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From tradition to innovation: The telecommunications metamorphosis with AI and advanced technologies

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ABSTRACT

Businesses in the telecommunications industry provide global communication using a variety of channels, including but not limited to mobile phones, landlines, satellites, the Internet, and other electronic media. These businesses built the networks that enable the global transfer of text, audio, speech, and video. Companies in the telecommunications industry include those that provide landline and cellular telephone service, as well as those that provide cable television, satellite television, and online access. Once upon a time, the telecommunications industry was dominated by a small group of extremely large multinational and regional conglomerates. The industry has been caught up in a wave of liberalization and innovation since the early 2000s. Government monopolies have been privatized in several nations, exposing them to an explosion of new rivals. As mobile services continue to grow at a faster rate than fixed-line ones, and as Internet traffic begins to surpass voice traffic as the dominant form of commerce, established marketplaces have been turned on their heads. The undertaken paper endeavors to highlight the vulnerabilities that the telecommunication networking sector could be facing in the present as well as the future in light of the usage of artificial intelligence as assistive and advanced tech.

Keywords: telecommunication; network; industry; cloud; AI; NGN

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1. Introduction

The fax, the first motorized communications device, was invented in the 1830s and marked the beginning of the modern telecommunications sector[1]. As with the time it takes to communicate a huge volume of data using modern mobile technologies, communication was cut from days to hours. With the development of technologies like the telephone, computer, video, radio, and mobile devices, the market was able to expand[1,2]. The way people work and live has shifted as a result of these innovations in technology. There was a period when people needed to use actual cables to communicate with each other. Mobile devices have become ubiquitous in today's culture. The use of wireless digital technologies is rapidly replacing older methods of contact. There used to be only a handful of major companies in this industry, but now it is much more fragmented and easier to break into. Large publicly-traded organizations provide the services, while specialized businesses sell and maintain the hardware necessary to make this kind of communication possible.

Despite the fact that network technology has advanced, traditional telephone calls still account for the vast majority of the industry's income. Less emphasis is being placed on voice communication and more on video, text, and data in the field of telecommunications[3]. Interactive entertainment or broadband information services are just two examples of the data-based computer application types that are making their way into homes and companies all over the world, due to the expansion of fast Internet accessibility. Digital Subscriber Line (DSL), which is the dominant broadband communication technology, has been ushering in a brand-new era. The most rapid expansion is occurring in mobile network-delivered services. It may be said that small business marketing decisions are the most competitive of all client marketplaces[4,5]. Hundreds of companies are competitors; therefore, brand recognition and effective billing systems are crucial to standing out from the crowd.

In contrast, businesses are still the industry's preferred clientele. Unlike individual consumers, businesses care more about the consistency and quality of their phone conversations and data transmissions, and are therefore less price-conscious. Some companies, like large multinationals, invest extensively in communication infrastructure to facilitate global operations[6,7]. Additionally, they have no problem shelling out extra cash for upscale options like private, high-definition video conferencing and encrypted networks. Wireless communication, telecom services, and telecom equipment are the three main components of the broader telecommunications industry.

These sub-sectors are further broken down into the following major categories:

- Conveyance without wires.
- Vehicle networking.
- Tools for making and receiving phone calls.
- Items and methods of processing.
- Interstate carriers.
- Services of domestic telecommunications.
- Various methods of transmission.

Traditional landlines have been threatened by the rise of mobile and WIFI phone services due to the ever-changing nature of modern communications. Telecommunications firms can struggle as a result of this or thrive as they adopt the new technology, integrate it into their operations, and see rapid expansion as consumers buy cutting-edge gadgets. The main objective of this state-of-the-art survey is to highlight the vulnerabilities that the telecommunication networking sector could be confronting in the present, as well as preview an overview of this emerging topic and indicates future directions to grow this research in light of the artificial intelligence usage as assistive and advanced tech. The following sections of this research work are arranged in the following order: section 2 illustrates the state-of-the-art, 2.1 reviews the life cycle and vulnerabilities of artificial intelligence (AI) systems, and 2.2 reviews the intelligent agents in telecommunications networks. Section 3 provides a detailed explanation of the approach and the evolution of modern telecommunication clouds. The analysis and discussion are presented in section 4. To sum up, we conclude this work in section 5.

2. Related reviews

After its inception in the 1950s, the field of AI flourished twice, in the 1960s and again in the 1980s. In the twenty-first century, advances in cloud and Internet computing have led to the widespread use of information infrastructure, which in turn has led to an expansion in the computing power of devices like the Graphics Processing Unit (GPU). This, in turn, sparked the creation of deep learning (DL), which has been credited with helping usher in AI's golden age. Examples of this mass acceptance and further advancement in the real world include the computer-programmed AlphaGo's defeat of the human Go game champion and the widespread usage of facial emotion recognition[8,9]. With the telecommunications cloud as the backbone of the information communication system, there are numerous openings for implementing AI technology, such as in network automation and optimization.

2.1. Life cycle and vulnerabilities of AI systems

Artificial intelligence systems can be split into two types: non-symbolic/connectionist artificial intelligence (cAI), and symbolic artificial intelligence (sAI)[10,11].

sAI is a rule-based system that relies on a human-readable Knowledge Base. Constraint solvers, rule-based systems with decision trees, and systems experts are all examples of sAI. Easily explainable, these systems are more complicated to build because they have to be built from scratch. On the other hand, cAI architectures are built from networks of millions of basic pre-built processors that are integrated in a way that mimics the work of the biological brain work. Convnets (CNNs), Recurrent Neural Networks (RNN), Deep Neural Networks (DNNs), Deep Belief Networks (DBN), and Support Vector Machines (SVMs) are all included in the broad category of connectionist artificial intelligence (cAI). Models for operational cAI are developed in a roundabout way, via training data, and are typically not understood by humans. Important concepts of modern cAI systems can be traced back to 1943[12]. The 1970s were a time of relative inactivity, Despite the fact that cAI systems only began to regain some traction in the nineties[13]. At the beginning of 2009, advancements in computing power and the availability of example data led to dramatic increases in the effectiveness of cAI systems. Therefore, they got a great turnout, with seemingly fresh recommendations for uses being made on a regular basis.

Unlike traditional computer systems and symbolic AI, connectionist AI technologies are not built by human programmers from scratch. Instead of directly coding the AI system, after identifying the appropriate finite element method, the developer selects a process whereby a machine learning algorithm is utilized to train an untrained AI system. Both supervised learning and unsupervised learning are viable scenarios for training an AI system. In the first approach, input data is pre-labeled to indicate the expected output. Machine learning involves repeating a series of training and validation cycles until the AI system achieves its desired level of performance. If the expected level of performance is not met after a set number of training iterations, the training process is terminated, and a new training session is initiated.

A new training session can be started using randomly generated initial conditions or the model parameters can be tweaked by hand based on the machine learning (ML) policy. After reaching the target performance, the model is tested on a separate test data set to ensure it is truly independent of the training set (as illustrated in **Figure 1**). After the AI has been trained, it can be used for inference, or prediction, on unseen input data. AI systems can be developed using either machine learning algorithms or pre-existing datasets to train connectionist AI systems. Nonetheless, symbolic AI systems are easy to understand and formed precisely by human developers. The distributed nature of cAI systems' decision-making and their own indirect design make them difficult to interpret. The use of this method for building-cAI systems can integrate life cycles, involving intricate data supply chains, pre-existing trained systems, and the underlying foundations of ML, which may impact the security and safety of the systems.

It's common knowledge that vulnerabilities in cAI systems are qualitatively different from those in traditional software. One such example is the so-called "adversarial examples," or data intentionally designed to trick AI systems[14,15]. In most real-world scenarios, cAI systems are inherently difficult to interpret and evaluate, which further increases their susceptibility to attack[16,17]. However, even if the trained system performs admirably, it is frequently impossible for a person to comprehend why the system arrived at its conclusions. When coupled with the intricate life cycle, it becomes a serious problem because it means that we can't be certain of the AI system's proper functioning, even in the absence of attacks. A good analogy would be human cognition, which is difficult to predict by other humans[18] and susceptible to manipulation and fallibility[19]. The difficulty in formally verifying cAI systems and the general lack of confidence among users are leading to low adoption rates for these systems.

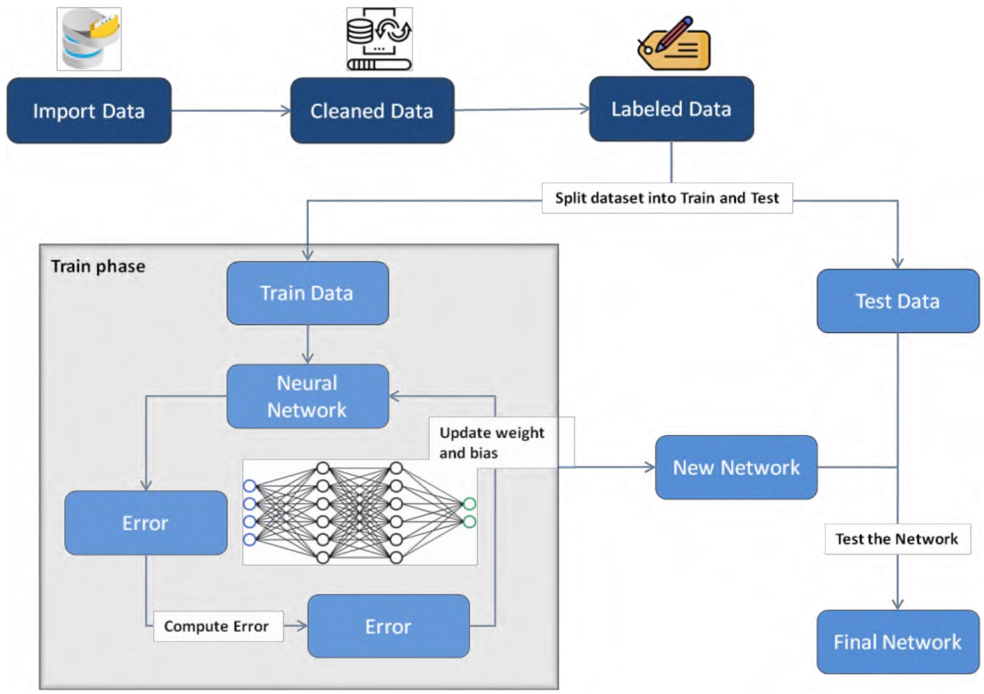

Figure 1. An artificial intelligence life cycle.

2.2. Intelligent agents in telecommunications networks

Both the volume of data transmitted and the number of devices connected to networks have increased rapidly in recent years. When networks are technological and cloud-based, the complexity of operation and maintenance skyrockets. In the period of the Internet of Things (IoT), the telecom business is at the forefront of technical development, spearheaded by smartphones and 5G broadband services[20,21]. Devices used in the IoT must be able to establish a connection at any time, from any location. Edge computing places stringent demands on the infrastructure of telecommunication clouds.

AI is being rapidly adopted in the telecom business, which is fueling this expansion and is projected to continue. Several AI use cases in network telecommunication can be identified:

- Improved service delivery in the telecom industry is made possible by AI-powered predictive analytics[22], which analyze large amounts of data using complex algorithms and machine learning methods to make predictions about the future[23]. This paves the way for operators to track equipment health and predict failure based on historical data.

- Communication Service Providers (CSPs) can use AI to predict and prevent failures in customer-facing communications infrastructure such as cell towers, utility poles, data center servers, and set-top boxes[24]. Short-term improvements in both root-cause investigation and problem prediction can be expected from increased network automation and intelligence. In the long run, these technologies will support broader strategic aims, such as the development of novel consumer experiences and the effective handling of growing business requirements.

- Using AI's superior analytical powers, the telecom industry is cracking down on fraud[25]. Telecom fraud, such as unauthorized network access, and bogus accounts, can be substantially reduced with the help of artificial intelligence and machine learning algorithms' ability to detect anomalies in real-time. As soon as the system detects fraudulent activity, it can automatically deny access to the perpetrator, limiting the harm[26].

- The communication services providers serve a massive population that conducts millions of transactions every day, all of which are prone to human mistakes. AI-based Robotic Process Automation (RPA) is a type of software used to automate various business procedures[27,28]. With RPA, telecoms may better manage their back-office functions and massive quantities of repetitive and rules-based tasks, bringing about higher efficiency across the board[29]. By automating complicated, time-consuming tasks like billing, data entry, management systems, and order fulfillment, RPA frees up employees to focus on greater value-add activities.

- Conversational AI platforms are another way that AI is being used in the telecom industry. In other words, these programmers, which go by the name "virtual assistants," have figured out how to automate and scale up individual interactions. The widespread use of AI in telecommunications is easing the strain on CSPs, caused by the avalanche of requests for assistance with setup, configuration, troubleshooting, and routine maintenance. Operators can use AI to introduce self-service features that instruct users on how to set up and use their devices independently[30].

Devices, networks, mobile services, geolocation data, complete customer profiles, and billing data are just some of the many types of information that AI can effectively combine and make sense of Telecoms can raise Average Revenue Per User (ARPU) with the help of AI-driven data analysis by intelligently upselling and cross-selling their services to existing customers. The telecommunications industry may better serve its customers by anticipating their needs and delivering tailored offers in the most appropriate ways.

3. Method

The telecommunications network is always being tested and confronted with new difficulties as technology advances in the field of communication. To accomplish the performance and litheness while supplying services and migration to the telecom cloud, networks must bring technology innovation and improvement, spanning IP networks to the cloud with software-defined infrastructure. There have been many significant advances in the evolution of modern telecommunication clouds, including 5G/6G[31], digitalization, cloudification, and the IoT. Each new technology poses formidable difficulties to the telecommunications cloud's design, and operation, including maintenance since it alters the existing network architecture in fundamental ways.

3.1. Cloud-based assistive approach

To put it simply, the communication cloud is really the backbone of the information technology sector. Due to its massive size and intricate design, the information society can directly count on the participation and support of countless network nodes[32]. Despite these obstacles, the telecommunications cloud now has access to exciting new possibilities made possible by the rapid progress of AI technology (see **Figure 2**). The ability to gather information and exploit data is crucial for telecom providers[33]. AI uses strong data analysis and knowledge extraction skills to aid operators in turning data into actionable insights and suggestions. Incorporating AI technology into telecommunication clouds is an attempt to address issues with efficiency and capability in existing infrastructure. In addition, the sector intends to offer adaptable digital and material services to people everywhere, realizing network intelligence with an "intelligent brain" in the communication network process.

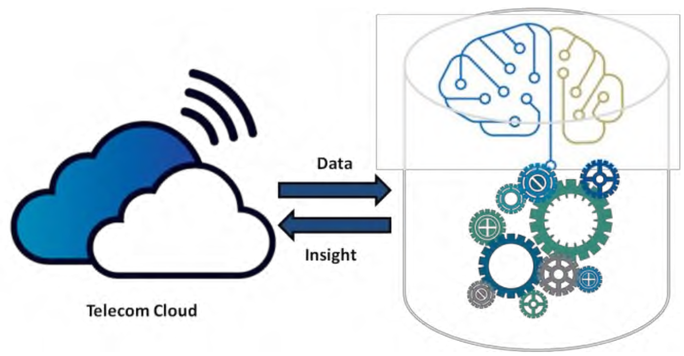

Figure 2. Cloud and AI-powered automation.

When it comes to the telecommunications cloud, the following applications are best suited for the incorporation of AI:

- By optimizing the network and automating the operations, costs can be reduced, and productivity increased.
- Big data-based analytics provide for effective value mining and risk protection in the context of large network data.
- Implementing unified open interfaces or standards for interoperability, as well as layer decoupling and control of networking resources, all by utilizing free source infrastructure.

3.2. Evolution of modern telecommunication clouds

Traditional machine learning algorithms, including decision trees, gradient boosting, logistic regression, and random forest, etc., are now widely used[34]. There have been significant advances in fields like cognitive technology thanks to the proliferation of deep learning techniques like Multilayer Perceptrons (MLPs), Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Long Short Term Memory Networks (LSTMs). Statistics, fitting, optimization, and data clustering are all common examples of use cases.

At present, AI technologies can be used in the administration and coordination of networks, as well as the design and operation of underlying link telecommunications[35]. But in the Ethernet interface, it is unusual to witness the true uses of those techniques. Given that there was a lack of detailed designs and purposes of AI technologies in this sector[36], and although most techniques are not fully proven, they are still just speculative results on paper. However, the direction of network intelligence has steadily earned acknowledgment from the industry, by expanding its investment in standards and technologies to go forward[37,38]. As AI aids in automating and optimizing the telecommunication cloud, the telecoms cloud in turn aids AI applications in three ways described in the following subsections.

3.2.1. Computational power

The deep learning AI algorithm is quite computationally intensive so it needs large computing infrastructure capable of supporting it during the training phase. Many data centers and cloud computing program infrastructures are owned and operated by the major telecom providers themselves due to network expansion[39]. The edge data centers and the core data centers will have a wide range of computational capabilities in the near future, thanks to the "convergence of cloud and network" trend in this expansion. Those AI algorithms are supported by large-scale AI infrastructure for computation and acceleration, which can be facilitated by further improvements[40,41].

3.2.2. Big data

The status of network elements, link traffic, alarm incidents, spectral efficiency, service logs, etc. are merely a handful of illustrations demonstrating the significant volumes of data that are being continuously generated by multiple nodes and service systems, which make up the telecommunications cloud[42]. The network's performance can be improved by analyzing and extracting useful structures and information from this data utilizing AI-related methods.

3.2.3. Many possible outcomes

The telecommunications cloud is rich in AI use cases, both internal and external applications. To begin, the telecommunications cloud is itself an advanced data system that is both massive in scope and in the scope of data it stores and constantly expanding in both directions. There is a wide range of scenarios where the use of AI technology could lead to increased performance or efficiency in the communication and networking industries, from initial research and development through actual network planning, construction, operation, and maintenance. The telecommunications cloud could benefit all sectors of society by meeting the computerization and intelligence requirements of a wide range of niche markets. This includes the smart city, transportation, healthcare, education, finance, manufacturing, agricultural sectors, etc. As more and more applications and services are made available through the telecommunications cloud, AI technology can be developed and promoted.

4. Analysis and discussion

Next-Generation Networks (NGN) have high requirements, including improvement of the repair productivity and network control, accuracy adjustments of resource provisioning, etc. Furthermore, operating challenges are a key barrier to full cloudification of the network, as the size of the telecom and its complexity increase. This is why the traditional form where issues are dealt with manually is not sufficient to support these requirements. However, the mobile transceiver has reached 5G[31]. As the fixed-line transceiver continues to evolve; such as the number of connections it can support, the network throughput, and latency; the number of possible use cases for mobile devices and customers continues to grow.

Changes in efficiency and adaptability are substantial and fundamental. The operation and 5G network maintenance face new challenges due to the network's growing complexity and users' rising demand for flexibility. The issue becomes more noticeable when dealing with matters that necessitate the use of conventional methods of operation and upkeep. Cloud service providers often take care of maintenance and upkeep[43–45]. Nonetheless, telecom providers are eager to operate virtual network functions above the cloud environments they constructed, so that they may exert complete authority over and responsibility for the underlying infrastructure.

The standard operating methods followed by the majority of telecom companies are illustrated in **Figure 3**. For their Virtualized Infrastructure Manager (VIM), they may opt for open-source software like Open-Stack, which can be used with bare metal or virtualization to host virtual network functions (VNFs) or physical network functions (PNFs), or Kubernetes which can be used with containers to host cloud-native network function (CNFs).

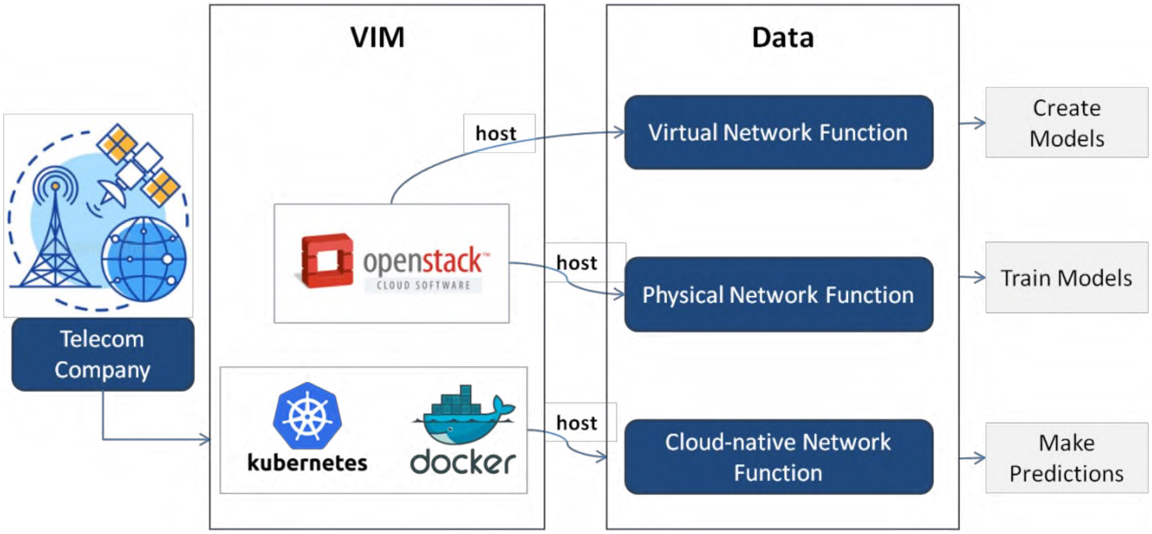

Figure 3. Network function virtualization.

As Software-Defined Networking (SDN), Software-Defined Wide Area Network (SD-WAN), and the Network Functions Virtualization (NFV) architectures are pushed more and more, network cloudification is sped up, new systems and solutions are developed, and the existing telecommunication infrastructure is put under increasing strain[46]. More possibilities are opening up as the telecommunications network evolves into the telecommunications cloud. Telecom operators can use AI to better control and optimize network services, operate internet protocols, and automate collaboration, all while benefiting from the procurement of materials by the telecommunications cloud and the big data collected by that cloud.

Telecom companies anticipate using AI for service quality, bandwidth allocation, network security, and network automation in response to the difficulties of network operations[47,48]. Moreover, it is anticipated that all AI-based automation would be closed-loop. Using the hardware technologies available in Open Network Automation Platform (ONAP)[49], China mobile, Quanta Computer, and Intel have been working together to establish a proof of principle of the benchmarking tool for giving up closed-loop automation of different types of network functions)[50] (see **Figure 3**). The prototype begins by keeping tabs on the network and the VNFs/PNFs/CNFs; it then uses this information to train an artificial intelligence model, which will later be used to make predictions about future tasks, and then it takes the appropriate steps based on those forecasts.

5. Conclusion

Commercial applications of AI-based machine learning, speech synthesis, and computational linguistics are already in existence, and these technologies can be rapidly combined with the telecommunication cloud's business operations to form massively scalable AI capabilities that can be used to provide customers with knowledge and experiences.

The advancement and improvement of AI technology and the cloudification of the telecommunications infrastructure go hand in hand. Some open-source telecommunications projects, such as Distributed Monitors and Analytics (DMA), etc., are already utilizing AI systems for VNF operating and edge computing.

Above all, AI can be used to enhance the quality of services provided by telecom providers, increase the scope of businesses' operations, and empower new services. We can improve our quality of life thanks to the proliferation of new opportunities presented by the rise of the telecommunications cloud.

Author contributions

Conceptualization, KS and SK; methodology, KS; validation, KS, SK and MLK; formal analysis, KS; resources, KS, AM; data curation, KS; writing—original draft preparation, KS; writing—review and editing, KS, SK, AM; supervision, SK and MLK. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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