Decentralized AI-Control Framework for Multi-Party Multi-Network 6G Deployments

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***Abstract*—Multiple visions of 6G networks elicit Artificial Intelligence (AI) as a central, native element. When 6G systems are deployed at a large scale, end-to-end AI-based solutions will necessarily have to encompass both the radio and the fiber-optical domain. This paper introduces the Decentralized Multi-Party, Multi-Network AI (DMMAI) framework for integrating AI into 6G networks deployed at scale. DMMAI harmonizes AI-driven controls across diverse network platforms and thus facilitates networks that autonomously configure, monitor, and repair themselves. This is particularly crucial at the network edge, where advanced applications meet heightened functionality and security demands. The radio/optical integration is vital due to the current compartmentalization of AI research within these domains, which lacks a comprehensive understanding of their interaction. Our approach explores multi-network orchestration and AI control integration, filling a critical gap in standardized frameworks for AI-driven coordination in 6G networks. The DMMAI framework is a step towards a global standard for AI in 6G, aiming to establish reference use cases, data and model management methods, and benchmarking platforms for future AI/ML solutions.**

I. Introduction

Artificial Intelligence (AI) is finding increasing adoption across communication technologies spanning network layers and business ecosystems. Already in 5G, where AI has been applied as an afterthought, the AI-based approaches have been used to address challenges in various parts of 5G networks. This trend is expected to continue in 6G, where AI will become an integral part of the network design and operation, which is sometimes referred to as *AI native*. With this, 6G networks hold the promise of an intelligent communication ecosystem through *connected intelligence*. This is in line with the convergence of sensing and processing within mobile networks, which marks a transition from mere data delivery systems to decentralized intelligence and response engines. Such convergence is particularly evident at the network edge, where the need for advanced applications intersects with the demand for enhanced functionality and security.

Despite the promise of AI, there remain obstacles to its wide adoption in communication networks. For example, the introduction of software-defined elements, such as the O-RAN Alliance's RAN Intelligent Controllers (RICs) [1], enables the control and management of Radio Access Networks (RANs) by multi-party applications. However, the control and management capabilities of these software-defined elements do not extend to optical networks, and related AI functions are still under active research and standardization.

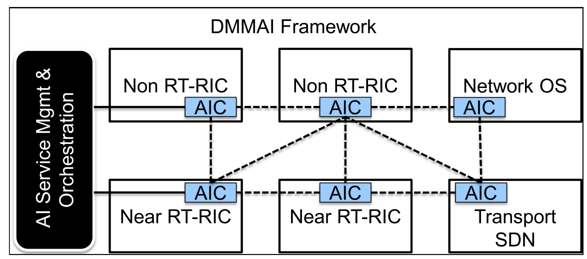

Fig. 1. DMMAI Framework facilitates end-to-end AI services.

The high throughput and low latency expected for many 6G applications are such that the optical links can no longer be simply viewed as fat pipes, but instead must be managed together with the radio resources for end-to-end efficiency and scale [2]. AI controls can play an important role in managing the diverse and complex requirements of these different network platforms. However, AI research is largely siloed within the wireless and optical research communities, and there is little understanding of how AI-based controls might interact and jointly manage resources across network domains [3]. Consequently, there does not exist any framework or accepted practice for AI-based control and management across radio and optical fibre networks.

This vision paper presents a blueprint for an AI Controller (AIC) designed for deployment across different network domains and nodes, enabling decentralized AI-driven network control, which was initially outlined at EuCNC [4]. The proposed Decentralized Multi-party, Multi-network AI (DMMAI) framework integrates AI-based orchestration across radio and optical fiber networks, addressing the current absence of a unified approach for such coordination. By facilitating seamless

AI-driven automation, monitoring, and self-repair, this work lays the foundation for a reference framework that supports global validation and standardization of AI in large-scale 6G networks. It also outlines key challenges in integrating AI across all network components, highlighting the need for standardized use-cases, data acquisition methods, and evaluation frameworks.

A. Related Work

Mobile networks are shifting from rigid, hardware-based RANs to flexible, software-defined architectures with open interfaces and disaggregation. This transition enables more adaptable networks, optimized through AI-driven control loops and exposed Application Programming Interfaces (APIs) for Machine Learning (ML) solutions, enhancing functionalities from mobility to the Physical (PHY) and Media Access Control (MAC) layers [5], [6]. The O-RAN alliance is standardizing AI-native networks, allowing operators to deploy third-party ML models for RAN orchestration [1], with working group 2 focusing on AI workflow architectures. Additionally, collaborations between ONAP and Acumos aim to integrate AI tools into the network architecture [7], while lightweight x/rApps are being developed for open-source RICs [8]. Efforts also explore integrating RIC-based network controls with Software-Defined Networking (SDN) [9], extending Pervasive AI and AI as a Service (AIaaS) approaches to the RIC [10].

While O-RAN provides a standardized AI/ML control framework for radio networks, transport and optical networks lack such an equivalent. Instead, they rely on SDN platforms like Open Network Operating System (ONOS) [11]. AI applications in optical networks primarily focus on offline Quality of Transmission (QoT) estimation, wavelength routing, and fault management [12], though online AI and hierarchical control extensions of ONOS have been explored [13]. Given the absence of standardized cross-domain AI-based control frameworks, their development would be highly beneficial.

Zero touch network and service management (ZSM) seeks to automate network resource orchestration using AI/ML, game theory, and optimization to meet 6G performance targets [10]. However, existing solutions often lack the agility and automation needed for seamless service adaptation. ETSI identifies AI/ML as essential for enhancing automation, data access, abstraction, supervision, and lifecycle management [14]. While AI/ML-driven optimization can operate across different timescales, ETSI NFV MANO primarily uses rule-based auto-scaling and auto-healing, with AI/ML considered only for data processing rather than direct automation [14]. Recent efforts propose decentralized zero-touch frameworks to address 6G network dynamicity, including Pervasive AI as a service [10], distributed decision-making entities [15], and deep reinforcement learning for Unmanned Aerial Vehicle (UAV) edge networks [16]. Deploying AI/ML in wireless networks remains challenging due to dynamic topologies, frequent retraining needs, and large dataset requirements. Distributed ML techniques are crucial to overcoming these limitations.

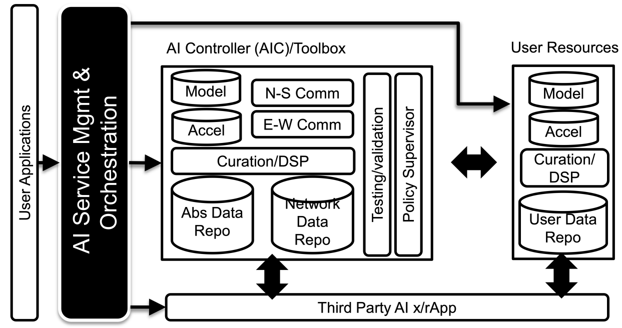

Fig. 2. The AI controller is composed of a set of repositories, virtual network functions, and interfaces. These interact with both user resources and x/rApps in order to carry out AI-based network functions/control.

To summarize, incorporating AI/ML into future network architectures is essential for evolving beyond traditional communication pipelines into intelligent compute-and-communicate networks. This transformation requires a framework that enables dynamic adaptation, resource optimization, and real-time decision-making. Recent literature highlights the growing role of distributed learning in this shift, as networks increasingly rely on decentralized intelligence to enhance scalability and responsiveness. Establishing such a framework will drive next-generation networks toward autonomous, adaptive, and computationally capable infrastructures.

II. DMMAI Framework

We have created the DMMAI framework to tackle the complexities of embedding AI/ML technologies into network architectures and to facilitate cohesive interaction across all network elements in both the radio and optical domains. It is designed to form a unified 'multi-network' approach. *Our framework is also meant to serve as a foundational blueprint, providing a detailed yet adaptable structure for further development and enhancements.* While it outlines the essential components and functionalities needed for effective AI/ML integration, it also maintains the flexibility to accommodate future expansions and technological evolutions, ensuring its applicability and relevance in the dynamic landscape of network technology. To achieve this, we leverage the O-RAN architecture, a widely accepted platform for multi-party applications (xApps/rApps) within a RIC, to explore its control mechanisms. Our goal is to develop a generic framework adaptable across network domains, extending its applicability beyond O-RAN to future 6G networks.

Figure 1 depicts the overall architecture of our proposed framework. It is composed of an AIC and a cross-controller network architecture. The AIC resides in various software defined networking environments including: near-Real Time (RT) RIC, non-RT RIC, transport SDN, and Network Operating System (NOS). In addition, an AI service management and orchestration platform facilitates end-to-end AI services within the network.

The AIC plays a pivotal role in enhancing the DMMAI framework's effectiveness and versatility. By decoupling various functionalities, it facilitates a powerful framework structure where AI controls can be integrated with different network nodes. This integration supports both North-South (N-S) and East-West (E-W) communication flows, laying a foundation for the development and implementation of advanced algorithms. One of the key advantages of this approach is the facilitation of group or swarm intelligence. This concept involves the coordinated actions of various network nodes, where decision-making and operational strategies are informed and enhanced by shared data insights. The simplicity and modularity of the AIC simplify the integration and testing of different AI-based platforms, while also allowing for the incorporation of diverse technological solutions. This flexibility ensures that the framework remains adaptable and scalable, capable of evolving with technological advancements and emerging network needs. The AIC design thus offers a unique balance – it is detailed enough to provide clear guidance on essential components, yet open-ended to allow for future extensions and enhancements.

Figure 2 illustrates the reference elements of an AIC, though these are not exhaustive. A specific AIC implementation may include all, some, or additional elements. The framework consists of four core components: (1) Data management (curation/DSP, abstracted data repository, network data repository), (2) Model management (model repository, accelerators), (3) Inter-AIC communication (N-S, E-W APIs/protocols), (4) AI management (testing/validation controller, policy supervisor). These building blocks interact with network elements accessible to the controller and may interface with AI x/rApps, external controllers, or orchestrators via RICs. The network data repository stores telemetry data, while the abstracted data repository maintains curated data for application use. AI workflows are orchestrated using these tools, supporting various user applications. The AIC can configure networks to optimize AI-driven services for different domains. For instance, x/rApps could leverage an AIC to enhance automation in an industrial O-RAN deployment.

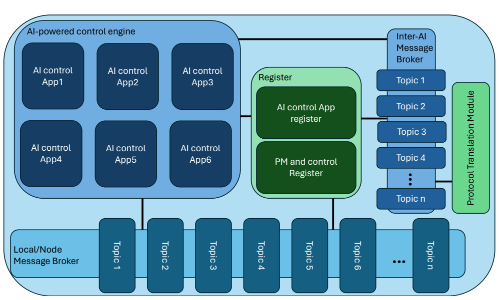

Fig. 3. Example of AIC building blocks implemented for the RAN-transport network integration.

Figure 3, shows a specific implementation of the AIC that was showcased at OFC 2024 [2]. The demonstration highlighted the advantages of inter-domain communication, particularly the latency reduction achieved through RAN and transport network interaction. It consists of five key modules: two Message Brokers, an AI-Powered Control Engine, a Register, and a Protocol Translation Module, ensuring flexibility across network nodes and domains. A Local/Node Message Broker manages north-south communication, handling performance measurements and control messages, while an Inter-AI Message Broker enables east-west communication between AI controllers. Both use a publish-subscribe model for scalability. The AI-Powered Control Engine runs AI control applications, manages communication via the brokers, registers applications, and retrieves performance and control parameters. The register stores information about network nodes, control parameters, and performance metrics, assisting in conflict resolution and inter-controller communication. The protocol translation module supports interoperability by adapting communication between different implementations of AICs. A simple comparison shows that this implementation captures the majority of the reference AIC components, particularly in data management, inter-AIC communication, and AI management. However, certain elements, such as model management and additional orchestration functions, may require further extensions or domain-specific adaptations. The specification of the different AIC elements depends on the networks and nodes in which the AIC is embedded, which is network technology dependent (e.g., radio vs optical).

A. Testbed Integration and Experimentation

The DMMAI framework is designed for seamless integration with existing testbeds, enabling experimentation with AI/ML-driven network automation. Its modular AIC architecture allows flexible adaptation to diverse network topologies and configurations, while standardized interfaces support collaborative development and testing. The framework's compatibility with virtualized network functions ensures scalable and realistic experimentation.

Different implementations of the framework are being developed and tested across multiple testbeds, including OpenIreland, COSMOS, COSM-IC, the IMEC wireless testbed, and the UoP testbed. These platforms provide the necessary infrastructure, comprising physical nodes such as end-user devices, base stations, radio front-ends, ROADMs, and switches, along with a computing architecture capable of hosting all software components. The envisioned deployment follows industry trends, utilizing a containerized environment on bare-metal clusters managed through OpenStack and Kubernetes.

The AICs can be collocated with virtualized network functions across different domains, such as radio and optical, to enable data collection, learning, and intelligent decision-making. The framework also establishes communication channels between distinct AICs, supporting east-west and north-south interactions for information and knowledge exchange, including federated learning. This cross-layer integration ensures effective cooperation between network elements within the same hierarchy level and across different levels.

III. Framework Applicability

The DMMAI framework builds on the well-established use-case families from the Hexa-X-II project, modifying and analyzing them through the lens of AI integration and distributed multi-domain learning for networks. By enabling decentralized, AI-driven techniques for managing and orchestrating network services in 6G ecosystems, the framework enhances efficiency, scalability, and adaptability across various domains. Its predictive and adaptive capabilities support self-optimizing and self-healing operations, reducing human intervention and enabling zero-touch AI service management. This is particularly valuable in vertical industries such as automotive and transportation, where dynamic and autonomous network optimization is critical.

A. RAN-Optical Transport Network Cooperation

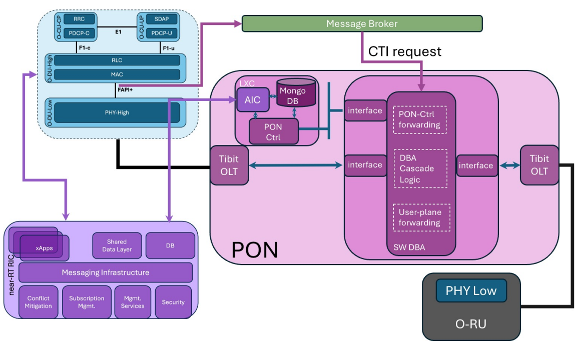

Fig. 4. RAN-transport network integration.

Figure 4 presents the OFC 2024 demonstration, showcasing the cooperative integration of Passive Optical Network (PON) transport in the fronthaul of the O-RAN by deploying AIC components across both domains. The key contribution is the implementation of the Cooperative Transport Interface (CTI) over a fully functional O-RAN over PON system using commercially available open networking equipment. By aligning the virtual Dynamic Bandwidth Allocation (DBA) in PON with the 5G MAC scheduler, this approach enhances coordination between the two network domains, addressing inefficiencies in independent operation. Traditionally, the lack of synchronization between PON and 5G RAN leads to resource allocation delays and reduced Quality of Service (QoS). The AIC improves scheduling coordination by utilizing upstream scheduling data from the 5G DU to proactively inform the PON DBA process. Deploying the AIC across both PON and RAN enables real-time scheduling adjustments, reducing latency and optimizing resource allocation. By embedding scheduling notifications in the PON's Bandwidth MAP (BWMap), the system dynamically aligns fronthaul bandwidth with user traffic demands.

B. Zero-Touch AI Service Management and Orchestration

The complexity of 6G networks necessitates a shift from manual network management to intelligent, automated orchestration. The Software-Based Architecture (SBA) of 5G and beyond, with virtualized functions and application services, requires dynamic and efficient management. Traditional decision-making methods, reliant on human intervention and rule-based algorithms, are slow and inflexible. To address these limitations, our framework integrates AI/ML with Network Function Virtualization (NFV), containerization, and SDN, enabling automated network management from the RAN to the core and data networks. This allows real-time adaptation, optimization, and self-healing, ensuring optimal network performance.

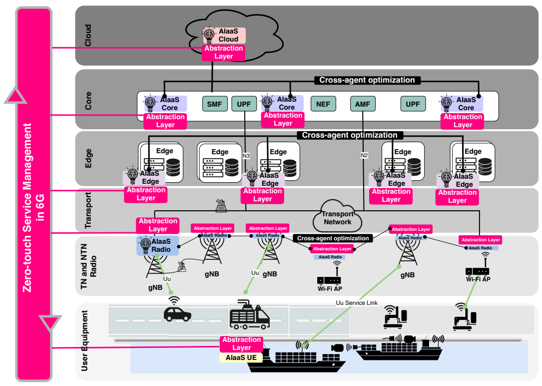

Fig. 5. ZSM anticipated in 6G to evaluate the utility of DMMAI.

The DMMAI framework facilitates experimentation with novel architectures, such as Multi-Access Edge Computing Application Orchestrator (MEAO) [17], a proof-of-concept solution that employs loosely coupled, intelligent orchestration elements. MEAO utilizes open, programmable interfaces to enable zero-touch service deployment, dynamic vertical application placement on distributed Multi-Access Edge Computing (MEC) nodes, and proactive state migration across different MEC domains. It continuously monitors network activity, leveraging decentralized, multi-agent intelligence to optimize network efficiency and resource allocation.

As 6G evolves into a network of interconnected networks, intelligence and automation must extend beyond the edge, integrating multiple radio access technologies such as LTE-U, 5G-NR, and Wi-Fi (as depicted in Figure 5). Decentralized AI models will play a critical role in holistically managing resources, enhancing energy efficiency, and ensuring high-quality service delivery. The DMMAI framework, with its AIC integration across diverse network nodes, enables this evolution, supporting intelligent, autonomous network management for future 6G deployments.

C. Distributed AI at different time scales

The O-RAN architecture envisions a network where RAN components expose manageable parameters and performance metrics, allowing for fine-tuning based on operator goals, network conditions, and traffic patterns. This enables intelligent control using AI/ML algorithms. However, current O-RAN implementations focus on applying AI to higher-layer protocols, limiting flexibility for lower-layer control at Distributed Units (DUs) and Radio Units (RUs). This constraint hinders the utilization of data-driven solutions requiring real-time or sub-millisecond control decisions, such as scheduling and beam management in sub-THz communication. These challenges are expected to intensify with the introduction of sensing, localization, and vertical applications demanding real-time performance and reliability. To address these limitations, O-RAN architectures should evolve to support control decisions across different timescales, including real-time operation with control loops shorter than current capabilities [18]. This requires consideration of factors like data availability and quality, application requirements, geographical constraints, and network workload. To that end, respecting timing aspects while ensuring a level of statistical guarantees on the offered end-to-end services involves designing communication protocols that involve privacy-aware, multi-modal, multi-party knowledge and data acquisition methods at scale. This demands efficient integration/aggregation of distributed intelligence and information in network planning, management, control, and operation. Furthermore, efficient quality-aware data compression and management is needed due to vast amounts of data.

Decentralizing the RIC architecture requires a balance between data availability and use-case-specific constraints, particularly in terms of latency and data quality. While data exchange between distributed RIC instances is essential, minimizing overhead and securing sensitive information are crucial considerations. Federated reinforcement learning, which enables cooperation without data sharing, offers a potential approach to address these challenges. The proposed DMMAI framework facilitates a platform to experiment with different strategies and measure the impact on the data exchange overhead, latency and data quality related to decision-making. The AIC architecture, with its modular design, allows us to quickly build prototypes of decentralized AI-based decision entities and instantiate them within different network entities. This further allows us to design intelligent algorithms to rely only on the data available at different network nodes and at different protocol layers.

D. Security and Authentication

The integration of AI/ML into the O-RAN architecture introduces new security challenges beyond the ethical concerns associated with AI/ML, such as potential biases and data privacy issues. A significant concern is the reliance on third-party ML models for zero-touch network management could open up vulnerabilities to malicious agents through the distribution of models via the public Internet. Phishing and Domain Name System (DNS) spoofing techniques can redirect legitimate model requests to repositories of malicious models, which can disrupt network performance in various ways. These malicious models can be (i) hampered by fine-tuning or retraining with intentionally flawed data, (ii) impersonated by counterfeit models that appear legitimate but provide inaccurate results, or (iii) neural trojans that function like genuine models but secretly incorporate malicious code without affecting system performance, making them difficult to detect [19].

Trust in AI systems is crucial, particularly in network environments where security, privacy, explainability, and reliability are paramount. In the complex multi-party, multi-network landscape, trust becomes even more challenging due to the increased number of stakeholders and potential attack vectors. The modular nature of the DMMAI framework supports the multi-party, multi-network vision and enables the quick prototyping of algorithms running in such environments. Therefore, it provides the necessary tools to study trust from three perspectives: 1) identifying attack surfaces in multi-party, multi-network architectures; 2) developing validation and testing methodologies; and 3) ensuring privacy preservation and explainability of AI methods. The framework is also envisioned to be easily integrated with existing testbed infrastructures, enabling data collection. This will also facilitate the detection of anomalies in such datasets, which may reveal vulnerabilities and attacks more rapidly and reliably.

IV. Research Challenges

As previously highlighted, 6G networks are not just about faster data transfer anymore. They are set to be adaptive compute-and-communicate systems. The DMMAI framework's flexibility allows easy integration with existing orchestration frameworks in different network domains and enables practical experiments and use-case studies. However, this flexibility opens up new research questions. This section aims to unpack these complex challenges, focusing on how the DMMAI framework prepares us for the multi-functional and dynamic nature of future 6G networks.

1) Orchestration of AI Controllers: A fundamental aspect of the DMMAI framework is the orchestration of different AI controllers to support both user and network services. This orchestration is heavily reliant on the management and curation of data and models across various network environments. It requires an understanding of how to harmonize these controllers end-to-end to support 6G network functions. The orchestration processes will focus on adopting a modern, modular, and cloud-based implementation that can be deployed in a cloud-native environment enabled to interact with all the other elements, e.g., the RICs, transport SDN, and NOS.

2) Decentralized AI Network Operations: Our framework serves as a foundational structure for studying decentralized AI operations across multiple network platforms. This includes the integration of AICs within software-defined networking environments, such as near-RT and non-RT RICs, SDN, and NOS. It aims to provide a cohesive framework for investigating research topics related to AI in network operations.

3) Energy Efficiency in AI and Communications: Addressing energy efficiency is a critical challenge for the DMMAI framework. This requires clarifying the energy cost by developing energy models for AI operations/computation, sensing, and communication, as well as the energy harvesting aspects. DMMAI aims to minimize energy usage in decentralized AI setups, ensuring that resources do not operate at full capacity during idle periods.

4) Complexity and Scale Management: The DMMAI framework is integral to managing the complexity and scale of future 6G networks. It addresses various challenges, including AI control plane coordination across different network technologies and domains, end-to-end data management and curation with quality-aware compression [20].

5) AIaaS Integration and Data Curation: The DMMAI framework involves specifying and implementing interfaces for inter-communication among various AIC instances, developing capabilities for optical AIC and inter-AIC optical-radio communication, and designing data curation functions. It is also crucial for defining and implementing workflows to facilitate the training and deployment of AI/ML models in AIaaS setups.

6) Data Collection and AI Foundation Model Research: A critical challenge that can be addressed with the DMMAI framework is efficiently collecting and processing vast, diverse data essential for AI foundation model research in 6G networks. This involves not only gathering data from multiple network sources but also ensuring its quality for developing scalable AI models. These models are fundamental for various intelligent network functions and must be computationally efficient and adaptable to the dynamic nature of 6G environments. Additionally, the framework must address data governance, ensuring privacy, security, and ethical AI practices. This encompasses managing data bias and maintaining model transparency and accountability.

7) Validation, Dissemination, and Standardization: It is critical to enable efficient and scalable inter-working and interoperability of AI/ML-based technologies in the multi-party eco-system of telecommunication systems while targeting 6G use cases and deployments. Validation and demonstrations of interoperability, preferably participated by and disseminated to main stakeholders such as operators, equipment, device and application vendors, shall pave the way for global standardization of AI-native networks as they iron out important issues such as training data sharing, model sharing/adaptations/versioning, reference models based minimum performance guarantees, and associated signaling etc. that the standardization must tackle.

V. Conclusion

This paper presents a vision for the evolution of 6G communication networks through the DMMAI framework. Moving beyond traditional data delivery, our approach focuses on developing networks into decentralized intelligence and response systems, essential for meeting the complex demands of future communications. Our work lays out a foundational strategy for AI-driven 6G networks, encapsulating the need for intelligent, flexible, and secure network systems. The DMMAI framework is designed to seamlessly integrate AI/ML technologies into network architectures across both radio and optical domains. Its structure is both detailed for immediate implementation and adaptable for future enhancements. Our exploration includes the framework's adaptability and integration in testbed environments and its capability for prototyping existing frameworks and investigating advanced network functionalities, e.g., security and authentication of AI/ML solutions. Our work also touches on various research challenges, underscoring the role that DMMAI will play in facilitating the development and application of AI in 6G networks.

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