International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2022): 7.942

Autonomous Telecommunication Networks: The Convergence of Agentic AI and AI-Optimized Hardware

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Abstract: ***The upcoming deployment of the sixth mobile telecommunication system (6G) offers the opportunity to make a radical change to the structure of the telecommunications industry, shifting from the current model of human-directed operations toward a model of learnable, adaptive, support-less autonomous operations. Operating the networks at scale makes it very complex to rely exclusively on humans, who are easily overwhelmed and can create significant operational delays. The resources needed to avoid excess dependence on humans are huge, driven not only by the size of the offered system but also by the fact that the systems are highly improbable, in such a way that the majority of failures happen infrequently and therefore the historical learning never covers the different possibilities. Additionally, waiting for human decisions can lead to unacceptable operational delays. Furthermore, the demands made on the networks are increasingly complex, requiring very precise responses. All these factors make it crucial to make autonomous networks a top priority for the future of our interconnections. The development of autonomous communication networks, operating both the physical and network layers, is not simple, nor is the journey to arrive at an operational stage. The purpose of this essay is to show the strategies leading to the absolute necessity of the convergence between the algorithms operating the communication networks and the optimizations performed to the telecommunication hardware. These concepts have already been developed in other industries. However, no articulation or in-depth examination of the convergence has been produced until now for telecommunications networks. In this essay, we put this convergence at the basis of artificial intelligence (AI)-enabled future autonomous networks, as well as on neutral network-based technologies. We conclude with a note on how the partnership between AI and hardware technologies will create the basis for autonomous telecom networks, and why we think that this is crucial.***

Keywords: Autonomous networks, telecommunication, agentic AI, AI-optimized hardware, intelligent infrastructure, self-organizing networks, self-healing systems, network automation, edge computing, real-time inference, adaptive decision-making, hardware acceleration, policy-based control, AI-driven orchestration, zero-touch management, cognitive radio, machine learning integration, 6G architecture, multi-agent systems, reinforcement learning, neural processing units, programmable networks, data plane optimization, control plane intelligence, energy-efficient AI, ultra-low latency, end-to-end automation, dynamic resource allocation, network slicing.

1. Introduction

Autonomous networks currently are the Holy Grail of telecommunications service providers and third-party companies shaping the future of connectivity. The vision is that, over the next couple decades, using intelligence networks start and maintain their operation autonomously, requiring little or no human intervention to maintain service availability, quality, and performance. This autonomy requires networks to sense whatever happens not only inside the network, but also at the edges, room to room, and between different operators' networks. This sensing capability is a necessary, but not sufficient, condition for the evolution towards these networks. Networks will also need to analyze what they detect and make decisions based on how their historical behavioral models, create new models, and adapt or propose actions to be performed to the network operational support systems. All of these processes must be performed at all network levels running on physical infrastructure that is also technologically advanced enough to fully support network autonomy.

In this context, our position is that significant technology advancement in two areas is required: AI and a new type of hardware that is optimized to fully support AI functions in networks. More specifically, networks will have to use an agentic type of AI, which embraces several technological aspects, such as: composite cognitive architectures; the strong version of the local learning hypothesis; the three level functional organization of learning-to-learn versus learning while doing; and communication through all available means, including the use of common languages, shared mental models, and gestures. It is the combination of agentic AI and AI optimized hardware that allows networks to become autonomic, creating always-on services based on resource zeroing. Convergence of agentic AI and AI optimized hardware will dynamically adapt telecom networks.

2. Overview of Autonomous Networks

Autonomous networks provide an innovative solution to the burgeoning complexity and cost of next-generation telecom infrastructure. Their ability to continuously optimize for changing business goals, evolving service demands, and constantly shifting underlying infrastructure is transformative, enabling wireless and wired networks, edge and central data centers, and all the devices they support to transform society, industry, and commerce. Autonomous networks apply the logic of self-driving cars and pilotless airplanes to the realm of telecommunications, using specialized Artificial Intelligence software and specialized AI-Optimized hardware to build networks that intelligently respond to changing requirements and learn from experience.

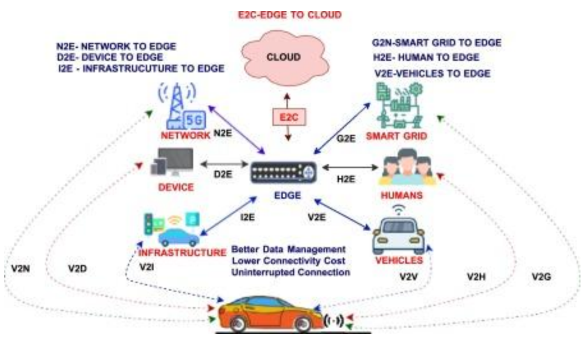

Figure 1: Autonomous vehicles in 5G and beyond

The transition to commercial viability of autonomous networks adds real-time control and closed-loop operation to the telecom network – moving the industry from semi-automated networks where many configurations and optimizations are locally optimized by people to autonomous networks where all activities over time from planning through configuration, control, and optimization are formulated as real-time learning and optimization problems under the guidance of humans who define the long-term goals and constraints. The paradigm shift to autonomous networks consists of several key related facets. In this document, we primarily focus on the increased capability driven by the convergence of generalized agentic AI, the new AI-Accelerator-Optimized hardware that is now available, and the vastly increased availability of new massive, expensively-labeled telecom datasets that will emerge in the coming years as industry services grow. However, other recent trends also help create this key transition, such as the use of deep reinforcement learning for network control.

3. The Role of Agentic AI in Telecommunications

Telecommunication networks are now becoming one of the biggest enablers of a wide range of services and solutions riding on the network. From mobile money, to social connections, to healthcare delivery, these networks are increasingly becoming a solvable problem not by designing a complex piece of hardware but by orchestrating Agentic AI decisions. We are rapidly converging towards a situation where increasing complexity of services is not only deferring the cost of hardware unrealistically but requiring levels of complexity in the technology development cycle and merging of expertise of such magnitude that we run the risk of asking the question whether the complex problem has to do more with building complex pieces of hardware or with having the right algorithm to orchestrate massive computing and telecommunications networks capabilities.

In this section we will outline the convergence of optimization models, first-principles based algorithms and heuristics, Federated Learning and Agentic AI to realize what we consider as the first phase of computing and telecommunications powered by Agentic AI, before real self-powered Agentic AI systems start completely taking over. As we will outline in these sections, Agentic AI capabilities will cut across the design, the deployment and the operational phases of future computing and telecommunications infrastructure, and will help ease the risk of transferring over the ever-increasing cognitive demand from specifically trained experts specialized in areas of communications networking and associated optimization to a rapidly growing generalist workforce in partnership with the algorithm-based Agentic AI solutions.

3.1 Defining Agentic AI

Agentic AI refers to Artificial Intelligence (AI) systems that can autonomously execute a range of complex actions in an environment, with minimal human coordination. Such actions would typically be planned and executed by multiple low-level AI methods or systems, possibly in multi-agent systems. Agentic AI capabilities include autonomously planning for a goal over a long horizon, notably with the ability to interleave planning and execution, to track and respond to an evolving environment during execution, when relevant, and to learn models of dynamic environments from few examples. Furthermore, agentic AI would be capable of working collaboratively with other agentic AIs and also with people, communicating complex information to them in an understandable and usable format.

What we mean by agency here is not human-level intelligence or self-awareness. For the purposes of this definition, we envision an agentic AI's particular achievements as being as capable as identifiable human specialists in those tasks over the relevant time horizon. However, we do believe that in many domains, agentic AI's goal is to achieve human-level capabilities. Such systems could be capable of achieving high capability levels in very hostile environments or in domains where human experience is currently critical. Thus, it must be noted that most existing learned AI systems do not currently exhibit these capabilities, especially recent reinforcement learning-based systems trained on immense computer resources. These systems are more akin to large coordinated collections of traditional AI algorithms, planning and related processes specifically developed for limited domains and requiring extensive human resources for development and deployment. Current intelligent agents are still a long way from cognition or agency. In particular, empathy for other agents, human or AIs, is a critical emotion for agents that interact socially – models of other agents that facilitate such interactions – and of cooperative learning and coordination may facilitate achieving tasks or goals.

Eqn 1: Goal-Directed Utility Maximization

$$EU(\pi) = \mathbb{E}\left[\sum_{t=0}^{T} \gamma^t \cdot U(s_t, a_t)\right]$$

Where:

- $U(s_t, a_t)$: Utility (reward) of state-action pair
- γ: Discount factor
- π: Agent's policy

3.2 Applications of Agentic AI in Network Management

In this work, we are mostly concerned with applications of Agentic AI in the management of telecommunications networks: 5G and 6G for the most part. Agentic AI can be applied for a wide range of tasks within network management: Element Management, Network Management, Operation Support Systems, Service Management, Experience Management, and Telco Cloud Management.

Most previous attempts at automation in telecommunications have focused on orchestrators that globally allocate resources but do not terminate into autonomous solutions that decide and implement for each network element what to do. Also, those attempts on automation did not develop deep learning modules capable of taking into account the time series with all measurements taken by each network element every x seconds over the entire life of the network. This is the duty of Agentic AI. The time series approach — deep learning modules that take into account the time series of each variable over the entire life of the network — was applied for the detection of 10 classes of cases in the Life of Network: (1) Corrupted Correlation (decrease of correlation with other elements), (2) High Traffic (high 95th percentile of traffic), (3) Intrusive Changes (high value of variation of the cross entropy of the data plane), (4) Degraded Measurements (high variation of the standard deviation of the data plane), (5) Misbehavior by All (high sum of the cross entropy with respect to all elements), (6) Jitter Anomaly (high value of the mean of the jitter in the data plane), (7) Singleton Cluster (transitory high triplet error), (8) Surprise Changes (high variation of the cross entropy with respect to the past), (9) Config Anomaly (high value of the number of configuration changes), (10) Surprising Load (high load after optical blocking).

4. AI-Optimized Hardware: A New Paradigm

As an additional benefit, in AI-Optimized Systems, intelligent chips drastically speed up every operation in a telecommunication network. These chips are designed specifically to run, essentially, AI-based autonomous functions. Interestingly, these optimized systems are radically different than classical specialized chips. In fact, these chips are fabricated to fit the requirements of an Intelligent Agent working on top of the technology stack. Hence, in our definition, AI-optimized hardware runs the common tasks with those unique and dynamic characteristics at unprecedented efficiency, and they deliver and accelerate the power of intelligent agents. The chips are designed by artificial intelligence generative-creation methods that advocate a design approach that is substantially different than the classical methods. Essentially AI-Optimized Chips enable autonomous self-acting systems, not those systems that require human guidance for every minute detail guidance. This chapter discusses what is different, and how to leverage those differences, such that the autonomous and self-sufficient components in a telecommunications network become possible. We illustrate the effect of AI-generative hardware designs on several chips, and argue the specific application requirements to enable the future of semiconductor chips with the history of evolution in optimization. We will show several directions in a type of exploratory analysis using Machine Learning methods and couple offloading and neural behavioral mapping optimization. We will showcase several circuit architectures in the domain of electromagnetics, photonics and circuit components that have exceeded the classical performance barriers and both classical and generative-optimizing workflows in the process. We are also going to discuss the security aspect of probing AI-optimized circuits for ethernet, photonics and wireless and how can we secure those learned designs for minimum security exposure.

Figure 2: A Comprehensive Review

4.1 Understanding AI-Optimized Hardware

Conventional computing hardware are designed to operate according to the laws of classical physics. The discovery of quantum physics enabled innovative solutions like quantum computing, which are capable of outperforming any classical computer in certain tasks. AI-optimized hardware refers to novel computing devices which are not only operated and controlled by AI algorithms, but also specifically designed according to the requirements of those algorithms. Even though still adhering to classical physics, AI-optimized hardware utilize the effects of chaos theory or other disciplines and are thereby capable of outperforming any traditional computing hardware in designing models based on AI algorithms or specifically tailored to support those algorithms. This capability allows for the design of AI-optimized hardware which are orders of magnitude more efficient and create orders of magnitude less entropy. The resulting models are able to operate many types of applications, including telecommunications, which are usually powered by classical, non-optimized devices, with significant improvements.

In the telecommunications sector, specific tasks can already be completed at low costs using conventional computing hardware. However, their operation causes a considerable amount of entropy. AI-optimized hardware allows new paradigms to be established. In the case of telecommunications, these new paradigms include the intelligent design of AI-optimized resources for the handling of specific and common telecommunications tasks, such as data encryption, the intelligent reconfiguration of optimizing protocols, AI-optimized virtualization, and many more. The availability of AI-optimized telecommunications resources enables novel installations, designs, and operations of telecommunications networks. Those networks are using AI for the optimization of internal tasks, services, and also for communications with the outside world.

4.2 Benefits of AI-Optimized Hardware in Networks

A major practical motivation behind the architecture of AI-optimized hardware is that the simulation of the Internet of Things (IoT), such as in smart cities, which is to be laid down on the network over the Edge, has unprecedented computational demands. These demands will not be completely satisfied by standard von Neumann computing architectures, which only a few parallel cores. This is not only for wide-area networks, but also for private cognitive radio networks, which require pointing and addressing of beams. The huge amounts of reflecting programming length of Microelectromechanical Systems (MEMS) are to be very accurately described over different lengths of time, so as to update the pointing of beams at low delay, and synchronize transmissions and receptions over beams at narrow pulses, without collisions, to fulfill the reaction time constraints of the applications for which such networks are designed. It is for these developments, as also for user equipment battery management, low Earth orbit communication by satellites, and the IoT, that new large-scale paradigms of designing the routing algorithms must be implemented.

Presently known classes of novel AI-optimized hardware, such as FPGA, NERONs, reconfigurable photonic processors, MEMS, RRAM, and valve-based computing, are discussed in detail below, and are summarized in a table. In particular, we explore the possibility of using DCPs which are FPGA clones that can dynamically switch between a few particular hardware configurations in nanoseconds, to design networks that substantially reduce load, interference, and latency for low Earth orbit satellite communication systems. Such DCPs are also used to very efficiently design phase controllers in smart antennas. The studies conducted show the AI-based development of keeping low threshold values is important in reducing the battery energy consumption and extensibility of the IoT.

5. Convergence of AI and Hardware

The convergence of AI software and AI-optimized hardware with capability-enhancing software for autonomous decision-making, planning, and resource optimization in telecommunications networks is expected to become increasingly tight and productive. There are two basic types of relationships between software and hardware upgrades: software-controlled hardware improvements and hardware-specialized accelerations of software-based performance advances. In the first type, hardware enhancements allow for orders-of-magnitude speed-ups of certain types of workload-intensive AI procedures that no previous generations of hardware devices or systems can achieve. In the second branch of integration synergy, new or better AI software systems become capable of controlling hardware for systems considered to be hardware-only when a more primitive style of capability-on-the-shelf telecommunications system management was being employed. For example, without advanced software, a data router controlled only by its embedded hardware was incapable of optimizing the data flow over its hardware connections.

Eqn 2: Computation Time for AI Workloads

$$T_{\text{comp}} = \frac{N_{\text{ops}}}{f_{\text{clk}} \cdot \text{IPC} \cdot P}$$

Where:

- N_{ops}: Total number of operations
- f_{clk}: Clock frequency
- IPC: Instructions per cycle
- P: Number of processing units (cores/threads)

As an illustration of accelerated hardware/software interaction, it is probable that present generations of AI are unable to specify as many new use cases for future generations of AI algorithm accelerators as will be expected by the advent of accelerated self-supervised learning techniques. It's a simple observation that faster copies of AI software will enable a new generation of AI tasks to be specified in ways that are useful and productive by larger numbers of people, in particular less-specialized amateurs, for many groups of useful problems. Exploiting a principle of evolutionary design, more originally productive AI software will emerge for the next generations of more accelerated deep-learning AI homes and devices, ready to assist us in user-centric, autonomous, home-centered tasks, from child-rearing to elder support.

5.1 Integration Challenges

However, the promise of convergence between AI software and hardware brings with it many challenges. Regarding hardware, increasing performance and decreasing the size of components create an ever-increasing need to manage the heat generated, especially for chips with a very high transistor density. Evolution is thus leading to two extreme routes: chips with architectures that are more and more specialized for a small number of applications, usually for the acceleration of AI-based applications and universal chips, more and more flexible, usually for a broader range of applications. Given the significant differences in processing architectures and approaches pursued in those two routes, the enabling of a tight integration of specialized disruptive AI chips and mainstream universal chips, within an ultra-low energy consumption regime, representing a balanced strategy, has become a core challenge for semiconductor and hardware manufacturers.
Regarding AI, a main challenge of this convergence is represented by the different timeframes which characterize the evolution of the two domains. The performance evolution of AI hardware is usually driven by a slow discrete technology roadmap. On the contrary, AI software has an exponential development, able to introduce novel disruptive software solutions, which usually render existing hardware immediately obsolete, long before hardware has enabled next-horizon applications. The experience accumulated so far has shown that AI hardware cannot just cope with the current demand of AI application performance, but has to be designed also for anticipating potential near- and medium-term demands, while at the same time maintaining high energy efficiency levels.

5.2 Synergistic Benefits

The potential synergies that could come from a convergence of agentic AI and AI-optimized hardware are tantalizing. Present allocated cost centers for data centers — the costs of real estate, energy, and bandwidth — prohibit companies in the migration towards an all-AI software architecture. Autonomous telecommunication networks would provide a relatively high revenue source of cost-effectively managing internal, external, and wholesale customer service and business process operations. Such IT cost reductions could be extended to industries such as retail, finance, healthcare, and cybersecurity intelligence analytics attribution, that will require billions of sensor devices migrating from 4G networks to 6G networks worldwide. Such AI-optimized edge devices could lower the barrier to entry to utilize agentic AI tools to assist decision-making.

The AI-enhanced intelligent management would lower both real estate and energy costs within the data centers, freeing capital from non-AI optimized industries to address AI-optimized industries at a lower deployment cost. This would allow wider adoption and enhance trust in a market. Such harmonious coevolution would address a raising tide of concerns for existing solutions, already seen in campaigns for "no code, low code" tools. AI has been known to disintermediate human resources from business processes since early successes in tasks such as mortgage application processing and in knowledge capture implementations of customer service agents. Industry is finally starting to see the light concerning an all-agentic AI future impacting managed services. The synergy from coevolution could accelerate a widening of the efficacy adoption frontier of AI.

6. Case Studies of Autonomous Telecommunication Networks

Recent advances in the fields of hardware and software deep reinforcement learning, miniaturized AI-optimized hardware such as GPUs and TPUs, and miniaturized network sensors and sensors with localized learning functions have enabled autonomous networking implementations that are much closer to L1 than L2 in the OSI stack. There have been successful implementations of autonomous wireless telecommunications links, and some higher-order network functions have also been implemented. Existing implementations are generally limited to either L1 layer or pt-pt function of a higher layer link function.

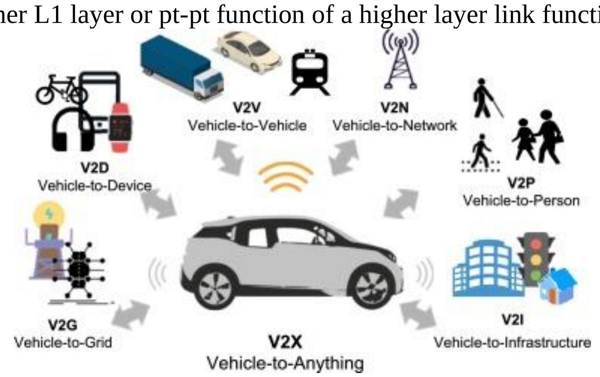

Figure 3: Autonomous vehicles in 5G and beyond

Certainly L1 links are easy to optimize because there is a single link (some jitter, slight signal beamsteering, single nulls), and every packet over that link has to be sent over that single link, and the actions taken for each packet are generally the same. Having a less fast and less reliable L1 link does not lend itself to AI-optimized higher layer functions. For instance, many L2 functions depend on timing (especially in wireless systems). The first implementations of L1 link optimization basically only optimized for SINR maximization, weighted capacity maximization, or expected capacity maximization. In future sections, we will present prioritized capacity, packet error rate, and threat minimization and probability distribution deviation definitions of the link optimization software's fitness. Having lower L1 performance leads to higher layer functions requiring more computational and memory overhead to keep main memory portion of L1 functional.

6.1 Successful Implementations

The multi-agent system area is devoid of successful deployments of implemented systems in the size and complexity of current telecommunication networks, indeed thoughtful implementations of multi-agent systems are scarce. In this chapter, we present some successful implementations both in telecommunication networks as well as other domains. One particular example combines the use of agent-based modeling with hardware for an AI-accelerated agent based

model of the networks. What is novel about this design is the use of an AI-hardware optimized for simulation.
Telecommunications is a natural domain for the agent-based approach. The networks themselves can be represented as agent based models where agents noted the discrete event nature of telecommunication networks. It is this feature that makes the use of hardware accelerated AI a real advantage for agent-based model of the telecommunications networks using the novel ai-hardware. Furthermore, the telecommunications networks are characterized by a scenery composed of nodes of thousands of types such as network elements, IP, VPN, VLAN, and BiDi used in communications networks and the corresponding IP routing and transmissions, electrical and optical switches, signal processors for the VPNs, VLANs used in photonic networks.

The complex and rich compositional structure of telecommunications networks has proven its efficiency in the telecommunications field and that is meant to contain the complexity of the multi-agent simulation as well as to be able to test its completeness with the accelerated dynamic testbeds for routing prototypes educated by the large available knowledge base of the telecommunications functions, features and algorithms involving databases.

6.2 Lessons Learned from Failures

Despite successful implementations, there have also been negative experiences with autonomous network initiatives. Most notable is the failure of a company that deployed balloons to provide telecom services to areas without good telecom infrastructure. The network ballooned out of control and had to be decommissioned, causing the project to be shut down. Such experiences provide valuable lessons. Here, we examine three negative experiences: one involving balloons, another with a well-known AI system, and a third related to an autonomous decentralized client.

Eqn 3: Regret in Decision Theory (Online Learning Failures)

$$R_T = \sum_{t=1}^{T} \left(\ell_t(a_t) - \min_{a^*} \ell_t(a^*) \right)$$

Where:

- R_T: Regret over T decisions
- ℓ_t: Loss at time t
- a_t: Action taken
- a^*: Optimal action

The network exploited two characteristics of balloon technology: large coverage areas and cheap deployment. Governments in underserved areas often subsidize major telecommunications operators in order to improve the area's connectivity. These subsidies are typically at least subsidized at some level. The approach had the major drawback that while balloons have some advantages during certain conditions, they also have major limitations. Balloons are restricted on a seasonal basis with temperature variations, there are safety concerns with them being above planes, and service is not high throughput because of the balloon size, especially when compared to terrestrial small cells. Also, the balloons were not autonomous. They were too fragile and too complex for total autonomy. These limitations on fragility and complexity applied to all three lessons the boutique probably failed to apply.

Specific types of AI technology, such as deep neural networks, have seen explosive growth. But in this regard, the deployment of autonomous networks should be cautionary. Similar to balloons in the telecom domain, there has been no deployment of a large-scale decentralized AI application with a careful cost-benefit analysis that includes consideration of fragility and complexity.

7. Regulatory and Ethical Considerations

The emergence of ATN raises considerable crucial regulatory and ethical scrutiny. First and foremost, Agentic AI impacts the management of AI decision-making in autonomous networks. Most AI services optimize either for the user or the developer but rarely for the network. Such a digital periphery, with much wider perspectives than any individual maker or user of a software service, indeed wonderland for possible externalities that are not optimized within the current regimes of AI technology – optimization for a service product, whether an online advertising feed or an AI-based moderation of a user's social network, with as little consequence as possible for the individual creators or the wider audience. Expertise in outside inspections of such an effect considered it the primary strategy of research and regulatory bodies to better mitigate the unintended externalities of existing technological regimes.

Another ethical consideration that arises from the prospect of cybernetic economies is the reliance on personal data. By and large, AI services as today are designed to save the user such personalized data as little as what is needed to optimize for specific goals. AI optimizing for the edge, however, sees the user merely as examples of a general stochastic process that generates requests for the content product of the network – online video, images, text, or SPE – and monetizes user-generated content based on advertisement. For this core business of large digital economies, and for the core business of specialized AI service agencies, every optimized digital economy collects insight on every user, since they are essentially commodity products. With the ATN approach to service delivery, that insight on individuals would not be available, as the number of edge agents is small compared to the plethora of users generating requests for such services. It would be impractical for any agent to take into account the specific smaller set of requirements of service provision by a very small digital economy if not by very serious economy-of-scales – i.e., a monopoly with most of the users in its ranks. A core strategic priority, therefore, for an ATN technology is to address the economic incentives that are created by the very need for thorough and seamless data trackers on each individual user to mitigate any trust that largely fund the smaller repositories for such personal knowledge.

7.1 Data Privacy in Autonomous Networks

The transition from conventional to autonomous telecommunication networks creates a wealth of opportunities for innovation in various domains, including new communication services, more efficient processing and management of resources, reduced capital and operational expenses, and a more sustainable impact of telecommunication systems. Deploying self-optimizing operations in these areas demands for a strict alignment with ethical principles and regulatory frameworks guiding the use of Artificial Intelligence agents making telecommunication network operations increasingly autonomous. The impact of Agentic AI on the economy, society, and the environment needs to inform the sustainable design of fully autonomous telecommunication networks guiding investment decisions and organizational redesign. Every time a user interacts with the physical world — be it through their devices or directly — a trail of data follows. While at first glance this information might not seem worth anything, how it is collected and processed makes this data valuable. When large sets of it are processed and merged with data coming from other sources and domains, it becomes unique. A wealth of personal identifiers are included in such data; physical and emotional traits, social relationships, behavioral tendencies and patterns, preferences, goals, objectives, fears, perceived rewards and risks, or triggers can all be derived from it and associated with the individuals behind the data. This means that it may be easy for the interested party to identify the individuals from whom such digital traces come and retrieve additional information of interest. Long-lasting data retention enables the re-identification even if data anonymization is applied. Thus, the amount of data collected, the duration of data retention, the lack of transparency regarding the use of this data, the potential use during the data's lifetime, and the degree of data accessibility represent the risk factors typical of so-called "Big Data".

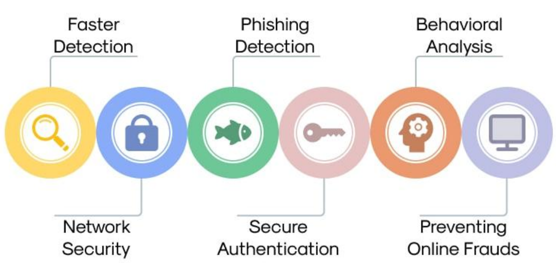

Figure 4: Decoding Data Protection: A Comprehensive Analysis and Guide

7.2 Ethical Implications of Agentic AI

Agentic AI systems are applications connected to the so-called 'real world' through sensors and effectors such as cameras, microphones, and other sensors - and motors, displays, and speakers - via which they receive collected data and in response to which they operate physical objects. Although not 'living', these systems 'act' by processing signals received from their environment and sending commands for action to the environment. They certainly can convey information to humans but the nature of their actions and the actors affected by those actions are much broader.

Agentic AI systems perform operations for states and operations that are governed by considering agents other than humans. Such as animals, other operating systems, and many physical systems such as the weather and ecosystems including the human ecosystem. The actions performed by these interconnected AI systems governed by commands from a few decision-makers can profoundly affect all agents, human and otherwise, that are part of the environment being monitored, sampled, modeled, and managed by these decision-makers.

The overarching principle for ethical Agentic AI is a simple extension of the ubiquitous principle of ethical AI that ethical AI must never harm humans, nor any living being, nor our collective future. Especially if we are indeed establishing a new AI ecology in which AI systems are actively managing much of our economy, societal activities, and even the future of our biosphere. Such as controlling the weather, ameliorating climate change, and avoiding pandemics. The requirement that ethical AI must never cause a virtual 'trolley problem' condition for the agentic AI systems governed by commands from a few, privileged decision-makers.

8. Future Trends in Autonomous Networks

As the decade-long trend for increased growth in Autonomous Intelligence continues, we summarize our understanding of the trajectory of future telecommunication networks. This is a combined conclusion synthesized from our analysis of the preceding chapters, with both technology emulating exponential growth, the theoretic understanding set by complexity, entropy and causality, coupled with the mismatch between Communications use and especially AI-Enabled telecommunications use, indicating that by the end of this decade, telecommunications networks will approach singularity to reach 100% utilization by complex AI and other network applications requiring more bandwidth and latency optimization than the quantum mechanical limits. Responding to this expansion in both use and via enabled by emergent AI, will be networks that have converged into an Inter-Planetary multi-optic networking fabric, with potentially quantum and optical tele-transmission links for connecting to satellites and planetary celestial entities, including Lagrange points and Low earth orbit Constellations. The Ground networks, more particularly, the Pop sites, will consist of AI and Quantum-optimized equipment, including interconnects, cooling, power supplies, antennas, collimators, filters, laser sources that will all be optimized, driven and enabled via agentic AI converged with the Hardware AI method with network Mechanicsware and Software all co-designed including the AI Optic connections. Here the Hybrid method includes Three-body Hardware-Software-Agentic AI plus Mechanic Convergence. At further extreme closes to the end of the decade, but also potentially at discretized steps across venue-testing, we can expect timescale

Paper ID: MS2312142403 DOI: https://dx.doi.org/10.21275/MS2312142403

predicted for neural forms of AI reaching capability and functional levels of Humans, Synergic Intelligence and enhanced Multi-Agentic Socio Affairs intelligence with Super-agents arriving.

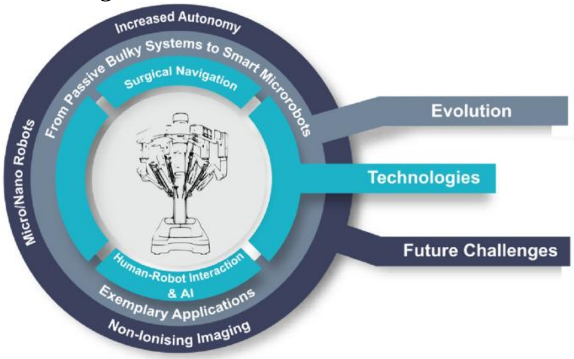

Figure 5: Robot-assistive minimally invasive surgery: trends and future directions

8.1 Emerging Technologies

Emerging technologies can be defined either as revolutionary technologies that will enable very novel applications, or as extreme evolutions of existing technologies, which will become enablers of advanced implementations of the existing families of applications and services. Autonomous and autonomous-like networks have increasingly been part of our common technical language since the autonomic computing vision put forward at the beginning of the second millennium.

Autonomous networks have been the dream of researchers since the invention of packet switching, but due to a lack of necessary technology enablers, certainly have not been the reality in telecommunication networks. New technology enablers progressively advanced the capabilities and reducing the cost of new-generation networks until now, when the latest new-generation telecommunication networks are putting to the test our technical and business knowledge of operating large commercial telecommunication networks. Emerging commercial technologies are removing the last barriers that limited the automation of the operational processes associated to the management of large scale networks. On the other hand, practical theoretical and experimental neural network and reinforcement learning implementations and applications have proven capable of capturing virtually any functional input output relation between elementary functions of these real life networks. Emerging extreme evolutions of current microcontroller technology to opto-electronic chip-on-chip 3D stacking packaging are promising to expand the computational power within a physical component at very low cost scale for all small scale components of the current AI hardware revolution.

8.2 Predicted Developments in AI and Hardware

Although such programs would be very useful, we are unlikely to see substantial improvements over current AIs until the very end of the current decade. In 2030 and beyond, we may see dramatic improvements in performance that would enable actually performing critical industrial functions, especially those related to space exploration, nuclear fusion, and generating companies with capabilities that can quickly adapt to rapidly changing and difficult contexts. Such developments are predicated on the following seven underlying advances in the capabilities of AI systems, especially Generalist AIs, improved, re-trained specialist models, Intelligent Procisioning supported by Advances in AI-Hardware Convergence, Faster and Cheaper AI Training Cycles, Improved Visual Control Systems, Specification, Sampling, and Control Driven Automation of Everything, and Automating Company Creation. The first of these seven is that not long after, if not before 2030, a subset of AIs surpass the capabilities of most humans from an economic perspective, competing directly with humans in all functions costing over 10 to 20 million dollars annually. With such capabilities, companies could operate with fewer, more talented humans, while the level of decision-making and execution throughout the organization could be vastly elevated. Advances needed to support this revolutionary trend would include re-identifying and better training specialist AIs better suited to specific, programmed functions while building large pools of Generalist AIs capable of guiding the actions of various persons and company teams from higher performance vantage points. These capabilities need to be developed to support Generalist AIs, specialists for functions not assigned to AIs, and the workforces in such companies that accompany AI involvement. Companies could harness these capabilities to elevate innovation and execution multipliers throughout the organization, while focusing on the relative few areas of operations guided by humans. Such processes would take time to develop, including human capabilities to develop complementary AI companies and management teams without needing overdependency on AIs.

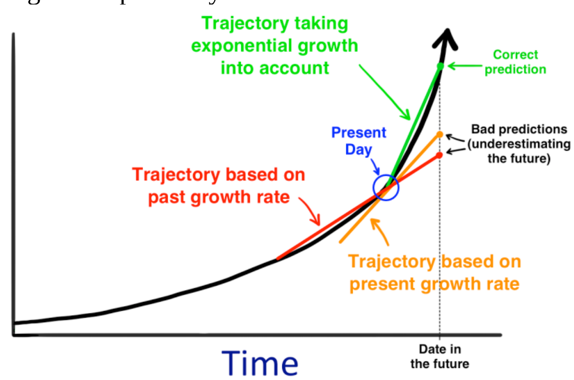

Figure: Is Current Progress in Artificial Intelligence Exponentia

9. Impact on Industry and Society

The birth and growth of Advanced Telecommunication Infrastructure (ATI) has created a number of industry and societal changes, but their amount has been limited compared to that what was originally foreseen and fireworks were announced. These have been two waves of changes. The first has been the information society, which was more of a gradual transformation because it happened over a period of few decades. The developed world went beyond agriculture and industry societies a long time ago. The second societal transition has been the beginning of the Knowledge Society (KS). Its impacts have not been only technological but also economical. The digital economy (DE) has been slowly taking its planned economy place.

The economic transformation has been specifically well described by the three pillars of the KS: the digital economy, knowledge and ICT. The DE relies on an advanced digital ICT-based infrastructure, which will be used by digital companies in order to develop and deliver their digital products and services. The digital economy, which develops on the basis of interconnected digital companies, applies technology to the design and production of goods and services to which more elements of intelligence and added value have been added. Their physical realization is made possible by deploying the technological infrastructure built by the telecommunication company, which takes a technological and regulatory monopoly on the infrastructure over a period of time. The basic inhibitors of the PI in the basic ATI monopoly are economies of scale and the huge capital investments required for building the digital ATI.

9.1 Economic Implications

While there are many challenges we will need to resolve before distributed autonomous telecommunications networks become a reality, the possible rewards are great. Lowering the monetary costs of building and operating the infrastructure for communications and information processing would lead to more intensive usage and increased GDP per capita. The faster the monetary costs are driven low, the more rapidly the economy could grow.

People think of GDP as a measure of the economy, but it is more than a measure; changes in GDP are one of the major drivers of social change. Via the feedback loop it forms with taxes, public sector outlays and consumer demand, GDP influences business investment decisions. By providing the majority of funds for private and public investment, business and government managers as well as investors are influenced, sometimes strongly, by GDP growth rates.

Just as changes in long-term GDP growth bounds influence the rate of change of wealth, income, and consumption expectations, which in turn influence many behaviors, including saving versus spending, public and private borrowing, and taxes, in addition to business investment, the reverse is also true. Changes in any of these areas are likely to influence GDP. It would make sense that increases in business investment would lead to GDP growth, considering the investment multiplier. And it's plausible that stock market performance, which affects consumption, would also influence GDP growth rates, at least over the short term. These estimates of the feedback loop between changes in GDP growth and general business activity are described below.

The implications for society relate both to the direct impact of the shifts upwards in per capita GDP themselves and to the structural change in the distribution of income and wealth across households introduced by the shift from a capitalist economy to a capitalist-sharing economy. The remainder of this chapter discusses how these economic implications of distributed autonomous networks will affect society in the future.

9.2 Social Changes Driven by Autonomous Networks

The emergence of Autonomous wireless networks and services will dynamically shift the relationships between businesses, communities, and governments. Such innovative and market-oriented building blocks will open gateways for hinting and discovering content, applications, and, who knows, even the goods and services we want, where and when we want them. This will earn for agencies like the proliferation of fast, easy, cheap, and tailored gateways kind of platforms that in turn link vendors, shippers, welcoming communities, and retailers, and take a small commission. Will be the first? Probably not. We remember how have opened gateways for the retail travel market, or how has arranged a buying alliance comprising millions of retailers. Gone are the days when missionaries carry our suitcases in a sacred mission to rescue needy destinations from a terrible destitution that was their major source of livelihood.

These dynamically assembled gateways will put at risk in no time the many business-cockroaches not free to be original, stuck in the old comfort zone of vertically integrated services built and offered from the bricks and mortar trunk of their national – or more often regional – monopolies, ensuring everything from sending and receiving means of transport to drivers and carriers, to ticketing and design, to inboard maintenance and supply. Prophecies for the incumbents: rethink your business models NOW. Or collapse. Most probably, we do not see the other vultures yet circling over you, but when your dust will settle you will focus on different diameters of the service and quality scales, pushed up at the extreme low price rim by a newly formed, virtually integrated consortium of business locals acting on a local niche. What was high-end but low-volume quality service becomes high-volume but low-end price service.

10. Technical Challenges and Solutions

The vision of nearly fully autonomous telecom networks, with independent decision making by network agents and minimal human intervention has inherent technical challenges. In this section we will reflect on some of these issues and propose potential solutions based on our research over the past decade in conjunction with colleagues.

10.1 Scalability Issues

One factor affecting scalability of agent based systems is the amount of message exchange among agents, as more low level actions of agents are being communicated, and the action sets become larger and larger. We have experimented extensively with using high level action abstraction sets, that allow for higher level negotiation amongst the agents to minimize the amount of message traffic generated. Instead of sharing detailed information about what is going wrong, and what should be done to mitigate the impacts, agents can agree on collaborating on a high level task, and then share lower level actions less frequently, e.g., every few minutes for the high level task, instead of every few seconds for the low level action updates. These types of tasks might include handling a specific service failure, or coping with significant demand changes. Once agreements are made for handling high level tasks, then agents share lower level action updates a lot less frequently.

To define such high level abstractions and how to use them. For example, we can examine clusters of users and service flows sharing a common set of routes to/from the core, and use this clustering as an indication of the likelihood of possible service level impacts due to small scale route changes at the core. Utilizing this clustering, agents at the core, can jointly decide with the agents at the cell towers/mobile relays, the best way to handle possible service impacts during core rerouting, while using less traffic and fewer signalling exchanges than without this additional information. This has the additional advantage of reducing the likelihood of service interruptions for users/flows that share common routes.

10.2 Scalability Issues

A multitude of intelligent models dedicated to the telecommunication networks can be devised using agentic reinforcement learning. For various components of a network, models may learn to develop automated policies for controlling, tuning, and operating network functions. Principle difficulties with realizing such a machine learning telecom in the present form are lack of scalability. Consider scaling a telecom network function load balancer from a data population of 1 or even 100 for which AI can be trained to operate a telecommunication function that deals with load balancing requests of several services, to a telco cloud that manages workloads dealing with load balancing requests in multiple areas such as B2B, B2G, B2H and B2E communications each with micro, small, medium, or big companies and various critical government and commercial public services that involves different strategies for load balancing requests. Obviously, mapping the M-dimensional spaces of action of inferring any one policy for a telecom function via recognition on a few data samples is burdensome and needs help from either a human expert or a strong structural bias. The reason is clear, one cannot walk through a polytope implicitly defined by trajectory tests in policy space through locally-measured cost so as to gather data needed to train M policies of a NN architectured to gathered data.

Transferring representation via agentic transfer learning with interpolation across domains of familiar objects could help avoid the M-fold difficulties but such ideas would need to be benchmarked over existing benchmarks for anomaly detection where hidden MDPs are discovered over preprocessed variants of original telecommunication domain generic training sets. Several transfer learning agents introduce mutual supervision loss to align predictions over relevant masked tokens to bridge the gap across domains. Other few-shot models based on a unique NeRF as a Scene Representation can scale to address the problem. Neural implicit representations with learned priors can also accelerate transfer learning across tasks and modalities with relational precision via gradient surgery on representation space and neural task encoding. Machine Learning in Operation with macro features using Neural task encoders, cross-context classifiers, capturing without expensive pixel data, how and when knowledge transfer can be accelerated, and what transfer mechanisms will accelerate telecom model scaling when massive data samples become available for training with all their details is a challenge.

10.3 Interoperability between Systems

The various systems and subsystems will need to work together in a seamless manner, interacting within a multi-agent multi-function environment over several hierarchical levels across the entire telecommunications sector, for the UTN concept to be realized. All the functions of all the suppliers of products and services – functionally disparate and distributed, independent, integrative, associative, cooperative yet competitive – need to be coordinated and orchestrated in an efficient way. These various and assorted systems must implement the optimal balance between self-management and central organization authority that will be essential for sustainable UTNs. The current top-down directives to reduce energy consumption and economize during the transition towards the softwarization of the networks need to be balanced against the telecommunications monopolies who have not typically been incentivized to sustain infrastructure investment.

One of the many current telecommunications pain points is the lack of interoperability between the various proprietary platforms, which has led to multi-vendor run-around, to different understandings regarding network and service restoration, to finger-pointing and lack of responsibility during outages, and to revenue and service degradation when such an outage occurs. While containerization and virtualization of network functions have been touted as the promises to solve this issue, the reality is that most of the procedures and special sauce are still proprietary and involved rights and access need to be established at multiple levels. Access and authorization and role can become painfully slow, cumbersome, sclerotic and clunky in practice, delaying market responses to unmet customer needs, and serve to inhibit system performance and lower system efficiency. Security matters and enforcement can both help as well as hinder the desired degree of interoperability, which might also change dynamically over time.

11. Security Concerns in Autonomous Networks

Emerging telecom systems that are envisioned to be fully autonomous and capable of self-healing introduce multiple security challenges to all aspects of network consumption and operation. For example, how the network infrastructure can be secured from adversarial use cases and cyber-attacks while being in a fully wireless communication mode – data and information are sent over the air and could be received and modified by adversaries – needs further understanding and research. This is in addition to already existing malice use cases in digital and cyber systems that witness an exponential increase year-on-year for the number of incidents, as detected by the available cyber detection telemetry and heuristic resources. The utilization of open, third-party-developed building blocks and reusable network functions and applications provided by individual verticals on top of common communication rails need to be scrutinized for lack of validation considerations and adversarial attacks along their entire life cycle and in all operational environments. A number of research avenues and explorations are powering the virtualization of existing network infrastructures with the capabilities for supporting multiple verticals, developing edge-cloud-based methodologies and adaptive closed-loop digital twins, improving autonomous behavior and adaptability against cyber-attacks using advanced countermeasure strategies, making use of federated ML, exploiting the quantum secure communication dimension, to name a few.

Considered cellular use cases that are accelerated for the deployment of 6G are focused on providing ultra-reliable low latency communication services, which are highly sensitive to disruption or inversion of normal behavior on short time scales. Security algorithms that are part of the digital, algorithmic-driven networks and sub-systems that operate the telecom ecosystem need to be modular, implement parallel processing and distributed dynamic architectures, be able to self-validate via multi-stage and cost-aware ML-based methodologies, and include countermeasures that recover the system as fast as possible on the inference time of the "normal" behavior. Achieving cyber-resiliency level autonomous behavior and protection against security breaches that compromise telecom networks from zero-day exploits is an ongoing challenge and imperative for 6G systems and beyond.

11.1 Cybersecurity Threats

6G mobile networks must not only be able to defend themselves from the attacks that current cellular networks are vulnerable to, but also mitigate new threats added by novel technologies. Besides the existing vulnerabilities introduced by limited processing power, interfaces and internet protocols that had not been designed with security in mind, and potential lack of accurate threat detection tools, new severe threats will emerge from the application of cutting-edge technologies such as the Internet of Things, AI, Quantum Computing, and Blockchain to telecommunications networks. This section describes the impact of the application of these new technologies on the security of cellular networks. We focus on 5G networks and the new functionalities proposed for 6G networks, as 6G security features have not been defined yet and their specificities will depend on the final design of these networks, which is still a matter of research.

AI-centric network management and automation, flexible service creation, and the support of a massive number of connected devices given by the introduction of IoT addressed by 5G mobile networks is key for the establishment of diverse sectors such as e-health, smart factories and logistics, linear and non-linear immersive media, smart cities, augmented reality and digital twins. However, in addition to the enormous size of 5G mobile networks, which through edge or cloud computing will have to support thousands of millions of devices, the technologies enabling the promises of 5G and beyond mobile networks (network slicing, autonomous closed-loop management systems, security, and resilience, and the convergence of physical and virtual worlds via parallelization and temporal-coherency enhanced digital twins) as well as their evolution through 6G mobile networks create new opportunities for new types of multi-dimensional multi-stage multi-actor, including massive failure and Selective Targeting attacks with new kinds of motivations and objectives. Indeed, the magnitude, volume and dimension of possible negative impacts on economic, security and privacy are unprecedented.

11.2 Mitigation Strategies

Different methods are being explored to influence agent behaviors in a positive direction. The first approach is to encourage following social and collaborative norms. In addition, researchers have created agentive systems that use three techniques to avoid harm - harm switches, space-time windows, and frequency of harm. Harm switches are associated with names or a few semantic categories, and whatever is associated with switches cannot be harmed prior to a task. The second mechanism sets up conditions with temporal detail of when something or someone can possibly be harmed, but only in a particular space. Space-time windows can also be used to set conditions of a task or the intrinsic properties of the agent. This technique is similar to a time window that humans or animals use to avoid harming human infants. The third tool monitors the frequency of harm to others when an agent is robotically performing its task or during initialization. The last technique can also be used to make sure that the frequency of harm is within the bounds of what humans consider acceptable operational behavior.

These early attempts by the research community, along with rules, guidelines, and regulatory frameworks can help minimize unacceptable risk to humans while making continuous improvements to autonomous network systems. Furthermore, the use of likely short windows of autonomy in initial phases, along with rigorous testing and validation and monitoring by humans will increase the integrity, efficiency, and productivity of these communication networks for society. These are our expectations, and we look forward to collaborating with the network research community to contribute towards these goals with our thoughts on the challenges and proposed solutions shared here. The use of agentive technologies is expected to permeate most, if not all, technologies we use in our daily lives, societal processes, and workforce.

12. User Experience and Human Factors

The emergence of autonomous systems in the telecommunication space implies interactions between users and these systems. Safe and effective interactions are crucial when a system may make certain decisions and take actions which are critical for the users. An important factor in user experiences of current AI-driven systems are user interfaces and the modalities they utilize. Current applications for image classification, translation, speech recognition, etc show that end users are comfortable interacting with invisible UI layers, which lets users focus on their goals without demanding the need to assess and decide on a specific interaction modality. User experience problems arise when asymmetries in interpretation between the UI and the users arise, leading to additional time and effort to reach a solution.

The usage of chatbots for customer service requests, and personal AI assistants indicate that users are comfortable using chat-based interfaces for specific tasks. There is, however, a limit with proactive actions on part of chatbots leading to failures of acceptance. Research has shown that if a human-agent team can jointly solve a problem, the user prefers to control the operation of the team, only consulting the chat interface for expertise reasons. This suggests that using chat-based dialogs for consultation can lead to greatly improved user experiences as compared to using chat-based interfaces solely for decision making and task execution. The current research is concentrated on building an understanding of effective interactions between users and AI systems.

12.1 User Interface Design in Autonomous Systems

The content of this section focuses on explainable AI, specifically in the context of user interface design for autonomous systems. Autonomous Systems (AS), such as self-driving cars and delivery-drones, are complex technologies, whose behavior is often hard to predict from user interaction or prior experience. At the same time, in many cases, especially regarding safety-critical applications, AS cannot operate independently of users or bystanders, for example, in shared spaces. For this reason, AS need to be able to communicate their 'state' or intentions to users without any reliance on interface artifacts, such as displays. This section discusses these challenges and points at the importance of User Interface (UI) design in the context of Explainable AI (XAI).

UI design for AS can be seen as a particular focus of XAI, the goal of which is to assist users in their understanding of how intelligent autonomous agents reach their decisions and conclusions. As the number of available AI technologies increases, the potential utility of XAI also continues to grow. Goals for XAI include improving the correct use and trust in AI technology, reducing the likelihood of uninformed users taking risky actions in response to AI decisions, or even having the research assist developers in finding flaws in their systems. However, designing good user interfaces for AI is a challenging task. AI is a domain in which users generally have very little specific knowledge. User conception of the AI technology will largely rely on their prior experience with technology, expectations derived from domain knowledge, and intuitive theories, all of which differ between users and can be incorrect.

12.2 Human-AI Interaction

Given the growing complexity of AI, the disparity between capabilities of many AIs and their users, and the automation that is being and will be performed by AIs, understanding and designing for Human-AI interaction (HAI) has grown in salience over the last couple of decades. Many of the avenues for HAI improvement fueled very recently by interest in the 'human-centered AI' principles and accompanying design guidelines for AI rest on core aspects illuminated by years of HAI research, including issues of expertise, shared mental models, interaction channels, task delegation, oversight, and communication. There is hardly a corner of AI design that is not impacted or at least inspired by research on how humans can best work with AI, and vice versa. HAI typically aligns with user-centric approaches to AI design, and desires to make users feel safe with AI and AIs more receptive to their users.

Human-Centered AI: Human-centered AI refers to a design principle rather than an actual research subfield: it is a set of principles and guiding applications that – prescriptively – guides researchers and designers into developing cognitive AI systems. HCAI-derived material typically expects a principled alignment of different and often conflicting levels of AI complexity and user capabilities. Ultimately, however, a HAI-usable AI is ideally also, somewhat closer to a traditional definition of utility, a useful AI, and a utilization-focused AI interface is a well-designed HAI.

13. Collaboration Between Stakeholders

Abstract: The deployment of new telecommunication networks, whether 5G or newer open radio access networks, will require unprecedented levels of collaboration and partnerships between multiple diverse stakeholders at the Telecom Industry. In this chapter, we discuss how Service Providers, Technology Innovators, Telecom equipment vendors, etc. can work in collaboration with each other to build and deploy the Autonomous Telecommunication Networks envisioned in this book. We further explain how Telecom service providers can work with the Government and National Regulatory Agencies to create policies and regulatory frameworks that can help accelerate the commercialization of fully autonomous networks.

With the advent of agentic AI, it is now possible to deploy autonomous telecom networks capable of delivering and meeting the next generation of deep, ultra-personalized and context-driven customer experiences and service level agreements. These autonomous networks leverage various AI technologies that together enable self-configuration, self-optimization, and self-healing. This exciting innovation is being generously funded by some of the world's largest Telecom service providers. The focus of these initiatives is the successful development, integration and deployment of AI-based autonomous Telecom network products. To further accelerate the commercial deployment of autonomous networks, it is imperative that stakeholders partner and collaborate while avoiding traditional siloed approaches. Such Commercial Partnerships, Government and Regulatory incentives should be established to enable a mutually incentivized growth ecosystem.

13.1 Industry Partnerships

The concept of partnerships in telecommunications is drawn from theories of network governance which argue that inter-firm cooperation goes beyond merely market processes and competition, and that firms increasingly are engaged in a greater variety of long-termed collaborative relationships. Subsequently, building strategic partnerships has become a key factor for firms to develop and maintain their competitiveness. The expanding internationalization of markets and the rapidly changing market conditions and technical environments has led many telecommunications companies to seek opportunities for growth through partnership strategies. As technologies diversify, applications which require provider specializations become more complex, and market segmentation creates an increasing demand for customized solutions, partnership and cooperation are becoming more attractive modes of operation within telecommunications markets. Furthermore, research suggests that partnerships can provide benefits such as securing critical resources and technologies, better content and technology integration, faster access to markets through joint marketing efforts, shared risks in new areas and an opportunity to gain insight into new capabilities, technologies, and applications at the same time. This new paradigm of telecommunications development, sharing, and co-opetition has resulted in a shift of focus for many telecommunications companies. Strategic partnerships are being developed to enhance network capabilities, add new services, enter new markets, and create new revenue models. These developments require that partnerships within the telecommunications ecosystem become more horizontal, more complex, more focused on specific applications, and more concentrated, resulting in vertical chains of specialized companies cooperating to deliver end-user services and applications.

13.2 Government and Regulatory Bodies

Whereas the previous subsection divulges on collaboration among industry players, this section explores the type of interactions that a very different group of stakeholders seek to develop, and on the unique present-day challenges that make it important for the latter to position themselves in preparation of ever-faster advancements of the industry. This distinctively different group is composed by government and regulatory bodies, actively seeking to stimulate discussion and participation from telco stakeholders to create frameworks for a convergence towards fully autonomous networked systems that autonomously self-organize, self-optimize, self-heal and self-provision – and therefore vital to the sustenance of society in a more technologically controlled future. Their perspectives are also enlightening venues for defining new schemes that can stimulate collaboration between smaller industry players and corporations or operators.

It is important to note that government bodies often vary significantly between countries or regions, and even at the same moment in time, as they may greatly reflect the local population axiological choices, culture and education. They therefore have very specific motivations, ranging from a desire to further engage their populace in the choices made regarding their communications networks, to a more economic or capitalistic approach, aiming at the independence of the local telecom network market – and therefore an increase of the tax revenue. Suggestions derived or emerging from the information provided and developed with industry participants therefore also offer a distinct structured manner by which governmental bodies may follow on past success with established industry associations, while better organizing activities and focal points for deeper industry engagement and discussion.

14. Conclusion

We have provided a feasibility-based exploration of some of the essential topics that must be addressed in order to create a telecom industry that can swiftly and efficiently cover the increasing demand for telecom services. And we have suggested that agentic AI, running on AI-optimized hardware, could enable 24/7 autonomous and vigilant AI operations that increasingly design and upgrade the dynamic operation of AI-driven telecom asset operation and management. Our conclusions from this exploration are that an intelligent telecom industry that can rapidly provide the basic service building blocks for all sectors of the economy can be created via the convergence of agentic AI and AI-optimized telecom hardware. Telecom corporations will be able to provide these critical service building blocks as an externality-free byproduct of creating increasing business value for themselves. As this future telecom infrastructure becomes operational, it will rapidly become essential to innovate and evolve consumer, enterprise, regional; and governmental AI software applications. AI is already starting to impact the iterative design of these application processes today. As growing numbers of these AI applications become incorporated in standard business and personal functions, they will drive rapid improvements in business efficiency and effectiveness in every sector of the world economy.

We expect, therefore, that the thesis we have presented in this work could incrementally enhance the agent-based decision-making features of globally-deployed autonomous telecom capabilities over time, catalyzing the phase transitions that are necessary to deliver the fundamental qualities of high performance and fast time-to-market to the entire global AI economy. Before we end this work, however, we would like to revisit some of the initial questions we posed in connection with our thesis exploration. They were: "What is the current state of hardware technology and what breakthroughs are required?" How can agentic AI become a driving factor to evolve telecom hardware and infrastructure?" And: "What kind of AI applications will utilize the AI-ready telecom future

Paper ID: MS2312142403 DOI: https://dx.doi.org/10.21275/MS2312142403

infrastructure?" We note that our thesis exploration indicates the possible emergence of an extensive global virtualized network of AI solutions. These AI solutions will be continuously fed, updated and enriched by input data and pensiveness supplied by the agents of each other distributed among the users of the telecom services provided by the telcos.

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