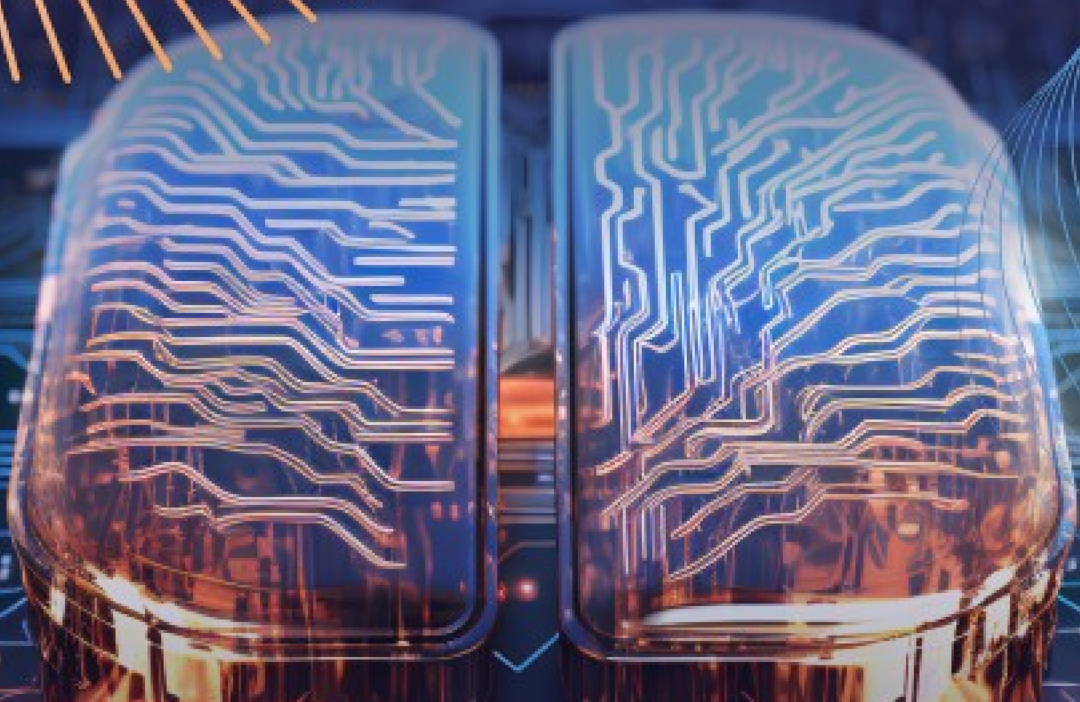
6GSNS

Smart Networks and Services
Joint Undertaking (SNS JU)

Reliable Software Networks
Working Group (SNWG)



White Paper

The AI/ML Landscape for Smart Networks and Services

Taxonomy, Standards & Innovation Pathways

DOI: 10.5281/zenodo.17708459
doi.org/10.5281/zenodo.17708459

January 2026

ACKNOWLEDGEMENT

Co-funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the SNS-JU. Neither the European Union nor or the SNS-JU can be held responsible for them.

EXECUTIVE SUMMARY

This document explores the role of Artificial Intelligence (AI) and Machine Learning (ML) in advancing smart networks and services, particularly in the context of the sixth-generation wireless network (6G). Key AI/ML concepts and terminology are clarified, current standardisation approaches are presented, while open implementations and research directions are described.

As explained in the document AI is the technology enabling machines to mimic human intelligence, while ML is the toolbox of algorithms and methods that allow machines to learn and improve performance. On this basis the reader is provided with a taxonomy of AI concepts (e.g., AI-native systems, agentic AI, large language models (LLMs), multi-agent systems (MAS), generative AI (GenAI), explainable AI (XAI) etc.) as well as the major ML types (from the fundamental learning methods to Federated Learning (FL).

Given the AI/ML taxonomy the document presents standardised frameworks for AI/ML integration in networks, including the AI/ML management framework from the 3rd Generation Partnership's Project (3GPP), the modular ML pipeline from the International Telecommunication Union - Telecommunication Standardization Sector (ITU-T), the AI/ML architecture from the Open Radio Access Network (O-RAN) Alliance, and AI/ML-related studies and developments in European Telecommunications Standards Institute (ETSI). The converged outcome refers to the importance of modularity, interoperability, and dynamic adaptation in AI/ML operations.

One step deeper, intensive AI/ML implementation efforts are currently allocated to the Agentic AI and the Multi-Agent systems, with one major challenge being the devise of efficient multi-agent communication protocols. In addition, since the lifecycle of ML models involves data collection, model training, validation, deployment, and continuous monitoring and retraining, the DevOps principles have been expanded to the Machine Learning Operations (MLOps) concept, while MLflow is introduced as key enabler for implementing MLOps practices in dynamic and distributed environments.

Finally, in the research and innovation domain the document underscores the importance of AI/ML in driving innovation, enhancing network performance, and addressing challenges such as security, trust, and sustainability in next-generation networks.

TABLE OF CONTENTS

TABLE OF FIGURES

ABBREVIATIONS AND ACRONYMS

Acronym	Description
5G	Fifth-generation wireless network
6G	Sixth-generation wireless network
3GPP	3rd Generation Partnership Project
A2A	Agent-to-Agent Protocol
AI	Artificial Intelligence
AN	Autonomous Networks
ACP	Agent Communication Protocol
ANP	Agent Network Protocol
API	Application Programming Interface
AIHP	AI Inference Host Platform
ATHP	AI Training Host Platform
CCN	Convolutional Neural Network
DT	Digital Twin
DAI	Discriminative AI
DRL	Deep Reinforcement Learning
ENI	Experiential Networked Intelligence
ETSI	European Telecommunications Standards Institute
F5G	Fifth Generation Fixed Networks
FL	Federated Learning
GenAI	Generative Artificial Intelligence
GAN	Generative Adversarial Networks
IoT	Internet of Things
INT/AFI	Autonomic Management and Control
ISG	Industry Specification Group
ITU-T	International Telecommunication Union - Telecommunication Standardization Sector
KPI	Key Performance Indicator
LLM	Large Language Model
ML	Machine Learning
MAC	Media Access Control
MAS	Multi-Agent Systems

MCP	Model Context Protocol
MTS	Methods for Testing and Specification
MnS	Management Service
mMTC	Massive Machine-Type Communications
MARL	Multi-Agent Reinforcement Learning
MLFO	Machine Learning Function Orchestrator
MLOps	Machine Learning Operations
NF	Network Function
NDT	Network Digital Twin
NFV	Network Functions Virtualisation
NTN	Non-Terrestrial Networks
O-RAN	Open Radio Access Network
PHY	Physical Layer
QoS	Quality of Service
RL	Reinforcement Learning
RIC	Radio Intelligent Controller
RNN	Recurrent Neural Network
SAI	Securing Artificial Intelligence
SDN	Software-Defined Networking
SNS JU	Smart Networks and Services Joint Undertaking
UAV	Unmanned Aerial Vehicle
URLLC	Ultra-Reliable Low-Latency Communication
V2X	Vehicle-to-Everything
VAE	Variational Autoencoder
XAI	Explainable Artificial Intelligence
ZSM	Zero-Touch Network and Service Management

1 INTRODUCTION

At the dawn of the AI era, the regulations around the deployment and provision of AI in telecom networks, cloud services, and digital platforms have been set by the European Union (EU)[1]; while already AI is intensively used as the main tool for enhancing connectivity and computing, improving network efficiency, supporting sustainability and advancing security[2]. Key AI research directions and priorities are reflected in the Strategic Research and Innovation Agenda (SRIA) of the Smart Networks and Services – Joint Undertaking (SNS-JU)[3], as well as in many related white papers from SNS-JU and its private side (i.e., the 6G-Industry association - 6G-IA), including the recent white papers on the European vision for the 6G Network ecosystem[4], and the survey on AI and ML components and approaches proposed by SNS-JU research projects[5].

However, the rapid growth of AI and ML research in the realm of smart networks and services has led to a fragmented and often unclear landscape. In many cases, terminology is used in an inconsistent manner, contributing to confusion and misalignment across different domains. Meanwhile, development and standardization efforts remain loosely coupled, with various initiatives often working in isolation or silos. Additionally, the widespread availability of AI/ML tools and platforms has fostered an "AI/ML for everything" approach without clear guidance on AI/ML most effective uses. This dynamic calls for a critical revisit of the foundational aspects of AI/ML in the context of networks, with a structured approach to better understand the current state of play.

This document serves as a primer that clarifies key AI/ML terminology, summarizes major current standardization efforts, and explores open implementations and innovation pathways. It provides a foundational resource for researchers, industry stakeholders, and policymakers, with the primary goal of aligning efforts and accelerating the development of AI-native networks and systems, particularly within the framework of SNS-JU research projects.

1 https://artificialintelligenceact.eu/

2 https://digital-strategy.ec.europa.eu/en/library/white-paper-how-master-europes-digital-infrastructure-needs

3 https://smart-networks.europa.eu/wp-content/uploads/2023/12/sns-ju-sria-2021-2027-second-edition-2023.pdf

4 https://6g-ia.eu/wp-content/uploads/2024/11/european-vision-for-the-6g-network-ecosystem.pdf

5 https://smart-networks.europa.eu/wp-content/uploads/2025/02/ai_ml_white-paper-sns_tb_v1.0.pdf

2 AI AND ML TAXONOMY

In research and innovation activities, various AI related terms are used, and many others are coined frequently, which sometimes creates a confusion of the actual content that each term describes. In this context, it has been noticed that AI is used interchangeably with the ML term, which makes things even more complex. Indeed, while AI refers to technologies that enable machines to mimic human intelligence for decision making and problem solving; ML is the toolbox used to achieve this behaviour. Hence, ML refers to the methods/algorithms/processes that enable machines to learn, i.e., to improve them in solving specific tasks with experience [1]. Given this separation of the AI and ML terms, ***a reference catalogue is provided, containing key definitions and concepts related to AI and ML, with an emphasis on their application to the communication networks domain.***

2.1 AI – A reference catalogue of terms and concepts

AI-Native systems. It is one of the most widely used terms recently coined to refer to the case where AI is an intrinsic part of a system. There are various analyses and more focused definitions on this; the following are considered among the most representative ones:

- Ericsson[6]: "AI native is the concept of having intrinsic trustworthy AI capabilities, where AI is a natural part of the functionality, in terms of design, deployment, operation, and maintenance. An AI native implementation leverages a data-driven and knowledge-based ecosystem, where data/knowledge is consumed and produced to realize new AI-based functionality or augment and replace static, rule-based mechanisms with learning and adaptive AI when needed."
- ITU-T[7]: AI-native networks refer to a new paradigm where AI is not merely an add-on feature but is deeply embedded in the core architecture, enabling unprecedented levels of automation, optimization, and intelligence. These networks will be capable of self-management, self-optimization, and even self-repair, allowing them to meet the demands of future applications that require high agility, precision, and speed.

AI model is a program/algorithm that has been trained on a set of data to recognize certain patterns or make certain decisions without further human intervention. Artificial intelligence models apply

6 https://www.ericsson.com/en/reports-and-papers/white-papers/ai-native

7 https://www.itu.int/en/ITU-T/focusgroups/ainn/Pages/default.aspx

different algorithms to relevant data inputs to achieve the tasks, or output, they've been programmed for.

AI agent[8] is a component designed to handle tasks and processes with a degree of autonomy within a system or network. In the literature various types of agents have emerged, including Goal based agents, Simple Model-based reflex agents, Utility based agents, and Learning Agents. These agents replace traditional Operations and Maintenance (O&M) engineers by performing reactive behaviours (e.g., responding to real-time network stimuli) and proactive behaviours (e.g., anticipating risks, setting new goals, and self-optimizing operations).

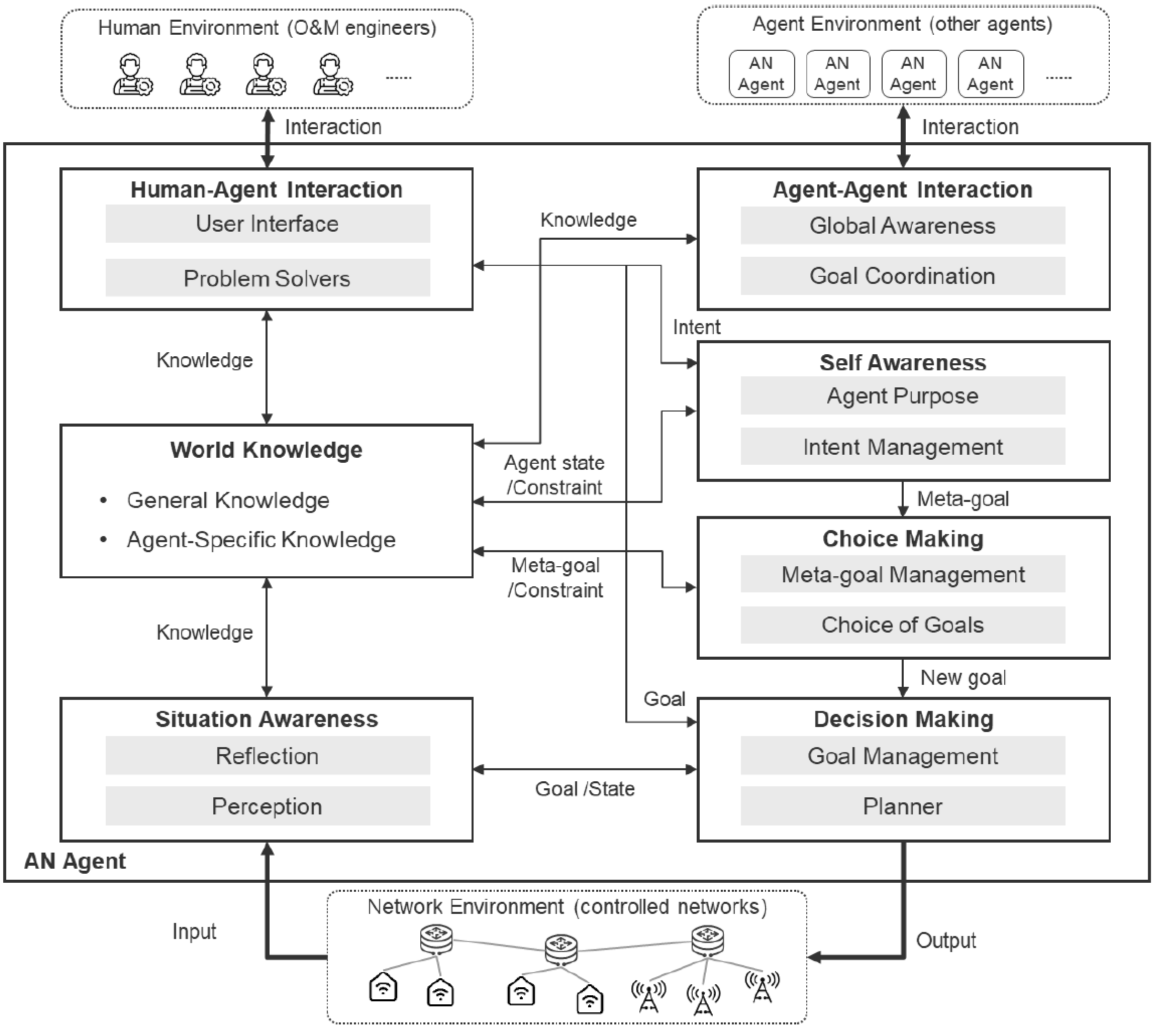


Figure 1: A representative reference architecture of an Autonomous Network agent [2]

Focusing on agents for Autonomous Networks (AN) (see Figure 1), they contain processes, such as: Situation Awareness, Decision-Making, Self-Awareness, Choice-Making, and World Knowledge/ A

8 https://www.ibm.com/think/topics/ai-agent-types

shared memory system containing domain-specific ontologies, operational rules, and learned expertise. Importantly, agents interact with both humans and other agents through Human-Agent Interaction (HAI) and Agent-Agent Interaction modules, forming a hierarchical, multi-agent ecosystem spanning business, service, and resource network layers. The report situates agentic AI as the next step beyond automation and ML, capable not only of predicting or classifying but also reasoning about goals, intents, and constraints. It contrasts narrow AI components (predictors, analyzers) with agentic systems that embody cognition, purpose, and ethical decision-making, emphasizing trust, runtime assurance, and human alignment.

Agentic AI[9] refers to an autonomous system that can make decisions and perform tasks without human intervention. In the network domain Agentic AI enables autonomous, self-learning, and self-optimizing networks by actively interacting with the "environment", learning from data, and making real-time decisions. The "environment" could be databases, LLM systems, observability tools, knowledge systems, etc. From the various ML tools Agentic AI mainly takes advantage of Reinforcement Learning (RL) to learn optimal actions by balancing exploration (using new strategies) and exploitations (using known strategies), receiving rewards or penalties based on its actions. In the literature, Agentic AI is defined in operational terms, as the technological foundation that allows an autonomous network agent to sense, reason, and act across dynamic network environments [2].

Large Language Models (LLMs). LLMs (e.g., GPT, Claude, Mistral) are pretrained in a vast amount of factual knowledge, usually from publicly available data sources. They enable **agentic AI** to understand, generate, and respond to natural language requests. In Europe, OpenEUROLLM[10], promises a series of foundation models for transparent AI in Europe, while the LLMs4EU project[11] focuses on training LLMs to ensure their conformity to European legislation (AI Act, GDPR, etc.). Integral to the LLMs architecture is considered the Retrieval-augmented generation (RAG) pattern for retrieving external data from a vector database at the time a prompt is issued. The prompts can be issued as "Intents" refer to expressions of objectives (or requirements) describing "what" to achieve. Then the system enables the mechanisms needed for realising the "HOW". LLM and ChatBots and used (among others) to realize intent-based interfaces/intent handlers.

Multi-agent Systems (MAS). MAS consists of multiple autonomous agents that interact and collaborate to perform complex tasks. While each operates independently, they can communicate, share and access a common knowledge base, and coordinate actions. In the context of Multi-agent

9 https://www.confluent.io/learn/agentic-ai/

10 https://openeurollm.eu/

11 https://ec.europa.eu/info/funding-tenders/opportunities/portal/screen/opportunities/projects-details/43152860/101198470

Reinforcement learning (MARL) has been proposed as a technique for decision making in a shared environment, which involves multiple autonomous agents. Practically, MARL aims at maximizing cumulative rewards through interactions among the agents.

Generative AI (GenAI) uses AI to create content, including text, video, code and images. A generative AI system is trained using large amounts of data, so that it can find patterns for generating new content. Related architectures, such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), Autoregressive models, Diffusion models, and Flow matching models, are poised to play a transformative role in the design, optimization, and automation of 6G networks. Unlike traditional discriminative models, GenAI focuses on modelling complex data distributions, enabling the synthesis of high-fidelity data, emulation of network dynamics, and the creation of intelligent digital agents. This trend is also reflected in the literature. In [3] candidate 6G applications and services are studied, presenting a taxonomy of state-of-the-art Discriminative AI (DAI) models, exemplifying prominent DAI use cases, and elucidating the multifaceted ways through which GenAI enhances DAI. In addition, in [4] the role of GenAI in the evolution of 6G networks is studied. An in-depth discussion of notable GenAI models is presented, outlining their application in enhancing key network components in technologies like Reconfigurable Intelligent Surfaces (RIS), Unmanned Aerial Vehicles (UAVs), Digital Twins (DTs), and Integrated Sensing and Communications (ISACs).

Explainable AI (XAI) is a set of processes and methods that allow human users to comprehend and trust the results and output created by machine learning algorithms[12]. The setup of XAI techniques include prediction accuracy, traceability, and decision understanding. As 6G networks increasingly incorporate intelligence across mission-critical functions from autonomous orchestration to real-time security the interpretability and transparency of these models become paramount. Explainable AI addresses this need by making AI decisions understandable to human operators, developers, and regulators. In traditional networks, decisions follow deterministic rule sets, sometimes using black-box models which make decisions difficult to interpret. XAI provides model-level (intrinsic) and post-hoc (extrinsic) interpretability methods such as Shapley Additive Explanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), saliency maps, and attention mechanisms [5]. Focusing on network processes, XAI is relevant to many use cases, since it enables the ability to enhance transparency and reliability in scenarios requiring real-time decision-making and high-stakes operational environments [6].

12 IBM definition

2.2 ML – Fundamental types for network optimisation

ML-based optimization algorithms with respect to the classical methods has been proposed with insightful guidance to develop advanced ML techniques in 6G networks [7]. There are three main types of learning: ***Supervised Learning***, ***Unsupervised Learning*** and ***Reinforcement Learning***.

- **Supervised Learning**. A category of ML that uses labelled datasets to train algorithms to predict outcomes and recognize patterns. Supervised learning includes methods like: Decision Trees, Naive Bayes, Support vector machine, Random Forest, Neural Networks, Linear regression, Logistic Regression, and K-Nearest Neighbour).
- **Unsupervised Learning**. A category of ML where unlabelled data is provided and patterns/insights are discovered without any explicit guidance or instruction. Unsupervised learning includes methods like: K-Means, Principal Component Analysis, and Singular Value Decomposition.
- **Reinforcement learning (RL)** [13] [14]. In RL, an agent learns to make decisions by interacting with an environment (it mimics the human trial-and-error learning process). RL includes policy and value-based RL methods, where value-based ones include Dynamic Programming, Monte Carlo, and Temporal Difference approaches. The well-known method in this category is Q-Learning**.**

In the literature, those fundamental types of learning have been studied extensively. For instance, in [8] a taxonomy of supervised and unsupervised models is provided highlighting their relevance to Quality of Service (QoS) prediction, network anomaly classification, and user profiling in dense wireless environments. Also, RL has been used for resource allocation, spectrum sharing, access point selection, and load balancing, since their inherent adaptability makes them suitable for real-time control in ultra-dense heterogeneous 6G deployments. Another example is the use of RL for Physical Layer (PHY) cross-layer security and privacy protection against with jammers, eavesdroppers, spoofers and inference attackers [9]. Beyond the fundamental types, various ML approaches and concepts have been coined.

Neural networks are complex supervised learning methods and rely on training data to learn and improve their accuracy over time. However, those methods have received a lot of attention since it mimics the way biological neurons work together to identify phenomena, weigh options and arrive at conclusions. Neural network consists of layers of nodes, or artificial neurons, one or more hidden

13 https://arxiv.org/pdf/2209.14940

14 https://spinningup.openai.com/en/latest/spinningup/rl_intro2.html

layers, and an output layer. Each node connects to others and has its own associated weight and threshold. If the output of any individual node is above the specified threshold value, that node is activated, sending data to the next layer of the network. Otherwise, no data is passed along to the next layer of the network. Neural networks have paved the way from traditional machine learning towards Deep Learning.

Deep learning (DL) is a learning method which uses hundreds or thousands of layers of a Neural Network to train its models. This category is further highlighted since GenAI systems are mainly based on DL techniques. Convolutional neural networks (CNNs), Recurrent Neural Networks (RNNs), Autoencoders and VAEs, and GANs are some examples of Neural Networks used for DL. In the network optimisation domain, CNNs are particularly effective in Channel State Information (CSI) prediction, interference classification, and beamforming optimization, while RNNs and their variants are suited for modelling temporal correlations in mobility prediction, traffic forecasting, and adaptive control of network services. At the PHY and Media Access Control (MAC) layers CNN/RNN are used for channel estimation and scheduling, emphasizing their capability for generalization in non-stationary wireless environments [10]. A detailed vision for DL in 6G is presented in [11], emphasizing areas such as adaptive resource allocation, intelligent network management, robust signal processing, ubiquitous edge intelligence, and endogenous security.

Deep Reinforcement Learning (DRL) is an expansion of the RL paradigm where DL (practically deep neural networks) are used to approximate functions (like value functions or policies) that would be too complex to model otherwise. DRL algorithms have been used for realizing resource (and slice) management autonomously [12].

Lastly, the protection of the training data and the need to keep them distributed into various places brought the concept of **Federated learning (FL)**. In Federated learning, instead of transferring data to a central point to train a model, models are trained locally where the data resides and then the models are passed to a central federation unit. In the networks domain FL addresses privacy and scalability challenges (by design) by enabling distributed learning across edge devices without centralizing data. It has been proved pivotal technique in 6G for vehicular networks, Internet of Things (IoT) sensor grids, and user-centric service customization. Also, the decentralized training paradigm of the FL approach aligns with the edge-native architecture of future networks. Indeed, as shown in [13], FL applies efficiently in distributed edge intelligence and secure model training, particularly under limited communication and computation resources. In the security domain, vulnerabilities and security threats in FL have been explored [14].

3 COMMON & STANDARD AI/ML APPROACHES

This section delves into the common and standardized approaches for integrating AI/ML into smart networks and services, with a focus on frameworks developed by leading organizations such as 3GPP, ITU-T, O-RAN, and ETSI. It outlines the operational workflows, lifecycle management, and trustworthiness indicators for AI/ML models, emphasizing modularity, interoperability, and dynamic adaptation. The section highlights the role of AI/ML in enabling automation, optimization, and autonomy in next-generation networks, while addressing challenges like data handling, model deployment, and performance monitoring. These frameworks serve as foundational pillars for advancing AI/ML-driven innovation in 6G networks.

3.1 3GPP AI/ML Management Framework for 5G Systems

The integration of AI/ML capabilities into 5G and beyond networks has emerged as a key enabler for automation, intelligence-driven optimization, and dynamic service provisioning. Within 3GPP, a comprehensive set of studies and specifications (primarily 3GPP TR 28.908[15] and 3GPP TS 28.105[16]) have formalized a reference architecture and management framework that addresses the lifecycle of AI/ML entities within 5G System (5GS) environments. This section details the architectural principles, lifecycle operations, and management services that underpin the 3GPP approach to AI/ML integration in 5G and beyond networks.

3.1.1.1 AI/ML Operational Workflow

The operational integration of AI/ML within 5G networks is governed by a clearly defined lifecycle model that includes the phases of training, emulation, deployment, and inference. Each phase is associated with a set of functional requirements and management responsibilities.

The **training phase** represents the starting point, where raw or pre-processed data is used to produce or update ML models. This process involves both initial training and retraining, followed by validation to assess generalization on unseen data. If the variance in performance between training and validation datasets is unacceptably high, retraining is triggered.

Following training, an optional **emulation phase** allows the operator to simulate the performance of an ML entity in a controlled, virtual environment. This phase is particularly useful for assessing inference behaviours prior to live deployment, minimizing operational risk.

15 https://www.etsi.org/deliver/etsi_tr/128900_128999/128908/18.00.00_60/tr_128908v180000p.pdf

16 https://www.etsi.org/deliver/etsi_ts/128100_128199/128105/17.04.00_60/ts_128105v170400p.pdf

In the **deployment phase**, the validated ML model is loaded into the AI/ML inference function that will consume it. The deployment process includes mechanisms for version control, rollback strategies, and integration with multi-vendor network environments.

Finally, during the **inference phase**, the ML model is used to support real-time or near-real-time decision making. Inference may operate continuously or be triggered by specific events or policies, and the inference results are monitored for quality and performance

As illustrated in Figure 2, this lifecycle model is adaptable to various types of learning, including supervised, unsupervised, and RL. For instance, RL may allow inference to begin concurrently with training, whereas supervised models require training to complete beforehand.

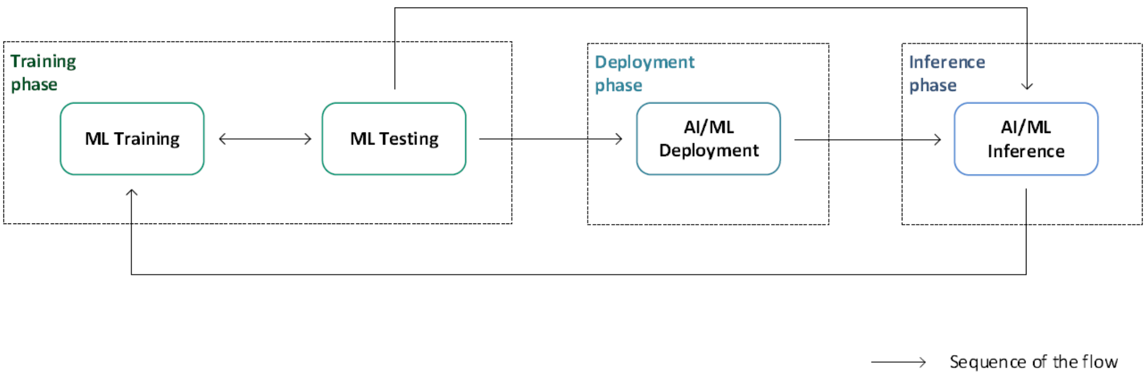


Figure 2: AI/ML operational workflow across training, deployment, and inference phases.

3.1.1.2 Training Phase Management

The training phase is central to AI/ML lifecycle management, and the 3GPP framework includes detailed provisions for initiating, controlling, and monitoring training activities. Operators or Management Service (MnS) consumers[17] may initiate training manually or define policies that trigger retraining automatically, for instance, in response to deteriorating inference performance or detected data drift.

Validation is a required subprocess that evaluates the model's behaviour on a held-out validation dataset. If the model underperforms or demonstrates signs of overfitting, it is returned to the training phase for further tuning. Testing then follows, using a separate test dataset to evaluate the model's robustness and suitability for operational deployment.

17 Based on the 3GPP's management architecture, an operator is the entity that manages the network, and within that system, various components or external entities can act as MnS (Management Service) consumers, which are the clients that use the services provided by MnS producers.

To ensure quality training, the framework supports a range of capabilities such as monitoring training data effectiveness, correlating measurements with training outcomes, and aggregating information-rich events from multiple sources. Notably, the event-based training mechanism allows models to be trained on high-quality events derived from raw network telemetry, reducing storage needs and increasing data relevance.

3.1.1.3 Emulation Phase Management

The emulation phase ensures model reliability before production deployment. It allows the ML model to be evaluated under conditions that simulate the target network environment. Emulation may be invoked on demand by the MnS consumer, who can configure parameters such as duration, load profiles, and expected performance thresholds.

During this phase, the inference function is exercised in a controlled context, and results are recorded to evaluate behaviour under expected and edge-case scenarios. The ability to emulate inference workflows supports scenarios such as resource allocation, anomaly detection, and performance prediction, where operational mistakes could lead to degraded service.

The emulation capability adds a valuable safety layer, especially for use cases involving mission-critical services or stringent Service-Level Agreements (SLAs).

3.1.1.4 Deployment Phase Management

Deployment of trained models is a managed process that includes model transfer, integration, and activation within the target inference function. The 3GPP framework provides mechanisms for model registration, version tracking, and policy-based deployment.

Operators are informed when new ML entities become available, and policies can be defined to trigger automatic deployment. These policies may consider factors such as network load, model performance, or update intervals. Monitoring tools allow visibility into deployment progress and can detect anomalies or errors during the activation process.

In complex networks with distributed components (e.g., edge clouds, RAN, core), deployment orchestration becomes essential. The framework supports both centralized and decentralized deployment models, depending on the architectural configuration of the network domain.

3.1.1.5 Inference Phase Management

Inference represents the operational phase where trained models are applied to real-time data for decision-making. This phase is tightly controlled to ensure reliable outcomes and minimize the risk of erroneous predictions.

Operators can configure inference activation manually, via schedule, or through policy-based mechanisms. For example, a model may be activated only during high-traffic periods or in specific geographical regions. Partial activation (e.g., A/B testing) is supported, allowing safe experimentation with new models.

Inference results are continuously monitored using Key Performance Indicators (KPIs) such as accuracy, latency, and explainability. The framework also supports the dynamic orchestration of multiple inference functions, enabling adaptive behaviour based on service needs or environmental conditions.

3.1.1.6 Trustworthiness and ML Entity Abstraction

Trustworthiness is an essential requirement in AI/ML operations, particularly in critical infrastructure such as telecommunications. The 3GPP framework incorporates trust-related indicators across all operational phases, including fairness, robustness, interpretability, and data integrity.

The concept of the ML entity abstracts the model and its associated metadata (e.g., training history, version, context, trust scores). This abstraction enables vendors and operators to exchange and manage models without disclosing sensitive internal architectures, thus ensuring interoperability and security.

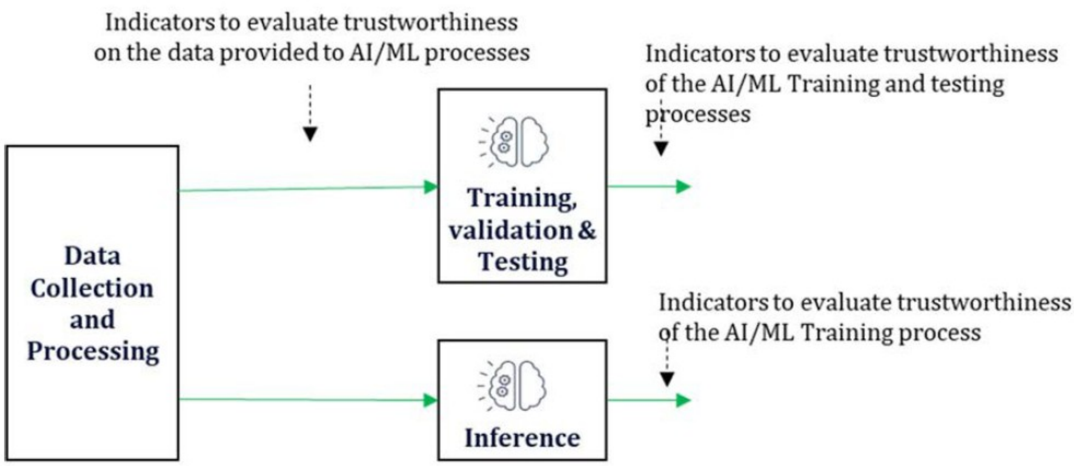


Figure 3: ML trustworthiness indicators.

To manage trustworthiness throughout the AI/ML lifecycle, the framework introduces a set of evaluative metrics and processes. These include assessments of data bias, model explainability, decision traceability, and adherence to regulatory and ethical constraints. Each ML entity carries its own metadata bundle describing the trust indicators applicable during training, emulation, deployment, and inference.

This approach is encapsulated in Figure 3, which highlights the layered structure of an ML entity, its management interfaces, and the associated trustworthiness dimensions. The model-centric encapsulation ensures that both operators and vendors can monitor, evaluate, and configure AI/ML functions in a controlled and accountable manner without requiring access to proprietary internal mechanisms.

3.2 ITU-T Frameworks for ML

The ITU-T Y.3172[18] architectural framework provides guidelines for integrating ML into future networks, addressing key challenges such as heterogeneous data sources, integration costs, and the alignment of ML functionalities with evolving network architectures. It defines a modular ML pipeline composed of logical nodes. The pipeline begins with the source (SRC) node, where data is generated, typically by user equipment or network nodes. This data is then aggregated by the collector (C) node to form a unified dataset. The preprocessor (PP) cleans and formats the data to meet ML input requirements. At the core of the pipeline, the model (M) node applies ML algorithms for tasks such as classification or regression. To ensure network compliance, the policy (P) node enforces operational rules, while the distributor (D) delivers the outputs to appropriate network nodes. Finally, the sink (SINK) node applies these ML outputs, often in the form of adaptive configurations or real-time network adjustments.

The framework is orchestrated by the ML Function Orchestrator (MLFO), a logically centralized entity responsible for coordinating the ML pipeline components, as depicted in Figure 4. The MLFO provides chaining of ML nodes to form complete pipelines and coordinates with the management subsystem to facilitate optimal model selection, deployment, and performance monitoring. This coordination supports dynamic adaptation to evolving network conditions and ML objectives (known as ML intent). Additionally, the framework may include an ML sandbox, a controlled environment for training, testing, and evaluating ML models, which isolates the impact of ML implementations on operational systems while allowing the use of simulated and real-world data to refine the models.

To support next-generation networks, the framework defines key architectural requirements such as correlating data across heterogeneous sources (e.g., RAN and CN), enabling a unified network view. It promotes flexible deployment and chaining of ML functions, coordinated with management subsystems for optimized performance. The framework also ensures interface interoperability through Application Programming Interface (API) recommendations and supports declarative ML

18 https://www.itu.int/rec/T-REC-Y.3172-201906-I/en

application indications to simplify configuration and adapt to dynamic network conditions. This framework is designed to support a wide range of use cases by enabling the dynamic placement of ML functionalities. For example, strategic deployment of ML components can facilitate network optimization through efficient traffic management and resource allocation, thereby supporting near-real-time, data-driven decisions that enhance QoS. Additionally, while the framework provides guidance on interfacing with ML functionalities, any integration of third-party ML solutions would require further adaptations by network operators.

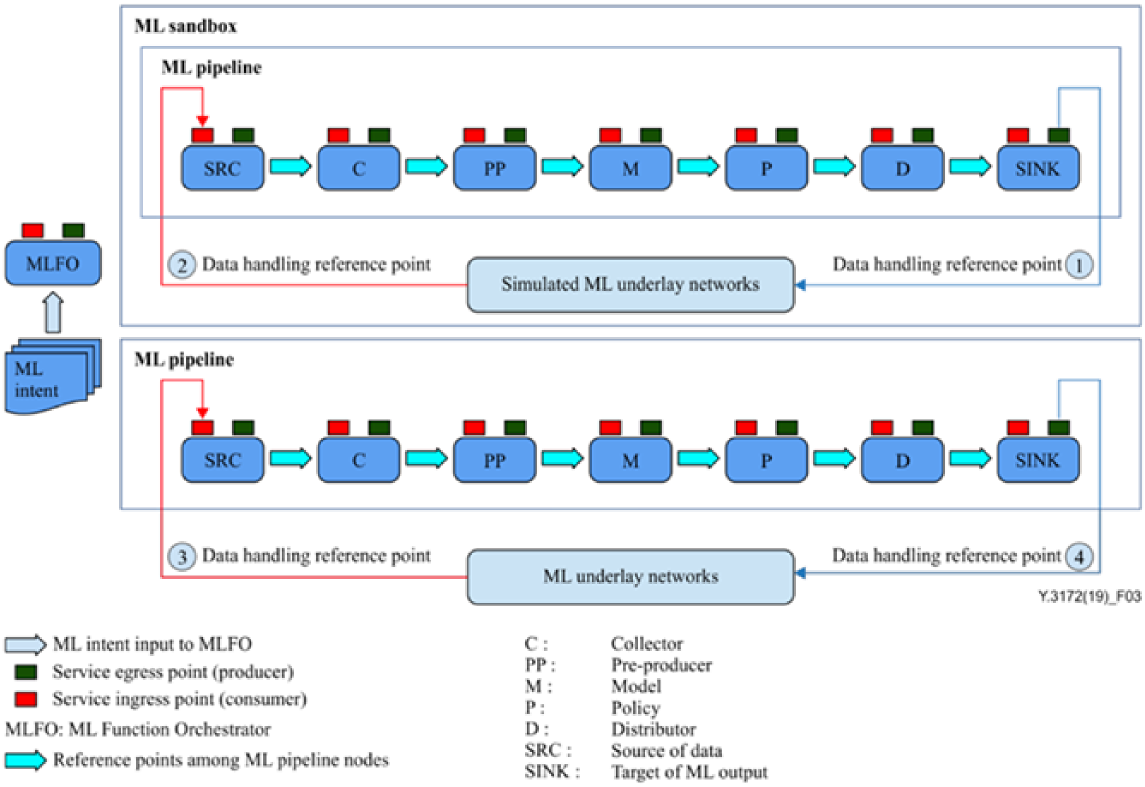


Figure 4: High-level architectural components of ITU-T framework.

On the other hand, the ITU-T Y.3174[19] recommendation extends the Y.3172 architectural principles by introducing a framework for managing the ML data lifecycle in IMT-2020 networks. It ensures consistent, real-time data handling across heterogeneous sources through timestamp alignment, coordinated flows, and retention policy enforcement. Designed for scalability, it supports both simulated and real-world data, minimizes latency for time-critical applications, and enables secure, adaptive application of ML outputs across the network. As shown in Figure 5, the framework defines key components for ML data handling. Data Models (DMs) specify data format, semantics, and exchange rules. The ML Metadata Store centrally manages DMs and their associated APIs to ensure

19 https://www.itu.int/rec/T-REC-Y.3174-202002-I/en

consistency and reusability. The ML Data Broker operates across the control and user planes (DBr-CP, DBr-UP) to translate and map data between ML overlays and underlying network components. The ML Database (MLDB) provides structured storage and retrieval capabilities for ML-related data, supporting both training and real-time applications. Additionally, standardized interfaces, such as API-g and API-s, abstract the requirements of ML applications (API-g) and map them to network-specific implementations (API-s), ensuring interoperability and scalability.

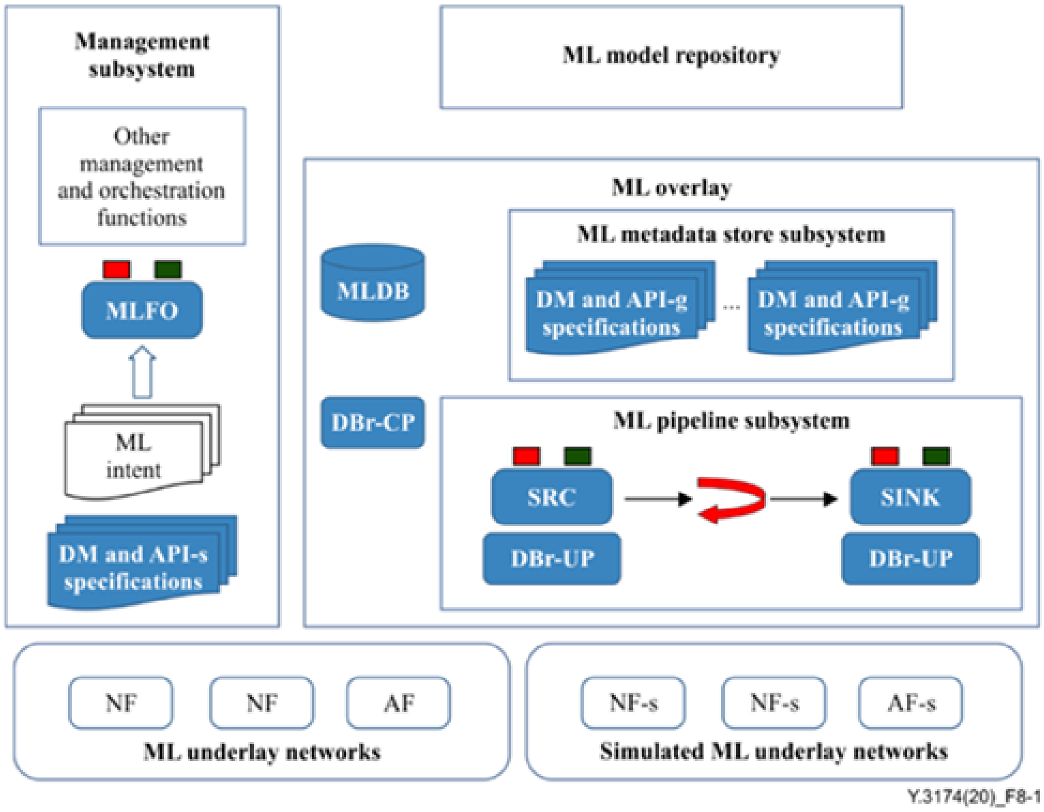


Figure 5: High-level architecture of the data handling framework.

The framework sets high-level requirements for heterogeneous data collection, real-time synchronization, and regulatory compliance. It supports scalable processing, seamless dataset integration, and low-latency optimization, with secure, adaptable data output across all network levels. It enables a wide range of use cases, including dynamic resource allocation, energy-efficient configurations, mobility prediction, and network optimization. It also supports real-time decision-making, fault detection, and service quality enhancement.

The ITU-T framework includes several functionalities for supporting AI/ML operations, including the modular ML pipeline, the sequence of logical nodes, as well as the overlay AI/ML functions that can be deployed. Moreover, the general architectural considerations of the AI/ML framework imply that is intended to work in a Service Based Architecture (SBA), including also functionalities related to algorithmic design and collaborative learning.

3.3 The O-RAN AI/ML Framework

O-RAN has proposed an AI/ML framework (AIMLF)[20] to support the ML models is depicted in Figure 6. The framework includes a portal to provide access to the end user, as well as a training manager that is the entity responsible for communicating with the Data Management and Exposure Services (DME) of the Non-RT RIC and performing the necessary operations to gather the training data. Moreover, there are two different platforms: the AI training host platform (ATHP) that is included in the logical architecture of the AIMLF and the AI Inference host platform (AIHP) that is deployed either in the Non-RT RIC or the Near-RT RIC. The former's internal architecture enables the platform to gather the training data, as well as to process them, extract the important features, follow the training pipeline and store the ML models in a model database. The AIHP is directly deployed to the network entity that will host the trained ML model, i.e., the Non-RT RIC or the Near RT RIC and serves as the model serving component, performing the required onboarding before deploying the inference service. It should be noted that the deployment location of the AI training functions may vary according to the diverse requirements of the use cases. Furthermore, O-RAN has also proposed a performance monitoring scheme.

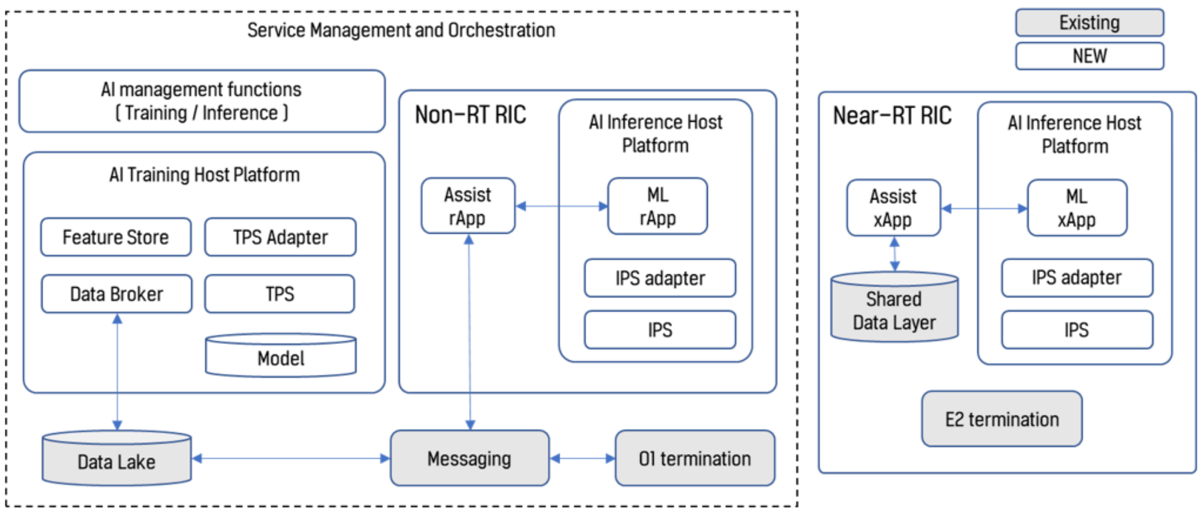


Figure 6: Performance Monitoring mechanism in the O-RAN SC AIMLFW project[21].

20 https://lf-o-ran-sc.atlassian.net/wiki/spaces/AIMLFEW/overview

21 https://research.samsung.com/blog/Enabling-Intelligent-RAN-Framework-in-O-RAN

The performance monitoring consists of a monitoring server connected to the ATHP and a monitoring agent that is deployed in the hosting network component (Near-RT RIC). In addition, performance analysis functions can be included in order to conduct post-processing analysis of the ML model performance. The end user (network operator) can connect through the portal to the performance monitoring system and retrieve information of the operating ML models.

The above monitoring process assumes that KPIs are stored as time series in an InfluxDB by a monitoring xApp (KPIMon), as well as the input/output of ML xApps (or request and response data from assist xApps). The implementation view of the O-RAN performance monitoring framework in the AIMLF is depicted in Figure 7.

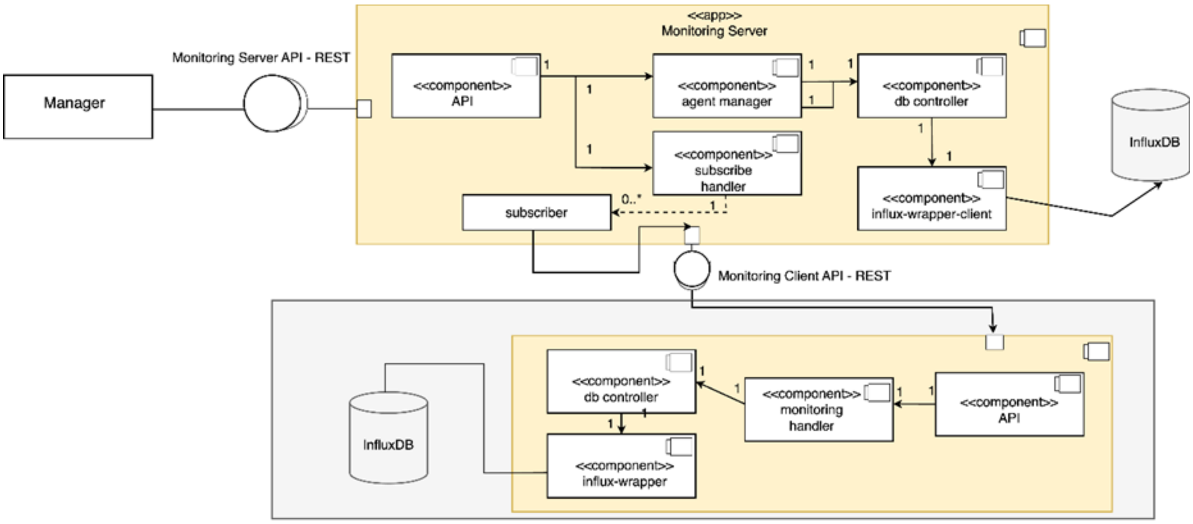


Figure 7: Implementation view of Monitoring in the AIMLF - components and interfaces.

The purpose of the performance monitoring functionality is to detect the degradation in the performance of the ML models that are operating in the RICs and avoid decline in the service quality.

Depending on the use case or the aim of the ML model, three general categories of analysis modules can be discerned:

- **Analysis of ML models input/output and trend.** Noteworthy, this analysis does not depend on the performance of the ML model itself but aims to detect drift by comparing actual and training inputs statistical properties. When a data drift is detected, ML model re-training may be needed.
- **Inference Accuracy of predictive models.** The inference accuracy of predictive ML models can be assessed analysing actual and predicted values. A degradation in performance is then detected when the actual inference accuracy differs from the required one.
- **ML-based Control Apps.** In the case of decision-making ML models, the network operator can assess the ML model performance indirectly through the impact on the network environment

of the RIC control messages (i.e., the ML model decisions). By tracking the temporal variation of KPIs collected from the network environment, the operator can decide upon the need for model retraining.

3.4 The ETSI perspective: AI as Network Autonomy Catalyst

ETSI positions AI as the driving enabler toward ANs, where networks exhibit 5 levels of autonomy, namely self-learning, self-protection, self-healing, self-optimization, and self-configuration, as shown in Figure 8. Although autonomy can conceptually exist without AI, the organization recognizes that AI accelerates the path to full network autonomy and acts as the foundation for zero-touch, intent-driven operations.

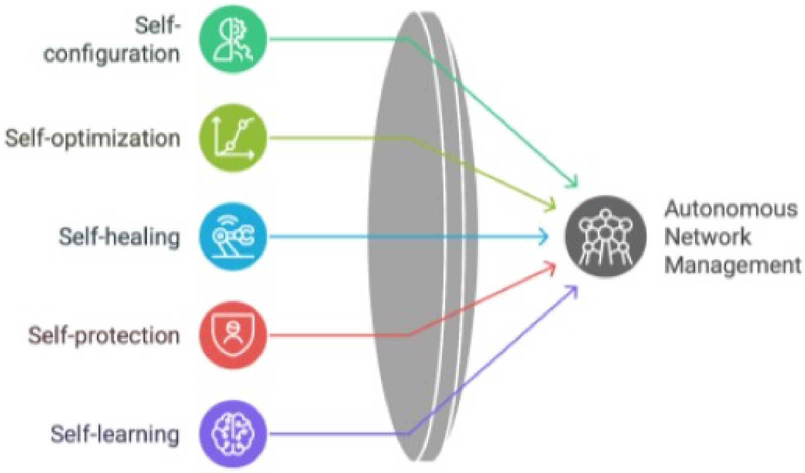


Figure 8: AI-enabled Self-X capabilities driving Autonomous Networks [15].

The current focus within ETSI is to achieve AN Level 4, the stage where networks operate with minimal human intervention, before progressing to complete autonomy [15]. This evolution promises operational cost reduction, sustainability gains, and new digital service opportunities. The integration of AI technologies such as Network Digital Twins (NDTs), GenAI, AI Agents, and intent-driven APIs is seen as critical to transforming service management and enabling digital transformation across sectors.

ETSI's work in this area involves Technical Committees (TCs), Industry Specification Groups (ISGs), and Software Development Groups (SDGs), each contributing domain expertise, spanning 5G/6G, Network Function Virtualization (NFV), Zero-Touch Network and Service Management (ZSM), Experiential Networked Intelligence (ENI), Fifth Generation Fixed Networks (F5G), Securing Artificial Intelligence (SAI), and software orchestration platforms such as TeraFlowSDN and OpenSlice.

3.4.1 Related ETSI Industry Specification Groups (ISGs)

ISG Experiential Networked Intelligence (ENI)

ETSI ISG ENI provides cognitive frameworks for closed-loop decision making in network operations. Recent achievements (Release 4) include:

- ETSI GS ENI 005 – Functional architecture incorporating cognitive networking, GenAI, and semantic policy models.
- ETSI GS ENI 019 – Models, interfaces, and APIs for representing and inferring network knowledge.
- ETSI GR ENI 051 – Agentic AI model introducing AI agents capable of reasoning, adaptation, and collaboration.
- Deliverables defining autonomy levels for IP and data-centre networks (GR ENI 007, 010, 035, 049).

ENI maintains 23 Proof-of-Concepts (PoCs) demonstrating AI-enabled decision loops in diverse network environments, including satellite-terrestrial cooperation. The work aligns with 6G ambitions, focusing on AI-native management, knowledge representation, and cognitive orchestration.

ISG Zero-Touch Network and Service Management (ZSM)

ZSM defines the architectural and operational foundations for AI-driven zero-touch automation. Key frameworks are listed below:

- Intent-driven closed-loop control using RL for dynamic resource optimization.
- NDT integration as analytics services for prediction, risk assessment, and visualization.
- Hierarchical closed loops (OODA-based) operating across micro to macro timescales for multi-domain optimization.
- XAI governance, employing blockchain-anchored audit logs to ensure traceability and accountability.

PoC validations include:

- Intent-driven RAN energy optimization (Deutsche Telekom, Huawei).
- Cloud AR/VR service deployment using CAMARA APIs (Telefónica).
- Explainable closed-loop management (EURECOM).
- Intent-based RAN resource management (NTT DOCOMO).

ISG Network Functions Virtualisation (NFV). ISG NFV Release 6 redefines telco clouds from cloud-native to AI-native systems, introducing the dual paradigm of:

- AI4Cloud – Using AI to enhance fault diagnosis, performance optimization, and OAM automation.

- Cloud4AI – Leveraging heterogeneous cloud resources (GPU, TPU, DPU) to support AI workloads and model training.

New studies explore:

- Serverless computing and WebAssembly (WASM) to improve AI application portability.
- Model-as-a-Service (MaaS) for deploying AI components in NFV ecosystems.
- xPU-enhanced infrastructures for AI acceleration.

ISG Fifth Generation Fixed Networks (F5G). ETSI ISG F5G extends AI-driven autonomy to fixed access and optical networks. Recent specifications (Release 3) include:

- GR F5G 019 – Fixed Network Autonomous Level Definition.[22]
- GS F5G 024 – F5G Advanced Architecture.[23]
- GS F5G 027 – End-to-End Management and Control.

AI supports closed-loop control, fault prediction, and QoE-aware optimization across fiber networks, bridging packet-optical integration and advancing toward F5G Advanced/5.5G evolution.

3.4.2 Related ETSI Technical Committees (TCs)

TC Securing Artificial Intelligence (SAI)

TC SAI focuses on trustworthy AI, addressing transparency, explainability, and adversarial robustness. Key deliverables:

- ETSI TS 104 224 – Explicability and transparency of AI processing (2025).[24]
- Ongoing work on AI auditing, ethical compliance, and continuous validation for AI decision traceability in networks.

SAI ensures that AI systems comply with EU AI Act principles, emphasizing secure model deployment, data privacy, and lifecycle management.

TC Methods for Testing and Specification (MTS)

MTS ensures quality and interoperability in autonomous systems. Innovations include:

- Model-based testing for AI-enabled behaviors.
- AI-driven test generation and runtime verification of closed loops.
- Development of ETSI TR 103 910[25] and TS 104 008, providing standardized test methodologies and KPIs for trustworthiness, robustness, and performance.

22 https://www.etsi.org/deliver/etsi_gr/F5G/001_099/019/01.01.01_60/gr_f5g019v010101p.pdf

23 https://www.etsi.org/deliver/etsi_gs/F5G/001_099/024/01.01.01_60/gs_f5g024v010101p.pdf

24 https://www.etsi.org/deliver/etsi_ts/104200_104299/104224/01.01.01_60/ts_104224v010101p.pdf

25 https://www.etsi.org/deliver/etsi_tr/103900_103999/103910/01.01.01_60/tr_103910v010101p.pdf

TC INT/AFI – Autonomic Management and Control

This group advances the GANA (Generic Autonomic Networking Architecture) model, focusing on cross-domain autonomy, policy-based self-management, and AI-enabled fault detection in multi-domain 5G and beyond networks.

3.4.3 ETSI Software Development Groups (SDGs)

ETSI TeraFlowSDN develops AI-ready SDN orchestration for multi-layer packet-optical control. PoCs demonstrate intent-based orchestration, Digital Twin-assisted automation, and closed-loop service assurance.

SDG OpenSlice (OSL) implements Network-as-a-Service (NaaS) delivery with AI-enabled intent translation. Utilizes GenAI to convert business intents into technical configurations and integrates multiple controllers for E2E lifecycle management.

4 OPEN IMPLEMENTATIONS AND TOOLS

This section explores open implementations and tools that support the integration of AI/ML into smart networks and services. It highlights the role of industry associations, open-source projects, and emerging multi-agent communication protocols in enabling interoperability and intent-based orchestration. It also introduces the concept of MLOps, which ensures reliable, scalable, and governable ML operations in dynamic environments. Tools like MLflow are presented as key enablers for managing the end-to-end lifecycle of ML models, addressing challenges such as fragmentation, governance, and sustainability in 6G networks.

4.1 Industry associations and open-source projects

The **TM Forum** [16] provides a detailed view of how agentic AI plays a central role in the evolution toward fully autonomous network operations. It discusses how Communication Service Providers (CSPs) are moving from traditional automation (rule-based systems) to AI-enabled autonomy, where intelligent systems reason, act, and adapt with minimal human intervention. The report emphasizes that Level 4 ANs represent a shift from “prescriptive supervision” (humans defining procedures) to “declarative, delegated autonomy,” in which AI does the reasoning. This embodies the essence of agentic AI: systems that can interpret human intent, make decisions, and execute actions across network domains autonomously. AI is embedded throughout the network lifecycle, from planning and orchestration to assurance and optimization, thus enabling intent-based, closed-loop management. These systems sense network conditions, reason over multi-domain data, and act dynamically to self-heal, self-optimize, and self-adapt, which aligns directly with the core attributes of agentic AI systems. The report also explores the growing integration of GenAI and multi-agent collaboration in network operations. GenAI is seen as an enabler of agentic workflows, where LLMs assist in decision-making, generate network configurations, support troubleshooting via natural language, and even build DT of the network.

In the same context, the telecommunications industry is undergoing a profound transformation as 5G networks architecture matures, Telcos are increasingly exposing their core capabilities through standardized APIs, notably via the **GSMA Open Gateway initiative[26] and CAMARA[27]**. These APIs aim to simplify access to network functions such as SIM swap detection, QoS management, and device location, enabling third-party developers to build applications that leverage real-time network

26 https://www.gsma.com/solutions-and-impact/gsma-open-gateway/

27 https://camaraproject.org/

context. However, this API-first approach inherits several structural limitations [17] Current network APIs are typically stateless, synchronous, and isolated, requiring the client to know exactly which capability to invoke and when. They offer little in terms of intent-based orchestration, persistent context, or adaptive negotiation, properties that are rapidly becoming essential as the software ecosystem shifts toward autonomous, goal-oriented agents. Those agents need to operate continuously, remember prior state, and adapt their behaviour to changing environments, including the underlying network.

4.2 Multi-Agent Communication Protocols

Stateless API interfaces are fundamentally misaligned with the new class of software that the AI agents introduce, and thus there are also discussions on approaches like the ones provided by Multi-Agent Communication Protocols. Model Context Protocol (MCP), Agent Communication Protocol (ACP), Agent-to-Agent Protocol (A2A), and Agent Network Protocol (ANP), are Multi-Agent Communication Protocols addressing interoperability in distinct deployment contexts. MCP provides a JSON-RPC client-server interface for secure tool invocation and typed data exchange. Specifically for the Telco Networks, MCP introduces four key innovations over traditional Telco APIs [17]:

1. **Session Persistence**: sessions maintain memory across time, allowing agents to interact contextually rather than through repeated one-shot calls.
2. **Intent Negotiation**: Agents declare high-level goals, and the network responds with available options, pricing, or fallback mechanisms.
3. **Context Subscription:** Agents can subscribe to real-time network state changes (e.g., congestion, user movement), enabling proactive adaptation.
4. **Monetization by Session or SLA:** open the door to new pricing models, including real-time QoS auctions, session-based SLAs, or priority bandwidth tiers.

ACP introduces REST-native messaging via multi-part messages and asynchronous streaming to support multimodal agent responses. A2A enables peer-to-peer task outsourcing through capability-based Agent Cards, facilitating enterprise-scale workflows. ANP supports open-network agent discovery and secure collaboration using decentralized identifiers (DIDs) and JSON-LD graphs. The protocols are compared across multiple dimensions, including interaction modes, discovery mechanisms, communication patterns, and security models. Table 1 below summarizes the related protocols.

Table 1: Multi-Agent Communication Protocols.

Protocol	Origin	Arch.& Transport	Sec.& Identity	Key Capabilities
MCP (Model Context Protocol)	Anthropic	Client-Server, JSON-RPC	User consent-driven	Connects models to external tools
A2A (Agent-to-Agent Protocol)	Google & partners	Peer-to-peer JSON-RPC over HTTP/S	Enterprise OAuth2	Agents advertise capabilities via “cards”
ANP (Agent Network Protocol)	Cisco / AGNTCY	Decentralized, DID-secured	Self-sovereign identity	Semantic web discovery, open & scalable architecture
ACP (Agent Communication Protocol)	IBM / BeeAI	REST-first, OpenAPI + WebSockets	Web-native security	Flexible endpoint discovery, multimodal integration

6G needs to acknowledge this evolving landscape and align with the latest developments by considering integration paths with these leading multi-agent communication protocols (i.e., MCP, A2A, ANP, and ACP). By doing so, future 6G architecture will remain future-proof, interoperable, and capable of supporting the next generation of agentic AI ecosystems.

Prototype Open-source solutions that exploit Multi-Agent Communication Protocols, and specifically the MCP for telco solutions are already emerging. Such an example is the implementation of an MCP server by ETSI SDG OSL[28] offering exposure of the whole product, Service and resources catalogues as well as product/Service order management via these MCP and-point and LLM integration offer a powerful intent-based environment for product/service management.

4.3 The MLOPs concept

The lifecycle of traditional software pieces has become relatively straightforward (including processes like deploy and integrate) with the aid of DevOps. However, when it comes to ML models unique challenges emerge. ML models involve data collection, model training, validation, deployment, and continuous monitoring and retraining. MLOps, refers to the combination of practices, tools, and organizational processes that support the end-to-end development, deployment, and maintenance of machine learning models in production environments. Its central goal is to ensure that ML systems are reliable, scalable, governable, and continuously improvable, especially when operating in dynamic or mission-critical settings.

The MLOps lifecycle begins with data engineering, where data is collected, cleaned, transformed, and versioned so that models can be trained reproducibly. This is followed by experimentation and model training, where practitioners track experiments, test different model configurations, and guarantee replicability of results. After training, models go through rigorous validation that assesses their

28 https://labs.etsi.org/rep/osl/code/org.etsi.osl.mcp.server

performance, robustness, interpretability, and resilience to distribution shifts. Deployment then packages the validated models using containerization and orchestration technologies, allowing them to operate efficiently and securely within production pipelines. Once deployed, MLOps focuses on continuous monitoring to detect data drift, concept drift, anomalies, or performance degradation, and it provides mechanisms for automated or controlled retraining and redeployment. Throughout this process, governance functions - such as model versioning, metadata management, access control, documentation, and audit trails - ensure that systems remain compliant, transparent, and aligned with responsible AI principles.

MLOps has become particularly important in emerging 6G network environments, where AI is envisioned as a native component of the architecture rather than a supplemental feature. Future networks will operate across a distributed continuum that spans cloud data centres, edge nodes, and end devices, and they will increasingly rely on learning-driven mechanisms to manage radio resources, coordinate network slices, optimize energy consumption, detect faults, and adapt to highly dynamic radio conditions. Because data distributions shift rapidly in large-scale telecom systems, MLOps provides the essential monitoring and retraining mechanisms that keep AI models accurate and dependable over time. Furthermore, the 6G vision prioritizes trust, explainability, security, sustainability, and regulatory compliance. MLOps contributes directly to these priorities by embedding auditing, responsible AI checks, explainability tools, and energy-efficient model lifecycle management within operational pipelines. In a domain where network reliability is paramount and failures can have large-scale impact, an operational backbone for managing the ML lifecycle becomes indispensable.

Within this context, the SNS JU (Smart Networks and Services - Joint Undertaking) plays a central role in shaping Europe's 6G research agenda. Its recent work highlights AI/ML as a foundational capability for next-generation networks, with numerous funded projects developing learning-based mechanisms for the radio access network, resource optimization, security, energy management, and network diagnostics. The SNS JU Technology Board's recent white paper [8] identifies close to two hundred ML-based mechanisms across its projects, demonstrating the breadth and depth of AI integration within the 6G ecosystem. These initiatives frequently rely on heterogeneous and distributed data sources that reflect different segments of the network, making privacy-preserving learning approaches - such as FL or decentralized analytics - highly important. Additionally, because early-stage 6G technologies depend heavily on simulation environments, DT, and synthetic data to generate training datasets, MLOps practices play a key role in ensuring data lineage, reproducibility, and the smooth transfer of models from simulation to real-world testbeds. As SNS JU projects increasingly move toward AI-native network functions that must update autonomously and continuously, the operational discipline provided by MLOps becomes the mechanism that ensures dependability, accountability, and trustworthiness.

Several challenges can be identified which accompany the adoption of MLOps, based on the insights of the SNS JU projects:

- One major challenge is the **fragmentation of tools and practices** across different projects, which can result in inconsistent workflows, duplicated effort, and difficulty in integrating AI components. A recommended approach is to develop shared architectural principles or a common MLOps reference framework that projects can adopt, ensuring greater interoperability.
- Another challenge relates to the **management of model governance and transparency** in highly distributed systems. SNS JU projects would benefit from coordinated governance policies that define model ownership, lifecycle responsibilities, audit procedures, and explainability requirements, especially for models influencing critical network operations.
- A further issue is the **complexity of deploying ML models across distributed infrastructure**, from cloud to edge. To overcome this, projects should adopt container-based, resource-aware deployment strategies and consider standardized orchestration layers that support portability and energy efficiency.
- **Sustainability** is also an emerging concern: as model training and retraining consume significant energy, it is recommended that projects integrate sustainability metrics directly into their MLOps pipelines, enabling models to be evaluated and optimized not only for performance but also for environmental impact.
- Finally, **capacity-building** remains essential; MLOps requires collaboration between data scientists, network engineers, and operations teams, and SNS JU could support cross-project knowledge sharing, training initiatives, and common toolkits to reduce the skill gap.

By addressing these challenges through coordinated practices, SNS JU can establish a stable and trustworthy foundation for the large-scale deployment of AI-native mechanisms in future European 6G networks.

From the MLOps' implementation point of view, **MLflow**[29] is an open-source platform designed to manage the end-to-end machine learning lifecycle, and it is often considered one of the foundational tools for implementing MLOps because it directly supports several of MLOps's key practices. MLflow

29 https://mlflow.org/

provides a set of components that help teams track experiments, package models, and deploy them in a consistent and reproducible way. Its core functionalities include:

- **MLflow Tracking** – A system for logging and comparing experiments, metrics, parameters, and artifacts. This makes model development more transparent and reproducible.
- **MLflow Projects** – A packaging format that allows data scientists to bundle code, dependencies, and configurations so that ML workloads can be executed consistently across environments.
- **MLflow Models** – A standardized format for packaging trained models so they can be deployed across different serving platforms (REST APIs, cloud services, edge environments).
- **MLflow Model Registry** – A central repository to version, manage, and approve models through stages such as *staging*, *production*, or *archived*. This enables controlled model lifecycle management.

5 AI AND ML FOR NETWORKS

AI/ML in networks has achieved remarkable advancement in B5G era and is gaining significant traction with the advent of 6G. Every component and building block of a wireless system that we currently are familiar with up to 5G, such as physical, network and application layers, will involve one or another AI/ML techniques for optimization in term of communication, security, energy consumption, performance and automations [18].

5.1 AI/ML in mobile network procedures

Network Management. AI-driven network management is central to the vision of autonomous 6G networks, enabling real-time control over network configuration, performance monitoring, fault remediation as well as Radio Resource Management. Traditional rule-based management frameworks are no longer sufficient to handle the scale, diversity, and agility demands of 6G environments. As a result, AI/ML models have been adopted to realize self-configuration, self-optimization, and self-healing functionalities. In addition, Zero Touch Management [19] and ML-Based Radio Resource Management [20], are emerging as the most attractive research fields in the AI/ML enabled network management domain.

Radio and access procedures. AI techniques in RAN enable intelligent cell selection, handover control, and RAN slicing. DRL is applied to optimize spectrum reuse and dynamic user association in heterogeneous access environments. AI/ML models at the PHY target real-time channel estimation, adaptive modulation, beamforming, and signal classification. DL architectures, including CNNs, DNNs, and autoencoders, enhance channel robustness and spectral efficiency. At the MAC layer, AI enables predictive scheduling, adaptive retransmission, and efficient spectrum allocation. Multi-agent DRL frameworks have shown potential in solving the problem of decentralized resource contention. Overall, there are multiple surveys in the literature, highlighting the AI/ML potential in the PHY [21]-[24] and MAC layers [25].

Transport network control. Software-Defined Networking (SDN) is a core architectural enabler for programmable, agile, and intelligent 6G infrastructures. By decoupling the control and data planes, SDN facilitates centralized management and real-time reconfiguration of network behaviour. With the integration of AI/ML, SDN systems are transitioning toward autonomous network operation, capable of predictive decision-making, context-aware routing, intent translation, and scalable orchestration. ML techniques including supervised learning, RL, and DL are increasingly embedded within SDN controllers to optimize traffic engineering, intrusion detection, fault management, and slice orchestration in 6G environments [26][27]].

Service orchestration. NFV enables the decoupling of network functions (NFs) from dedicated hardware by running them as software instances on commodity servers. NFV plays a critical role in the cloud-native evolution of 6G networks, where network services such as firewalls, load balancers, and mobility anchors must be dynamically instantiated, scaled, and migrated across heterogeneous infrastructures. Incorporating AI/ML techniques into NFV frameworks brings intelligence to orchestration processes such as Virtual Network Function (VNF) placement, chaining, scaling, and fault recovery. These learning-based enhancements improve resource utilization, reduce service deployment latency, and support closed-loop automation under dynamic network demands [28][29].

Security and Trust enforcement. In the context of 6G networks, where the attack surface expands with the proliferation of intelligent devices and edge components, AI plays a crucial role in enabling proactive, real-time security mechanisms. Extended surveys in the literature explain in detail the AI-enabled security and trust challenges for 6G networks [30][31]. According to these studies, AI/ML models are used to detect a wide range of security threats including zero-day attacks, spoofing, DDoS intrusions, and data exfiltration. Advanced hybrid DL approaches such as ensemble methods combining convolutional networks with recurrent units or attention layers are used to capture both spatial and temporal threat signatures. These models not only offer high detection accuracy but are also capable of adapting to evolving threat landscapes through continual learning paradigms.

Digital Twin frameworks. DTs are high-fidelity virtual representations of real-world physical systems that continuously mirror the state, behaviour, and context of their physical counterparts. In 6G networks, DTs are envisioned as essential components for real-time monitoring, predictive optimization, and closed-loop control across layers from radio access and core networks to end-user applications and services. The integration of AI into DT frameworks transforms them from passive replicas into cognitive entities capable of learning, reasoning, and adapting over time [32]. AI-enhanced DTs enable proactive decision-making by simulating "what-if" scenarios, forecasting network evolution, and autonomously controlling network behaviour under diverse constraints.

Network Slicing. Network slicing enables the creation of virtual, logically isolated networks over a shared 6G infrastructure, each tailored to specific service requirements such as Ultra-Reliable Low Latency Communications (URLLC), Enhanced Mobile Broadband (eMBB), or Massive Machine-Type Communications (mMTC). AI/ML models are increasingly used to support real-time slice orchestration and lifecycle management, addressing the challenges of resource elasticity, SLA enforcement, and performance isolation. In the literature, the role of explainability and security in network slicing is highlighted as well [33][34]; specially towards enhancing transparency and reliability in scenarios where real-time decision-making and high-stakes operational environments are needed.

Network Dimensioning and Planning. AI-enhanced network planning tools enable the efficient design and deployment of 6G infrastructure, optimizing base station locations, frequency reuse, and backhaul provisioning [35]. The benefits of AI/ML on network dimensioning and planning have been indicated by many studies [36] already. Many factors call for use of AI/ML tools for the network dimensioning and planning in the beyond 5G era, with major ones a) the concepts of multitenancy and network slicing that require dynamic dimensioning and planning for the virtual sub-networks defined on top of physical networks and resources; as well as b) the densification of the network infrastructure (since higher frequency bands are adopted) and the convergence of multi-RAT communications (e.g., the N3IWF of 5G core), that make the dimensioning and planning problem more complex [37].

E2E SLA Assurance. End-to-End (E2E) Service Level Agreement (SLA) assurance is a cornerstone of intelligent and autonomous 6G networks, ensuring that diverse service requirements such as latency, reliability, throughput, and energy efficiency are continuously met across heterogeneous domains spanning RAN, transport, core, and edge. Traditional static SLA monitoring mechanisms lack the adaptability required for dynamic, multi-slice, and multi-domain 6G environments. AI/ML-driven assurance frameworks enable proactive and predictive SLA management by leveraging real-time telemetry data and cross-layer analytics [38].

Service Elasticity. Service elasticity allows a network to dynamically adjust resource allocation and service configurations in response to changing traffic demands, user mobility, and application requirements. In 6G networks, elasticity is essential to maintain service continuity and efficiency under highly variable and heterogeneous conditions. AI/ML-driven elasticity frameworks enable intelligent scaling of network functions and slices across network domains. Predictive models analyze historical and real-time data to forecast demand fluctuations and trigger proactive scaling actions, minimizing both over-provisioning and resource starvation [39].

5.2 AI/ML integration in other types of networks

AI/ML in IoT Networks. IoT devices form a dense, heterogeneous data layer that demands ultra-low latency, energy efficiency, and decentralized intelligence. AI/ML models are increasingly deployed at the edge using TinyML, a lightweight machine learning paradigm tailored for microcontrollers and low-power IoT endpoints. These models enable real-time inference for applications such as anomaly detection, activity recognition, and environmental sensing. Representative AI/ML algorithms that can help in developing energy efficient, secured and effective IoT network operations and services can be found in [40]. As in other network types, AI-enabled security and explainability are also applicable to IoT networks [41].

AI/ML in Vehicular Networks. In Vehicular-to-Everything (V2X), AI supports URLLC, traffic flow optimization, and cooperative perception. Federated and generative models are gaining traction. V2X communication is a cornerstone use case for 6G, demanding URLLC, predictive mobility support, and real-time collaborative decision-making. AI/ML enables this through several critical roles: predictive beamforming, vehicular traffic flow optimization, and cooperative perception across vehicles and infrastructure nodes. Recent research emphasizes the use of FL to train models on distributed vehicular data without violating privacy, and GANs for synthetic data augmentation and scenario simulation in edge-cloud environments [42][43].

AI/ML in UAV Networks. UAVs are integral to the 6G vision for providing on-demand, mobile, and resilient communication services, especially in emergency recovery, rural coverage, and edge data collection scenarios. Their dynamic mobility introduces challenges in trajectory planning, coverage continuity, and interference control. AI and ML solutions for UAV networks are grouped into those that enable new applications [44] and those that enhance the network operation, by improving various design and functional aspects such as channel modelling, resource management, positioning, and security [45].

AI/ML in Data Networks. As 6G pushes toward intelligent, hyper-connected ecosystems, data networks including both the core and transport segments must evolve to support dynamic traffic flows, high throughput, ultra-low latency, and pervasive analytics. Traditional traffic engineering and data routing mechanisms are no longer sufficient to meet the demands of massive-scale applications such as XR, DT, and industrial automation. The integration of AI/ML techniques into data networks includes all the aspects of the data life cycle management [46]. The potential gains include real-time analytics, predictive congestion control, intelligent routing, and self-optimizing packet delivery, significantly enhancing efficiency and resilience.

AI/ML in Non-Terrestrial Networks (NTN). NTNs are poised to expand 6G coverage to global and underserved regions. They introduce high dynamics in latency, mobility, and propagation, necessitating AI/ML support for predictive and adaptive operations [47]. Unlike terrestrial networks (with mostly fixed base stations), NTNs involve highly mobile nodes moving in three-dimensional space, and thus, the network topology changes continuously due to orbital motion or flight paths. ML models can learn and predict these dynamics, enabling adaptive routing, link scheduling, and beam management in real time. In addition, since traditional optimization methods struggle with the spatiotemporal complexity of NTNs; AI excels in learning from dynamic patterns.

6 CONCLUSIONS & WAY FORWARD

Intensive efforts in the research community, standardisation bodies and open implementation projects highlight the transformative potential of AI/ML in advancing smart networks and services, particularly within the context of 6G networks. AI/ML already plays a critical role in driving innovation, enhancing network performance, and addressing key challenges such as security, trust, and sustainability. In this context, several AI/ML-related concepts have emerged, expanding the terminology, with recent additions including agentic AI systems and the development of AI-native networks and systems. In addition, the integration of AI/ML into network management, service orchestration, and optimization is considered essential for achieving autonomous, intelligent, and adaptive networks. Furthermore, there is a need for standardized frameworks and open implementation practices to ensure reliable, scalable, and governable AI/ML operations. Overall, AI/ML has become a crucial enabler of 6G connectivity, unlocking its full potential and paving the way for the next generation of intelligent, connected networks.

REFERENCES

[1] Book Chapter: Artificial Intelligence in 5G and Beyond Networks, By Dimitris Tsolkas, et al, Book: Applied Edge AI, Edition 1st Edition, First Published 2022, Imprint Auerbach Publications, Pages 31, eBook ISBN 9781003145158.

[2] Joseph Sifakis, Dongming Li, Hairong Huang, Yong Zhang, Wenshuan Dang, River Huang, Yijun Yu, “A Reference Architecture for Autonomous Networks: An Agent-Based Approach” (Huawei & Université Grenoble Alpes, 2025) https://arxiv.org/abs/2503.12871

[3] A. Celik and A. M. Eltawil, "At the Dawn of Generative AI Era: A Tutorial-cum-Survey on New Frontiers in 6G Wireless Intelligence," in IEEE Open Journal of the Communications Society, vol. 5, pp. 2433-2489, 2024, doi: 10.1109/OJCOMS.2024.3362271

[4] M. Sheraz et al., "A Comprehensive Survey on GenAI-Enabled 6G: Technologies, Challenges, and Future Research Avenues," in IEEE Open Journal of the Communications Society, vol. 6, pp. 4563-4590, 2025, doi: 10.1109/OJCOMS.2025.3568496.

[5] H. Sun et al., "Advancing 6G: Survey for Explainable AI on Communications and Network Slicing," in IEEE Open Journal of the Communications Society, vol. 6, pp. 1372-1412, 2025, doi: 10.1109/OJCOMS.2025.3534626.

[6] S. Wang, M. A. Qureshi, L. Miralles-Pechuán, T. Huynh-The, T. R. Gadekallu and M. Liyanage, "Explainable AI for 6G Use Cases: Technical Aspects and Research Challenges," in IEEE Open Journal of the Communications Society, vol. 5, pp. 2490-2540, 2024, doi: 10.1109/OJCOMS.2024.3386872.

[7] Y. Shi et al., "Machine Learning for Large-Scale Optimization in 6G Wireless Networks," in IEEE Communications Surveys & Tutorials, vol. 25, no. 4, pp. 2088-2132, Fourth quarter 2023, doi: 10.1109/COMST.2023.3300664

[8] K. Trichias et al, “AI/ML as a Key Enabler of 6G Networks: Methodology, Approach and AI-Mechanisms in SNS JU”. Zenodo, Jan. 31, 2025. doi: 10.5281/zenodo.14623109

[9] X. Lu et al., "Reinforcement Learning-Based Physical Cross-Layer Security and Privacy in 6G," in IEEE Communications Surveys & Tutorials, vol. 25, no. 1, pp. 425-466, Firstquarter 2023, doi: 10.1109/COMST.2022.3224279.

[10] A. Salh et al., "A Survey on Deep Learning for Ultra-Reliable and Low-Latency Communications Challenges on 6G Wireless Systems," in IEEE Access, vol. 9, pp. 55098-55131, 2021, doi: 10.1109/ACCESS.2021.3069707.

[11] L. Jiao et al., "Advanced Deep Learning Models for 6G: Overview, Opportunities, and Challenges," in IEEE Access, vol. 12, pp. 133245-133314, 2024, doi: 10.1109/ACCESS.2024.3418900.

[12] Hurtado Sánchez, J.A.; Casilimas, K.; Caicedo Rendon, O.M. Deep Reinforcement Learning for Resource Management on Network Slicing: A Survey. Sensors 2022, 22, 3031. https://doi.org/10.3390/s22083031

[13] Driss, M. B., Sabir, E., Elbiaze, H., & Saad, W. (2023). Federated learning for 6G: Paradigms, taxonomy, recent advances and insights. arXiv preprint arXiv:2312.04688.

[14] Sirohi D, Kumar N, Rana PS, Tanwar S, Iqbal R, Hijjii M. Federated learning for 6G-enabled secure communication systems: a comprehensive survey. Artif Intell Rev. 2023 Mar 12:1-93. doi: 10.1007/s10462-023-10417-3. Epub ahead of print. PMID: 37362891; PMCID: PMC10008151.

[15] ETSI White paper, Editors: Luigi Licciardi, Helene Schmidt (ETSI), AI in the evolution of Autonomous Networks ETSI perspectives and major achievements, Rel. 1.0 – 2025. https://www.etsi.org/images/files/ETSIWhitePapers/ETSI-WP-69-AI-in_the_evolution_of_Autonomous_Networks.pdf
[16] TM Forum report "Autonomous Networks: In Search of Best Practice" (December 2024)
[17] Barros, Sebastian, Extending the Model Context Protocol (MCP) for Telco Networks (April 09, 2025). Available at SSRN: http://dx.doi.org/10.2139/ssrn.5211843
[18] J. Du, C. Jiang, J. Wang, Y. Ren and M. Debbah, "Machine Learning for 6G Wireless Networks: Carrying Forward Enhanced Bandwidth, Massive Access, and Ultrareliable/Low-Latency Service," in IEEE Vehicular Technology Magazine, vol. 15, no. 4, pp. 122-134, Dec. 2020, doi: 10.1109/MVT.2020.3019650
[19] E. Coronado et al., "Zero Touch Management: A Survey of Network Automation Solutions for 5G and 6G Networks," in IEEE Communications Surveys & Tutorials, vol. 24, no. 4, pp. 2535-2578, Fourthquarter 2022, doi: 10.1109/COMST.2022.3212586.
[20] I. A. Bartsiokas, P. K. Gkonis, D. I. Kaklamani and I. S. Venieris, "ML-Based Radio Resource Management in 5G and Beyond Networks: A Survey," in IEEE Access, vol. 10, pp. 83507-83528, 2022, doi: 10.1109/ACCESS.2022.3196657.
[21] A. Alzailaa et al., "," in IEEE Access, vol. 13, pp. 119457-119499, 2025, doi: 10.1109/ACCESS.2025.3586800.
[22] N. A. Khan and S. Schmid, "AI-RAN in 6G Networks: State-of-the-Art and Challenges," in IEEE Open Journal of the Communications Society, vol. 5, pp. 294-311, 2024, doi: 10.1109/OJCOMS.2023.3343069.
[23] N. Ye, S. Miao, J. Pan, Q. Ouyang, X. Li and X. Hou, "Artificial Intelligence for Wireless Physical-Layer Technologies (AI4PHY): A Comprehensive Survey," in *IEEE Transactions on Cognitive Communications and Networking*, vol. 10, no. 3, pp. 729-755, June 2024, doi: 10.1109/TCCN.2024.3382973
[24] W. Chen et al., "AI assisted PHY in future wireless systems: Recent developments and challenges," in China Communications, vol. 18, no. 5, pp. 285-297, May 2021, doi: 10.23919/JCC.2021.05.019.
[25] A. Valcarce, P. Kela, S. Mandelli and H. Viswanathan, "The Role of AI in 6G MAC," 2024 Joint European Conference on Networks and Communications & 6G Summit (EuCNC/6G Summit), Antwerp, Belgium, 2024, pp. 723-728, doi: 10.1109/EuCNC/6GSummit60053.2024.10597082.
[26] Pathak, Y., Prashanth, P.V.N., Tiwari, A. (2023). AI Meets SDN: A Survey of Artificial Intelligent Techniques Applied to Software-Defined Networks. In: Kumar, M., Gill, S.S., Samriya, J.K., Uhlig, S. (eds) 6G Enabled Fog Computing in IoT. Springer, Cham. https://doi.org/10.1007/978-3-031-30101-8_16
[27] F. Song, D. Qin and C. Xu, "A Survey of Application of Artificial Intelligence Methods in SDN," 2022 IEEE 2nd International Conference on Software Engineering and Artificial Intelligence (SEAI), Xiamen, China, 2022, pp. 237-242, doi: 10.1109/SEAI55746.2022.9832340
[28] A. A. Gebremariam, M. Usman and M. Qaraqe, "Applications of Artificial Intelligence and Machine Learning in the Area of SDN and NFV: A Survey," 2019 16th International Multi-Conference on Systems, Signals & Devices (SSD), Istanbul, Turkey, 2019, pp. 545-549, doi: 10.1109/SSD.2019.8893244.

[29] Zehra, S.; Faseeha, U.; Syed, H.J.; Samad, F.; Ibrahim, A.O.; Abulfaraj, A.W.; Nagmeldin, W. Machine Learning-Based Anomaly Detection in NFV: A Comprehensive Survey. Sensors 2023, 23, 5340. https://doi.org/10.3390/s23115340

[30] Y. Siriwardhana, P. Porambage, M. Liyanage and M. Ylianttila, "AI and 6G Security: Opportunities and Challenges," 2021 Joint European Conference on Networks and Communications & 6G Summit (EuCNC/6G Summit), Porto, Portugal, 2021, pp. 616-621, doi: 10.1109/EuCNC/6GSummit51104.2021.9482503.

[31] V. Ziegler, P. Schneider, H. Viswanathan, M. Montag, S. Kanugovi and A. Rezaki, "Security and Trust in the 6G Era," in IEEE Access, vol. 9, pp. 142314-142327, 2021, doi: 10.1109/ACCESS.2021.3120143.

[32] M. Sheraz, T. C. Chuah, Y. L. Lee, M. M. Alam, A. Al-Habashna and Z. Han, "A Comprehensive Survey on Revolutionizing Connectivity Through Artificial Intelligence-Enabled Digital Twin Network in 6G," in IEEE Access, vol. 12, pp. 49184-49215, 2024, doi: 10.1109/ACCESS.2024.3384272.

[33] H. Sun et al., "Advancing 6G: Survey for Explainable AI on Communications and Network Slicing," in IEEE Open Journal of the Communications Society, vol. 6, pp. 1372-1412, 2025, doi: 10.1109/OJCOMS.2025.3534626

[34] Dangi, R.; Jadhav, A.; Choudhary, G.; Dragoni, N.; Mishra, M.K.; Lalwani, P. ML-Based 5G Network Slicing Security: A Comprehensive Survey. Future Internet 2022, 14, 116. https://doi.org/10.3390/fi14040116

[35] Salama, Ramiz, Chadi Altrjman, and Fadi Al-Turjman. "A Survey of Machine Learning Methods for Network Planning." NEU Journal for Artificial Intelligence and Internet of Things 2.3 (2023).

[36] A. Kaloxylos, A. Gavras, D. Camps Mur, M. Ghoraishiand H. Hrasnica, “AI and ML – Enablers for Beyond 5G Networks”. Zenodo, Dec. 01, 2020. doi: 10.5281/zenodo.4299895

[37] A-S Charismiadis, et al “A reinforcement learning approach for vertical-oriented network planning in 5G and beyond networks”, TechRxiv, Dec. 2025. Doi: https://doi.org/10.36227/techrxiv.176541599.90887522/v1

[38] D. De Vleeschauwer, C. Papagianni and A. Walid, "Decomposing SLAs for Network Slicing," in IEEE Communications Letters, vol. 25, no. 3, pp. 950-954, March 2021, doi: 10.1109/LCOMM.2020.3033042.

[39] S. S. Sefati et al., "A Comprehensive Survey on Resource Management in 6G Network Based on Internet of Things," in IEEE Access, vol. 12, pp. 113741-113784, 2024, doi: 10.1109/ACCESS.2024.3444313.

[40] M. R. Mahmood, M. A. Matin, P. Sarigiannidis and S. K. Goudos, "A Comprehensive Review on Artificial Intelligence/Machine Learning Algorithms for Empowering the Future IoT Toward 6G Era," in IEEE Access, vol. 10, pp. 87535-87562, 2022, doi: 10.1109/ACCESS.2022.3199689

[41] Quincozes, Vagner E., et al. "A survey on IoT application layer protocols, security challenges, and the role of explainable AI in IoT (XAIoT)." International Journal of Information Security 23.3 (2024): 1975-2002.

[42] Claudio Casetti, Carla Fabiana Chiasserini, Falko Dressler, Agon Memedi, Diego Gasco, Elad Michael Schiller, AI/ML-based services and applications for 6G-connected and autonomous vehicles, Computer Networks, Volume 255, 2024, 110854, ISSN 1389-1286,https://doi.org/10.1016/j.comnet.2024.110854.

[43] Wang, Donglin, et al. "A Survey on the Role of Artificial Intelligence and Machine Learning in 6G-V2X Applications." arXiv preprint arXiv:2506.09512 (2025).

[44] M. -A. Lahmeri, M. A. Kishk and M. -S. Alouini, "Artificial Intelligence for UAV-Enabled Wireless Networks: A Survey," in IEEE Open Journal of the Communications Society, vol. 2, pp. 1015-1040, 2021, doi: 10.1109/OJCOMS.2021.3075201.
[45] Bithas, P.S.; Michailidis, E.T.; Nomikos, N.; Vouyioukas, D.; Kanatas, A.G. A Survey on Machine-Learning Techniques for UAV-Based Communications. Sensors 2019, 19, 5170. https://doi.org/10.3390/s19235170
[46] D. C. Nguyen et al., "Enabling AI in Future Wireless Networks: A Data Life Cycle Perspective," in IEEE Communications Surveys & Tutorials, vol. 23, no. 1, pp. 553-595, Firstquarter 2021, doi: 10.1109/COMST.2020.3024783.
[47] S. Mahboob and L. Liu, "Revolutionizing Future Connectivity: A Contemporary Survey on AI-Empowered Satellite-Based Non-Terrestrial Networks in 6G," in IEEE Communications Surveys & Tutorials, vol. 26, no. 2, pp. 1279-1321, Secondquarter 2024, doi: 10.1109/COMST.2023.3347145

APPENDIX – AI/ML DICTIONARY

AI/ML related term	Description
AI-Native systems	A system where the AI is an intrinsic part of it.
AI model	A program/algorithm that has been trained to recognize certain patterns or make certain decisions without further human intervention.
AI agent	A component designed to handle tasks and processes with a degree of autonomy within a system or network
Agentic AI	The type of artificial intelligence that is designed to exhibit autonomous decision-making and behaviour, often with the capability to act independently within certain defined constraints or goals.
LLMs	Pretrained models in a vast amount of factual knowledge, usually from publicly available data sources to enable agentic AI to understand, generate, and respond to natural language requests.
Multi-agent Systems	A system where multiple autonomous agents interact and collaborate to perform complex tasks.
Generative AI	The use of AI models to create content, including text, video, code and images.
Explainable AI	A set of processes and methods that allow human users to comprehend and trust the results and output created by AI/ML systems
Supervised Learning	A category of ML that uses labelled datasets to train algorithms to predict outcomes and recognize patterns.
Unsupervised Learning	A category of ML where unlabelled data is provided and patterns/insights are discovered without any explicit guidance or instruction.
Reinforcement learning	A category of ML that follows a trial-and-error learning process by interacting with the environment.
Neural networks	Complex supervised learning methods that mimic the way biological neurons work together to identify phenomena, weigh options and arrive at conclusions.
Deep learning	A learning method which uses hundreds or thousands of layers of a Neural Network to train its models.
Deep Reinforcement learning	An expansion of the RL paradigm where Deep Learning (practically deep neural networks) are used to approximate functions.
Federated learning	A distributed learning approach where instead of transferring data to a central point to train a model, models are trained locally where the data resides and then the models are passed to a central federation unit.
ML model training phase	The phase during which raw or pre-processed data is used to produce or update an ML model.
ML model emulation phase	The phase during which the performance of an ML entity is assessed/validated in a controlled virtual environment.

ML model deployment phase	The phase during which a validated ML model is loaded into an AI/ML inference function that will consume it.
ML model inference phase	The phase during which the ML model is used to support real-time or near-real-time decision making.
MLops	Machine Learning Operations, refers to the combination of practices, tools, and organizational processes that support the lifecycle of ML models.
MLFLow	MLflow is an open-source platform designed to manage the end-to-end machine learning lifecycle.

LIST OF EDITORS & REVIEWERS

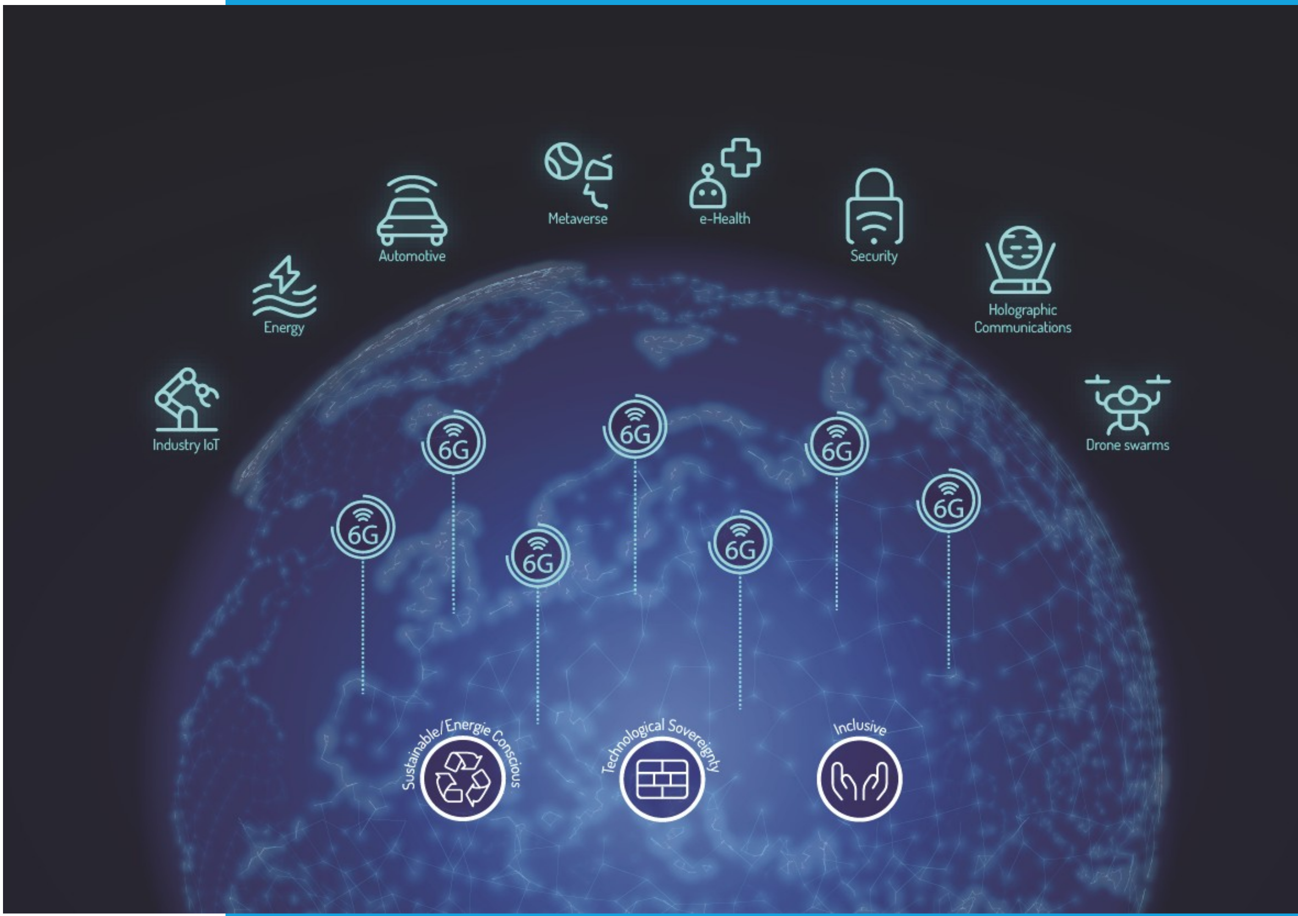
Name	Company / Institute / University	Country
Document editors		
Dimitris Tsolkas	Fogus Innovations & Services P.C.	GR

Name	Company / Institute / University	Country
Paper Reviewers		
Anastasius Gavras	EURESCOM GmbH	DE
Kostas Trichias	6G Industry Association (6G-IA)	BE

LIST OF CONTRIBUTORS

Name	Company / Institute / University	Country
Dimitris Tsolkas	Fogus Innovations & Services P.C.	GR
Souvik Paul	Lenovo	DE
Antonio Skarmeta	Universidad de Murcia	ES
Christos Tranoris	Unicersity of Patras	GR
Ricard Vilalta	Centre Tecnològic de Telecomunicacions de Catalunya	ES
Ramon Agüero	Universidad de Cantabria	ES
Cyril Shih-Huan Hsu	University of Amsterdam	NL
Chrysa Papagianni	University of Amsterdam	NL

The SNS JU projects have received funding from the Smart Networks and Services Joint Undertaking (SNS JU) under the European Union's Horizon Europe research and innovation programme.



Website: https://smart-networks.europa.eu/sns-ju-working-groups/

Co-funded by the European Union