6GSNS

Smart Networks and Services Joint Undertaking

Technology Board

AI/ML as a Key Enabler of 6G Networks

Methodology, Approach and AI-Mechanisms in SNS JU

WHITE PAPER

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EXECUTIVE SUMMARY

The Smart Networks and Services Joint Undertaking (SNS JU) is spearheading Europe's efforts to establish global leadership in 6G telecommunications. Under the Horizon Europe program, SNS JU has initiated numerous projects integrating Artificial Intelligence (AI) and Machine Learning (ML) as foundational components of future networks. These AI/ML solutions address critical 6G objectives, such as enhanced performance, energy efficiency, and advanced security, reflecting a comprehensive and collaborative approach to innovation in telecommunications.

The SNS JU Technology Board (TB), the collaborative body of the leading technical experts of all ongoing R&I projects, has performed a survey across 33 R&I projects from the first two phases (Call 1 and Call 2) of the SNS JU, that are engaging in the development of AI-based solutions, to better understand the approach, methodologies and models used by AI experimenters, as well as to generate insights regarding the network layers that AI mechanisms are applied to, the data sets used for training, the goal of the developed mechanisms and more. Based on the analysis of the TB survey, the following highlights can be identified:

- ***199 AI/ML-based mechanisms*** are being developed by 33 Call 1 and Call 2 projects, with applications addressing (among others) Radio Access Network (RAN), resource management, network diagnostics and energy efficiency.
- Learning approaches include ***supervised learning*** (50%), ***reinforcement learning*** (25%), and ***unsupervised learning*** (15%), with hybrid techniques also employed.
- In terms of methodology, ***Neural networks*** and ***deep learning dominate*** (51%), followed by reinforcement learning (20%) and decision-based methods (10%).
- ***Explainable AI (XAI) solutions***, though less common, are emerging as crucial for transparency and regulatory compliance.
- In terms of ***Data training sets***, the projects leverage a mix of *synthetic* (41%), *real* (33%), and *mixed* datasets (16%), combating the limited real-world data availability.
- ***Input data sources*** predominantly include RAN metrics (38%) and cross-domain data (14%), while ***AI-mechanisms' output*** focuses on radio optimization (32%), security (17%), and resource management.
- ***Model performance metrics*** such as accuracy and precision dominate, followed by ***application-specific metrics*** like Quality of Service (QoS).
- ***Privacy-preserving approaches***, including federated learning, are widely adopted.

Through emphasis on collaboration and transparency the SNS JU experimenters are laying the ground work for the first AI-native 6G mechanisms, targeting performance, network management and sustainability enhancements. As such, the SNS JU drives innovation and reinforces Europe's technological sovereignty, ensuring alignment with global efforts on ethical and sustainable AI integration.

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ABBREVIATIONS AND ACRONYMS

3GPP	3rd Generation Partnership Project
5G	5th Generation
5G-ACIA	5G Alliance for Connected Industry and Automation
6G	6th Generation
AI	Artificial Intelligence
B5G	Beyond 5G
CAPEX	Capital Expenditures
CCI	Commonwealth Cyber Initiative
CDF	Cumulative Distribution Function
CHEDDAR	Communications Hub for Empowering Distributed Cloud Computing Applications and Research
CNF	Cloud Native Function
CNN	Convolutional Neural Networks
CSA	Coordination and Support Action
CSI	Channel State Information
DDPG	Deep Deterministic Policy Gradient
DNN	Deep Neural Networks
DoD	Department of Defence
DQN	Deep Q-Networks
DRL	Deep Reinforcement Learning
DT	Decision Trees
E2E	End-to-End
EAIB	European Artificial Intelligence Board
eMBB	Enhanced Mobile Broadband
EMF	Electric and Magnetic Fields
EPSRC	Engineering and Physical Sciences Research Council
EU	European Union
FL	Federated learning
GAN	Generative Adversarial Networks
GDPR	General Data Protection Regulation
GPAI	Global Partnership on Artificial Intelligence
ICT	Information and Communication Technology
ITE	Information Technology Equipment
ISAC	Integrated Sensing and Communication
KPI	Key Performance Indicator
LCM	Life Cycle Management
LIME	Local Interpretable Model-agnostic Explanations
LLM	Large Language Models
LMLC	Low Mobility Large Cell

LSTM	Long Short-Term Memory
MEC	Mobile Edge Computing
MIMO	Multiple Input Multiple Output
ML	Machine Learning
mMIMO	Massive MIMO
mMTC	Massive Machine Type Communications
MSIT	Ministry of Science and ICT
NIST	National Institute of Standards and Technology
NOMA	Non-Orthogonal Multiple Access
NSF	National Science Foundation
NWDAF	Network Data Analytics Function
OPEX	Operating Expenditures
OSNR	Optical Signal-to-Noise Ratio
PAWR	Platforms for Advanced Wireless Research
PCA	Principal Component Analysis
PGW	Packet Gateways
QoE	Quality of Experience
QoS	Quality of Service
R&I	Research and Innovation
RAN	Radio Access Network
REASON	Realising Enabling Architectures and Solutions for Open Networks
RF	Random Forest
RINGS	Resilient and Intelligent Next G Systems
SHAP	SHapley Additive exPlanations
SME	Small to Medium Enterprise
SNS JU	Smart Networks and Service Joint Undertaking
SVD	Singular Value Decomposition
TB	Technology Board
TCO	Total Cost of Ownership
UE	User Equipment
VM	Virtual Machines
VNF	Virtualized Network Functions
XAI	Explainable Artificial Intelligence
XGMF	XG Mobile Promotion Forum

1. INTRODUCTION

Artificial Intelligence (AI) technologies have experienced remarkable growth in recent years, transforming industries with their ability to analyse data, automate processes, and deliver intelligent solutions. This rapid evolution has been fuelled by advancements in machine learning and neural networks, making AI a cornerstone of innovation. In the telecommunication sector, AI has the capability to profoundly change the way future networks operate by enabling autonomous and predictive functionalities on multiple network layers. As such, AI has already been nominated as one of the major building blocks of future 6G networks by prominent standardisation bodies and associations [1][2], while the vast majority of global telecommunications stakeholders are prioritizing research into AI-based technological enablers [3], as 6G is expected to offer AI-native functionalities.

The Smart Networks & Service Joint Undertaking (SNS JU)[1], is a public-private partnership operating autonomously under the Horizon Europe Programme, responsible for funding research and innovation activities in Europe regarding telecommunications networks and services. More than 60 projects are already operational under the umbrella of the SNS JU, researching, developing, testing and validating technological solutions for the advancement and development of 6G networks. Several of these projects are developing AI/ML based solutions, as part of their efforts to deliver the stringent Key Performance Indicators (KPIs) set forth for 6G [1] and to generate innovative AI-based services.

This white paper is produced by the SNS JU Technology Board (TB), which is the main collaborative body of SNS JU technical experts, and aims to introduce the work taking place within the SNS JU projects, relevant to AI/ML. An overview of the projects is provided while details and statistics about the AI/ML based solutions developed within the SNS JU are also presented including the goal of the AI mechanisms, the learning type & method, the network segment they are implemented on, characteristics of the AI models used and information about the training data sets and the output of the mechanisms. It is the hope of the SNS JU TB that this paper will assist in the understanding of the work performed within the SNS JU on the very important topic of AI, promote the AI solutions developed in Europe and foster synergies with other global AI and 6G experts.

1.1. INTRODUCTION TO SNS JU PROJECTS

The SNS JU aims to foster Europe's technology sovereignty in 6G by funding projects that shape a solid Research and Innovation (R&I) roadmap and deployment agenda by engaging a critical mass of European stakeholders and facilitating international cooperation on various 6G initiatives. The SNS JU, has taken over from the 5G Public Private Partnership (5G PPP)[2], and has already funded 63 projects from its first two calls, while an additional 16 projects will start on January 2025 from call 3. A comprehensive roadmap of SNS JU reaching 2031 and comprising 3 different phases is presented in Figure 1, while additional information can be found on the SNS JU website[1].

[1] https://smart-networks.europa.eu/

[2] https://5g-ppp.eu/

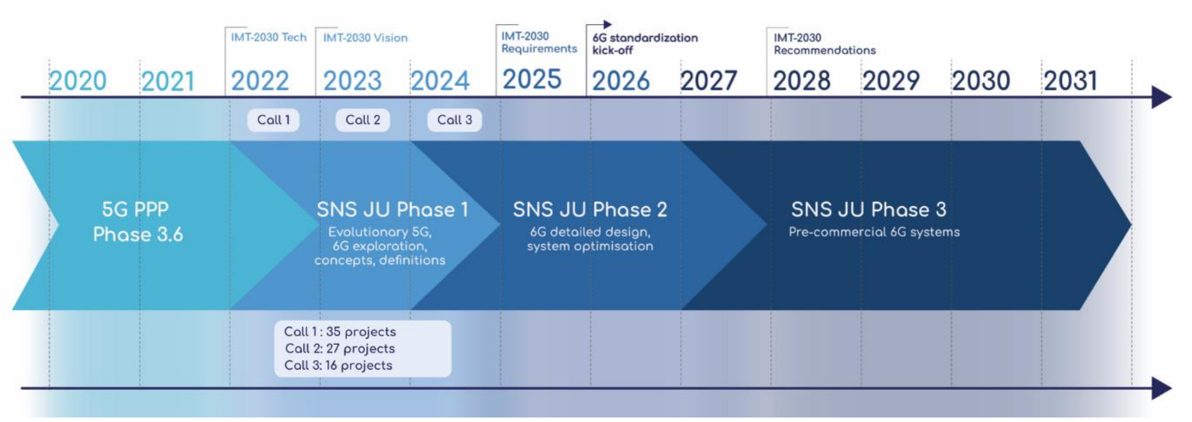

Figure 1: SNS JU Roadmap including the different Phases and active calls

From the ongoing 63 projects, 60 of them are R&I projects, while another 3 are Coordination and Support Actions (CSA) supporting the operation the SNS JU operation and promoting and facilitating the work taking place. 35 projects were funded as part of the 1st call, with 288 unique beneficiaries receiving approximately 250 million € funding, while the 2nd call funded 28 projects with 222 unique beneficiaries sharing 132 million € of additional funding.

As the 35 call 1 projects have been operational for a couple of years now, some concrete samples of their work are currently being evaluated, and some first insights are becoming available. At the same time, call 2 project solutions are maturing after almost 1 year of work, and offer significant know-how in the further development of technologies and solutions for B5G and 6G networks. As several of these solutions are AI-based and/or instantiate novel AI services, it is now a good point in time to present an overview of the approach and AI/ML solutions developed by the SNS JU projects.

1.2. SNS JU PROJECTS WORKING ON AI/ML

Before jumping into the analysis of the SNS JU AI solutions and their characteristics, it is important to understand the role that AI/ML solutions play in the work of the SNS JU projects, and why AI is considered one of the main building blocks of 6G networks. The SNS JU experimenters are working on a multitude of novel technological enablers, that stand to significantly increase the performance and/or efficiency of contemporary mobile networks or to even offer innovative services that were not feasible before.

In a survey conducted by the SNS OPS CSA project and presented in June 2024 [4], the 60 Call 1 and Call 2 R&I projects were asked to identify the key technologies they utilize in their work and the main technological aspects they are investigating. The results are depicted in Figure 2, where AI/ML-powered technologies are ranked as the top aspect that SNS JU projects are investigating (49 out of 60 projects). Even though this fact only provides a very high-level view of the engagement of SNS JU projects with AI/ML solutions, as there were no further insights provided at that stage with regards to the exact role of AI/ML within each project, it still paints a very strong picture when it comes to the faith that AI enjoys among the SNS JU researchers as one of the key elements of the future networks and services.

Figure 2: Technological issues / aspects addressed by SNS Ju Call 1 & Call 2 projects

Based on these results, the SNS JU TB agreed that it is important to further investigate the role that AI/ML solutions play in the SNS JU projects, to analyse the approach that the various projects are taking and to derive overall statistics about the more prominent methods, types, data and approaches used for AI solutions, within the SNS JU.

In an extensive survey conducted directly by the SNS TB, ***33 SNS JU projects***[3] provided detailed information about the AI mechanisms and solutions they are working on, which resulted in the analysis presented in this paper. The gained insights are presented here, to raise awareness and promote the AI solutions being developed within SNS JU, and to assist in the alignment with the global AI and 6G communities on approaches, methodology and use of data for AI mechanisms.

1.3. PAPER STRUCTURE

The rest of this document is structured as follows. Section 2 provides an overview of the AI/ML landscape, exploring regulatory frameworks, international trends, and architectural considerations for 6G. Section 3 categorizes solution types, network segments, goals, use cases, and solution maturity levels, Section 4 outlines methodologies and learning

[3] The remaining 16 projects, out of the 49 that had declared some sort of engagement with AI/ML, are only superficially using some AI components, thus did not take part in this survey. This 33 projects that participated in the survey can be found in the List of Contributors.

approaches, Section 5 examines explainability, complexity, and monitoring of AI/ML solutions and Section 6 addresses datasets, focusing on input training data, output mechanisms, and privacy/security issues. The document concludes with a summary of findings and a roadmap for future work (Section 7).

2. AI/ML LANDSCAPE & SNS CONSIDERATIONS

Before diving into the details of the AI/ML mechanisms developed in SNS JU, it is important to understand the global landscape around AI research and the variables that may affect AI-related research, as the SNS JU does not work in isolation, but as part of a global effort. This section provides an overview of the AI regulatory framework in Europe, the International AI research efforts that work in tandem with EU efforts and an analysis of the architectural implications that AI/ML mechanisms will have on 6G network architecture.

2.1. AI REGULATORY FRAMEWORK

As the adoption of AI accelerates across industries, establishing regulatory frameworks has become a top priority for governments and international organizations. These frameworks aim to ensure that AI technologies are developed and deployed ethically, transparently, and in alignment with the public interest. While specific approaches vary across regions, several notable initiatives are shaping the global regulatory landscape for AI.

In Europe, the proposed AI Act stands out as a landmark regulation. Introduced by the European Commission in April 2021, the AI Act seeks to create a harmonized framework for the development and use of AI across the EU [4]. The legislation adopts a risk-based approach, categorizing AI systems into four levels of risk: unacceptable, high, limited, and minimal. High-risk AI systems, such as those used in critical infrastructure, law enforcement, and education, will be subject to stringent requirements, including mandatory risk assessments, transparency obligations, and compliance with European standards. The Act also includes provisions to ban certain AI applications, such as real-time biometric surveillance in public spaces, unless under narrowly defined circumstances. Alongside the AI Act, the EU's Ethics Guidelines for Trustworthy AI, developed by the High-Level Expert Group on AI, emphasize principles such as human agency, privacy, and accountability [6].

A key component of the AI Act is its focus on creating a robust ecosystem for compliance, innovation, and enforcement across all EU member states. Central to this ecosystem is the establishment of the European Artificial Intelligence Board (EAIB), which will oversee the implementation of the regulation and ensure consistency in its application. The EAIB will provide guidance, coordinate efforts among national supervisory authorities, and facilitate the sharing of best practices across the EU [7].

The AI Act defines specific obligations for different roles in the AI value chain, including providers, users, and importers of AI systems. Providers of high-risk AI systems are required to conduct rigorous conformity assessments to ensure their systems meet requirements related to risk management, data quality, transparency, and cybersecurity. Furthermore, these providers must implement robust post-market monitoring to identify and address any risks that may arise during the lifecycle of the AI system. Users of high-risk AI systems, including organizations and individuals, are required to maintain proper oversight, ensure the systems are used for their intended purposes, and report any malfunctions/misuse [4].

The Act also emphasizes the need for transparency in AI systems. Providers of AI technologies must ensure that users are informed about the capabilities and limitations of

AI systems. For example, in cases involving AI-enabled deepfake technology or chatbots, users must be explicitly notified that they are interacting with an AI system. This transparency is critical to fostering public trust and ensuring informed consent in the use of AI systems [4][8].

To support small and medium-sized enterprises (SMEs) and startups in complying with the AI Act, the European Commission plans to establish a series of "AI Regulatory Sandboxes." These sandboxes will provide a controlled environment for experimentation, allowing organizations to test their AI systems under the supervision of regulatory authorities without the risk of immediate penalties. This initiative aims to balance innovation and compliance, ensuring that businesses can develop cutting-edge AI solutions while adhering to ethical and legal standards [7].

Another significant aspect of the AI Act is its integration with existing EU legislation on data protection, such as the General Data Protection Regulation (GDPR). By aligning the requirements of the AI Act with the GDPR's emphasis on privacy and data security, the EU aims to ensure that AI systems respect individuals' fundamental rights. For instance, the use of biometric data in high-risk AI systems must comply with GDPR standards, including obtaining explicit consent and demonstrating a legitimate interest [9].

In addition to the AI Act, the EU has introduced complementary initiatives to advance its regulatory and ethical AI framework. For example, the Coordinated Plan on Artificial Intelligence 2021 Review outlines actions to accelerate investment in AI, boost AI innovation capacity across member states, and ensure the ethical and human-centric use of AI technologies [10]. This plan emphasizes the importance of cross-border collaboration and the development of AI that aligns with European values.

The EU's regulatory approach is also notable for its efforts to influence global AI standards. By establishing a comprehensive framework that balances innovation, ethics, and public trust, the EU aims to set a benchmark for AI governance worldwide. The AI Act has the potential to shape international discussions on AI regulation, encouraging other regions to adopt similar frameworks or align their policies with the EU's approach. As part of this strategy, the EU actively participates in multilateral initiatives such as the Global Partnership on Artificial Intelligence (GPAI) and works closely with international organizations like the OECD to promote interoperability in AI governance [11][12].

While progress has been made, significant challenges remain in harmonizing AI regulations across jurisdictions. Differences in legal traditions, economic priorities, and societal values lead to varied approaches, posing risks to interoperability and international collaboration. Addressing these challenges will require ongoing dialogue and cooperation among governments, industry stakeholders, and civil society, ensuring that the benefits of AI are equitably distributed while mitigating risks.

2.2. AI INTERNATIONAL LANDSCAPE

The development of 6G is a priority for researchers around the world and AI/ML is an integral part of many of the supporting funding programs. While most countries that include focused research programs on 6G include AI/ML as a component in these programs, several countries have specific programs focused on the use of AI in networks, including the US, China, and the UK. The 6G SNS JU program also includes projects specifically formed around cooperative research with other countries outside the EU, focusing on a variety of technological aspects including AI.

Worldwide 6G Initiatives involving AI/ML (Non-EU)

- Telecoms Hubs (UK)
- REASON (UK)
- Next G Alliance (USA)
- PWSCIF (USA)
- RINGS (USA)
- IMT-2030 (6G) PG (China)
- Bharat 6G Alliance (India)
- Brasil6G (Brazil)
- XGMF (Japan)
- 6G Forum (South Korea)

The Engineering and Physical Sciences Research Council (EPSRC) and DSIT in the UK joined forces to create three Telecoms Hubs (TITAN[4], HASC[5], and CHEDDAR[6]), all unified across a national research infrastructure program called JOINER[7]. The Communications Hub for Empowering Distributed Cloud Computing Applications and Research (CHEDDAR) in particular will explore how cloud systems and AI can bolster communications. The use of AI is also included in each of the other two hubs, which focus on spectrum and connectivity. Other national projects include the use of AI in networks, such as Realising Enabling Architectures and Solutions for Open Networks (REASON[8]) which will leverage AI techniques for network-edge and network wide automation as one of five main project objectives. The UK participates in the EU Horizon Europe program and includes institutions that are associated partners on multiple 6G SNS JU projects.

The US 6G national roadmap [13] was developed by the Next G Alliance and includes AI Native Wireless Networks as one of six priority areas. The roadmap identifies five areas in which AI is expected to play an important role for networks and devices: AI-based PHY/MAC, AI-assisted mobility, AI-optimized resource allocation AI for orchestration, AI for security. The US National Science Foundation (NSF) partnered with the Department of Defence (DoD), the National Institute of Standards and Technology (NIST) and several industry partners to fund research on Resilient and Intelligent Next G Systems (RINGS) [14] of which the use of AI/ML in 6G networks is a priority. The $1.5B Public Wireless Supply Chain Innovation Fund is a 10 year national program managed by the NTIA. While the priority of the program is on open and interoperable wireless technologies, the use of AI is called out as an important feature in

[4] https://www.titancambridge.com/

[5] https://uktin.net/navigate-uk-telecoms/government-funded-projects/hasc-hub-all-spectrum-connectivity

[6] https://cheddarhub.org/

[7] https://joiner.org.uk/

[8] https://reason-open-networks.ac.uk/

these future systems. US research on 6G builds on the NSF Platforms for Advanced Wireless Research (PAWR) which provide research infrastructure for 6G research including the use of AI/ML [15]. The NSF has funded 25 AI Institutes, two of which deal directly with 6G networks: Athena AI Institute (edge computing and next generation networks) and the AI-EDGE Institute (edge wireless networks and distributed Intelligence). The NSF also funds a large scale engineering research centre, Smart Streetscapes [9], which includes research on intelligent wireless edge technologies. In addition to national funding, states are funding research on 6G such as the Commonwealth Cyber Initiative[10] (CCI) that conduct research on AI for 6G.

The Ministry of Science and ICT (MSIT) in South Korea developed a 6G R&D Implementation plan that identifies an ultra-precision network as a major priority alongside low earth orbit satellite communications. As part of this strategy, ultra intelligence is one of six focus areas, seeking to apply AI to all sections of the network, including core and wireless [16]. South Korean government, industry and academic programs related to 6G are coordinated by the 6G Forum, which includes a working group on AI and Big Data. MSIT developed the K-Network 2030 Strategy to position South Korean as a model country for future networks and calls out the use of AI for power optimization of base stations [17]. A new collaborative project between the SNS JU and the Republic of Korea has been included in the SNS JU work programme of 2024, focusing on 6G RAN and AI aspects, and will commence in the beginning of 2025.

In Japan, the development of 6G was recently unified under the XG Mobile Promotion Forum (XGMF). Major national research funding ($450M) is administered by NICT and their Beyond 5G/6G white paper [18] highlights the use of AI/ML in optimal control and zero-touch autonomous control and orchestration, including integration with Digital Twin methods . A new collaborative project between the SNS JU and Japan has also been included in the SNS JU work programme of 2024, with AI as the main focal points, and will also commence in the beginning of 2025.

China recently launched its Artificial Intelligence Plus program which is specifically focused on 6G wireless technology R&D to leverage AI to promote new industrialization[11] . The IMT-2030 (6G) Promotion Group provides industry coordination within China related to 6G. This group released a white paper in 2023 that describes in detail seven typical use cases for convergence of mobile communications and AI of most interest to network operators [19], including ML model and data formats and specifications.

The Bharat 6G Alliance is the major 6G program in India and it focuses its research on AI/ML on the air interface for the development of 6G networks [20]. Similarly, AI/ML is one of 5 key research areas in the Brasil6G national program in Brazil [21]. Research will explore the use of AI/ML in network functions and algorithms, coding, MIMO beam forming and mobility management in mmWave.

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[9] https://cs3-erc.org/wi-edge/

[10] https://cyberinitiative.org/

[11] https://global.chinadaily.com.cn/a/202403/08/WS65eab174a31082fc043bb82f.html

2.3. AI ARCHITECTURAL IMPLICATIONS FOR NEXT GENERATION SNS

Different AI architecture choices can lead to different implications for the current as well as future 6G network architecture and features under consideration. Specifically, given the heterogeneity of services alongside the challenges of provisioning value proposition to the end user, it is vital that the various AI/ML architectures be evaluated on a cost-benefit basis.

2.3.1. DIFFERENT TYPES OF AI/ML ARCHITECTURES

2.3.1.1. CENTRALIZED AI/ML ARCHITECTURE

Typically, in centralized AI/ML models, both the training and inference steps are carried out in a centralized server/location. This is because, firstly the data is collected from various other data-collecting/generating nodes and then a centralized model is trained over that data. Secondly, during inference, data points from these data-collecting/generating nodes are streamed to the central node where the AI/ML model is running, and then a prediction/estimation is generated based on the trained AI/ML model. This prediction/estimation is then passed to the data-collecting/generating nodes, which in turn use it to make network optimization decisions. Note that, these network optimization decisions may range from simple power control mechanisms, all the way to VNF/CNF scaling decisions as well as network slice deployments and design, etc. Figure 3 illustrates a centralized AI/ML architecture.

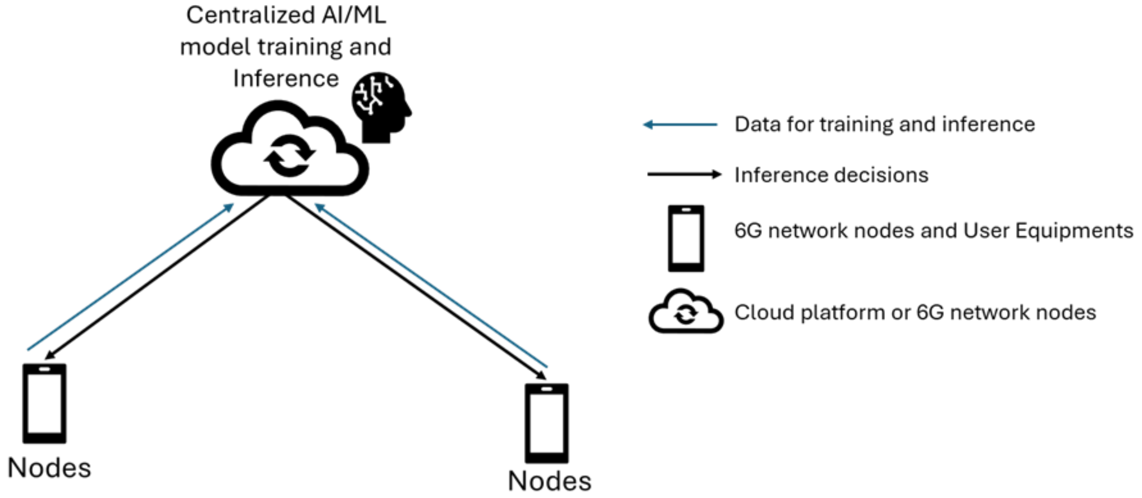

Figure 3: Centralized AI/ML architecture

2.3.1.2. FEDERATED AI/ML ARCHITECTURE

Federated learning (FL) is a distributed machine learning approach where data remains localized, and only model updates are shared across participating nodes. Concretely, there is a global model which is trained using anonymized and sub-sampled datasets, thus provisioning it with privacy from the point-of-view of data. Next, the model updates are shared with the edge nodes participating in the federated architecture based on the learnt global model. The nodes either directly utilize the global model updates to update their own local models or they utilize it as a baseline to fine-tune their model via additional data collection. Lastly, both the global and local model inferences are utilized to perform a variety of tasks such as optimize resource allocation, predictive maintenance, and user experience without exposing private data. Such a setup, as mentioned earlier, ensures privacy and security, which is one of the main value propositions that 6G aims to provide over 5G. Figure 4 illustrates the FL AI/ML architecture.

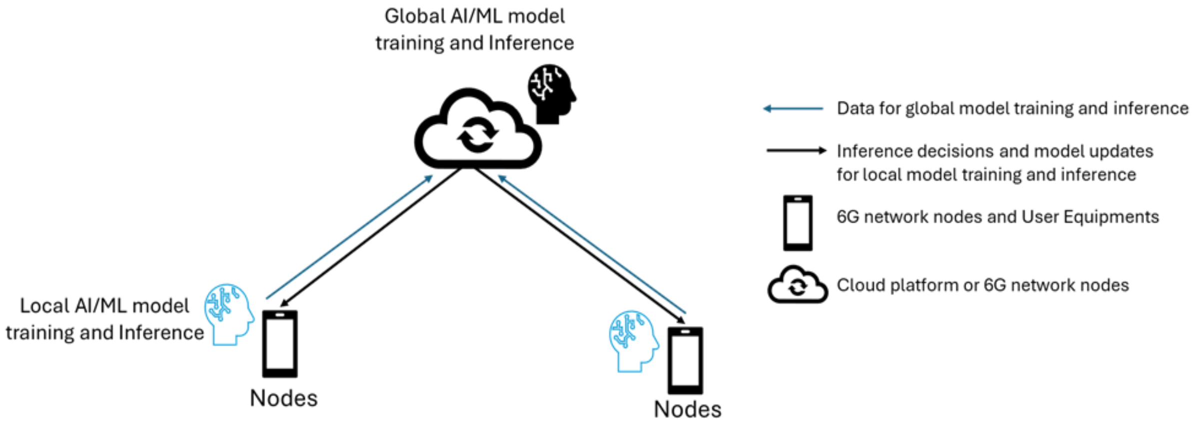

Figure 4: Federated/Distributed AI/ML architecture

2.3.1.3. ADDITIONAL AI/ML ARCHITECTURES

Besides the above-described architectures which attract a big part of the research community's attention, there are additional architecture that may be considered:

- **Offline & Online Learning**: Offline learning refers to the process where models are trained offline, while the inference is done online. This is different from online learning, wherein the training and inference are both done online, i.e., the model is first learnt based on real observations and later when the training objective is reached it is used for inference [24]. Offline methods are preferred when near instantaneous/real-time decision making with a sufficiently large sample space is needed, while online methods perform better when training data is unavailable or difficult to transfer/stream and there is enough compute and time availability near the edge.
- **One-sided Model**: The one-sided model refers to the AI/ML architecture wherein the training and inference is done from a single network node, which in this case may either be the UE, gNB, core network function (CNF) or a management and orchestration function/entity.
- **Two-sided Model**: The two-sided model refers to the AI/ML architecture wherein the training and inference is done between two collaborative nodes, such as UE and gNB, gNB and other CNFs, or for that matter any two 6G system nodes.

2.3.2. IMPACT OF AI/ML ARCHITECTURES ON 6G

While the previous section described various AI/ML architectures, in this section we analyse the impact of the choice of AI/ML architectures on several 6G performance, operational and architectural aspects.

- **The Total Cost of Ownership (TCO)**: is characterized by two components, namely the Capital Expenditures (CAPEX) and Operating Expenditures (OPEX). The choice of AI/ML architectures will impact both these components.
  - CAPEX: 6G systems will deploy AI/ML models in a variety of use cases as well as network nodes [25]. To deploy such diverse AI/ML models, 6G systems would need to consider deploying AI/ML specific hardware, data collection processes, training hardware and software and more, leading to increased CAPEX for operators and vendors.
  - OPEX: The continuous utilization of AI/ML models, deployed across the various layers of the 6G E2E system, to perform various tasks such as anomaly detection, resource optimization, etc. will inevitably result in the consumption of additional power and potentially cloud resources, which may lead to increased OPEX for operators.
- **Data-OPS Pipelines:** Data Operations (DataOps) focuses on the efficient management, processing, and analysis of data to support decision-making and system optimization. Concretely, to manage the training and inference processes for the myriad AI/ML models that will be deployed within the 6G system, an efficient DataOps pipeline will be needed. A brief analysis on the multitude of aspects that the 6G systems would need to consider follows, derived from [23] and [26]:
  - Data Fusion and Aggregation: Combine diverse data streams (e.g., telemetry, user metrics, and network state) for holistic decision-making.
  - Privacy-Preserving Data Management: Ensure data security and compliance while maintaining analytical capabilities.
  - Intent-Driven Data Processing: Automate and optimize data workflows based on user-defined goals (intents).
  - Real-Time Data Operations: Support latency-critical applications like URLLC through rapid data processing and low-latency decision-making.
  - Closed-Loop Data Pipelines: Establish feedback loops to refine models and operations based on observed outcomes.
  - Interoperable Data Ecosystems: Facilitate seamless data sharing across multiple domains while maintaining security and trust.
- **ML-OPS Pipelines:** Machine Learning Operations (MLOps), focuses on the streamlined deployment, scaling, and management of machine learning (ML) models in production environments. It combines practices from DevOps, DataOps, and AI/ML development to address challenges like reproducibility, scalability, and

collaboration in ML workflows. From a 6G system standpoint, the following aspects should be considered to manage the AI/ML workflows:

- End-to-End Model Pipelines: Automating the training, deployment, and retraining of ML models for dynamic network management.
- Privacy-Aware MLOps: Addressing privacy challenges in federated learning while managing ML pipelines.
- Scalable Model Deployment: Deploying ML models at scale across heterogeneous and distributed 6G infrastructures.
- Closed-Loop Automation: Automating feedback loops where model performance informs subsequent adjustments or retraining.

The integration of AI/ML will lead to a profound impact on how the 6G system architecture is designed. Specifically, aspects related to compute requirements, Application Programming Interfaces (APIs), data storage requirements, DataOps, MLOps, privacy and security, multi-stakeholder, etc., will need to be considered in finer detail. All of these components will have to be designed carefully, while also considering the use case requirements. Table 1 summarizes the aforementioned aspects, their requirements and the impact on 6G system.

Table 1: Impact on 6G architecture due to AI/ML

Aspects	Requirements	Impact on 6G Architecture
Interfaces	Standardized APIs and intent-based communication	Flexible, scalable interfaces for AI/ML workflows
Compute Resources	Additional capacity for real-time AI/ML processing	Heterogeneous computing at edge and core
Data Storage	Efficient and scalable storage for diverse datasets	Distributed data lakes and meta-data management
Privacy and Security	Secure, privacy-preserving mechanisms for sensitive data	Federated learning and privacy-preserving technologies
Multi-stakeholder needs	Collaboration frameworks for diverse operators and providers	Multi-tenant architectures and governance frameworks

3. OVERVIEW OF AI/ML WORK IN SNS

Before diving into the technical details of the AI mechanisms and the respective analysis of the model structure, data use and methodology, it is important to properly define the scope and structure of this survey. This section provides information regarding the projects that contributed to the survey, the number and high-level category and goal of the analysed AI mechanisms and the maturity of the AI solutions, in order to provide a thorough understanding of the project input before moving ahead with the analysis.

3.1. SNS PROJECTS & AI SOLUTIONS STATISTICS

As discussed in Section 1.2, 33 SNS JU R&I projects provided detailed information regarding the AI mechanisms and solutions they are working on, which enabled the analysis presented in this white paper. Figure 5 provides a categorisation per call of the projects that develop AI/ML mechanisms, as well as the number of AI/ML solutions being currently developed within the SNS JU. Out of the 33 R&I projects in total that develop AI/ML solutions, 22 of them come from call 1 (67%) developing 149 AI-based solutions (~75% of the total AI solutions), while approximately 50 AI-based solutions (~25% of total) are developed by the eleven projects of call 2. The larger number of call 1 projects engaging with AI-based solutions can be explained by the fact that there are more call 1 projects than call 2 overall (35 vs 27), while another contributing factor may be that call 2 projects have been operational for less than a year and hence are still investigating the suitability of AI-mechanisms for their work. The statistical analysis that will be presented in the following sections, is based on the characteristics of these 199 AI-based solutions.

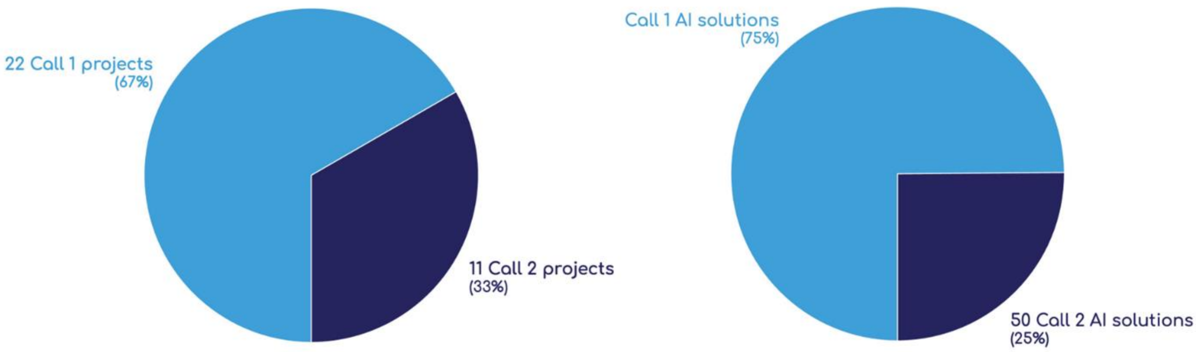

Figure 5: Analysis of SNS projects (left) and AI solutions (right) included in the survey.

3.2. HIGH LEVEL CATEGORISATION OF SOLUTIONS

The projects examined were categorized based on the High-level category of solutions they apply AI/ML mechanisms on. Eight (8) such high-level categories have been defined as depicted in Figure 6. Those range from Network Planning to Network Diagnostics, and Network Optimization for different parts of the network.

From Figure 6 it can be derived that 17 projects use AI/ML for Optimization and Control at the RAN level and another 17 create AI/ML solutions for Network Diagnostics and Insights at all network parts. Network Optimization for Compute Infrastructures and Network Optimization and Control for Security are addressed by 14 and 11 projects, respectively. It is worth noting that half of the projects only address one or two areas, whereas the other half addresses between three and seven categories.

As depicted in Figure 7, out of the 199 solutions reported, 36.6% are developed to address Network Optimization and Control at the RAN level, and almost 19% examine solutions for the Network diagnostics and insights, on any level (RAN/Core/Transport category). Network Planning accounts for only 3.3% of the total number of solutions.

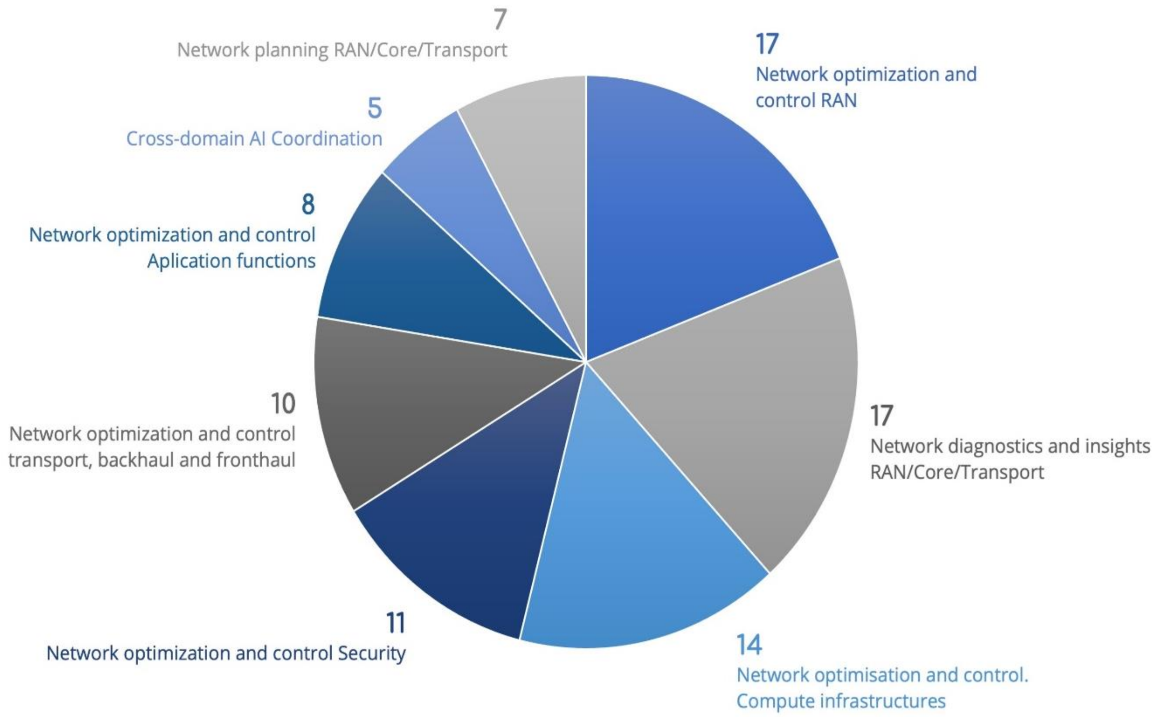

Figure 6: Number of Projects Dealing with Each Category

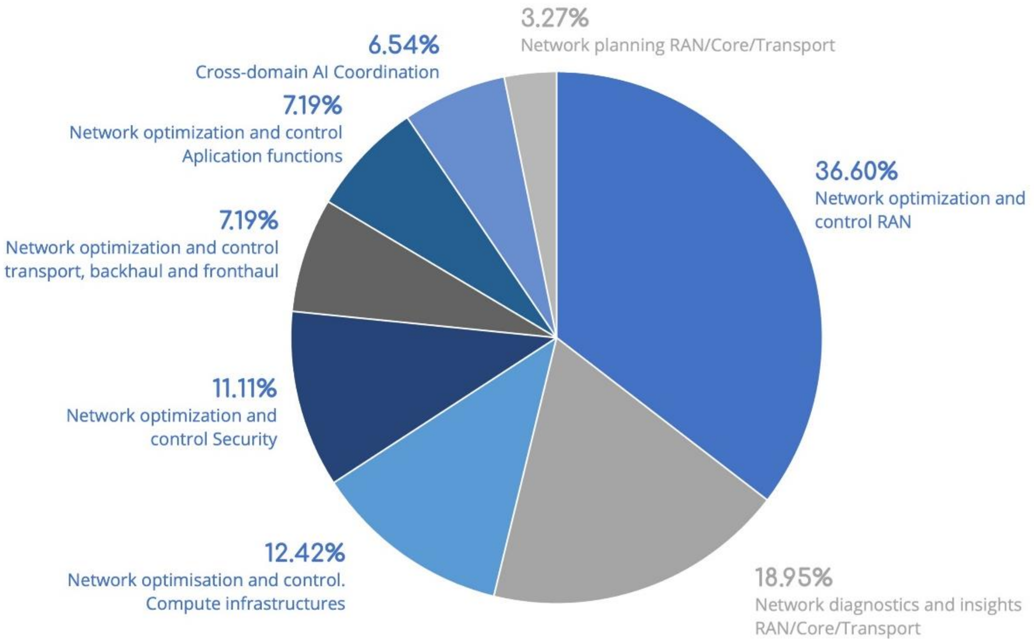

Figure 7: Percentage of Solutions in each Category.

3.3. NETWORK SEGMENTS

SNS JU experimenters develop AI/ML mechanisms that are applied on different network segments. This section provides insights regarding the specific network segments that the SNS JU mechanisms address including *Far edge,* Radio Access Network (RAN)*, Fronthaul, Backhaul, Transport, Edge* and *Core*. Far edge refers to end equipment/devices with compute capabilities (e.g., UEs, IoT devices etc.); RAN refers to the radio access part of the network, i.e, to gNBs or other radio units; Fronthaul and Backhaul refer to the nodes which are topologically split/decoupled from the radio units and realize the lower and the higher part in the protocol stack of the radio processes, respectively; the Transport segment includes the network nodes (switches etc.) which transfer the user data between the radio and the core network; the Edge segment refers to nodes with compute resources which are physically located close to the access part of the network; and the Core network includes those nodes that bridge the telecom operator's domain with the internet.

Figure 8 depicts the statistical analysis of the targeted network segments by AI/ML mechanisms within the SNS JU. Irrefutably the complexity and the challenging nature of the RAN has attracted most of the solutions counting roughly for the 43% of the total solutions. Application of AI-based mechanisms in cross-domain solutions, i.e., solutions affecting multiple different layers, are the second most popular, while Edge and Transport AI-based solutions are also attracting the interest of a significant number of projects. Overall, it can be observed that a large variety of AI-based mechanisms are developed within the SNS JU, covering all the network layers and showcasing the pervasive nature of AI within 6G network research and development efforts.

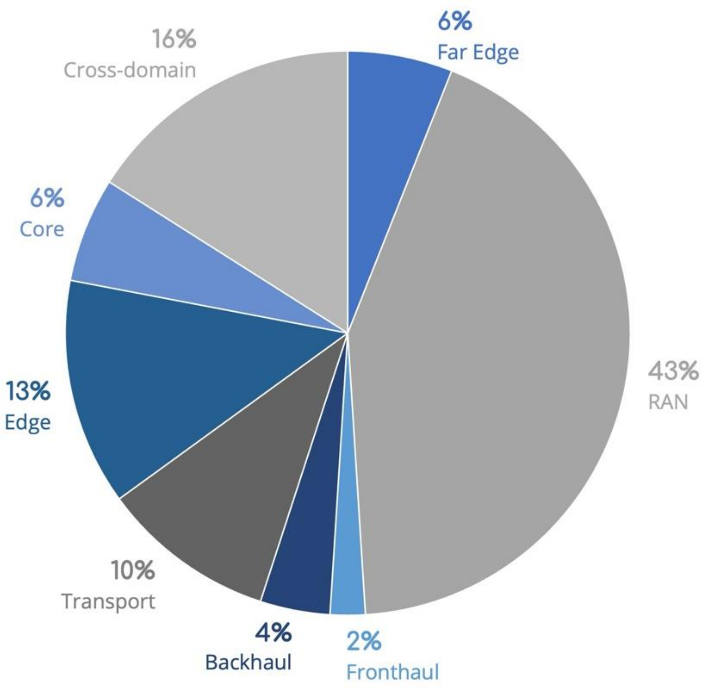

Figure 8: Targeted Network Segments by AI/ML mechanisms within SNS JU

3.4. GOAL OF AI/ML MECHANISMS

The goals of using AI/ML mechanisms in SNS projects span a great variety depending on the key focus area of the project within the scope of 6G development. The summary of the comparison of goals and baseline of using AI/ML mechanisms is shown in Figure 9. It is clearly visible that the vast majority (31%) of technical enablers in SNS projects are using AI/ML for optimization purposes under a wide variety of topics including resource allocation, quality of service (QoS), radio link quality, Integrated Sensing and Communication (ISAC) performance, and device performance. Another significant portion of technical enablers (i.e., 19%) related to security, privacy, and trust is associated with AI/ML mechanisms. Around 29% of the technical enablers from SNS projects are using AI/ML methods for improving throughput and channel state information (e.g., Channel State Information - CSI) and enhancing energy efficiency in wireless communication systems. Nearly 7% of technical enablers that use AI/ML mechanisms have goals related to the estimation of certain features like traffic flows, quality of experience (QoE), network performance, or user equipment (UE) distribution. Network management and automation is another area in which the SNS projects are applying AI/ML techniques. Finally, about 9% of the selected enablers aim to improve AI/ML model training itself, reflecting a focus on advancing the underlying algorithms.

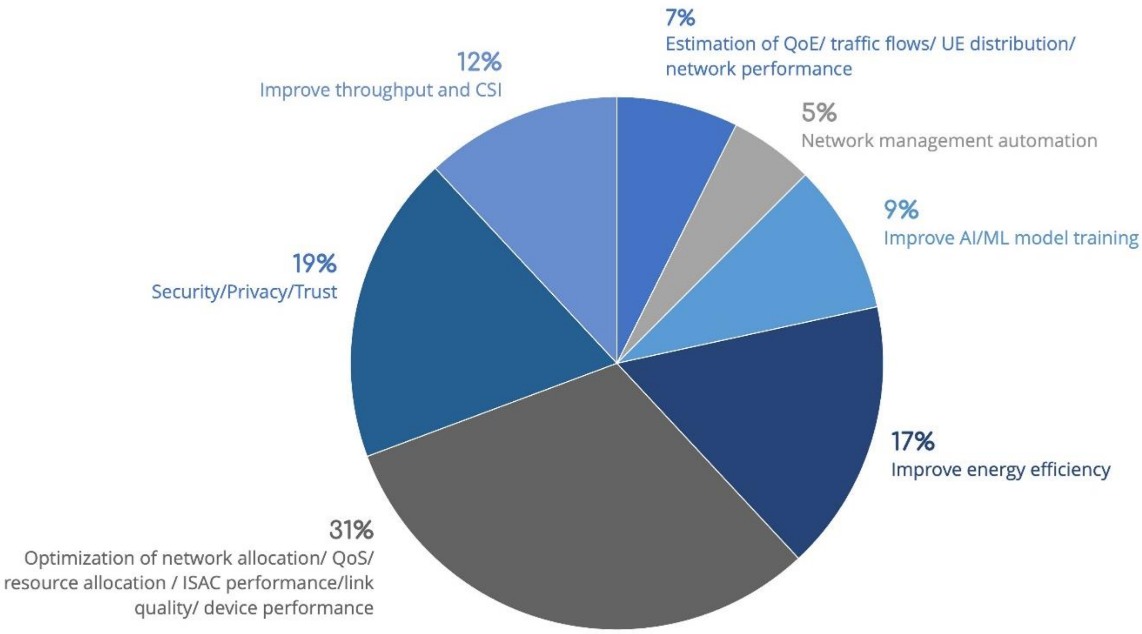

Figure 9: Goal and baseline comparison of AI/ML mechanisms

3.5. USE CASES ADDRESSED

Another interesting classification of the SNS JU AI-based mechanisms is according to the specific Use Case that they address. 27 different use cases have been identified during this survey, spanning the whole spectrum of entities and activities in a 6G environment, both at the service level, but also regarding Management and Orchestration, Monitoring, Scheduling, Resource Allocation and many more. Figure 10 lists all the use case categories sorted in order of occurrence within the SNS JU projects.

Use cases that relate to the Radio aspect at the Physical Layer are the most prevalent with 16.67% of the AI-based solutions addressing them, followed very closely, at 16.13%, by those addressing Security and Anomaly Detection. Resource Allocation in the network and Security and Privacy account for 10.75% and 7.53%, respectively. It is worth noting that 7% of the use cases are not dealing with the network operations or the services and applications but are of general purpose or agnostic. Use of AI/ML for Computing Resource Allocation is at 6.45% and addressing Energy Efficiency is at 5.38%.

Once again, the wide applicability of AI mechanisms within the SNS JU and the significant variety and differentiation of the developed solutions for diverse use cases, are verified, indicating that SNS JU researchers are building a wide knowledge base on AI-applicability in 6G network aspects.

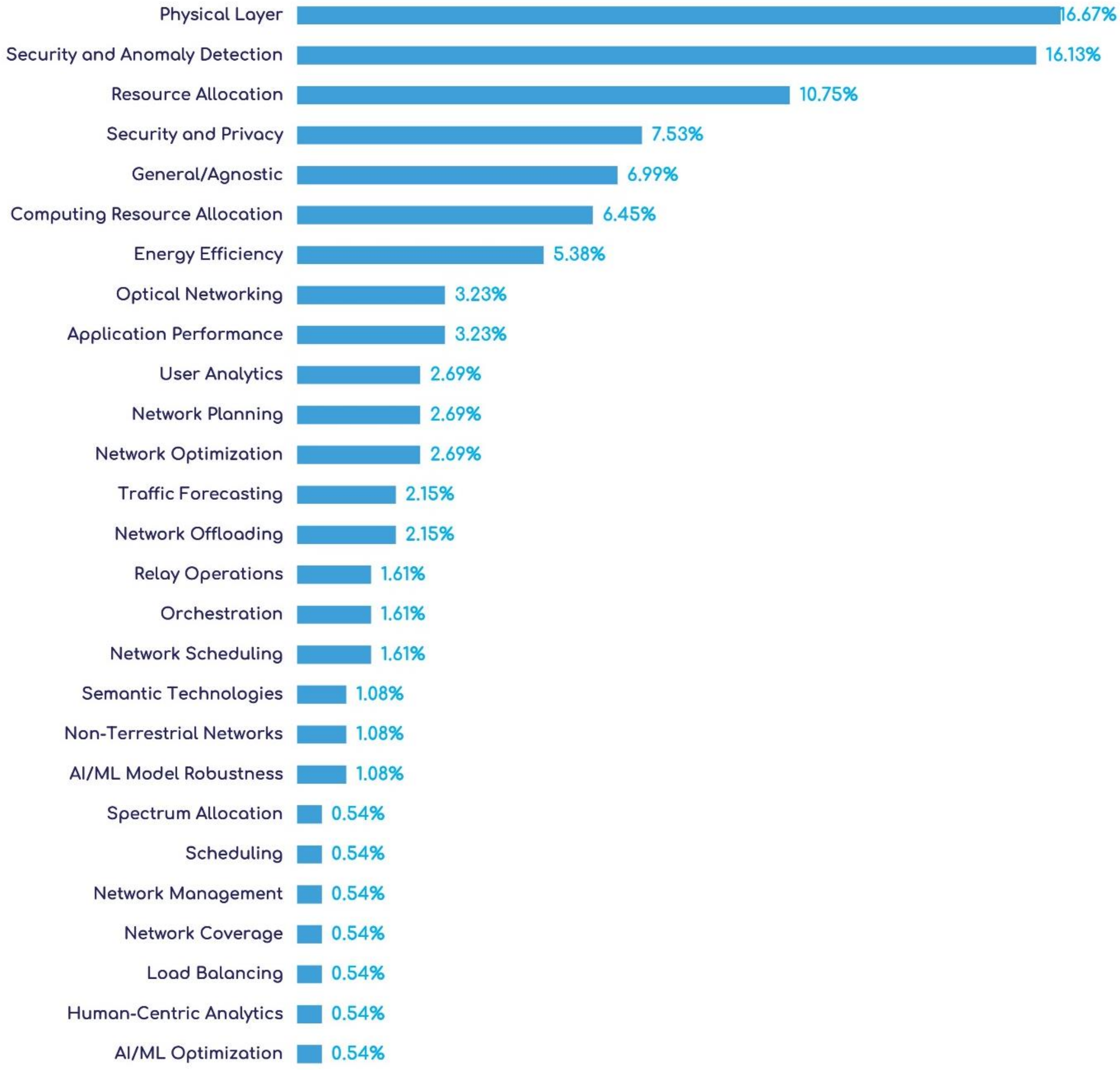

Figure 10: Breakdown per Use Case

3.6. MATURITY OF AI/ML SOLUTIONS

The survey also attempted to investigate how advanced each of these 199 AI-based solutions are, by analysing their Maturity Level (ML). Each SNS project was asked to categorize each of their AI solutions according to three maturity levels namely:

- ML1: Conceptual design
- ML2: Preliminary results available
- ML3: Consolidated / mature results available

Figure 11 depicts the analysis of the maturity levels of the AI solutions developed within the SNS projects, while Figure 12 presents a break-down per call. It can be observed that the majority (62%) of AI-based solutions developed within SNS, are at a stage where preliminary results of the AI-mechanism are available (ML2), while mature results are available for about 17% of the mechanisms and another 21% are at the conceptual design phase. It is also interesting to note that while call 1 and call 2 projects both have a substantial number of AI mechanisms at a conceptual stage and at a preliminary results phase, mechanisms at a mature (consolidate) stage (ML3) are only available by call 1 projects. This makes sense, as call 2 projects have only been operational for less than a year at the time of writing of this white paper, and they did not have the time to fully develop, test and validate their mechanisms. It is expected that call 2 projects will also reach ML3 for several of their mechanisms within the next year.

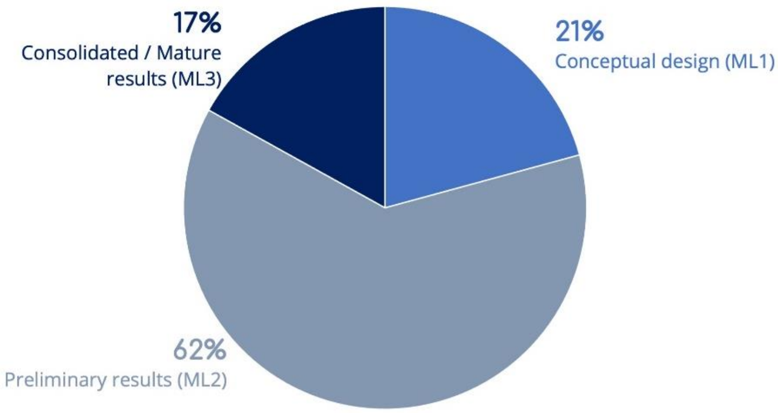

Figure 11: Analysis of the Maturity Level (ML) of AI solutions included in this survey.

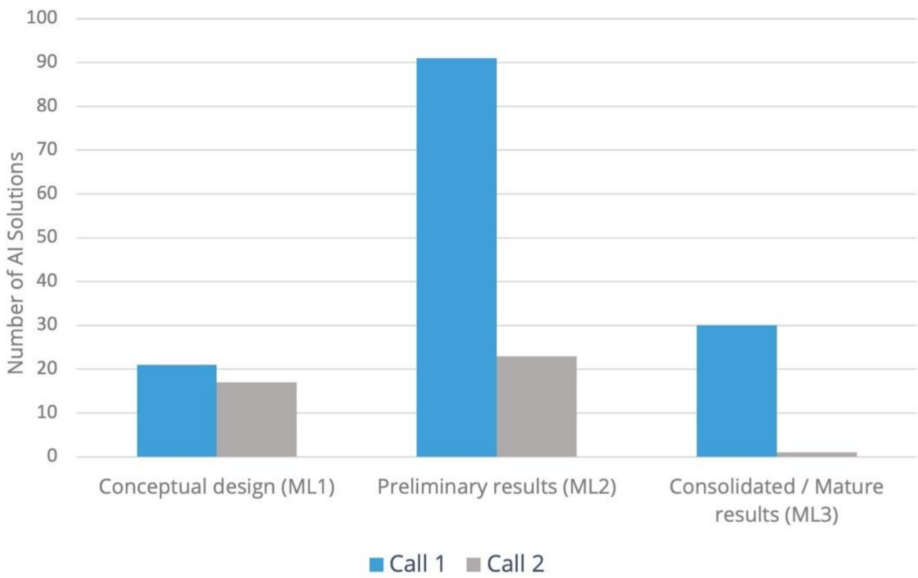

Figure 12: Maturity Level of AI/ML solutions per SNS Call

4. AI/ML METHODOLOGIES IN SNS

4.1. LEARNING TYPE

AI refers to technologies that enable machines to mimic human intelligence when it comes to decision making and problem solving. To achieve this behaviour the Machine Learning (ML) toolbox is used. ML includes the methods (i.e., the algorithms/processes) that enable machines to learn, i.e., to improve them in solving specific tasks with experience [27]. There are three main types of learning: ***Supervised Learning***, ***Unsupervised Learning*** and ***Reinforcement Learning*** (RL) [28]. 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 includes methods like: K-Means, Principal Component Analysis, and Singular Value Decomposition; while RL includes policy and value-based RL methods, where value-based ones include Dynamic Programming, Monte Carlo, and Temporal Difference approaches.

Neural networks are complex supervised learning methods and rely on training data to learn and improve their accuracy over time. However, this method has 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 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 is a learning method which used hundreds or thousands of layers of a Neural Network to train its models. Convolutional neural networks (CNNs), Recurrent neural networks (RNNs), Autoencoders and variational autoencoders, and Generative adversarial networks (GANs) are some examples of Neural Networks used for deep learning. Within the Deep learning category, the generative methods (Generative AI) are further highlighted, since they attract a lot of attention due to the plethora of the related application domains.

Finally, it is worth mentioning that due to the rapid increase and use of AI in different network domains and applications, new challenges emerge, including the concepts of explainability and decentralization. On the one hand, ***Explainable*** artificial intelligence (XAI) is a set of processes and methods that allows human users to comprehend and trust the results and output created by machine learning algorithms. On the other hand, the request for protection of the training data and the need to keep them distributed into various places brought the concept of Federated learning. 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.

Given this analysis, Figure 13 depicts how the learning mechanisms used for the SNS JU AI/ML based solutions are distributed among the three main learning types (Supervised, Unsupervised, and RL). An additional category (depicted as "other" in Figure 13) was added to include the cases that semi-supervised or mixed approaches are adopted by the SNS JU projects. Having studied 199 ML solutions from 33 SNS-JU projects, almost half of them target the Supervised learning type, while RL approaches follow covering 24% of the solutions. The plethora of well-defined Supervised learning algorithms with available reference implementations justifies the preference against the Unsupervised ones. Also, the problems under study are mainly referring to the RAN network segment (as depicted in Figure 8) implying that task-driven learning is more suitable for RAN procedures compared to data-driven, The lack of data for training and the dynamic nature of the problems in RAN segment justify that 24% of the solutions use RL methods (trial-and-error based learning).

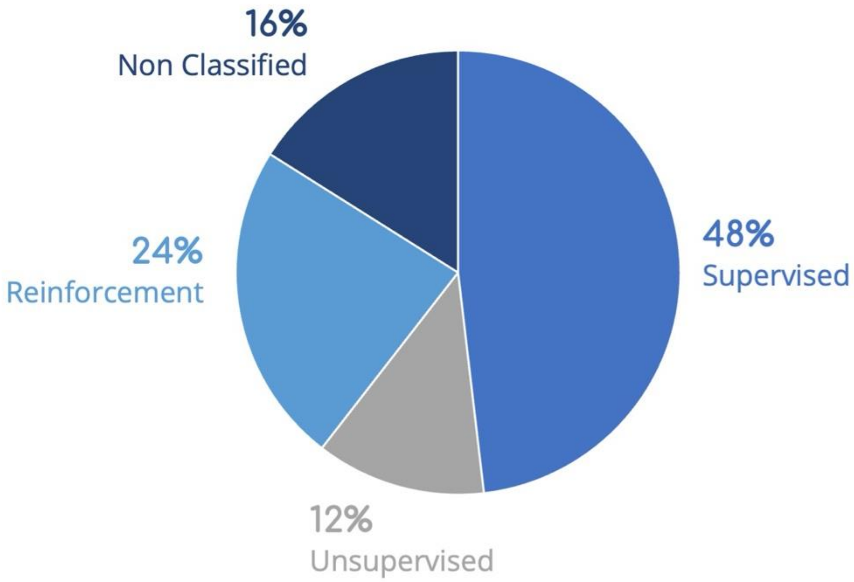

Figure 13: Utilized Learning Type by SNS JU mechanisms

4.2. AI/ML METHODS

The inputs collected from the survey also included the specific AI/ML methods used in SNS projects. To better study the inputs provided by the SNS JU projects we cluster them in six categories, five main ones and a sixth one where hybrid versions are included (i.e., methods that combine approaches from the main categories. The six categories identified are as follows:

- M1: Neural Networks and Deep Learning methods
- M2: Reinforcement Learning methods
- M3: Decision-based methods
- M4: Unsupervised methods
- M5: Explainable AI methods
- M6: Hybrid methods

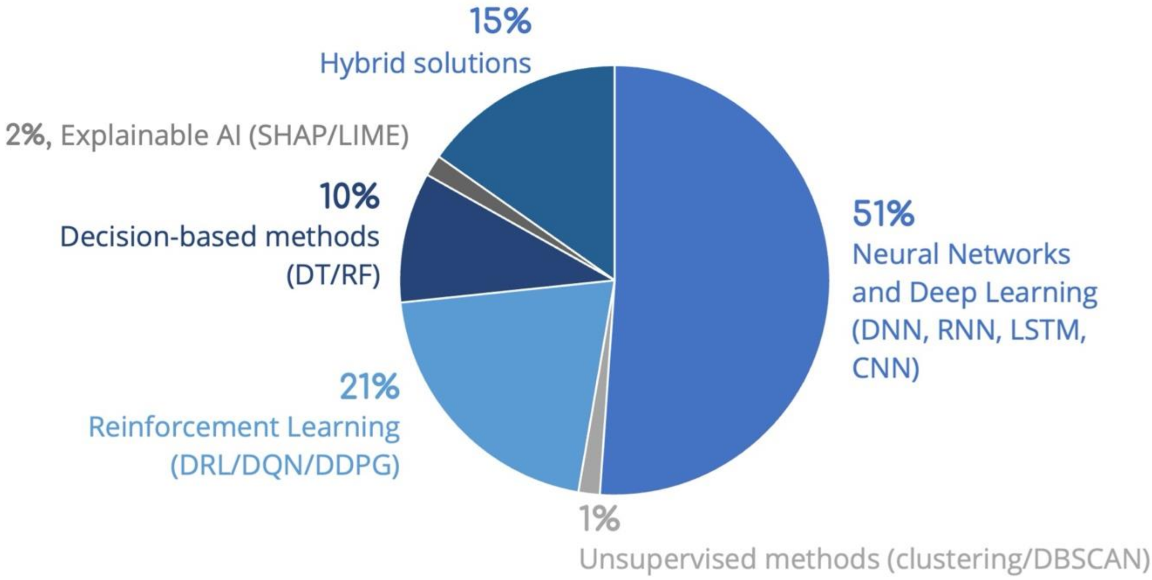

Figure 14: Distribution of AI/ML methods used in SNS projects

As shown in Figure 14, the majority of the projects (51%) use neural networks and deep learning-based methods to develop their technical solutions. This includes many variants of techniques such as Deep Neural Networks (DNN), Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and Generative Adversarial Networks (GANs). The next most popular approach, with about 21%, is to use reinforcement learning methods such as Deep Reinforcement Learning (DRL), Deep Q-Networks (DQN), and Deep Deterministic Policy Gradient (DDPG) techniques. Decision-based approaches such as Decision Trees (DTs) and Random Forest (RF) methods are used around 10% from the total. Both unsupervised methods like clustering or DBSCAN, and explainable AI (XAI) techniques like SHAP or LIME are used by very few enablers. Approximately 15% of the technical enablers use multiple methods from the given categories. This includes the Large Language Models (LLMs) that use Generative AI (GAI), XAI to interpret their decisions or incorporate RL for fine-tuning responses.

5. AI MODELS IN SNS

5.1. MODEL EXPLAINABILITY

Artificial Intelligence (AI) has become integral to various sectors, making decisions that significantly impact society. However, many AI models, especially complex ones like deep neural networks, operate as "black boxes," providing little insight into their decision-making processes. This opacity raises concerns about trust, accountability, and fairness. AI model explainability addresses these issues by making AI systems' operations transparent and understandable to humans.

AI model explainability refers to the methods and techniques used to make the decision-making processes of AI models transparent and comprehensible. It enables stakeholders to understand how inputs are transformed into outputs, ensuring that AI systems are making decisions based on relevant and fair criteria. This transparency is crucial for building trust, facilitating regulatory compliance, and identifying and mitigating biases within AI systems.

Explainable AI can be categorized into two main types:

- **Post-Hoc Explainability**: These methods are applied after the model has been trained and deployed. They aim to interpret and explain the decisions of complex models without altering their internal structures. Techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) fall into this category.
- **Interpretable Models**: These are models designed to be inherently understandable. Their decision-making processes are transparent by design, making them easier to interpret. Examples include decision trees, linear regression models, and k-nearest neighbours (kNN).

5.1.1. COMMON AI EXPLAINABILITY METHODS

Several methods are employed to achieve AI model explainability. We can apply the classification above to the explainability methods described in this section:

- Shapley Additive exPlanations (SHAP, Post-Hoc): A unified approach that assigns each feature an importance value for a particular prediction, based on cooperative game theory. SHAP values provide a consistent and interpretable measure of feature importance.
- Feature Importance (Post-Hoc): This method assesses the contribution of each input feature to the model's predictions. By ranking features based on their impact, stakeholders can understand which variables most influence the model's decisions.
- Decision Trees (Interpretable Model): These models split data into branches to represent decisions and their possible consequences. Their hierarchical structure makes the decision-making process transparent and easy to follow.

- k-Nearest Neighbours (kNN, Interpretable Model): An instance-based learning method that classifies data points based on the majority label among their 'k' closest neighbours. Its simplicity allows for straightforward interpretation of decisions.
- Other Interpretable Models (Interpretable Model): Models such as linear regression and logistic regression offer mathematical simplicity and clear relationships between inputs and outputs. Rule-based models and decision lists also fall into this category, providing straightforward if-then rules for predictions.

5.1.2. TRENDS IN AI EXPLAINABILITY

The demand for explainable AI has surged across industries due to regulatory requirements, ethical considerations, and the need for trust in AI systems. According to a report by Markets and Markets[12], the global explainable AI market size was valued at USD 6.2 billion in 2023 and is projected to reach USD 16.2 billion by 2028, at a CAGR of 20.9% during the forecast period.

Industries such as telecoms, finance, and legal services are increasingly adopting explainable AI to ensure compliance and maintain stakeholder trust. In the telecoms sector, explainable AI is being used to optimize network management and enhance customer experience. For example, telecom companies leverage AI models to predict network failures and customer churn. Explainability methods, such as SHAP or decision trees, allow operators to understand the key factors contributing to network anomalies or customer dissatisfaction, leading to informed decision-making and tailored service improvements.

Additionally, explainable AI supports fraud detection and billing accuracy in telecommunications. By providing insights into how anomalies or discrepancies are flagged, these tools ensure transparency, enabling telcos to address customer concerns and enhance service credibility.

In summary, AI model explainability is essential for fostering trust, ensuring compliance, and promoting ethical AI practices. As AI continues to permeate various sectors, the emphasis on developing and implementing explainable models is expected to grow, aligning technological advancements with societal and industry-specific values and expectations.

5.1.3. XAI METHODS USED IN SNS PROJECTS

According to the definitions above, and taking all the inputs from SNS Projects, we have analysed the responses and clustered them into the following categories[13]:

- Intrinsic Interpretable Models: These are projects the have reported models that are inherently understandable by design (e.g., decision trees, kNN)
- Explainability Methods: These are projects that have reported models Post Hoc (LIME, Feature Importance, or others mentioned)
- No Info: For projects that have not reported enough information.

[12] https://www.marketsandmarkets.com/Market-Reports/explainable-ai-market-47650132.html

[13] Some projects are using a mix of AI Explainability methods, some of them falling in the two main categories. In this case, the Project result is reported in both categories.

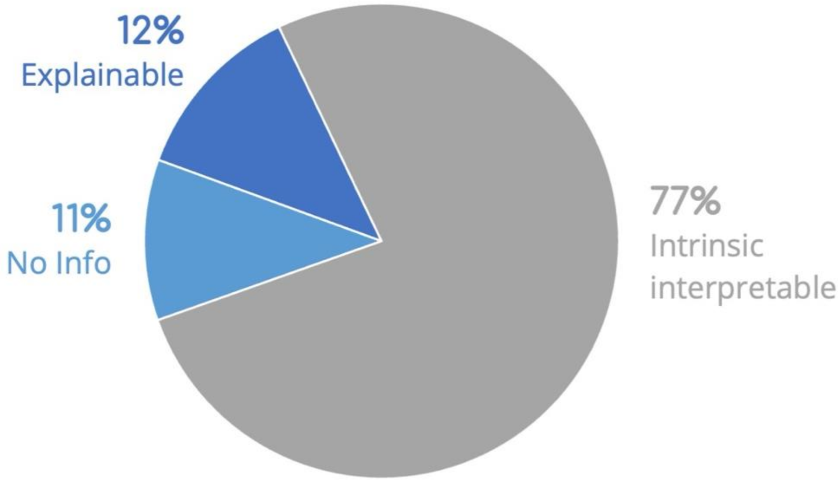

Figure 15: Distribution of XAI methods used in SNS projects

As shown in Figure 15, the majority of the projects reported AI methods (~77%) use intrinsic Interpretable AI, meaning projects have reported models that are interpretable by design. Some of the results reported include Neural Networks in several flavours (DNN, RNN, CNN, LTSM, …), Decision trees, kNearest Neighbours, Linear Regression, etc. Only few projects (~11%) report models that include Explainable AI like SHAP and -LIME, while approximately 12% did not report any information about Explainable AI.

5.2. MODEL COMPLEXITY / TIMESCALE OF OPERATIONS

The inputs collected from the survey also included the inference timescale of the AI/ML solutions used in the SNS projects. In this context, *inference* refers to the process of using a trained model to make runtime predictions or decisions on new, unseen data. Typically, RAN solution require ultra-fast decision-making (real-time), while decisions in the core or backhaul, may deal with less strict requirements. Regarding the runtime inference, the analysis revealed a diverse distribution; we categorized these timescales into three main groups, inspired by classifications from the Open Radio Access Network Alliance (O-RAN) [29] and the 5G Alliance for Connected Industry and Automation (5G-ACIA) [30]:

- Real-Time (<10ms),
- Near Real-Time (10ms–1s)
- Non Real-Time (>1s)

These thresholds serve as indicative benchmarks rather than strict definitions, as some respondents reported qualitative categorizations (e.g., "near real-time") rather than precise numerical values. Notably, 44% of respondents did not report a clear timescale, often citing dependencies on factors such as the kind of AI/ML model, targeted platform, implementation setup (e.g., window), and hardware. Among the ones that did report a timescale for their mechanisms, as shown in Figure 16, 42% were classified as real-time, and

38% as near real-time, reflecting a significant focus on latency-sensitive applications. Conversely, 20% of the solutions operated in the non-real-time domain, catering to use cases less constrained by latency.

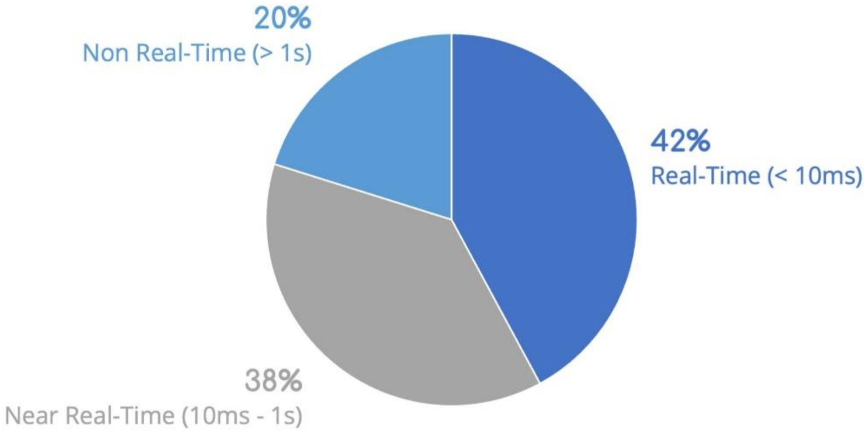

Figure 16: Timescale of Inference of the AI/ML solutions in SNS JU

The survey additionally explored the model complexity, where different factors have been identified as contributors, with the top five being the model architecture (i.e., number of layers), the learning approach adopted (e.g., shallow ML, DL, RL/DRL, GenAI), the number of model parameters, the model hyperparameters, and the feature space size. Figure 17 illustrates the distribution of the top five factors contributing to model complexity, where "Yes" refers to the percentage of projects considering the factor.

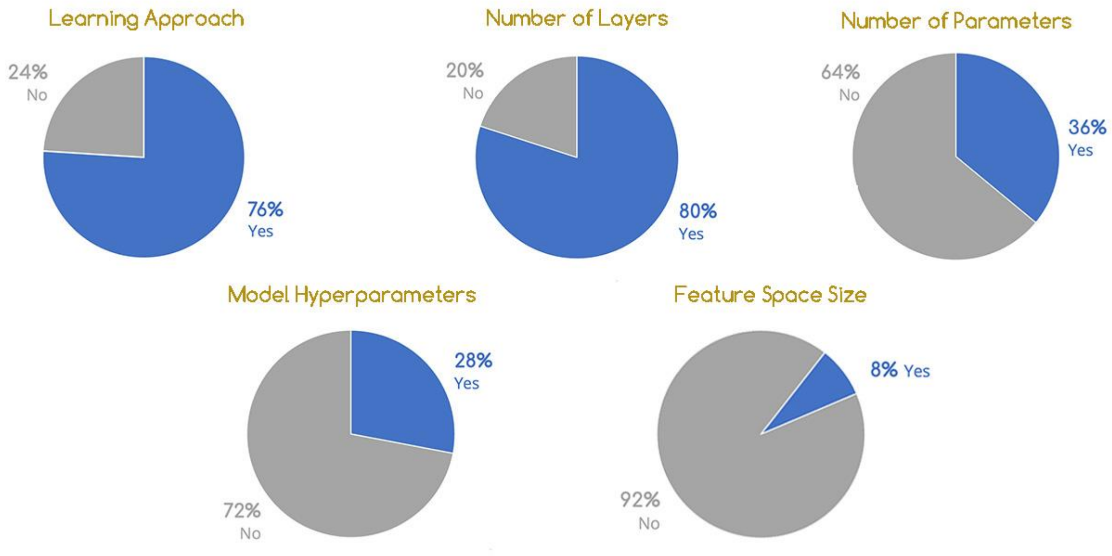

Figure 17: Distribution of the top five factors contributing to model complexity.

Another factor that correlates indirectly to model complexity is the training time. In fact, an increased training time often reflects a more complex model's architecture, a higher model's parameter count, or a large/high-dimensional datasets processed by the model.

Using this factor, we categorized the model complexity into four levels: Very Low (milliseconds), Low (seconds to minutes), Medium (hours), and High (days), depending on the time required for training the model. As shown in Figure 18, the provided inputs revealed that 65% of the proposed models have a "Low" complexity, while 13% exhibit a "High" complexity. A closer investigation of the provided inputs highlights that models with low complexity leverage ML algorithms or DL approaches with a number of layers with fewer than 10. Furthermore, the provided inputs underline that high complexity are associated with GenAI models.

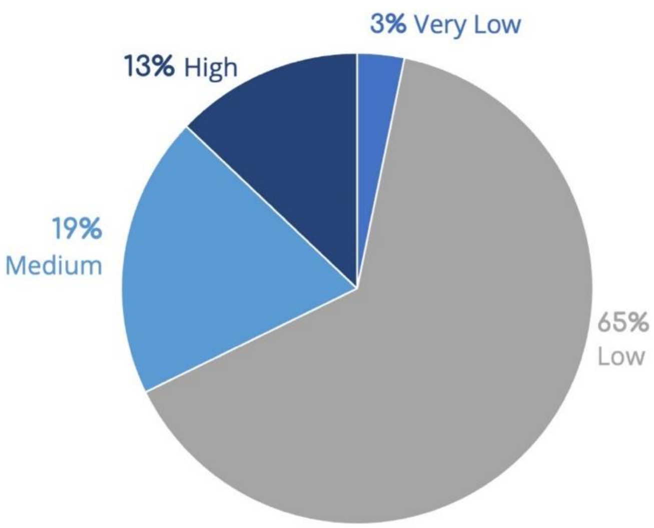

Figure 18: Model complexity categorization based on training time

5.3. MODEL MONITORING

Model monitoring refers to the process of closely tracking the quality of ML models, allowing to ensure that the ML models are always delivering the desired quality level. The inputs of the survey revealed various metrics that the projects adopted to monitor the efficiency and effectiveness of the developed models. These include the model performance metrics (e.g., accuracy, precision, recall, F1 score), the model efficiency metrics (e.g., training time, inference time, communication cost, and energy efficiency), security metrics (e.g., adversarial attack success rate and number of inference requests), privacy metrics (e.g., privacy attack success rate and differential privacy delta), explainable AI metrics, and application-specific metrics (e.g., QoS, spectrum efficiency, beamforming gain, and cell data rate).

The analysis of the provided results, depicted in Figure 19, show that model performance metrics are the predominant metrics (39%) adopted in assessing the model quality, followed by application-specific metrics (27%) and model efficiency metrics (22%). Meanwhile, metrics related to robustness, privacy preservation, and explainability are less considered, indicating that these important metrics, which underpin the trustworthiness of AI models, are still not receiving adequate attention.

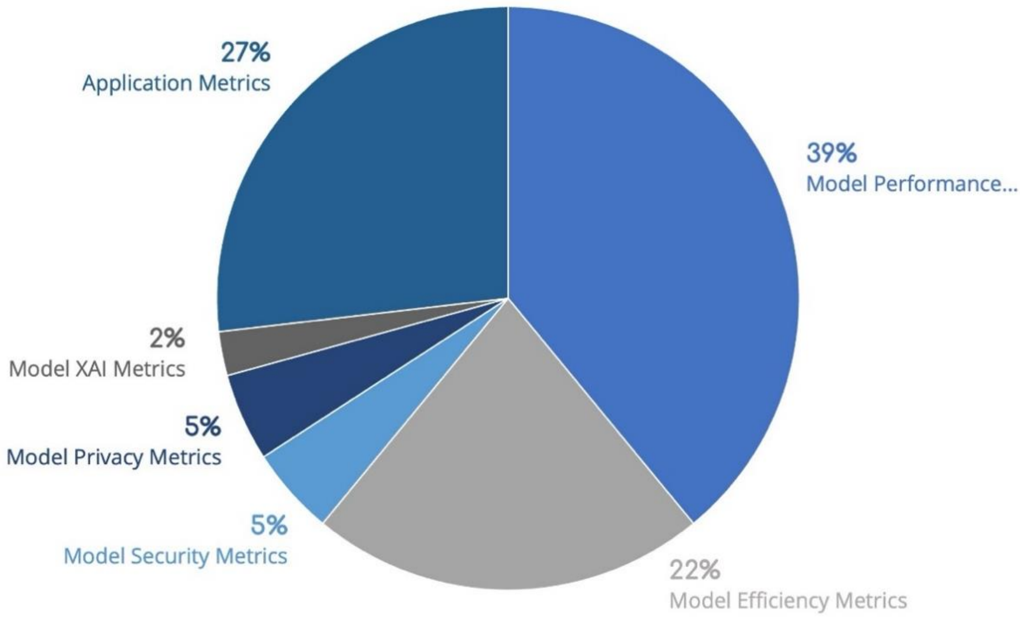

Figure 19: Distribution of model monitoring metrics in 6G SNS Projects.

In terms of model monitoring phase, the collected inputs, as shown in Figure 20, unveiled that 26% of the projects focus on the evaluation of the performance metrics during the training phase, 26% monitor the model during the serving phase, and only 7% consider both training and serving phases. Given that the model performance and trustworthiness may change over the time, it essential to implement continuous monitoring through both training and serving phases.

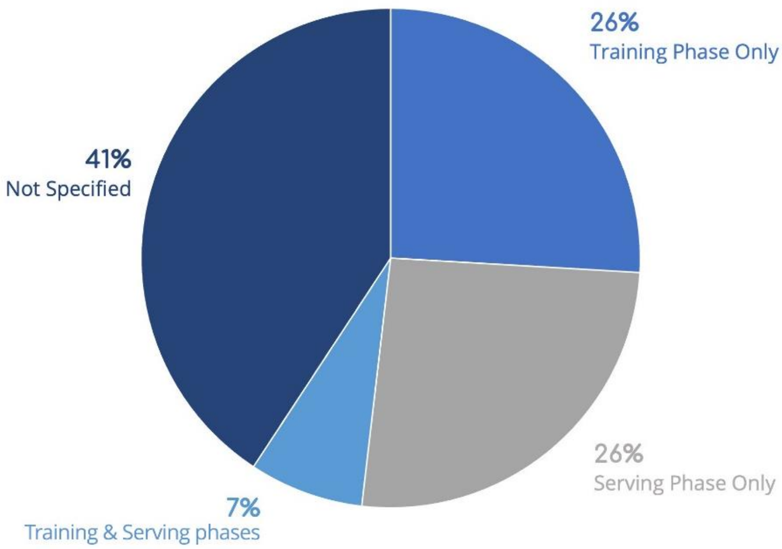

Figure 20: Model Monitoring Phases Considered in 6G SNS Projects

6. AI DATASETS USE WITHIN SNS

6.1. TRAINING DATASETS

The survey additionally explored the origins of the datasets used for training the AI/ML solutions of the SNS projects, in terms of source. Regarding the source, datasets were categorized into three main types, as illustrated in Figure 21; Real, which accounted for 33% of the solutions, Synthetic with 41%, and Mixed in 16% of the cases. 10% of responses did not specify the type of dataset employed. A slight preference among SNS projects for synthetic and mixed datasets can be observed, which collectively represent the largest share. This trend highlights the challenges of compiling purely real-world datasets for training AI/ML models, particularly within the networking domain.

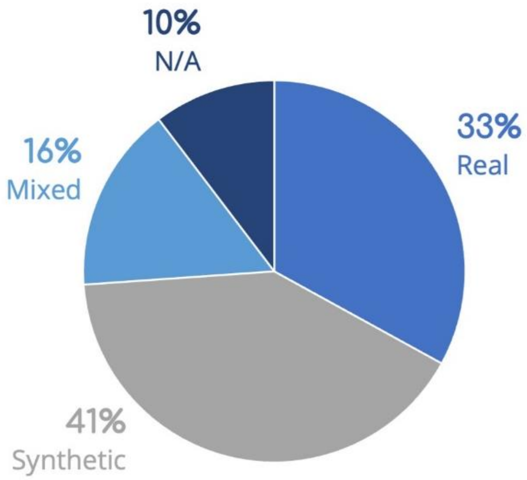

Figure 21: Source of the Datasets used for training the AI/ML solutions within SNS JU

SNS JU projects have the aspiration to share their utilized datasets (at least partially) to facilitate the development of AI-enabled mechanisms and to support the global research community. It can be understood that several restrictions may apply (e.g., use of confidential data from operators, security/privacy concerns) which prohibit the SNS JU experimenters from sharing the entirety of their datasets. However, a significant effort is underway to create such an SNS JU database.

6.2. DATA SOURCES

The purpose of this specific question was to collect information on the sources of training data used across various solutions. Based on the responses from participating projects, a mapping process was conducted to classify the recorded input data sources into higher-level categories. These categories were defined according to the origin and nature of the input data. Table 2 provides the definitions of the used input data categories.

Table 2: AI input data source classification categories for SNS JU

Data Category	Definition
Radio Access Network (RAN)	Data related to radio measurements, channel conditions, interference patterns, and the allocation of Physical Resource Blocks (PRBs), as well as the association of users to base stations.
Network Level Metrics	Aggregated traffic data, packet-level statistics derived from sources such as pcap files network topology details, and link-level metrics
Computing Resources	Metrics associated with CPU and RAM utilization, resource consumption by containers or Virtual Machines (VMs), as well the capabilities of physical nodes
Core	Information originating from central network elements, such as Packet Gateways (P-GWs), Network Data Analytics Function (NWDAF), and signalling processes related to Network Functions (NFs).
UE Metrics	Data that directly represents user-level conditions—such as user behaviour, geographical position, or in-vehicle measurements.
Application-Level Metrics	Data collected at the application level, including video frames, application logs, user Quality of Experience (QoE) indicators, and other application-specific measurements.
Security & Privacy	Datasets and indicators related to attack detection, anomaly alerts, and other security-related Key Performance Indicators (KPIs)
Cross-domain	Inputs may cover more than one domain—for example, mixing RAN measurements with computing metrics or combining network and application data.
Optical	Optical-layer metrics, such as Optical Signal-to-Noise Ratio (OSNR), Q-factors, and the parameters required for optical filtering
Other	Any input that does not readily fit into the previous categories
N/A	No information was provided

Figure 22 presents the analysis of the sources of training data used by SNS JU researchers, and it can be observed that RAN-related inputs account for the majority of contributions, representing 38.42% of the recorded responses. The Cross-domain category follows with 14.29%, highlighting how network integration often causes input training features span multiple domains. Network-level Metrics are also significant (13.79%), while Computing resources are also present, indicating a trend on managing workloads, virtualization, and computational resource allocation. Optical metrics, though less frequent, indicate specialized use cases involving optical transmission parameters. Similarly, Security-related inputs are less common compared to RAN and Computing Resources, likely due to the smaller number of Security-focused projects.

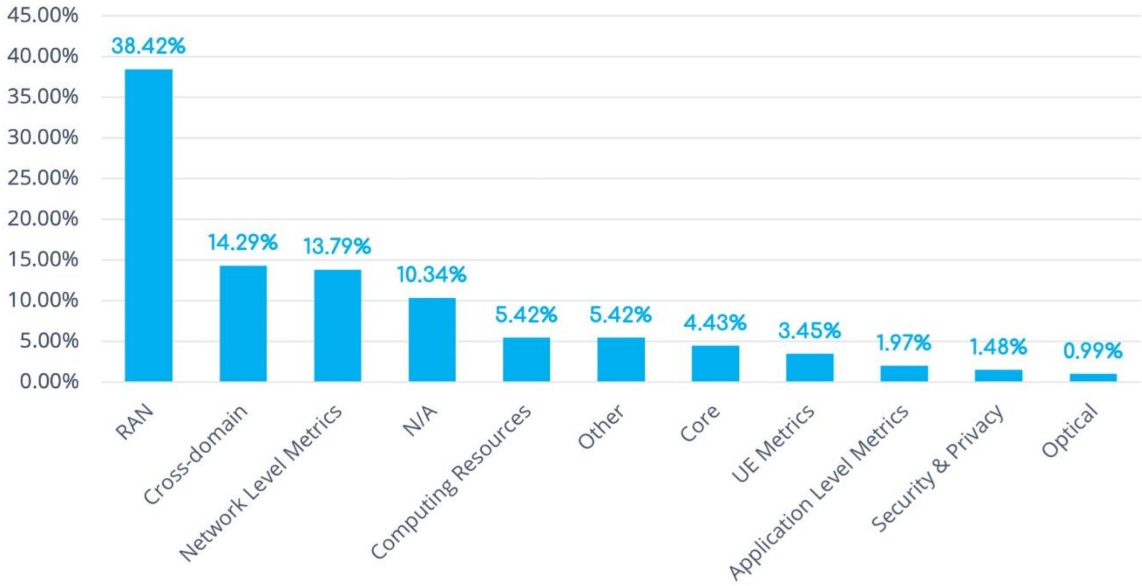

Figure 22: Sources of input training data for SNS JU projects AI mechanisms.

The Cross-domain category was further analysed (in total 28 entries) to identify the specific domains from which data were sourced, as illustrated in Figure 23. The results show a range of combinations, with 'Network Level Metrics & Computing Resources' and 'RAN & Computing Resources' emerging as the most frequent (14.29%). This is followed by 'Application Layer Metrics & Computing Resources' and 'RAN & Network Level Metrics,' each contributing 10.71% of the specific category. Other combinations include 'RAN & Optical,' 'UE & Computing Resources,' and 'RAN & Core,' all recorded at 7.14%. The remaining combinations, such as 'RAN & UE,' 'Computing Resources & Network Level Metrics,' and 'UE & Network Level Metrics & Security KPIs,' each account for 3.57%.

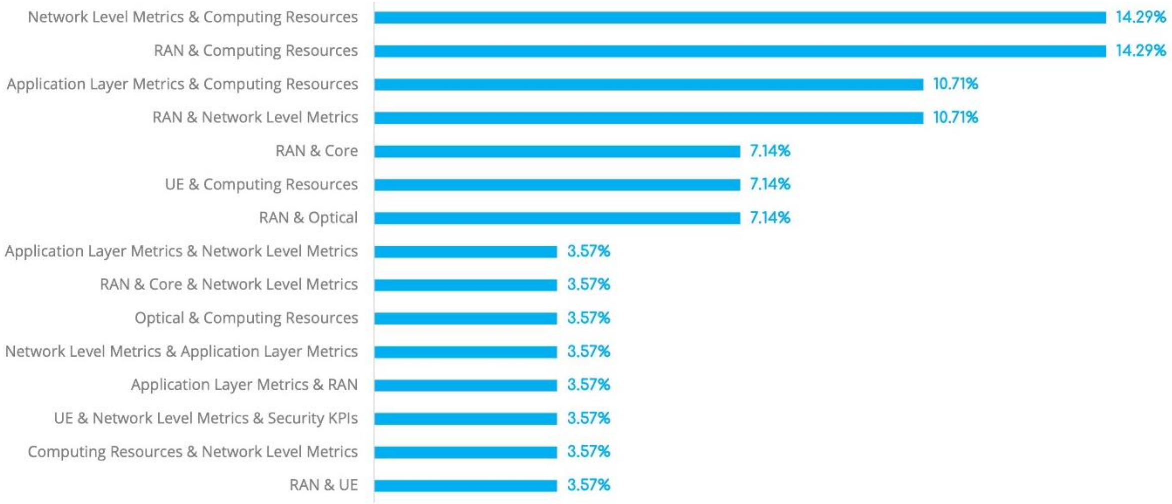

Figure 23: Input data domains under the "Cross-domain" category

6.3. OUTPUT DATA BY AI/ML MECHANISMS

Besides investigating the data that SNS JU projects use as input for their AI mechanisms, insights regarding the output data produced by these mechanisms were also sought out, in order to highlight the output of the AI/ML model, i.e., the specific action -classification, prediction, decision selection. Following a similar methodology as described in Section 6.2, a mapping process was carried out to organize the recorded data into higher-level categories. Table 3 provides the definitions of the used output data categories.

Table 3: AI output data classification categories for SNS JU

Data Category	Definition
Radio Optimization	Improving the operations of radio networks. These results involve adjusting coverage areas, beamforming, estimating channel states, or scheduling radio resources more effectively.
Computing Resources Optimization	The output aims at better CPU or RAM usage, improved container or VM operations, or more efficient VNF placement.
Network-Level Optimization	Outputs include predicting throughput and latency, or enhancing link utilization.
Energy Efficiency Optimization	Outputs focusing on reducing energy consumption or enabling more energy-efficient operations.
Traffic Forecasting	The AI/ML model predicts future traffic demands
Traffic Classification	Classify traffic types.
Application-Level Optimization	For outputs that improve what applications deliver to the end user—improving Quality of Experience (QoE), better handling of video streams, or ensuring reliable application-level metrics.

User-Level Metrics	The results focus on user-centric data, such as predicting user's position or behaviour, or QoS.
Security-Privacy-Trustworthiness	Outputs relate to detecting attacks, responding to attacks (e.g., Moving Target Defence), or handling trust and privacy aspects.
Optical Optimization	The AI/ML model improves optical signals and related parameters.
Cross-domain Optimization	The AI/ML model acts on multiple domains, e.g., joint RAN-Core configuration.
Other	Outputs that do not fall under the previous categories.
N/A	No information was provided.

As shown in Figure 24, Radio Optimization accounts for the largest share of AI/ML model outputs, representing approximately 32% of the recorded responses. This is followed by Security-Privacy-Trustworthiness at ~17% and Computing Resources Optimization at 10.84%, as the key focus areas for AI/ML applications. Network Metrics Optimization is also well-represented (7.88%). Smaller categories, such as Energy Consumption (3.45%), Traffic Classification (0.99%), and Energy Consumption Prediction (0.49%), indicate more niche use cases.

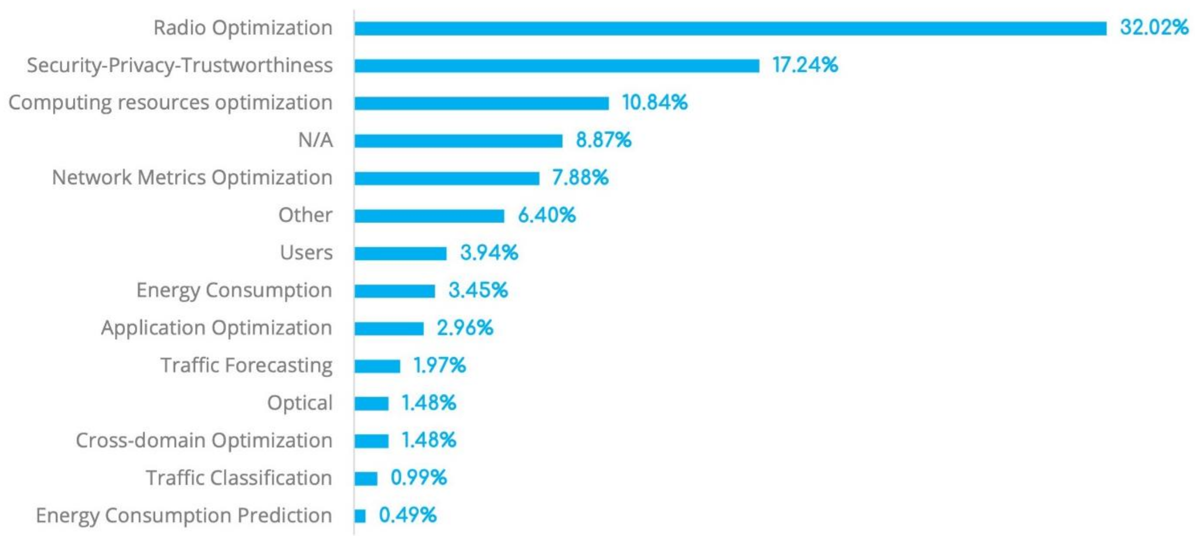

Figure 24: The output produced by the AI/ML models.

While Radio Optimization remains the most popular category, the results highlight a diverse range of AI/ML outputs spanning multiple domains, demonstrating a range of optimization objectives. Finally, N/A accounts for 8.87% of responses, which may reflect the current maturity level of project results.

6.4. DATA PRIVACY & SECURITY

Security and privacy with regards to the used AI mechanisms is another topic investigated by the TB questionnaire. Notably, a substantial 73% of the projects did not provide information on their privacy and security strategies. This gap indicates among others that these aspects have not yet been assessed, are under study, or remain an open discussion point within the project scope, particularly as regulatory and ethical considerations in 6G systems continue to evolve.

The classification of data privacy and security mechanisms in the AI/ML solutions that did respond, reveals an emerging focus on privacy-preserving methodologies as shown in Figure 25. Among the solutions that take security and privacy into account (54 AI-enabled mechanisms), 45% leverage the inherent privacy benefits of Federated Learning and Multi-Agent Learning based mechanisms, showcasing a growing trend toward decentralized and secure data handling. These approaches enable models to be trained collaboratively without directly sharing sensitive data, aligning well with the increasing emphasis on data privacy in next generation networks. Additionally, 9% of the solutions employ Probabilistic techniques such as differential privacy, while 20% utilize other tailored mechanisms, including cryptography, token-based approaches, and explainable AI (XAI), to address security and privacy concerns. Interestingly, 26% of the solutions reported no significant privacy or security concerns, citing factors such as local training, the absence of private or personal data, or the use of data that do not reveal identifiable patterns.

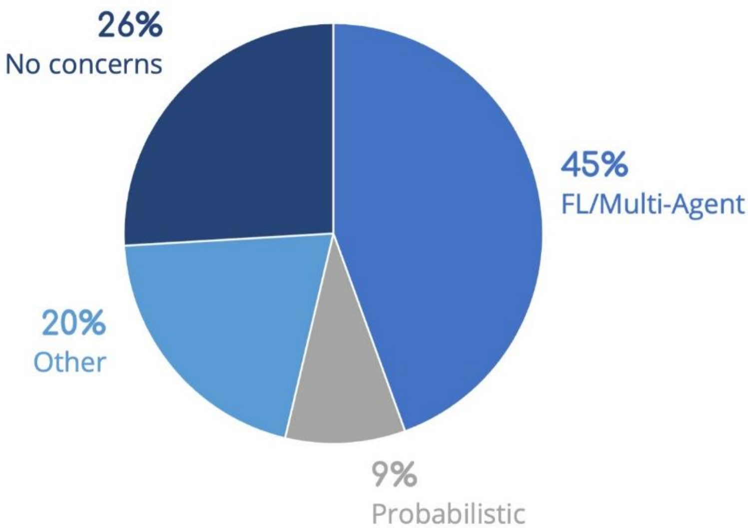

Figure 25: Data Privacy and Security mechanisms in the AI/ML solutions used in SNS projects

7. CONCLUSIONS & WAY FORWARD

7.1. INSIGHTS ON SNS JU WORK ON AI/ML

The Smart Networks and Services Joint Undertaking (SNS JU) is at the forefront of European efforts to advance 6G telecommunications, leveraging AI/ML as key enablers. This initiative, funded under the Horizon Europe program, comprises 33 projects in its first two calls that explore innovative AI/ML solutions to address critical challenges in network performance, resource management, and security. As the global race toward 6G intensifies, a comparative analysis of SNS JU projects and international AI research reveals unique strengths and opportunities for Europe in shaping the future of AI-driven networks. The key findings regarding the use of AI/ML in SNS JU projects, from the presented TB survey, can be summarized as follows:

1. **AI as a Cornerstone of 6G Networks**: SNS JU projects recognize AI as a foundational element of 6G, emphasizing its transformative potential across network layers. *33 SNS JU projects* are currently developing *199 AI/ML based mechanisms* for use in different layers of 6G networks. These solutions aim to address stringent Key Performance Indicators (KPIs) for 6G, such as energy efficiency, ultra-reliable low-latency communication (URLLC), and advanced network management.
2. **Diverse AI Applications**: SNS JU projects cover a wide spectrum of applications, impacting all the envisioned layers of 6G networks. These applications include:
    - **Radio Access Network (RAN) Optimization**: Approximately 45% of AI-based solutions focus on RAN optimization, addressing complex challenges such as resource allocation, interference management, and beamforming.
    - **Network & Device Optimization**: A wide variety of optimization mechanisms is developed including resource allocation, quality of service (QoS), radio link quality, Integrated Sensing and Communication (ISAC) performance, and device performance.
    - **Energy Efficiency**: AI is used to optimize energy consumption, contributing to sustainable network design.
    - **Explainability and Model Monitoring**: The adoption of Explainable AI (XAI) techniques ensures transparency and trustworthiness, crucial for regulatory compliance and stakeholder confidence.
3. **Datasets and Methodologies**:
    - **Datasets**: Around 41% of SNS projects utilize synthetic datasets, 33% use real datasets, and 16% use mixed sources, showcasing a strong reliance on

synthetic data due to the challenges in accessing large-scale real-world datasets in telecommunications.

- **Learning Types**: Supervised learning dominates (50%), with reinforcement learning (25%) and unsupervised learning (15%) also playing significant roles. Hybrid approaches that combine multiple methodologies account for the remaining solutions.
- **AI Methods**: Neural networks and deep learning methods account for 51% of AI solutions, followed by reinforcement learning (20%), decision-based methods (10%), and explainable AI techniques (5%). Hybrid methods, combining several categories, are also prominent.

4. **Model Monitoring and Complexity**: Model monitoring is a key focus area, with 39% of projects using performance metrics like accuracy, precision, and F1 scores, while 27% use application-specific metrics such as QoS and spectrum efficiency. The majority of models are categorized as having low or medium complexity, with only 13% of solutions classified as highly complex.
5. **Multiple I/O data streams**: A detailed classification of the data sources and output of the SNS JU AI mechanisms was provided, showcasing the large variety of data used within the SNS JU. Eleven input data categories were identified with RAN data being by far the most popular followed by cross-domain and Network-level metrics. In terms of output data, most SNS JU mechanisms provide Radio optimization metrics, followed by trustworthiness parameters and computing resource optimization parameters.

The SNS JU researchers are well aware of the global AI ecosystem they operate in, and the importance of alignment with international efforts and initiatives and stay in close contact with standardization efforts as the significant role that AI will play in the defined 6G architecture, has been well established. The provided analysis of the EU AI regulatory framework sets the tone for any AI-relevant developments within Europe, while the already well-established international collaboration of SNS JU projects with other regions and global initiatives, ensures alignment and cross-education on a global level.

7.2. OPPORTUNITIES & WAY FORWARD

The SNS JU's phased approach allows for applying lessons learned and course-correcting where and when necessary. By investigating in depth the approach taken by the SNS JU researchers and the AI mechanisms being developed, the first step towards closely monitoring and evaluating the progress of AI-enabled mechanisms for 6G networks within the SNS JU has been taken. This analysis provides the foundation for future benchmarking and validation activities which will further shape the output of AI research in Europe.

The SNS JU's comprehensive approach positions Europe as a leader in ethical, explainable, and sustainable AI for 6G. Key strengths include:

- **Transparency and Trust**: The integration of XAI methods ensures compliance with Europe's regulatory frameworks, such as the AI Act and GDPR, setting global benchmarks for trustworthy AI.
- **Sustainability**: By prioritizing energy-efficient AI mechanisms, SNS JU projects align with global sustainability goals, a critical differentiator in the 6G landscape.
- **Global Synergies**: Collaborative initiatives with other regions and key global stakeholders underscore Europe's potential to lead multilateral research efforts, fostering alignment on standards and interoperability.

The analysis presented in this white paper also assists in drawing the roadmap for future AI research within the SNS JU, as several challenges can be identified. Addressing the following areas can further solidify Europe's leadership:

- **Scaling Real-World Data Access**: Efforts should be made to promote data-sharing agreements across public and private entities to improve access to real-world datasets.
- **Advancing AI Techniques**: Greater investment is needed in cutting-edge AI methods, such as generative AI, self-supervised learning, and neuromorphic computing, to push the boundaries of innovation.
- **Model Robustness and Privacy**: Emphasizing privacy-preserving AI and ensuring robustness against adversarial attacks will be crucial as networks become increasingly autonomous.
- **Continuous Monitoring and Feedback**: Implementing closed-loop monitoring systems across training and serving phases will enhance model reliability over time.
- **Standardization Leadership**: Active engagement in shaping global standards for 6G will ensure Europe's priorities are reflected in international frameworks.

In conclusion, the SNS JU projects reflect a robust and forward-looking agenda that not only drives AI innovation for 6G but also reinforces Europe's strategic autonomy in telecommunications. Through its emphasis on collaboration, transparency, and sustainability, the SNS JU provides a strong foundation for Europe's leadership in the global AI and 6G ecosystem.

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CONTACTS

SNS Technology Board (TB) Chairman:

Konstantinos Trichias, 6G-IA

Kostas.trichias@6g-ia.eu

AI/ML Task Force Leader

Maria Christopoulou, IIT Demokritos, PRIVATEER

maria.christopoulou@iit.demokritos.gr

SNS WGs:

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

LIST OF EDITORS

Name	Company / Institute / University	Country	Project
Konstantinos Trichias	6G Industry Association	Belgium	TB Chairman
Maria Christopoulou	NCSR Demokritos	Greece	PRIVATEER
Pawani Porambage	VTT	Finland	Hexa-X-II
Chafika Benzaïd	University of Oulu	Finland	RIGOUROUS, 6G-SANDBOX
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Akshay Jain	Nokia	Finland	Hexa-X-II
Daniel Kilper	Trinity College Dublin	Ireland	6G-XCEL
Chen Tao	VTT	Finland	6G-Cloud

LIST OF CONTRIBUTORS

SNS Project	Website	Contributors
5G-STARDUST	https://5g-stardust.eu/	Tomaso de Cola (DLR), Daniele Tarchi (CNIT), Marius Caus (CTTC), Roshith Sebastian (DLR), Benjamin Barth (DLR)
6G-CLOUD	https://www.6g-cloud.eu/	Tao Chen (VTT), Nikolaos Dimitriou (NCSR Demokritos), Akis Kourtis (NCSR Demokritos), Antonio Skarmeta (UMU), Anastasios Giannopoulos (FDI), Sotirios Spantideas (FDI), Slawomir Kuklinski (WUT)
6G-DISAC	https://www.6gdisac-project.eu/	Henk Wymeersch (Chalmers University of Technology), Placido Mursia (NEC), Giyyarpuram Madhusudan (Orange), George Alexandropoulos (NKUA)
6G-NTN	https://6g-ntn.eu/	Alice Piemonti (Martel Innovate), Vito Cianchini (Martel Innovate), Massimo Neri (Martel Innovate), Riccardo Campana (UniBo), Carla Amatetti (UniBo), Husnain Shahid (CTTC), Miguel Angel Vazquez (CTTC), Zheng Li (Orange), Abdelhamed Mohamed Sayed Ahmed (Orange), Laurent Reynaud (Orange), Ji Lianghai (Qualcomm), Ted Hsu (Qualcomm)
6G-PATH	https://6gpath.eu/	Ioannis Chochliouros (OTE), Luís Cordeiro (ONE), Anna Brunström (KAU), Filipe C. Pinto (ALB), Pedro Rito (IT)
6G-SHINE	https://6gshine.eu/	Gilberto Berardinelli (AAU), Saeed Hakimi (AAU), Ramoni Adeogun (AAU), Pedro Maia de Sant Ana (Bosch), Baldomero Coll-Perales (UMH), Fotis Foukalas (COGNINN), Christos Tsakos (COGNINN)
6G-TANDEM	https://horizon-6gtandem.eu/	Thomas Feys (KUL)
6G-TWIN	https://6g-twin.eu/	Sébastien Faye (LIST), Ion Turcanu (LIST), Gaetano Volpe (POLIBA), Miguel Camelo Botero (IMEC)
6G-XCEL	https://www.6g-xcel.eu/	Dan Kilper (TCD)
6G-XR	https://6g-xr.eu/	Mohammed Al-Rawi (IT), Mariana Kyrova (Matsuko), Rafael Rosales (Intel), Antti Pauanne (UOULU)
ACROSS	https://across-he.eu/	Alberto Mozo (UPM)
ADROIT6G	https://adroit6g.eu/	Vasos Vassiliou (CYENS)
BeGREEN	https://www.sns-begreen.com/	Miguel Catalan Cid (i2CAT), Joss Armstrong (Ericsson), Juan Sanchez-Gonzalez (UPC), JosepXavier SalvatLozano (NEC Lab Europe), Mir GHoraishi (Gigasys Solutions)

CENTRIC	https://centric-sns.eu/	Ramoni Adeogun (AAU), Saeed Hakimi (AAU), Septimia Sarbu (Oulu), Alvaro Valcarce (Nokia), Sebastian Cammerer (NVIDIA), Ahmet Sedar Tan (Interdigital), Alexander Chiskis (Sequans), Carla Fabiana Chiasserni (CNIT), Matteo Zecchin (KCL), Aakash Saini (Nokia)
DESIRE6G	https://desire6g.eu/	Marios Avgeris (UvA), Chrysa Papagianni (UvA)
DETERMINISTIC6G	https://deterministic6g.eu/	James Gross (KTH Stockholm)
ETHER	https://ether-project.eu/	
FIDAL	https://fidal-he.eu/	Sofia Karagiorgou (UBITECH), Christos Tranoris(PNET)
Flex-Scale	https://6g-flexscale.eu/en	Dimitris Uzunidis (UPAT), Gabriel Otero (UC3M), David Larrabeiti (UC3M), Ioannis Tomkos (UPAT), Farhad Arpanaei (UC3M)
Hexa-X-II	https://hexa-x-ii.eu/	Pawani Porambage (VTT), Hamed Farhadi, Merve Saimler (Ericsson), Mehmet Karaca, Leyli Karaçay (Ericsson), Dani Korpi (Nokia), Ricard Vilalta, Pol Alemany, Daniel Adanza (CTTC), Milan Zivkovic (Apple), Vasiliki Lamprousi (Wings), José Miguel Mateos Ramos (Chalmers), Nassima Toumi (TNO), Anastasios Zafeiropoulus (NTUA)
HORSE	https://horse-6g.eu/	Fabrizio Granelli (CNIT), Xavi Masip (UPC)
NANCY	https://nancy-project.eu/	Stylianos Trevlakis (INNO), Theodoros Tsiftsis (INNO), Athanasios Tziouvaras (BI2S), Emanuele De Santis (CRAT), Jernej Hribar (JSI), Carolina Fortuna (JSI), Blaz Bertalanic (JSI), Shih-Kai Chou (JSI), Hatim Chergui (i2CAT), Juan Sebastian Camargo (i2CAT), Miguel Catalan Cid (i2CAT), Giorgos-Nektarios Panayotidis (CERTH), Kostas Loumponias (CERTH), Giorgos Koutidis (CERTH), Theofanis Xifilidis (CERTH), Sotiris Soukaras (CERTH), Dimitrios Kavallieros (CERTH), Theodora Tsikrika (CERTH), Stefanos Vrochidis (CERTH), Ioannis Kompatsiaris (CERTH),
NATWORK	https://natwork-project.eu/	Antonios Lalas (CERTH), Virgilios Passas (CERTH), Alexandros Papadopoulos (CERTH), Sarantis Kalafatidis (CERTH), Asterios Mpatziakas(CERTH), Konstantinos Giapantzis (CERTH), Georgios Agrafiotis (CERTH), Aristeidis Papadopoulos (CERTH), Nikolaos Makris (CERTH), Donatos Stavropoulos (CERTH), Athanasios Korakis (CERTH), Anastasios Drosou (CERTH), Wissem Soussi (ZHAW), Gökcan Cantali (ZHAW), Gürkan Gür (ZHAW), Sumeyya Birtane (UESSEX), Shankha Gupta (UESSEX), Mays AL-Naday (UESSEX), Joaquín Escudero (GRAD), Manh Nguyen (MONT), Vinh La (MONT), Edgardo Montes de Oca (MONT), Péter Vörös (ELTE), Mohammed Alshawki (ELTE), Sandor

		Laki (ELTE)
ORIGAMI	https://sns-origami.eu/	Andres Saavedra (NEC), Marco Fiore (IMDEA), Marco Gramaglia (UC3M)
PREDICT-6G	https://predict-6g.eu/	Carla Fabiana Chiasserini (Polito), Marc Molla (Ericsson), Rafael Rosales (Intel), Margarita Cabrera (UPC), Josep Vidal (UPC)
PRIVATEER	https://www.privateer-project.eu/	Antonia Karamatskou (INFILI), Nikolaos Papadakis (INFILI), Anastasios Bikos (IQU), Kostas Ramantas (IQU), Apostolos Garos (SPH), Maria Christopoulou (NCSR Demokritos)
PROTEUS-6G	https://proteus-6g.eu/	David Larrabeiti (UC3M), Dimitris Uzunidis (UPAT), Gabriel Otero (UC3M), Ioannis Tomkos (UPAT), Jose A. Hernandez (UC3M)
RIGOROUS	https://rigourous.eu/	Chafika Benzaid (OULU), Antonio Skarmeta, Pablo Fernandez, Jorge Bernal (UMU)
ROBUST-6G	https://robust-6g.eu/	Ömer Faruk Tuna (Ericsson), Leyli Karaçay (Ericsson) Betül Güvenç Paltun (Ericsson), Günes Kesik (Ericsson), Bartlomiej Siniarski (UCD), Madhusanka Liyanage (UCD), Chamara Sandeepa (UCD), Thulitha Senevirathna (UCD) Manuel Pérez (UMU), Giovanni Perin (UNIPD), Marios Kountouris (EUR), Nikolaos Pappas (LIU)
SAFE-6G	https://safe-6g.eu/	Harilaos Koumaras (NCSR Demokritos), Ilias Alexandropoulos (NCSR Demokritos), Vasiliki Rentoula (NCSR Demokritos), Spyridon Georgoulas (NCSR Demokritos), Vaios Koumaras (INFOLYSiS)
SEASON	https://www.season-project.eu/	Carlos Hernández-Chulde, Ricardo Martinez, Ramon Casellas (CTTC), Luis Velasco (UPC)
SNS ICE	https://smart-networks.europa.eu/csa-s/#SNS-ICE	Kostas Trichias (6G-IA), Alexandros Kaloxylos (6G-IA)
SNS OPS	https://smart-networks.europa.eu/csa-s/#SNS-OPS	Miguel Alarcón (Martel)
SUNRISE-6G	https://sunrise6g.eu/	Kostas Ramantas (IQU)
TERRAMETA	https://terrameta-project.eu/	Sourabh Solanki (UniLu), Abuzar Adam (UniLu), Rafael Aguiar (INESC TEC), Luis Pessoa (INESC TEC), Kyriakos Stylianopoulos (NKUA), George Alexandropoulos (NKUA).
VERGE	https://www.verge-project.eu/home	Oluwatayo Yetunde Kolawole (Samsung UK), Joan Pujol (Samsung UK), Berend Gort (Nearby Computing), Godfrey Kibalya (Nearby Computing), Angelos Antonopoulos (Nearby Computing), David Lopez (CTTC), Charalampos Kalalas (CTTC), Jordi Perez-Romero (UPC), Oriol Sallent (UPC), Irene Vila (UPC)

Reviewers

Name	Company / Institute / University	Country
Anastasios Gavras	Eurescom	Germany
Georgios Gardikis	Space Hellas	Greece

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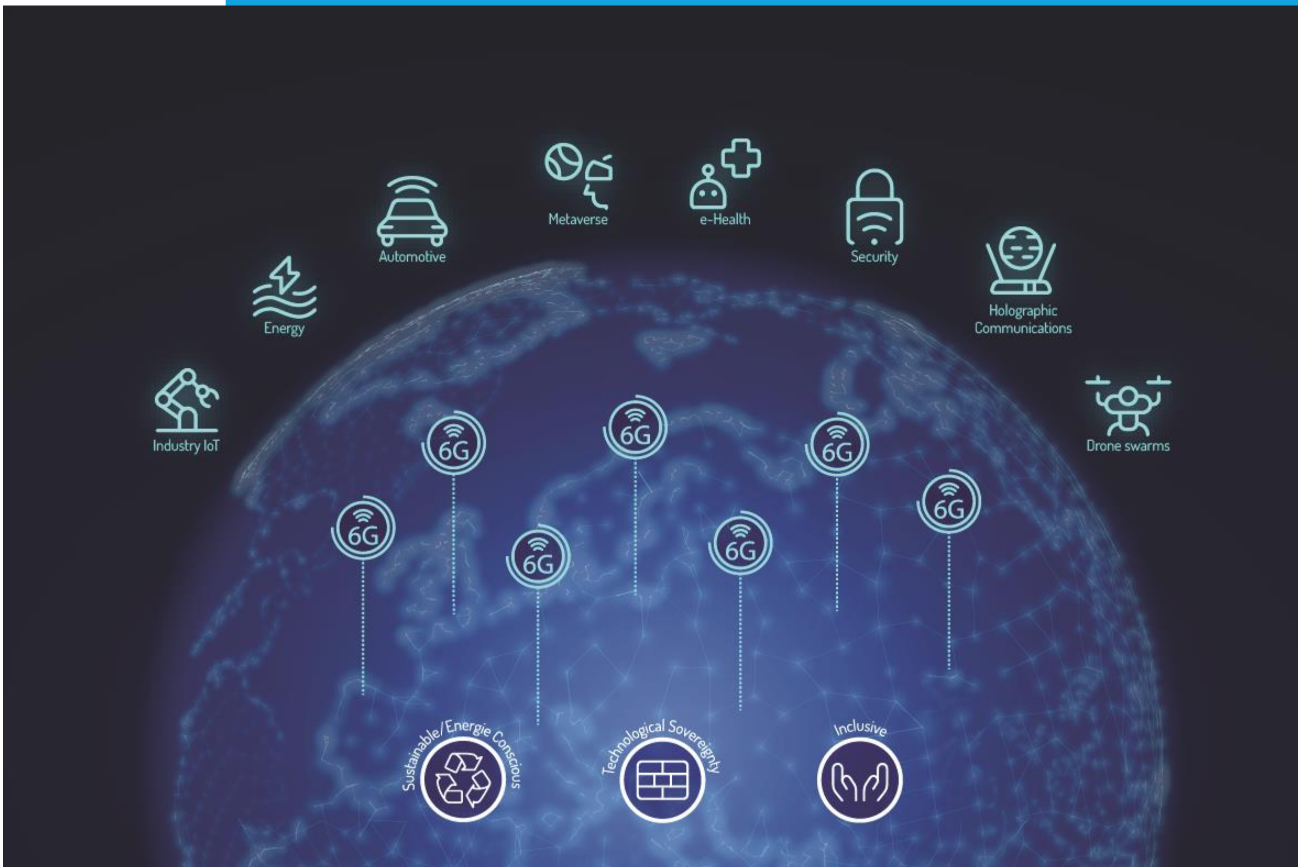

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