a concrete understanding of the role and limitations of AI in every application and domain. Some of the potential applications of AI in mobile networks and their interconnections that we cover in this section are illustrated in FIGURE 2.

1) OPEN-RAN OPTIMIZATION

AI has been increasingly adopted in air interface parameters optimization, cell coordination, power control, and interference management. In particular deep learning has been applied for RAN optimization tasks in 5G networks and as a valuable asset in the evolution of O-RAN [26]. Studies have been supporting intelligence in disaggregated Open RAN [27], and innovative techniques like multi-agent team learning (MATL) have emerged in virtualized Open RAN architectures [28].

We provide examples for the following applications of AI in RAN optimization and divided it in two main categories:

- resource management, including link adaptation problems such as modulation and coding scheme (MCS) selection [29], antenna selection [30], and beamforming [31]
- cell coordination, including interference and mobility management

These applications have a crucial impact on energy efficiency, as highlighted in FIGURE 2.

Power Control aims at controlling/allocating the transmit power to maximize signal to interference and noise ratio (SINR) or spectral efficiency with minimal energy usage. In order to select the optimal transmit power with dynamically changing channel statistics, the power control policy needs to be updated frequently. The power control problem can be solved with sophisticated numerical optimization, however, ML helps to achieve a similar performance reducing computational complexity [32]. ML techniques such as deep neural network (DNN), multi-agent reinforcement learning, and centralized training with decentralized execution help to achieve superior performance by avoiding multi-objective optimization issues [33], [34].

a: MODULATION AND CODING SCHEME (MCS) SELECTION

is a critical MAC function that chooses the modulation and coding scheme based on channel state information (CSI), packet/data size, and system constraints like reliability measured by block-error rate (BLER). This selection process often involves a trade-off between data rate and BLER depending on channel quality. 5G standard methods such as inner loop link adaptation (ILLA) or outer loop link adaptation (OLLA) utilize lookup tables for MCS selection or adjust the MCS by correcting the predicted SINR, respectively. ML techniques can enhance performance by selecting MCS based upon predicted SINR and without relying on ground-truth data [35]. Reinforcement learning-based MCS selection is a promising approach for selecting the appropriate MCS to maximize throughput and make quick decisions for multiple users [36], [37]. This high-layer decision process fundamentally relies on accurate physical-layer intelligence, where Automatic Modulation Classification (AMC) identifies incoming modulation schemes in real time [38], and next-generation designs like Super Constellations (e.g., SAPSK [39]) enable ultra-high data rates. Recent advances include CNN-based AMC robust to phase imperfections (PI) [38], which uses polar transformations and asymmetric kernels to mitigate oscillator mismatches and imperfect CSI, improving low-SNR classification. Concurrently, AI-driven modulation optimization is essential for 6G super constellations, as they must balance spectral efficiency with phase noise (PN) resilience and energy constraints [39]. For instance, SAPSK [39] employs a triangular polar lattice and Generalized Polar Distance Detector (GPD-D) to achieve $\mathcal{O}(1)$-complexity detection while optimizing ring counts via SNR/PN-aware SEP approximations—enabling AI-aided dynamic adaptation.

b: ANTENNA SELECTION AND BEAMFORMING

Massive MIMO is an integral part of communication systems for 5G and beyond. The trend of employing larger antenna arrays in ultra-dense mobile environments makes antenna selection a challenging problem. Traditional beamforming algorithms result in high computational complexity and energy consumption, thus necessitating the application of AI for antenna selection and beamforming [40]. A large body of studies on AI-assisted antenna selection algorithms suggests that AI algorithms can significantly reduce the selection complexity and achieve up to 82–88% of a full antenna array's spectral efficiency with the selected subset of antennas [40], [41]. Jointly optimizing the antenna selection and beamforming using AI algorithms have been studied recently in [42] and [43]. Furthermore, recent studies have also explored the use of AI for dynamic beamforming and phase control in RIS-assisted systems, where intelligent surfaces can complement traditional antenna arrays to further enhance coverage and energy efficiency [44], [45].

c: SPECTRUM MANAGEMENT

Due to the inherent complexity of the spectrum allocation problem between multiple users or networks [46], ML has been used as a powerful tool to deal with existing non-linearities. One such example is the vehicular-to-everything (V2X) networks [47], where the distributed spectrum management algorithms based on ML have been shown to yield promising results in 5G systems [48]. Both supervised and reinforcement learning-based solutions have been proposed for spectrum management [49], [50]. Additionally, the reinforcement learning-based dynamic spectrum access scheme in [51] achieves nearly considerable enhancements in average channel utilization compared to slotted ALOHA.

d: INTERFERENCE MANAGEMENT

Interference is one of the factors affecting the quality of wireless links. It can be minimized through effective management of inevitable intra-cell and inter-cell interference. Interference management encompasses schemes such as interference avoidance, interference suppression, and interference exploitation [52]. The interference avoidance scheme proactively allocates resources, such as frequency, power, the number of resource elements, and proper MCS selection with or without inter-cell coordination. Interference suppression techniques aim to eliminate interference when it occurs by utilizing precoding methods and/or filtering mechanisms such as successive interference cancellation. Conversely, in the case of interference exploitation, interference can constructively add up at the receiver to enhance performance [53]. Due to non-linear dynamics and the non-stationary nature of interference, conventional interference management techniques may not help to achieve stringent requirements for some use cases. Consequently, ML helps achieve better performance either through prediction-based interference management, such as recurrent neural networks (RRN) like long short-term memory (LSTM) [54], or through the direct suppression of interference using reinforcement learning [55].

e: MOBILITY MANAGEMENT

ensures that moving devices maintain connectivity when leaving the coverage of their serving cell by handing over to another cell. Therefore, not only a suitable target cell but also an optimal time instance have to be found, avoiding radio link failures and unnecessary handovers or ping pong effects. Furthermore, the reservation of resources at potential target cells for so-called conditional handover needs to be minimized for efficient operation. ML can help to predict movements or the radio conditions of the device [56] and trigger handovers in an comparable optimal way. With the emergence of beamforming, the handover problem became more complex and was addressed by [57] with a LSTM approach.

2) NETWORK FUNCTION MANAGEMENT

Strategic placement of network functions enabled by AI is critical for optimizing network performance, enhancing user experience, and meeting diverse service requirements. It should be noted that the strategic utilization of network functions also impacts RAN optimization and vice-versa.

a: NETWORK SLICE MANAGEMENT

primarily focuses on resource allocation at network slices by solving NP hard problems. AI algorithms work as an important enabler in providing real-time approximate solutions [58]. Various studies have proposed ML-based approaches to improve network slicing, such as hybrid learning algorithms for traffic classification [59], data-driven models for resource redistribution [60], and experimental prototypes integrating ML for radio resource configuration [61]. Deep reinforcement learning (DRL) has been explored for resource allocation in network slicing, demonstrating potential improvements in optimizing resources within each slice. This optimization can enhance performance isolation, which ensures consistent and predictable performance for each slice regardless of traffic in other slices. Reinforcement learning can also enable customization of resource allocation according to specific service requirements [62], [63], [64]. However, it can be computationally expensive to train a DRL model and requires a careful design of its reward function [65].

b: EDGE COMPUTING

effectively reduces latency and facilitates content caching as well as delivery at the edge. To achieve this objective, edge nodes are organized in various topologies like star, mesh, and hybrid topologies. Star topologies rely on a centralized system with a centralized server, while mesh topologies offer a decentralized architecture where each device is connected to every other device, therefor reducing latency [66]. An advanced form of edge computing, MEC (Mobile edge computing) brings edge computing functions directly into the mobile network in which computational resources are deployed at the network's edge, such as cellular base stations. This approach minimizes latency [67], reduces energy consumption, and improves the performance of real-time applications like augmented reality (AR), autonomous vehicles, and IoT systems [68]. Additionally, edge servers with hardware accelerators support computationally intensive machine learning tasks, such as object detection, vision processing, and natural language processing. AI algorithms can predict and anticipate dynamic changes in edge computing scenarios, enabling proactive decision-making and resource allocation. Additionally, they can predict user behavior and content popularity, enabling efficient content caching at the edge [68], [69], [70], [71]. Moreover, AI-driven techniques are used to refine the placement of edge servers, improving resource utilization, enhancing scalability, and enabling efficient computation through seamless integration [72].

c: VIRTUALIZED NETWORKS/NETWORK FUNCTION VIRTUALIZATION (NFV)

By decoupling network functions from physical hardware, virtualized networks provide greater flexibility, scalability, and efficiency in managing network resources. However, managing the network resources can create additional bottlenecks as well, in the form of optimization and virtualization complexity, especially when considering varying network topologies and capabilities of different flavours of NFV [73]. AI can enhance the resource allocation in NFV by predicting network states. Additionally, AI can facilitate dynamic adjustments in NFV deployments by detecting topology changes and supporting virtual machine migrations [74].

3) CHANNEL STATE INFORMATION (CSI) ENHANCEMENT

The efficient estimation of the channel between the RAN and end devices is important in realizing the data rate, spectral efficiency, latency, and reliability requirements [75]. Additionally, accurate CSI also required for the optimization of system parameters in the RAN. There are two main CSI-enhancement tasks in 5G RAN where AI can play a significant role: CSI estimation and CSI compression.

a: CSI ESTIMATION

In large antenna array transceiver systems, an accurate estimation of CSI is challenging due to multiple reasons, e.g., user mobility, limited number of orthogonal pilots, and the dynamic nature of the wireless environment. The main challenge in 5G systems for accurate CSI estimation is the tradeoff in the design and implementation of the pilot signals. On one hand, their length should not be too small as this will limit the maximum number of orthogonal signals, and on the other hand larger pilot signals reduce the available time for uplink and downlink communication [76]. Recently, [77] and [78] proposed ML algorithms that can estimate and predict the CSI in massive MIMO systems in presence of pilot contamination and high mobility.

b: CSI COMPRESSION

Apart from the above-mentioned challenges, in frequency division duplex (FDD) mode of communication, uplink and downlink CSI do not follow the radio channel reciprocity property due to significantly different carrier frequencies [79]. Therefore, traditional pilot signal-based estimation of downlink CSI is not feasible in FDD, and the typical resolution of this problem is achieved through CSI feedback. To reduce the amount of overhead due to this feedback, autoencoder-based CSI feedback systems [80], and CNN-based algorithms [81] have been proposed.

4) LOCALIZATION

The positioning capabilities of 5G NR signals are enhanced by wideband signals, massive antenna arrays, and the use of both centimeter and millimeter bands. These signals are designed for both uplink and downlink positioning and the 5G system already supports carrier bandwidths of around 100 MHz in the sub-6 GHz bands (FR1) and 400 MHz in the supra-24 GHz bands (FR2). Leveraging this higher bandwidth and the extensive data generated by 5G networks, ML algorithms are efficiently utilized for hybrid positioning [82] and AI-based fingerprinting [83].

5) ANOMALY DETECTION

In 5G networks, AI-based applications play a crucial role in developing advanced security measures for both the core network and the RAN. For instance, AI-driven anomaly detection systems in the RAN utilize machine learning algorithms to identify and mitigate unusual behaviors and potential threats, thereby safeguarding network integrity and performance [84]. However, to fully leverage the potential of AI in anomaly detection, it is crucial to address the "black box" nature of many AI algorithms. Explainable AI techniques can provide insights into the decision-making process of these algorithms, and enable network operators to understand and trust the identified anomalies. Similarly, in the core network, AI can enhance intrusion detection systems (IDS) by monitoring network traffic for suspicious activities and effectively preventing potential cyber-attacks before they can cause harm [85]. Additionally, AI contributes significantly to various security functions such as threat intelligence, malware detection, intrusion prevention, fraud management, as well as spectrum and traffic anomaly detection [86], [87], [88], [89], [90], [91], [92]. Achieving these objectives often involves integrating other novel technologies, such as blockchain, to further enhance security measures [93]. These AI-enhanced security solutions not only improve detection and response rates but also contribute to an adaptive security posture necessary for the dynamic nature of 5G networks. This ensures robust security management and resilience against sophisticated cyber threats, maintaining the integrity and reliability of the network.

6) PREDICTION OF NETWORK STATES

In the rapidly evolving landscape of 5G and emerging 6G networks, predicting network states and user behaviors has become increasingly important to ensure optimal network performance and Quality of Service (QoS).

a: QUALITY OF SERVICE

AI techniques, including federated learning, can contribute to optimizing network performance and enhance QoS in 5G core networks [94], [95], [96], [97], [98]. Applying ML to proactively manage the network and fulfill safety-critical requirements has been successfully demonstrated, for example in V2X communication in [99], discusses pitfalls such as concept drift and overly optimistic results by insufficient test design. In this context, While ensuring user data privacy and security, AI also facilitates user tracking, real-time location services, handover optimization, user authentication, and beam steering [100], [101]. Some studies, such as [95], [102], and [103], also propose using AI to estimate and predict parameters like congestion, traffic load, channel estimation, etc, and accordingly upscale or downscale the network infrastructure.

b: USER EQUIPMENT (UE) TRAJECTORY PREDICTION

promotes the performance and robustness of 5G networks [104]. In [105], trajectory predictions involving both offline and online training and utilizing clustering algorithms are developed and highly accurate prediction of the next base station (up to 94%) is achieved [105]. A CNN-LSTM-based trajectory prediction algorithm has also shown an almost five-fold reduction in the number of handovers [106]. AI-enhanced trajectory prediction can also improve localization accuracy.

7) SELF-ORGANIZING NETWORKS (SON)

It has been demonstrated that self-organization is a key driver for improving operations, administration, and maintenance (OAM) activities in cellular networks. Many works argued that ML techniques for self-configuration, self-optimization, and self-healing algorithms have the potential to simplify operational tasks and reduce costs in beyond 5G networks [12], [49], [107], [108], [109]. Other AI approaches such as precoding real-time buffer-based self-healing [110] or reinforcement learning based tilt-optimization for self-healing [111], [112], enhance network reliability and efficiency. The role of AI in enabling self-healing and autonomous maintenance in 6G networks is also of crucial importance due to the increasing complexity and scale of these networks. AI can enable proactive identification and resolution of network issues, to ensure uninterrupted service availability and optimal network performance.

8) DIGITAL TWIN

This technology has recently gained significance in Industry 4.0, but the current advances in compute and network capabilities provided by 5G and supporting technologies are not efficient enough to effectively oversee automation or formulate optimal decisions for the dynamic adaptation of digital twins [113]. Digital twin-based systems rely on an array of sensors to identify changes in the target and monitor interactions with it. AI agents at the application and infrastructure levels, such as task learning, movement prediction, and predictive maintenance, are a true embodiment of Digital Twins [114].

Despite the promising potential of AI in 5G as mentioned above, several technical challenges still hinder its full-scale deployment, such as dependency on historical data, computational complexity, and model interpretability as well as limitations in respective research methodology. Addressing these challenges, as described in the following Sections in detail, is crucial for the successful integration of AI in 6G networks.

B. RESEARCH METHODOLOGY LIMITATIONS

As outlined in Section II-A, in the last few years research has successfully introduced ML methodologies for tackling cellular communications problems. Some of these first research attempts have focused on a controlled training environment, ignoring to an extent the complexities of deploying ML algorithms in commercial networks. In ML, simulations are usually preferred for training due to their control and access to data. However, they often fail to capture important characteristics and nuances of real-life deployments. Just like 5G, this shortcoming becomes particularly significant in 6G as well, where dynamic network behaviors and diverse user interactions will add layers of complexity. In real-world deployments, the training datasets collected might violate some of the preconditions that ML models and other theoretical approaches have. A prominent example will be the stationary assumption that is easily violated from datasets collected from the radio environment [99]. Even though a non-stationary dataset can be handled by online ML models, or through some type of life-cycle management, both methods bring their own challenges and aspects. Another often overlooked issue is the identical structure of the dataset. Many of the datasets for wireless networks used for research have a similar structure [115]. Random sampling isn't suitable due to the strong correlation in the data, because data is assumed to be i.i.d. A strong match between samples may inhibit the learning of the sample underlying patterns. In an extreme situation, the ML model may learn just the correlation structure. For example, when predicting any time series, e.g., 'cell throughput over time (due to changing network environment such as neighboring cell deactivation, and neighboring antenna tilt changes), a mean square error (MSE)-targeted-trained model may indeed lead to a prediction with a lower MSE than say, the baseline. There is still a high chance though that this prediction bears a much lower correlation, or even a *negative* correlation against the reality/ground truth – as the environment changes over time. In other words, the trends of the rise and fall in the predicted time series could even be exactly opposite to that in reality, which defeats the very purpose of the model training the root cause being that the correlation, an equally important metric for a time series prediction, was never taken into account in the loss function [116], [117], [118]. Moreover, the reliance on historical data can limit the adaptability of AI algorithms to dynamically changing network conditions. To address this limitation, it is necessary to explore the integration of real-time data analysis and adaptive learning algorithms that can continuously learn and adapt to evolving network environments. This shift towards real-time AI can enable more proactive and dynamic network optimization, leading to improved performance, efficiency, and reliability in 6G networks.

The lack of standardized datasets for evaluating machine learning models poses an important challenge to the wireless communication research community. Researchers currently rely on self-produced datasets, which can lead to unreliable performance estimations and hinder meaningful comparisons across different models. Establishing standardized datasets is essential to ensure accurate model evaluation and drive progress in ML-empowered 6G research.

Beyond data-centric challenges, a further methodological limitation is the inherent opacity of the models themselves. Explainability methods have been used to improve the transparency and interpretability of data workflows and ML models, that are often perceived as black boxes. The effectiveness of such techniques has been questioned in [119] where results from explainable AI (XAI) methods were presented to domain experts. The domain expert has shown that XAI methods tend to be more informative than explanatory, not being able to provide explanations integrating different perspectives.

In the future the focus will shift to more realistic simulation environments. This can be achieved by enhancing simulation techniques, using better product simulators or digital twins, and integrating real data to represent complex situations. To address the previously mentioned limitation of model adaptability in dynamic environments, transfer learning techniques are becoming pivotal in this context, as they reduce the necessity for extensive retraining and enhance the adaptability of models to new environments and data types. Equally important is the development of robust models that can handle a variety of scenarios. This is achieved using diverse training datasets and the incorporation of methods such as reinforcement learning, where models evolve by interacting with their environment. Similarly, to tackle the methodological hurdles of data access and privacy that compound the lack of diverse datasets, federated learning is an emerging key component in decentralized data processing within 6G networks.

This approach, where AI models are trained across multiple decentralized devices, is instrumental in understanding diverse real-world scenarios. Federated learning enhances privacy by allowing models to be trained locally on devices, eliminating the need to share training data. Instead, it optimizes neural networks by sharing local model weights. This enables the utilization of a wide array of real-time data from various sources, completely bridging the gap between virtual simulations and reality while maintaining data privacy among vendors.

As mentioned above, it should be emphasized that the lack of standardized datasets and the prevalence of self-produced datasets in wireless communication research can lead to overestimation or underestimation of model performance and hinder effective performance comparison, thereby impeding the progress of AI integration.

C. OPEN CHALLENGES AND REQUIREMENTS

This paper aims to address the open challenges and requirements for AI integration in 6G networks from two perspectives. We first delve into the key challenges hindering the seamless enabling of AI into 6G, including latency, complexity, security, and ethical considerations. Subsequently, we explore how AI can be leveraged to meet the demanding requirements of 6G networks, such as enhanced network management, automation, and optimization. By analyzing both the challenges and opportunities, this work aims to provide a comprehensive overview of the potential and the most critical limitations of AI in 6G that contributes to a more informed and effective approach towards developing intelligent and autonomous 6G networks.

1) KEY CHALLENGES FOR ENABLING AI IN 6G NETWORKS

To improve the uptake of AI in 6G, as stated before, AI-based solutions need to overcome several potential challenges in 6G networks. Several real-life scenarios are explored in this work, such as cell coordination, RAN resource management, and CSI enhancement challenges that are discussed in detail in subsection III-C. Some of the major challenges of incorporating AI in 6G are highlighted in the following. It is important to note that these challenges are also present in 5G but with a greater extent of AI integration in 6G, these challenges are likely to amplify even further.

a: LATENCY

While a well-designed AI/ML model can perform inference with very low latency, its integration into the network introduces a computational delay that must be carefully managed within the stringent end-to-end latency budget of 5G-and-beyond applications. The key challenge is not the inference time in isolation, but the holistic management of the entire processing pipeline. Therefore, the appropriate placement of AI/ML functions and analytics is pivotal. For example, utilizing AI/ML at the network edge can reduce the communication latency by avoiding a round-trip to a centralized server [120]. However, this requires sufficient computing resources at edge nodes, and the processing on these nodes contributes to the overall latency budget [121]. This creates a fundamental trade-off between communication and computation latency that must be carefully analyzed for different use cases and network deployments [121]. Since 6G is expected to support life-critical applications with guaranteed latency consistency [122], it is crucial to employ a range of strategies. These include developing highly-optimized, low-complexity AI/ML algorithms, utilizing model compression techniques, and ensuring their efficient deployment on specialized hardware to meet the hyper-stringent latency requirements of 6G.

b: COMPLEXITY AND SCALABILITY

In 6G systems, AI/ML functionalities will be deployed as a distributed system of modular components, each specialized for a specific task, rather than as a single monolithic model attempting to handle all network operations. While this modular approach is more practical, it introduces a significant challenge in managing the complexity and ensuring the scalability of the overall system. As networks grow, the number of interconnected AI/ML components will increase dramatically. The challenge, therefore, shifts from the complexity of a single model to the complexity of orchestrating a vast number of heterogeneous modules. Ensuring that this system of components can scale efficiently—maintaining performance and stability as the network and number of services grow—while managing the inherent trade-offs between the complexity and performance of each individual module, remains a critical area of research [123].

c: TRAINING AND INFERENCE RESOURCE REQUIREMENTS

While the initial training of large-scale AI/ML models can often be conducted offline where computational resources are less of a constraint, 6G networks will require models that can adapt to highly dynamic conditions. This necessitates online, continuous, or federated learning approaches, where the time and resources for frequent retraining become a significant operational challenge. Beyond training, the inference requirements for a live 6G network present a critical concern. With the ambition to connect everything everywhere, a vast number of AI/ML models will need to be concurrently deployed across a heterogeneous infrastructure, from resource-constrained IoT devices to powerful edge servers. This large-scale deployment requires efficient resource management and, as the reviewer noted, often dedicated inference hardware to run models with low latency and high energy efficiency. Therefore, techniques such as model compression and quantization, alongside hardware-aware AI/ML design, are essential for ensuring that both continuous training and large-scale inference are feasible within the resource budgets of 6G systems.

d: SUSTAINABILITY

Sustainability is a critical design pillar for 6G, with a focus on minimizing energy consumption and operational costs. The integration of AI/ML presents a fundamental duality in this context: it is both a source of new energy demands and a key enabler for advanced energy-saving solutions. On one hand, AI/ML contributes to energy consumption. The baseline power draw of 6G networks is already expected to increase due to more complex radio hardware needed to meet enhanced KPIs. Layered on top of this, the continuous training and large-scale inference of sophisticated AI/ML models require energy-intensive computational hardware (e.g., GPUs, TPUs), adding to the overall power budget. On the other hand, AI/ML is arguably the most powerful tool for improving network energy efficiency. It can enable highly effective optimization strategies that are not possible with traditional methods. Concrete examples include:

- Intelligent RAN Operation: AI/ML can predict traffic fluctuations to dynamically activate or deactivate base station components (i.e., "sleep modes"), significantly reducing power consumption during periods of low demand.
- Dynamic Power Control: AI/ML algorithms can precisely manage the transmit power of both user devices and network infrastructure, ensuring quality of service with the minimum required energy.
- Network-wide Optimization: AI/ML can optimize end-to-end network functions, such as energy-aware traffic routing and placement of virtualized network functions, to lower the total system-wide energy footprint.

The ultimate sustainability challenge is therefore to ensure that the energy savings achieved through AI/ML-driven optimizations are substantially greater than the energy consumed by the AI/ML systems themselves, leading to a net-positive impact on the network's economic and environmental feasibility.

e: ADAPTABILITY TO ENVIRONMENTAL DYNAMICS

Communication networks operate in dynamically changing environments with varying network conditions, traffic patterns, and user demands. ML algorithms need to adapt and learn in real-time to handle these dynamics effectively. There is also the issue of accurate training data collection in such conditions, as the accuracy and performance of ML depends on data availability. For physical layer applications like modulation and equalization, accurate data collection is important. As mentioned earlier, the dynamic nature of wireless networks can introduce unwanted errors into the data set due to inaccurate channel estimates. While ML models trained for a specific environment may fail to generalize and thus require extensive retraining, having multiple models for specific environments may require a complex model life cycle management procedure. Therefore, it is crucial to have generalizable models that can adapt to various environments and perform well in diverse network settings.

f: SECURITY, RELIABILITY, AND MONITORING

Integrating AI in 6G networks necessitates robust security measures against cyber threats and adversarial attacks, alongside enhanced reliability through redundancy and fault-tolerant designs. AI models can be vulnerable to adversarial attacks, where malicious actors manipulate input data to cause the model to malfunction. Additionally, data poisoning attacks can compromise the integrity of training data, leading to flawed AI models. To mitigate these risks, robust security measures such as adversarial training [124], input validation [125], and data sanitization [126] techniques are necessary. Comprehensive monitoring frameworks, that incorporate AI-driven anomaly detection and predictive maintenance, are crucial for real-time assessment of system performance and security. Rigorous testing, validation, and certification processes must be established, including standardized benchmarks for evaluating AI systems under various network conditions. Addressing regulatory compliance and ethical considerations requires developing governance frameworks that ensure transparency and accountability. A collaborative approach involving researchers, industry players, and policymakers is essential to implement these measures effectively, and balancing the potential of AI with associated risks.

g: ETHICAL CONSIDERATIONS

The integration of AI/ML in 6G networks raises crucial ethical considerations that must be carefully addressed. While it is true that many AI/ML functions may operate on anonymized physical-layer data, a significant number of advanced optimization and service-customization features will inevitably leverage user-derived or user-proximate data, making ethics a vital design concern. For instance, data privacy remains a primary issue. AI/ML-driven mobility management and beamforming rely on precise user location and trajectory data. Even if anonymized, this data can be vulnerable to re-identification, and its handling must comply with stringent privacy regulations like GDPR. Furthermore, the risk of algorithmic bias is a significant concern in core network functions. An AI/ML model for network slicing or resource allocation, if trained on historical data reflecting societal biases, could learn to unfairly prioritize traffic for certain applications or user groups over others, leading to discriminatory service quality. Similarly, an anomaly detection system could be biased against atypical but legitimate user behavior. To mitigate these risks, principles of fairness and transparency must be embedded into the AI/ML development lifecycle for 6G. It is not enough for the systems to be performant; they must also be equitable and auditable. Addressing these ethical challenges is therefore not a secondary objective but a prerequisite for the responsible and successful deployment of AI/ML in 6G networks.

h: EXPLAINABILITY

With the growing use of complex AI/ML models in telecommunications, their inherent ''black box'' nature presents a significant operational challenge. Explainability, in this context, refers to the ability to provide human-understandable justifications for a model's decisions, often by identifying which input features had the most significant impact on a given output. While a real-time explanation for every microsecond-level decision may be impractical, explainability is nonetheless crucial for the overall lifecycle management, trustworthiness, and adoption of AI/ML in 6G networks.

From a network operator's perspective, explainability is essential for several practical reasons:

- Troubleshooting and Debugging: If an AI/ML model governing resource allocation begins to degrade network performance, the operator must understand why. Explainability techniques can reveal whether the issue is caused by unexpected input data (e.g., unusual channel conditions, a specific user's mobility pattern) or a flaw in the model itself, which is critical for rapid debugging.
- Building Trust and Ensuring Reliability: For an operator to deploy an AI/ML system for a critical function like power control, they need confidence that the model is making decisions based on valid network principles (e.g., high SINR leads to lower power) and not spurious correlations. Explainability provides this assurance.
- Auditing and SLA Compliance: When a service disruption occurs for a high-value network slice, the operator must be able to audit the system and determine the root cause. An unexplainable AI/ML system makes it impossible to provide such guarantees or to verify compliance with Service Level Agreements (SLAs).

Therefore, improving the interpretability of AI/ML models is a critical path for ensuring they can be safely and reliably deployed, managed, and trusted in complex 6G environments.

i: TRUSTWORTHINESS

While enhanced performance is a primary goal of employing AI/ML, guaranteeing trustworthiness is a foundational principle for 6G design. Trustworthiness ensures that an AI/ML system operates reliably, securely, fairly, and transparently. Beyond the widely researched areas of security and privacy, other aspects such as robustness, fairness, and transparency require special attention in the context of 6G. *Robustness* refers to the system's ability to maintain performance under unexpected conditions or direct adversarial attacks. For example, an AI/ML model used for traffic classification must be robust against data poisoning attacks, where malicious actors intentionally feed it misleading data during training to cause future misclassifications. *Fairness* implies the mitigation of unjust bias in AI/ML-driven decisions. In a 6G context, an AI/ML-powered scheduler for network slicing must allocate resources equitably among users or tenants according to their service agreements, without systematically disadvantaging certain groups based on their location, device type, or other characteristics present in the training data. *Transparency* requires that an AI/ML system's operations are explainable and auditable. For instance, if an automated AI/ML system decides to block a device for security reasons, the network operator must have access to a traceable and understandable log of which model made the decision and based on what specific input data. This auditability is essential for troubleshooting, accountability, and building operator confidence. Integrating these principles into the entire AI/ML lifecycle—from data collection to model deployment and monitoring—is a prerequisite for the wide-scale adoption of automated decision-making in 6G networks.

2) UNRESOLVED CHALLENGES AND LIMITATIONS FROM THE 5G ERA

Despite the numerous applications of AI/ML in 5G, the ambitious vision of fully autonomous, end-to-end intelligent networks has not yet been fully realized [127]. Several foundational and practical challenges remain, highlighting the gap between 5G's capabilities and the requirements for future 6G systems. Understanding these limitations is crucial for developing the next generation of AI/ML-driven networks.

A primary set of challenges relates to network automation. For instance, the envisioned prevalence of automated healing and optimization through Self-Organizing Networks (SON) has not materialized to the extent anticipated [128]. Similarly, network slicing, a key 5G enabler, still faces significant hurdles; the dynamic slicing and coordination of slices across domains via AI/ML techniques remain elusive, with many technical problems still unresolved [129], [130]. While solutions using reinforcement learning [131] or blockchain [132] have been proposed, they introduce their own complexities. The limited trust in AI-proposed actions, which often require human validation, remains a significant barrier to achieving full autonomy [133], [134].

Furthermore, the deployment of distributed intelligence faces its own constraints. The use of edge intelligence is often hampered by a lack of sufficient data and model complexity for resource-constrained edge devices [135]. User movement has a significant impact on mobile edge computing (MEC), leading to challenges in energy consumption and resource management [136]. The realization of AI/ML-driven dynamic spectrum sharing is likewise impeded by scalability concerns and the need for robust authentication and access control mechanisms [137], [138].

Finally, specific high-value use cases continue to struggle with limitations. The prediction of user mobility, which is critical for proactive network management, is still limited by gaps in coverage and restricted access to traveler data [139], [140]. In vehicular (V2X) and smart city applications, the unreliability of latency-sensitive coordination via AI/ML poses a challenge for autonomous systems [122], [141], [142], [143]. Even personalized 5G services and automated customer support are restricted by privacy regulations that limit data collection and the need for significant human oversight for complex queries [144], [145], [146]. These unresolved issues from the 5G era form the baseline of challenges that 6G systems must overcome.

III. AI IN 6G

Building upon the insights gained from the previous sections, we now navigate through a set of technical enablers that can solve the outlined limitations. Specifically, we unravel the recent advancements in AI-based concepts and the technological methods that have potentially paved the way for deep integration of AI in wireless communication.

A. ENABLING CONCEPTS

Realizing 6G requires adopting new AI-driven concepts in parallel with the basic AI-based solutions [147], such as innovative data-sharing frameworks, hybrid models and data-driven solutions, intent-based networking, and adaptive architectures. These will shape intelligent and adaptive communication systems, enhancing flexibility, efficiency, and user-centric services in the 6G ecosystem. These enabling concepts encompass various frameworks, architectures, and paradigms, that will play a crucial role in shaping the future of intelligent and adaptive communication systems. By embracing novel data-sharing frameworks, hybrid models, data-driven solutions, intent-based networking, and adaptive network architectures, the 6G ecosystem can unlock new levels of flexibility, efficiency, and user-centric service delivery. It should also be noted that 6G will witness the arrival of new evolutions of end-user devices that rely on new AI operating systems and AI-powered firmware [148].

1) DATA SHARING FRAMEWORKS

In the 6G era, there will be a growing need for diverse, high-quality datasets to train robust ML models across various network layers [149]. Data sharing frameworks such as domain-specific data consortia, data marketplaces, and decentralized data sharing via blockchain, along with distributed learning methods like federated learning, can help to incentivize data contribution while ensuring privacy. By leveraging frameworks like GAIA-X [150], stakeholders can accelerate the development of advanced ML models, optimize network performance, and unlock the full potential of 6G communication networks.

- *Domain-specific data consortia* can be potentially formed by industry stakeholders, research institutions, and/or government agencies to pool resources and share data within specific domains. By collaborating within a consortium, members can access a larger pool of data, accelerating ML model development and improving network performance. The challenges of data privacy within domain-specific data consortia in 6G communication networks parallel those seen in medical data sharing, where sensitive data from multiple sources must be securely shared among stakeholders. Techniques such as differential privacy, data anonymization, and access control measures [151], [152] are widely used in medical consortia to address these issues, and similar approaches can be applied to protect 6G data across different network layers.
- *Data marketplaces* can facilitate the exchange of datasets between data providers and consumers. These platforms can offer data licensing, pricing, and access control mechanisms to ensure data privacy and incentivize data sharing. By participating in data marketplaces, organizations can monetize their data assets and gain access to valuable external datasets.
- *Decentralized data sharing*: Blockchain technology can enable secure, transparent, and decentralized data sharing in 6G networks [153]. Blockchain-based data sharing platforms can provide secure mutual authentication across networks with different trust domains and allow for the secure exchange of data without relying on a central authority [154]. This approach can enhance data privacy and security while incentivizing data sharing through token-based rewards.
- *Data federation techniques* offer an agile and efficient solution by providing a meta-database management system that transparently integrates multiple autonomous databases into a single federated database. This approach allows for federated query answering, where users can query multiple data sources through a unified interface without the need for data copying, movement, or transformation. By utilizing data virtualization, data federation reduces the risk of errors and decreases data preparation costs while maintaining real-time data freshness [155]. The integration techniques of data federation systems ensure efficient data access and modification, making it a critical component for optimizing data utilization from heterogeneous sources in 6G networks.

2) HYBRID MODEL AND DATA-DRIVEN SOLUTIONS

Algorithms that rely on models describing the physical properties of systems (referred to as model-based methods) are based on simplified assumptions to ensure mathematical tractability. However, the performance of these algorithms in practice heavily depends on the accuracy of these assumptions, which often imposes stringent hardware requirements (such as having a highly linear system) or protocol requirements (such as the availability of channel state information). To alleviate these strict requirements, pure data-driven supervised learning techniques can be applied. However, these methods typically require large datasets during the training phase, particularly when deep neural networks are involved. A significant drawback of purely data-driven methods is their limited ability to cope with abrupt changes of the distributions of signals caused by the dynamic nature of the propagation environment. By the time a sufficiently large dataset is collected, the wireless environment might have evolved to the extent that the dataset becomes irrelevant for training. These changes can occur very rapidly, especially in the lower layers of the communication stack.

To combine the domain knowledge of model-based methods with the adaptability of data-driven techniques, hybrid approaches are essential. These methods can be broadly categorized into two main types:

- **Model-Assisted AI/ML:** In this approach, knowledge from a physical model is used to design a more efficient or effective AI/ML architecture. For instance, understanding the mathematical structure of a problem can help in designing a neural network that requires significantly less training data and converges faster than a generic, purely data-driven model. This makes the AI/ML solution more robust and better suited for the dynamic nature of wireless systems.
- **AI/ML-Assisted Models:** Conversely, this approach uses AI/ML to enhance traditional model-based algorithms. AI/ML can be used to learn complex parameters or patterns from real-world data that are difficult to model analytically. This learned knowledge is then fed into a conventional model-based algorithm, improving its accuracy and performance in practical scenarios.

Both approaches have shown promise. As an example of Model-Assisted AI/ML, knowledge about the structure of the maximum a posteriori (MAP) estimator can be leveraged to develop fast, adaptive learning algorithms that automatically identify the right level of complexity required for a task. This results in a significant reduction in the required training data and allows for efficient real-time operation on GPUs [156], [157]. Following a similar philosophy, another study incorporated high-level features of cell load into a learning framework to enable accurate load prediction from very small sample sets [158]. An example of AI/ML-Assisted Models was applied to MIMO systems, where statistical knowledge learned from measurement data was used to guide a model-based algorithm for estimating the angular power spectrum. This significantly narrowed the search space and improved the accuracy of the final estimate [159].

3) INTENT BASED NETWORKING

Intent-Based Networking (IBN) is an approach to network automation that enables networks to be managed based on high-level business or service goals, known as "intent". Instead of manually configuring network devices, administrators specify the desired outcome, and the IBN system automatically translates this into network policies, orchestrates their deployment, and continuously monitors and adjusts the network to ensure the intent is being met.

While the core concept is not novel, IBN is gaining significant traction in various standardization bodies like TM Forum, 3GPP SA5, and ETSI ZSM. As an example, TM Forum defines intent as "the formal specification of all expectations, including requirements, goals, and constraints given to a technical system" [160]. This focus on intent aligns with the multi-technological and software-driven development roadmap envisioned for 5G and 6G systems, suggesting a significant role for IBN in the future of mobile networks [161]. In a recent overview by Wei et al. [162], the challenges of intent-based networking (IBN) in 6G are discussed along with approaches to translate users' business intents into appropriate network configurations and operations, aligning with the vision for AI-enabled 6G networks. That work explores strategies for networks to continuously learn and adapt to the environment to meet intelligent service demands and address issues such as time-varying radio propagation. Moreover, the introduction of innovative functions, such as orchestrating new path elements like reconfigurable intelligent surfaces (RIS) [163], mandates the development of novel AI algorithms and pipelines. Whereas IBN fundamentally aims to minimize human intervention and favour the integration of AI algorithms, a tradeoff emerges with the introduction of the "human in the loop" concept. From an ML standpoint, incorporating human intervention necessitates additional investigation, particularly regarding data and model training perspectives [164]. These two areas demand careful examination to ensure seamless integration of human oversight within the automated framework of IBN.

4) AI-NATIVE ADAPTIVE NETWORKS

While current network operations rely on AI/ML for partial improvements in siloed functions, such as in Self-Organizing Networks (SONs) as stated in Section II, 6G envisions a truly **AI-native architecture**. In this paradigm, AI/ML is not an add-on but a fundamental component of the network fabric, enabling holistic, cross-domain control loops that create a new level of adaptiveness.

The key innovation of this approach is the ability to perform **cross-layer and cross-domain optimization**. Instead of optimizing individual components in isolation (e.g., scheduling [165], slicing [166], or network planning [167]), an AI-native framework can jointly manage these functions. For instance, a central AI orchestrator could analyze real-time data from across the network [168] to understand the intricate dependencies between different domains. It could then make intelligent trade-off decisions, such as slightly modifying a network slice's resource allocation to significantly improve the energy efficiency of a base station or adjusting a user's modulation scheme based on predictive channel models [169], [170] to enhance mobility robustness. This ability to continuously perform a global optimization across traditionally separate functions is what will allow 6G networks to become truly autonomous, adaptable, and efficient, moving far beyond the capabilities of today's systems.

B. ENABLING TECHNIQUES

Due to recent advancements in AI, a diverse set of enabling techniques has emerged that can potentially provide performance gains, increase efficiency, and enable new capabilities for the realization of new use cases alongside the enabling concepts that were discussed in III-A. In this section, we delve into a selection of these techniques and focus on those that have shown particular promise for addressing the challenges and requirements of 6G networks. These include context-aware ML, distributed ML, multi-task learning, transfer learning, model compression, AI-specific hardware solutions, communication control co-design, joint communication and sensing, generative AI, and deep unfolding methods. While other valuable techniques exist, such as neuro-symbolic AI, evolutionary computation, and deep reinforcement learning, they have been omitted from our in-depth exploration due to their extensive overlap with other domains or their currently limited maturity for large-scale deployment in the 6G context. Appropriately utilizing these techniques in areas like adaptive modulation, intelligent beamforming, antenna selection and power control at the physical layer enhance energy efficiency and spectrum utilization, while resource scheduling and traffic management at the data link layer ensure efficient bandwidth allocation, reduce latency and better user experience. At the network layer, energy-aware routing and intelligent spectrum sharing further optimize capacity and power usage. Together these approaches make AI essential for enabling cross layer optimization in 6G.

When estimating the impact of various AI-related techniques on 6G in Table 1, we have targeted four key aspects that we believe have the highest importance: *Adaptability*, *Performance*, *Sustainability*, and *Trustworthiness*.

- **Adaptability** in this work covers factors such as positive impact on reducing the network's complexity, improving the model's generalization capability, and maintaining the network's scalability. These factors are essential in ensuring that any AI technique that will be utilized in the overall architecture can effectively handle the diverse and dynamic nature of 6G networks, adapt to varying conditions, and scale to meet increasing demands.

TABLE 1. Estimated impact of novel AI-based techniques on key measures for 6G networks.

Approach	Adaptability	Performance	Sustainability	Trustworthiness
Contextual Machine Learning	High	High	High	Medium
Distributed Machine Learning	Medium	Medium	Low	Low
Multi-task Machine Learning	Medium	Low	Medium	Low
Transfer Learning	High	Medium	High	Low
Model Compression	Low	Medium	High	Low
AI System-on-Chips (AI-SoCs)	Low	High	High	Low
Communications Control Co-Design	Low	High	Medium	Low
Joint Communication and Sensing	Low	Low	High	High
Generative AI	High	Medium	High	Low
Deep Unfolding	High	Medium	High	Medium

- **Performance** is estimated through metrics like reducing network latency, lowering model training time (for online training-specific scenarios), improving overall accuracy, and optimizing inference time. These metrics directly impact the efficiency and effectiveness of the utilized AI techniques in delivering the desired outcomes by satisfying timing and quality of service constraints. Specifically in O-RAN systems, optimizing inference time and reducing latency ensures that xAPPs and dAPPs meet important timings needs for real-time and non-real-time applications. Similarly, in edge computing, reducing inference time enable real time processing with lower latency and reduces dependence on cloud resources.
- **Sustainability** emphasizes reducing energy consumption and costs while improving limited resource utilization. This also includes the AI-based optimization solution to utilize renewable energy for sustainable development [171], as 6G aims to be environmentally friendly and cost-effective. Hence, it is essential to estimate the impact of AI-based solutions on these sustainability metrics to ensure long-term viability and economic feasibility.
- **Trustworthiness** encompasses maintaining reliability, preserving safety, security, and privacy, and enhancing interpretability. These factors are critical in ensuring that an AI-based network operates reliably, safeguards user data and privacy, and provides transparent and interpretable decisions.

Due to the natural complexity in comparing the impacts of the techniques on these key aspects individually, Table 1 reflects the authors' positions based on their technical expertise. The impact levels are categorized as *High, Medium*, and *Low*, according to each technique's potential benefits and trade-offs concerning the designated measures above.

1) CONTEXTUAL MACHINE LEARNING

The dynamic and heterogeneous nature of 6G environments necessitates that AI/ML models move beyond static assumptions and instead actively adapt their behavior based on real-time network context. This involves using a rich set of auxiliary information—such as user location and mobility, current network load, time of day, and application type—as explicit inputs to the decision-making process [172]. By leveraging this live context, AI/ML algorithms can provide personalized and efficient services tailored to specific scenarios, leading to high performance gains in network latency and accuracy.

In smart city environments, for example, such adaptive algorithms can optimize resource allocation and energy efficiency by leveraging real-time data from various sensors and devices, contributing to high sustainability [173]. These algorithms can dynamically adjust network parameters like bandwidth allocation, Quality of Service (QoS) settings, and security protocols to ensure optimal performance as users transition between different environments (e.g., indoor to outdoor, urban to rural). A clear application is in localization, where using contextual information like non-line-of-sight conditions and multipath effects can significantly improve upon traditional trilateration and fingerprinting techniques [174]. By using predictive analytics and pattern recognition that incorporate real-time context, these adaptive models can offer more precise and reliable localization solutions [175], [176]. While these techniques offer high potential for adaptability and performance, the complexity of interpreting models that rely on a wide array of contextual inputs may present challenges for trustworthiness, which could be mitigated through advancements in explainable AI techniques. These trade-offs are reflected in Table 1, where the 'High' impact of contextual learning on adaptability, performance, and sustainability is noted, alongside a 'Medium' impact on trustworthiness due to the aforementioned interpretability challenges.

2) DISTRIBUTED MACHINE LEARNING

With the increasing scale and complexity of 6G systems, training AI/ML models exclusively on a centralized server is often not feasible due to network bandwidth limitations and growing privacy concerns [177]. Distributed ML offers a paradigm for decentralized data processing, but its practical deployment must consider significant operational constraints. For instance, commercial networks are multi-vendor environments, and proprietary models are unlikely to be shared between vendors. Therefore, initial deployments of distributed ML will likely be confined to a single vendor's ecosystem or a single operator's network.

Despite these constraints, distributed techniques are critical for enabling real-time, adaptive applications like augmented reality and autonomous vehicles. Two primary models are envisioned:

- **Centralized Training with Edge Inference:** In many scenarios, particularly those involving computationally limited end-user devices, a large AI/ML model will be trained centrally where data and computational resources are abundant. The resulting trained model is then deployed to edge devices, which are used solely for low-latency inference.
- **Decentralized Training:** For applications requiring rapid adaptation to local conditions, frameworks like federated and split learning allow for training to be distributed across more powerful edge nodes (e.g., base stations or MEC servers). In federated learning, for example, local nodes collaboratively train a global model by only sharing model updates, keeping sensitive data on-device to preserve privacy [178]. This approach reduces communication overhead, improves real-time decision-making, and enables faster model adaptation without centralizing raw data.

Deploying federated learning on edge computing platforms is a promising strategy for 6G networks that will leverage distributed edge devices as federated learning clients for local model training while using network devices as servers for global model aggregation.

3) MULTI-TASK MACHINE LEARNING

While some functions in a wireless system are distinct and best served by specialized models, many core operations, particularly within the Radio Access Network (RAN), are deeply interdependent. Traditionally, tasks like channel estimation, beam prediction, and resource allocation are handled by separate, individually optimized models [179], [180]. This approach can be inefficient, as each model must independently learn similar underlying features of the radio environment.

Multi-task learning (MTL) is an emerging approach that addresses this by training a single model to perform multiple related tasks simultaneously, which is highly promising for optimizing closely related RAN functions. For instance, an MTL model for the RAN could be designed with a shared neural network body that learns a rich, general-purpose representation of the radio channel. This shared representation would then feed into multiple, smaller task-specific "heads" that produce the final outputs for channel estimation, beam prediction, and resource allocation.

This MTL architecture provides two key benefits. First, by learning a shared representation, the model can leverage inter-task dependencies, allowing knowledge gained from one task (e.g., channel estimation) to improve the performance of another (e.g., beam prediction). Second, it is far more computationally efficient, as the bulk of the network's parameters are shared across tasks, reducing both training time and resource utilization during inference. Neglecting these potential similarities between related RAN tasks and training separate models can lead to suboptimal performance and higher computational cost.

4) TRANSFER LEARNING

This technique enables knowledge transfer and sharing across different domains and environments, which is highly relevant for 6G networks that operate in diverse scenarios [172]. It contributes to high adaptability by allowing models to rapidly adapt and generalize to new operating conditions. By leveraging knowledge gained from one environment or task in a model, transfer learning can effectively reduce the need for extensive training data in each specific new scenario, thereby accelerating the learning process for other ML models and potentially improving performance. For instance, in a 6G healthcare applications, where obtaining large amounts of labelled data for specific conditions could be challenging, the models could be initially trained on data from one hospital. The learned knowledge could then be transferred and applied to a different task at another hospital. Capitalizing on previously acquired knowledge helps to not only improve diagnostic accuracy, but it also speeds up model development through efficient use of the available data. This 'domain adaptation' approach could thus help improve the speed and reliability of the delivery of the 5G/6G-enabled preventive and curative healthcare services. Similarly, the work presented by Alshahrani et al. [181] explores the application of transfer learning in the context of network anomaly detection. The authors propose a transfer learning framework that enables the detection of anomalies in network traffic by leveraging knowledge from previously observed data patterns. Their findings reveal that the transfer learning model significantly outperforms traditional anomaly detection methods, particularly in scenarios where the network conditions are dynamic and unpredictable.Transfer learning's ability to facilitate knowledge sharing across domains and environments is particularly valuable for 6G networks, as it minimizes the need for costly data collection and training in every specific scenario, offering high sustainability through reduced resource utilization.

5) MODEL COMPRESSION

Enabling resource-efficient learning is crucial for integrating ML on 6G edge devices with limited computational resources. To this end, model compression techniques can be employed to reduce the size of ML models without significant loss in performance [182], [183]. Various model compression strategies can be utilized, including model pruning, quantization, knowledge distillation, low-rank weight matrix approximations, sparsity introduction, dimensionality reduction through feature engineering, and dynamic inference in-training network pruning [184]. These techniques offer high sustainability benefits by reducing the model footprint, memory requirements, computational demands, and energy needs of ML models, making them well-suited for resource-constrained edge devices in 6G networks. However, while all these techniques can effectively reduce model size, careful optimization is necessary to strike a balance between compression and maintaining sufficient performance for the intended tasks, potentially providing some positive impact on performance metrics like latency and accuracy.

6) AI SYSTEM-ON-CHIPS

To enable efficient ML inferencing on resource-constrained 6G edge devices, in addition to model compression techniques, comprehensive overview into ML-specific hardware accelerators and optimized frameworks for low-power inferencing is also essential. Hardware accelerators, such as specialized AI System-on-Chips (AI-SoCs), are designed to accelerate ML computations, with the goal of improving the performance and speed of model inferencing on edge devices [185]. These AI-SoCs often leverage parallel processing units like FPGAs, GPUs, TPUs, or NPUs to optimize the execution of computationally intensive matrix operations inherent in neural networks that offer high-performance gains. Complementing the hardware advancements, optimized software frameworks provide efficient implementations of machine learning algorithms tailored for low-power devices, further contributing to sustainability objectives such as reduced energy consumption. The combined advancements in specialized AI hardware accelerators and optimized low-power inferencing frameworks can enhance the energy efficiency of ML model deployment on 6G edge devices with limited computational resources [186]. However, developing AI-SoCs involves addressing trade-offs between performance, power consumption, and cost, necessitating careful balancing of these factors for widespread adoption in IoT and edge devices.

7) COMMUNICATIONS CONTROL CO-DESIGN

Enabling future cyber-physical systems, such as large-scale robotics and autonomous vehicle platoons, requires an extremely tight integration between their communication protocols and control algorithms. Communications-Control Co-design is a forward-looking research area that aims to break the traditional design silo where communications and control are optimized separately. While acknowledging that this approach is highly complex and its practical implementation is a significant long-term challenge, it is crucial for achieving the stringent latency and reliability demands of the most advanced 6G use cases.

The core idea is to create an adaptive system where the communication strategy is dynamically tailored to the immediate needs of the control application. AI/ML is a key enabler for this vision. For example, in a multi-agent system (MAS), AI/ML can be embedded into a joint physical layer abstraction (PLA) model to predict the future communication needs of an agent based on its current task and environment [187]. This allows the network to proactively allocate resources or change transmission parameters to ensure control-critical messages are delivered reliably and on time [188]. By using AI/ML to create this synergy, the co-design of communication and control systems can lead to significant improvements in overall efficiency, collaboration, and decision-making for complex distributed systems [189].

8) AI-DRIVEN JOINT COMMUNICATION AND SENSING

AI is critical for realizing the full potential of Joint Communication and Sensing (JCAS) in 6G networks, providing significant enhancements beyond core communication functionalities. Sensing, as a broad concept, involves extracting environmental information through various sensors, and AI can help unlock these systems' full capabilities. By integrating AI, advanced sensor fusion, beamforming optimization, and sensing algorithm enhancements become possible, overcoming the limitations of traditional methods. Specifically, AI empowers sensor fusion by combining data from diverse imaging sensors such as radar, Light Detection and Ranging (LiDAR), and cameras, improving localization, tracking, and object detection accuracy. Furthermore, even in complex and dynamic environments, AI optimizes beamforming and beam steering in JCAS, enabling real-time adjustments that ensure more efficient communication and sensing. These AI-driven advancements are essential for achieving high precision, adaptability, and performance required in 6G networks. LiDAR and camera sensors typically require additional hardware separate from the communication infrastructure. In contrast, radar sensors can be more easily co-located with communication hardware, and, in some cases, radar and communication systems can share hardware or spectrum resources. This integration is called JCAS or Integrated Communication and Sensing (ICAS). Current approaches to generating images from radar or JCAS data already utilize machine learning techniques [190]. However, leveraging the distributed nature of the network can further enhance sensing capabilities. This can be achieved through sensor data fusion, where data from multiple distributed sensors—either of the same type or different types—are combined to improve sensing accuracy and reliability. This fusion enhances individual sensor performance by utilizing localized and network-wide information, enabling more robust and precise environmental sensing.

Different applications impose specific requirements on the latency of sensor responses. Optical cameras, microwave radar, and LiDAR sensors are predominantly employed in applications where safety is critical. Its observation range capabilities constrain each of these sensors. Integrating multiple sensors within the same observation area makes it possible to mitigate the risks associated with single points of failure and augment the fidelity of data obtained from individual sensors. However, it is critical to acknowledge that an increase in the number of utilized sensors correlates with an increase in the volume of data throughput. JCAS has the potential to enhance spectrum utilization significantly and to reduce both hardware costs and power consumption through this integration [191]. ML plays an essential role in the fusion of distributed sensor information [192]. It can improve inaccuracies in the sensed measurement data and sensor limitations. Additionally, the ability of ML algorithms to adapt over time allows them to recognize new patterns in data, thereby enhancing the system's predictive accuracy. Furthermore, the integration of ML facilitates the automation of data processing tasks.

9) GENERATIVE AI

A key challenge in developing AI/ML for 6G is the scarcity of large and diverse datasets required for training robust models. Preparing suitable datasets is difficult due to the dynamic nature of wireless environments and the vast number of parameters involved. Generative AI offers a powerful solution to this data bottleneck.

a: SYNTHETIC DATA GENERATION

One major application is the generation of synthetic data. Generative models like Generative Adversarial Networks (GANs) can learn the underlying patterns from existing real-world datasets to generate new, realistic data that mimics the characteristics of a 6G network [193]. It is important to note that many of these models, particularly diffusion models, are data-intensive and require substantial initial datasets to train effectively. However, their value lies in creating diverse and rare scenarios (e.g., extreme interference conditions) that may not be present in the collected real-world data, thus improving the robustness and generalization of AI/ML models trained on this augmented data. This approach allows researchers to evaluate network algorithms in a wide range of simulated environments before real-world deployment. Nonetheless, this technique has limitations. AI-generated data may not perfectly capture all the complexities of real-world network behavior, and training models solely on synthetic data can lead to unexpected performance issues in a live network [194], [195]. Furthermore, the quality of the synthetic data depends heavily on the initial seed dataset, and any biases or errors can be amplified in the generated data, leading to flawed or biased models [196].

b: FOUNDATION AND LANGUAGE MODELS FOR NETWORK OPERATIONS

A second, distinct application of generative AI involves leveraging large-scale models for network control and interaction. **Foundation models**, which are large models pre-trained on vast amounts of general data, are particularly promising [197]. In a communications context, a foundation model could be pre-trained on diverse datasets from many wireless environments. While the initial pre-training is data-intensive, this general-purpose model can then be **fine-tuned** with a much smaller, task-specific dataset to adapt it for a particular use case, such as multi-modal beamforming or super-resolution localization in a new environment [198]. This fine-tuning approach makes it feasible to develop specialized, high-performance models without requiring massive data collection for every new task.

This paradigm also includes **Large Language Models (LLMs)** and their more efficient counterparts, **Small Language Models (SLMs)**. While their direct role in physical layer processing is limited, they are poised to revolutionize network management and the human-network interface. LLMs can provide a natural language interface for network orchestration, allowing operators to issue complex commands in plain English [199], [200]. SLMs, with their lower computational requirements, are suitable for deployment on resource-constrained devices at the network edge, enabling more intelligent and responsive human-IoT interactions.

10) DEEP UNFOLDING

Compared to other application areas of AI, decision-making and optimization in wireless communication systems are often subject to strict latency constraints. Device-specific hardware limitations and energy budgets can restrict the amount of computation that can be performed on a given device. Moreover, the fast-varying nature of mobile networks calls for frequent acquisition of training data, which can limit the network's performance. While these restrictions render the application of AI challenging, many aspects of wireless networks have been studied for decades so that comprehensive domain knowledge is available in the form of relatively accurate physical models. Leveraging these models can lead to a significant reduction in computational cost and training overhead, that will lead to sustainable AI-based solutions in 6G networks. Model-driven AI approaches such as deep unfolding achieve this by starting with a model-based algorithm for a given task and then learning only certain building blocks or design parameters of that algorithm with ML techniques such as backpropagation and stochastic gradient descent. By unfolding a certain number of iterations of a model-based algorithm and interpreting the iterates as layers of a neural network, deep unfolding provides a straightforward means to design deep learning architectures. This approach can enhance the performance of ML models by leveraging domain knowledge to initialize the models with strong priors, and potentially lead to faster convergence and better accuracy. Additionally, by offloading part of the computation to the model-based algorithm, deep unfolding can reduce the computational complexity of the AI component, further improving the sustainability and enabling deployment on resource-constrained edge devices. Deep unfolding has been identified as a promising enabler for edge intelligence in 6G communication systems [201]. It has been successfully applied to various signal processing problems including beamforming, MIMO detection, and channel decoding (see [202], [203], [204], [205], [206],

[207] and references therein). By combining the benefits of model-based algorithms and data-driven learning, deep unfolding can improve the adaptability of ML models to the dynamic nature of wireless networks while ensuring high performance and sustainability. However, it is important to note that the effectiveness of deep unfolding depends on the availability of accurate physical models and the ability to effectively integrate them with the learning process. If the physical models fail to capture the complexities of the real-world system or if the integration with the learning process is suboptimal, the potential benefits of deep unfolding may be limited and negatively impact the trustworthiness of the resulting ML models.

TABLE 2. Mapping network functionalities with AI technologies.

Network Functions	AI Technologies
Air interface optimization	Context-aware ML, AI-SoCs, Communications control co-design, Deep unfolding
Cell coordination	Multi-task ML, Communications control co-design
Function placement	Distributed ML, Model compression
CSI enhancement	Model compression, Deep unfolding, Generative AI
Localization	Context-aware ML, AI-SoCs, JCAS
Anomaly detection	Transfer learning, Generative AI, JCAS
Prediction of network states	Context-aware ML, Transfer learning, Distributed ML

C. SUMMARY AND IMPACT OF AI-ENABLED NETWORK FUNCTIONS

Leveraging the discussed AI techniques, it is anticipated that there will be significant improvements in key 6G network functionalities. Based on earlier discussions, we next summarize which enabling technologies can have a major impact on network functionalities and how these AI-enabled network functionalities impact the adaptability, performance, sustainability, and trustworthiness of 6G. In Table 2, network functions are mapped to various AI technologies that will potentially enhance their performance comparably. The impact of AI-enabled network functions on adaptability, performance, sustainability, and trustworthiness is depicted in FIGURE 3. A detailed explanation of this impact is provided below.

1) AIR INTERFACE OPTIMIZATION

To optimize the air interface for 6G networks, context-aware ML, AI-SoCs, communications control co-design, and deep unfolding will potentially play pivotal roles. Context-aware ML is a promising technology to enhance the air interface by dynamically adjusting parameters based on real-time environmental and contextual data, leading to more efficient spectrum use and reduced latency. AI-SoCs is another promising technology anticipated to enable the integration of advanced AI algorithms directly at end-users, providing high-speed processing capabilities essential for real-time optimization. Communications control co-design will ensure that control algorithms are closely integrated with communication protocols, resulting in more coherent and efficient data transfer processes. Deep unfolding will improve signal processing optimization by accelerating convergence and enhancing accuracy. These technologies will collectively enhance adaptability and performance. However, the need for substantial computational resources and advanced hardware may affect sustainability. Trustworthiness could also be impacted due to the complexity of the algorithms and the potential difficulty in ensuring their transparency and reliability.

2) CELL COORDINATION

Coordination among cells in 6G networks will be primarily driven by multi-task ML and communications control co-design. Multi-task ML will potentially enable the system to handle various coordination tasks simultaneously, such as interference and mobility management, thereby improving the overall efficiency and reliability of the network. Communications control co-design will ensure that the algorithms controlling the cells are optimized for seamless integration with the communication protocols, leading to more effective and synchronized cell operations. The integration of these technologies is expected to result in high adaptability and performance. However, similar to air interface optimization, the focus on high performance and sophisticated control algorithms may pose challenges to sustainability and trustworthiness.

3) RAN RESOURCE MANAGEMENT

Optimization of network resource management will potentially benefit from distributed ML and model compression. Distributed ML will potentially enable the decentralized training and deployment of locally optimal function placements, facilitating performance enhancement while preserving the privacy of local data. This decentralization approach will further enhance scalability and resilience. Model compression techniques will reduce the size and complexity of ML models, making it feasible to deploy them in resource-constrained sites without significant performance loss. AI-enabled resource management will ensure that the network can adapt to changing conditions and maintain high levels of performance. Sustainability will be high due to the efficient use of resources enabled by model compression and reduced computational complexity in a distributed ML framework. Additionally, employing techniques like federated learning in function placement will significantly improve trustworthiness.

4) CSI ENHANCEMENT

Enhancing CSI will potentially utilize a variety of AI techniques, including model compression, deep unfolding, and generative AI. Model compression algorithms will significantly improve CSI estimation at end devices with limited resources, which can then be fed back to base stations. This

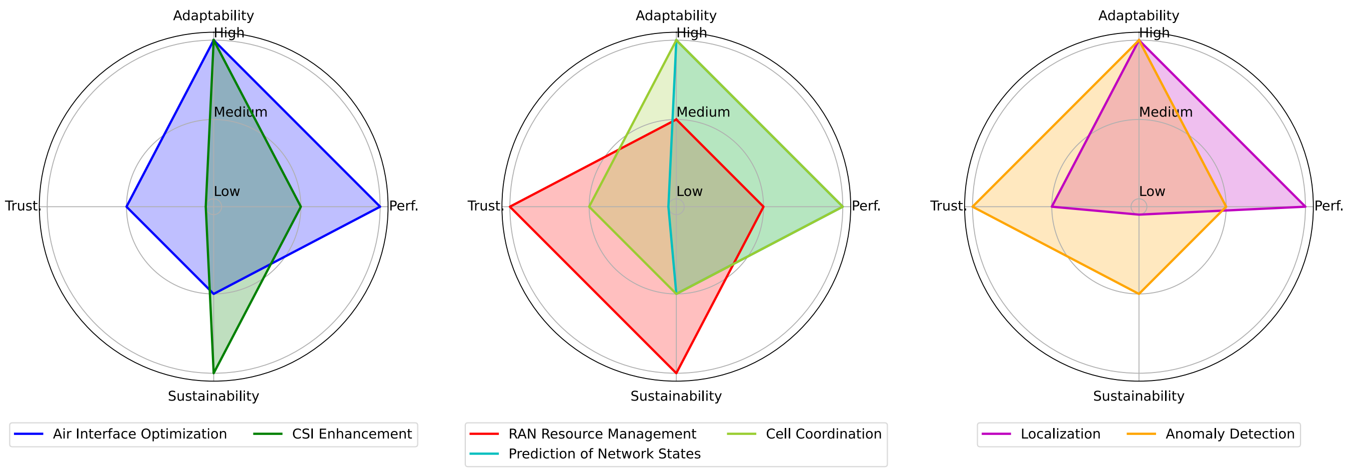

FIGURE 3. The potential impact of AI-enabled network functionalities on adaptability, performance, sustainability, and trustworthiness.

approach will be especially beneficial in frequency division duplex mode of communication, where, unlike time division duplex mode, downlink CSI is not reciprocal to uplink CSI. An efficient technique to feedback the downlink CSI can reduce the channel overhead and also provide significant performance enhancement in terms of spectral efficiency. Deep unfolding will accelerate the convergence of estimation algorithms, while generative AI will provide realistic datasets to develop robust ML models suitable for dynamic mobile environments. The combination of these technologies will result in high adaptability and sustainability due to the efficient use of resources and improved prediction accuracy. Performance improvement might be moderate, depending on the complexity of scenarios, while trustworthiness can be affected by potential risks associated with the use of generative AI.

5) LOCALIZATION

Context-aware ML, AI-SoCs, and JCAS techniques will be key to enhancing localization capabilities. Context-aware ML will potentially improve the accuracy of location estimates by considering environmental and contextual factors, allowing the network to dynamically adapt to changes and provide precise positioning information. AI-SoCs will enable the integration of sophisticated positioning algorithms into end-user devices, offering real-time processing capabilities essential for accurate localization. Additionally, JCAS will combine communication and sensing functionalities, enhancing the network's ability to detect and refine location data. These technologies are expected to result in high adaptability and performance as they enable the network to provide accurate and timely location information. However, the reliance on advanced hardware and the complexity of integrating communication and sensing might pose challenges to sustainability, necessitating careful management. For localization, trustworthiness will be a major concern for users; therefore, efficient utilization of JCAS and other techniques to predict and mitigate security threats will be necessary.

6) ANOMALY DETECTION

Anomaly detection will be primarily enhanced by transfer learning, JCAS, and generative AI. Transfer learning will help to adapt anomaly detection models across varying network conditions, offering high adaptability and sustainability. Generative AI will replicate different network attacks to prepare anomaly detection models to predict and identify these attacks. JCAS will further enhance anomaly detection by integrating sensing data. These technologies are expected to result in high adaptability and trustworthiness, enabling the network to quickly identify and respond to anomalies. However, their impact on network performance will be moderate, and sustainability might also be moderately influenced due to the use of transfer learning to reduce computational demands.

7) PREDICTION OF NETWORK STATES

Context-aware ML, transfer learning, and distributed ML will be key for predicting network states. Context-aware ML will adjust predictions in real time, achieving high adaptability and sustainability with moderate performance improvements. Transfer learning will enhance adaptability and sustainability by utilizing pre-trained models. Distributed ML will ensure that these predictions can be made across a decentralized network, improving scalability and resilience. These technologies are expected to result in high adaptability and performance, enabling the network to accurately predict and respond to changes. However, the need for extensive data and computational resources might lead to medium sustainability and lower trustworthiness due to potential security vulnerabilities.

IV. STANDARDIZATION AND REGULATORY EFFORTS

Standardization plays a pivotal role in enabling the integration of AI solutions into telecommunication systems and unlocking the full potential of these technologies. Active efforts are underway across various standards bodies such as the 3rd Generation Partnership Project (3GPP), The European Telecommunications Standards Institute (ETSI) and O-RAN Alliance to establish frameworks, interfaces, protocols, and best practices surrounding applications in this sector. Due to space limitations and to maintain relevance to the main objectives of this paper, we cover only some exemplary task forces and working groups of these standardization bodies and their efforts in the following.

A. 3GPP

The 3GPP is a partnership bringing telecommunications standardization organizations together to develop standards for different mobile generations. These technical specifications guarantee interoperability among multiple vendors and network operators. 3GPP has three technical specification groups (TSG). Each TSG has different working groups (WGs) developing standardization for a specific layer and part of the mobile network. The 3GPP uses an approach of different "Releases", each of them providing a stable standard for implementation of features at a certain point in time, whereas extensions and additional functionality are being studied in subsequent Releases [208]. Several 3GPP TSGs [209] conduct studies and develop specifications to incorporate AI-related matters across various network segments.

The 3GPP RAN1 group is focusing on Layer 1- physical layer. In RAN1, the general AI framework includes the aspects of the lifecycle management of ML models and functionalities comprising model training, deployment, inference, monitoring, and updating. The study further includes a discussion on the potential impact of specification related to a common framework and use case-specific aspects, e.g., enhanced performance monitoring of ML models, new use case-specific metrics, KPIs, etc. RAN1 has explored potential performance benefits of augmenting the air interface with AI features and the corresponding specification impact. The pilot use cases were selected, in part, to provide sufficient diversity to identify a common AI framework, including life cycle management aspects, applicable for subsequent 3GPP use cases. The use cases considered in the study include enhancements in CSI feedback, beam management and positioning accuracy. CSI compression is the only two-sided model use case considered. In here, a model is used to compress CSI on the UE side and another model at the network is used to decompress the UE's CSI report. AI-based CSI compression enables improved channel quality reporting while reducing the uplink overhead. Nonetheless, jointly training both models without exposing device implementations from each side can be a real challenge. Different inter-vendor training collaboration approaches are being investigated. As stated in [210], CSI prediction at the UE side is another enhancement that enables better robustness against channel aging problem. For beam management and positioning use cases, the model can be either at the UE or network. For beam prediction in time and/or spatial domain, ML models can reliably select "best" beams with fewer measurements, overhead, and latency. Finally, significant gains have been observed from using AI-based positioning accuracy enhancements for different scenarios, including, e.g., those with heavy non-line-of-sight (NLOS) conditions.

The 3GPP RAN3 group is focusing on RAN architecture and related network interfaces. Its work has explored the use cases like energy saving and load balancing or mobility optimization with respect to AI-related signaling, which can be used for model training, inference, and feedback [211].

The 3GPP RAN4 group is focusing on performing simulations, defining test procedures, and deriving the minimum requirements for transmission and reception parameters, and channel state information reporting. As any 3GPP feature, testability and interoperability should be ensured while operating using AI features. Traditionally, the RAN4 framework uses static requirements and testing that may not be suitable for ML-based algorithms as these evolve over time and are potentially sensitive to the data. Consequently, RAN4 must determine a new approach for establishing requirements and conducting testing to ensure reliable UE indications when running ML models. 3GPP has concluded that AI-based beam management and positioning enhancements are supported as part of Release 19, while it will continue studying CSI enhancement use cases [210].

The 3GPP SA1 group is focusing on Services. The SA1 studied use cases and requirements for ML model distribution, transfer, and sharing between application endpoints in Release 18 while laying the groundwork for distributed learning architectures. The subsequent Release 19 defined concrete requirements for direct network and device connectivity to enable these model exchanges [212].

The 3GPP SA2 group is focusing on System Architecture and Services. The SA2 explored architectural extensions allowing 5G systems to serve as transmission platforms for external AI-based services and introduced monitoring capabilities, quality-of-service (QoS) policies, and federated learning assistance features. They also investigated how to incorporate ML into the core network and focused on further enhancing the Network Data Analytics Function (NWDAF) with ML components for automated network optimization. The NWDAF consists of the model training logical function (MTLF) and NWDAF analytics logical function (AnLF). The MTLF is responsible for the training of ML models that AnLF uses to produce the analytics or predictions requested by the end consumer [213].

The 3GPP SA5 group is focusing on Management, Orchestration and Charging. The SA5 studies the capabilities and services enabling the management of AI in the network. Such capabilities include management and operations for training, testing, validation, emulation, inference, and ML entity deployment. In Release 18, the SA5 conducted a study on ML management by capturing different use cases, requirements, and solutions. Their normative work addressed mostly the training aspects, such as different use cases for ML training requested by different entities, ML models, and entity selection. The specification furthermore captures the information model definitions for ML management. Further extensions towards inference and other ML-related aspects are announced to be captured in the future [214]. Furthermore, SA5 introduces the *Management Data Analytics Service* (MDAS), which may leverage ML in performing analytics and predictions of the network states for specific use cases like energy saving and mobility optimization [215].

The 3GPP SA6 group is focusing on Application Enablement and Critical Communication Applications. The SA6 conducts the Release 19 study on application layer support for AI services. The study aims to identify capabilities and services at the application enabling layer needed to support AI operations. Several topics and key issues are considered, such as "support of architecture enhancement and functions for application layer AI services", "AI-enhanced application data analytics enablement services", and "support for federated learning" [216].

B. ETSI

ETSI is a vast standardization organization for information and communication technology (ICT). Among various activities, ETSI is one of the 3GPP partners and its Zero-touch network and Service Management Group (ETSI ZSM) has undertaken critical efforts related to integrating AI and automating service lifecycles. The goal of ZSM is to enable end-to-end network and service automation, which can be seen as complementary to other standardization efforts. The ZSM 012 working group [217] focuses on specifying new AI-enabled capabilities and augmenting existing ZSM frameworks to support single-domain networks as well as complex cross-domain ecosystems. These ML-powered extensions are formally defined as new management services built atop foundations like service descriptors and interaction paradigms established in earlier ZSM specifications (ETSI GS ZSM 002 [218]). The high-level enabling areas include execution environments to deploy, run, and manage ML models; data pipelines for collection, ingestion, storage, and analytics; closed-loop automation leveraging ML inferences; and mechanisms to ensure trustworthiness, explainability, and governance. Standardizing these functions crucially allows management systems to leverage AI alongside conventional paradigms. It enables harnessing insights from network data, adapting policies based on dynamic user behaviors, mitigating complex cross-domain issues, and reducing manual oversight. Academic research in these domains directly feeds into ZSM's specifications, driving next-generation autonomous network operations.

C. O-RAN ALLIANCE

O-RAN Alliance is an open, world-wide organization of mobile operators, vendors as well as academic and research parties aiming at re-shaping the Radio Access Network following the intelligence, openness, virtualization and interoperability principles. The AI aspects are discussed in different O-RAN Technical Work Groups and are captured in O-RAN specifications. For example, the Technical Work Group 2 (WG2- the Non-Real-Time RAN Intelligent Controller and A1 Interface Work Group) defines the AI/ML workflow services including the AI/ML training services, AI/ML model management and exposure services as well as AI/ML model performance monitoring services [219]. Respectively, the Technical Work Group 3 (WG3- the Near-RT RIC and E2 Interface Work Group) focuses on developing specifications for the Near-RT RIC and the E2 interface. The E2 interface establishes the communication link between Near-RT RIC and distributed RAN components enabling AI-driven applications (xAPPs) to monitor and control RAN elements with latencies in between 10 milliseconds and 1 second [220].

All in all, incorporating AI necessitates revisiting many aspects of networking: applications, management plans, network functions, protocols, and devices. The standardization work by 3GPP, ETSI, O-RAN, and related groups lays a critical foundation in this regard by aligning different stakeholders to create interoperable ML-defined systems. These specifications will directly shape development practices and help drive adoption at a global scale across telecom ecosystem participants like chipset vendors, infrastructure providers, application developers and network operators. Understanding this standards landscape can, therefore, provide valuable context for both applied and theoretical academic research.

D. REGULATORY PERSPECTIVE AND POLICY CHANGES

In the transition to the 6G era, it is essential to revise existing policies and establish new ones to address the unique challenges and opportunities that may arise. In terms of data regulation, stricter regulations on data privacy and security should be implemented to protect personal information and prevent unauthorized access or misuse. Transparent and accountable data governance frameworks should also be developed to ensure ethical and responsible data use. Standards for AI in networking need to be established to ensure interoperability, reliability, and fairness. Guidelines and regulations should be developed to promote the responsible and ethical use of AI in networking, addressing potential biases and discriminatory decision-making algorithms.

The regulatory frameworks are evolving and will impose requirements for AI usage across different industries. The European AI Act [221] is an example of such efforts categorizing the AI systems according to the risks they impose, and defining the policies with respect to the obligations of such AI systems. The AI systems can be categorized into four levels of risk: unacceptable risk, high risk, limited risk, and minimal risk. Whereas the AI systems belonging to unacceptable risk level will be prohibited to enter the market, the AI systems falling into other categories will be subject to different obligations, e.g. risk assessment and mitigation, transparency obligations, etc. The AI systems that impose no risk will not be subject to any obligations and can be freely used. Although the actual enforcement of such regulations may still take time, the industry already needs to take the necessary steps towards the goal of building and strengthening the AI trustworthiness. The industry players have a key role in adopting such legal and regulatory frameworks leveraging on the legalization efforts and standardization agreements.

Trustworthiness requirements encompass many aspects such as (i) sustainability, (ii) reliability, safety, and security, (iii) fairness and (iv) transparency. For instance, to fulfill AI/ML trustworthiness requirements on sustainability, energy-efficient AI/ML methods can be employed by vendors to optimize the usage of computational resources required for training and inference using data and model compression techniques such as quantization and pruning. Some AI/ML trustworthiness requirements can target intentional attacks from adversaries (e.g., data poisoning attack, model extraction attack) in the data, training, and inference stages. In some use cases such as network slicing fairness and transparency requirements should be satisfied. For instance, when a Network Slice Provider (NSP) deploys ML for predictive network slice admission control, it should treat Network slice consumers (NSCs) equally and in a fair manner corresponding to the business contracts. In the event of unfair and frequent network slice requests being declined by the NSP, the corresponding NSC must be informed of the rationale behind the rejection to maintain transparency.

In the context of communication network different stakeholders may have different responsibilities and roles towards achieving AI trustworthiness. The network operator, who understands the context and knows where the AI/ML models are deployed may configure specific AI/ML trustworthiness policies for the AI/ML models which the vendor must be able to comply with. The network vendor who develops the AI/ML models and provides technical support for their solutions to the network operator, needs very detailed explanation on the behavior of their AI/ML models in a given context, e.g., to be able to troubleshoot in case of a fault or failure or to improve the AI/ML performance or AI/ML trustworthiness of their solutions.

Standardization plays a critical role in enabling multi-vendor interoperability of AI/ML solutions, ensuring compliance with AI/ML regulations, and fostering confidence among consumers of these solutions across the entire network. For example, this may involve defining standardized methods for auditing AI/ML models, which provide insights into the actions performed by the models without disclosing their internal workings, as well as establishing standard quantitative metrics to monitor and evaluate the trustworthiness of AI/ML models.

Spectrum allocation policies should be revised to accommodate the increased demand for wireless connectivity in the 6G era, for example by reallocating underutilized spectrum bands and exploring new frequency ranges. AI-driven spectrum sharing techniques, such as cognitive spectrum sharing, should also be promoted to optimize spectrum utilization. Additionally, policies should prioritize safety, security, and fairness alongside innovation. Robust security and privacy schemes should be implemented to protect against cyber threats, and policies should ensure fair access to and use of 6G networks, bridging the digital divide and preventing marginalized groups from being left behind [222].

V. CONCLUSION

As we observe the evolution from 5G to 6G, there will be much more complexity and many different types of services needed. Because of this, more intelligent, flexible, and robust strategies will be required. This paper explored how artificial intelligence and machine learning techniques can play a key role in overcoming the challenges of 6G networks and enabling innovative new applications. We looked at how AI techniques have been used in various areas of 5G networks so far, such as network planning, resource allocation, traffic management, and security. However, fully deploying AI and extensively utilizing it for 5G has faced some obstacles, like not having enough data available, the high complexity of computations needed, and difficulties in interpreting the models. To address these limitations for 6G, we proposed upgrades to infrastructure like using more edge servers and enhancing the overall network architecture. Additionally, we outlined ideas on how AI could contribute to enabling brand-new services and applications for 6G. Concepts like data sharing frameworks, hybrid models combining AI and traditional methods, intent-based networking that aligns with user needs, and adaptive network architectures that can change based on conditions were discussed as ways to utilize AI for 6G to a considerable extent. We also explored emerging AI techniques like context-aware machine learning, distributed machine learning, multi-task learning, transferring knowledge between different models, compressing AI models, specialized AI hardware chips, communication control co-design, joint communication and sensing, and deep unfolding technique. We evaluated how each of these could impact key requirements like flexibility, performance, environmental sustainability, and trustworthiness for 6G networks. Moreover, we showed how different AI algorithms and applications could contribute to designing the 6G network itself, planning its operation, and to predictive modeling of the wireless environment. This can guide researchers, developers, and companies in realizing the vision of AI-enabled 6G that meets the desired goals. Finally, we discussed current standardization efforts by major telecommunication industry groups to develop AI-related standards, policies, and regulations. This includes data privacy rules, guidelines for ethical and trustworthy AI usage, spectrum allocation reforms, security schemes, and ensuring fair access. This paper's insights into the potential roles and challenges of AI in 6G can inform and influence the standardization and regulatory efforts by 3GPP, ETSI, O-RAN Alliance, and other regulatory bodies, contributing to the development of comprehensive and effective frameworks for AI governance in 6G networks.

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