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Data Engineering And Analytics For 5G-Driven Customer Experience In Telecom, Media, And Healthcare

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Abstract

Telecommunications service providers play a central role in creating, distributing, and managing customer experience across multiple sectors, such as healthcare, media, sports, and others. These providers generate and collect an unprecedented amount of mobile data and leverage this intelligence to help other sectors in transforming customer experience, [1]products, and services. However, telecom providers face a stiff challenge in transforming data into insight and innovation and helping others become the data product leaders in their sectors. The key challenge is unique in being a business-to-business, data-as-a-product market facing steep competition across telecom and non-telecom sectors, while dealing with complex data governance and ownership issues. This chapter focuses on the transformation of telecom, media, and healthcare services, focusing on the creation and management of customer experience in a 5G-driven world using data analytics and engineering.

We present a framework to address these challenges of enabling telecom providers to become innovation enablers, creating market differentiation through intelligent productization of data. By tying together aspects of Data Engineering, Product Management, and Domain Knowledge, we first present five principles of Data Product Management covering the dimensions of Strategy, Structure, Governance, Quality, and Enablement. Next, we map the principles to four layers of the Data Pipeline — Collection, Curation, Custody, and Consumption — to derive a set of recommended patterns. We discuss these principles through six detailed case studies, covering telecom and non-telecom sectors, illustrating the best practices used showing how these recommendations improve business outcomes with reduced time to market and costs. Thereafter, we discuss the impact of 5G on the principles and patterns, wrapping up with a summary of the chapter.

Keywords :Keywords: *Data engineering, data analytics, 5G technology, customer experience, telecom networks, media platforms, healthcare systems, real-time analytics, user behavior, network performance, cross-sector data integration, edge computing, personalized services, big data, predictive analytics, latency reduction, digital transformation, quality of service (QoS), data pipelines, streaming data, interoperability, customer satisfaction, mobile connectivity, telemedicine, content delivery, service optimization, intelligent networks, AI-driven insights, data-driven decision-making, multisector analytics.*

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1. Introduction

Fifth Generation (5G) wireless technology has become the de facto standard of mobile networks and embedded systems globally. Wireless networks such as the Internet that are accessible at any moment, also referred to as a Tactile Internet have transitioned to the status of Lifelines. Tangible connectivity advantages of 5G or other advanced Low Power Wide Area Networks (LP-WAN) converge with intangible desire for true connectivity, heightening customer experience demand in service industries such as Telecom, Media, and Healthcare. Data engineering and analytics for consumer-facing functions that have intuitive connectivity are ideal for addressing this "more is less" problem. Examples of such functions or products include Customer Experience Management (CEM), Zero Touch service Control (ZTC), Augmented and Virtual Experience (AVX), and Personalized Mediation (PM). It is understandable that purpose of such functions is "to be as transparent as possible".

Most existing works on Data Science frameworks for TMC have focused on Temporal or Spatial Analysis. Recently, demand for Artificial Intelligence (AI) based solutions has risen exponentially. Generic solutions have incorporated Cloud based services. Data Engineering Systems avoid centralization latency of Cloud and work better for bigger on-device data and analytics. In-device tasks could be collaboration, contextual observation or in-depth learning. Performance constraints of device CPU and battery, however, limit use of usual codes. Intensive Parallel Processing of Quantum Neural Networks (QNN) accelerators scaled down for energy optimisation, Co-Bit Quantum Programming (CBQP) avoids on-device quantum state. These advances make collection and engineering of in-device data easy. Domain models and application inspired Structured Data generate rich and lower-dimensional out-device data. This chapter describes the approach in-depth in the context of data engineering for CEM. It also sketches a summary of the key concepts from Quantum Computing needed to understand the chapter better.

2. Understanding 5G Technology

While 5G Networks hold enormous promises for telecoms and tech giants, it is important to realize that 5G is as much hype as it is opportunity. 5G is one of a series of Radio Access Technology initiatives designed to create a unified means of communication that can provide ubiquitous service to growing user demands. In addition to a desire for increased bandwidth, networks are also evolving to meet a burgeoning demand for low-latency, sensor-based connectivity, driven largely by automotive and industry applications. Not every country is enthusiastic about their 5G ambitions, however: in the early 2020s, the UK, for example, has expressed reluctance to roll out 5G networks primarily because of the unprecedented cost associated with its investment for its countrywide deployment and its unavailability of additional revenue from mobile use.

Fig 1 : Burning Issue] 5G Technology - Civilsdaily

Indeed, 5G is as much hype as it is opportunity. 5G is a core function of digital transformation strategies, whereby conventional companies from banking to agriculture aim to enhance revenues by creating new business models that take advantage of real time data and analytics generated from connected devices. Digital transformation frameworks are recognizing the centrality of telecommunications, not least to improve company efficiencies through enterprise and operational capabilities, but also in defining new opportunities in their consumer offerings. Data Engineers, Data Scientists, and Analysts working with telecoms face a steep learning curve and an unprecedented opportunity to take what they have done in previous efforts with 4G and below to scale them to unparalleled heights. Some telecoms have indeed disbanded their conventional monolithic data warehouse structures in favor of hybrid data lakes that take advantage of both Cloud and edge computing technologies. The partially untethered nature of 5G driven devices is accelerating moves among telecoms to explore use cases beyond their model for rural areas.

2.1. Overview of 5G Networks

5G (Fifth Generation) networks represent a paradigm shift from the preceding 4G (Fourth Generation) mobile networks, addressing the shortcomings of 4G in providing ultra-reliable and low-latency communication for critical applications such as automated driving and factory automation that have gained substantial traction in the last decade. Moreover, while 4G has predominantly targeted the smartphone market, 5G is designed to deliver high throughput connectivity on a massive scale for a diverse range of devices supporting a variety of application domains, including telecommunications, media, entertainment, and healthcare for both residential and business customers.

The implementation of 5G relies on a novel, holistic architecture that introduces several new and innovative technologies. At a high level, the 5G architecture comprises the User Equipment (UE) operated by end-usage customers, the radio access network incorporating new technology elements such as the next generation NodeB (gNB) base station, and the transport network connecting the gNB with the 5G Core Network (5GCN) that supports a new service-based 5G System (5GS). The 5GS offers two main types of services, namely enhanced mobile broadband (eMBB) services for high-capacity data transfer between the UE and cloud applications using the so-called User Plane of the 5GS, and ultra-reliable low-latency communication (URLLC) services for critical machine-to-machine applications that depend on extremely low latency and high reliability. The 5GCN is designed to offer a range of capabilities, including network slicing, to cater to industrial customers in addition to the usual telecommunications capabilities tailored for consumer applications. However, the ambitious 5G vision has created unprecedented challenges in the design and deployment of 5G networks and services.

2.2. Key Features of 5G

5G technology, the fifth generation of wireless system technology, was developed on the evolution of fourth generation technology. Unlike the evolution of the previous generations, that were based on higher transmission capacities or higher data rates, 5G technology aims to address the mass machine-type communication in vertical domains such as telecommunications, media, healthcare, automotive, and manufacturing. Its aim is to support diverse and vertical scenarios in the current mobile broadband, ultra-reliable low-latency communication, and massive machine-type communication. 5G technology has been standardized and is being rolled out globally. This dedicated wireless solution has a chance to

boost the above industries, enabling low-cost massive connectivity, gigabit mobile broadband, high-speed reliable services for safety, and low-latency time-sensitive applications.

Relying on millimeter waves, massive multiple-input multiple-output (MIMO), and small cells, 5G will deliver more flexible and optimized networks for telecom operators, internet service providers, and enterprises compared to the previous generations. 5G will also use cloud-based virtualization-based mobile edge computing technology to deliver low-latency and low-cost services for telecom and corporate customers. By 2030, it is expected that 5G technology will have brought strong revenue growth for the telecom and media sectors, while powering innovations and economic development in the transport and healthcare verticals, enabling market expansion of 5G-ready companies. Gaining insight in the new normal of 5G-driven telecom and media operators and industries is the key to fulfilling such potential.

2.3. Impact of 5G on Various Industries

While 5G technology has been developed as a telecommunication standard and infrastructure, it will have a much broader impact on various business sectors due to 5G's unique features and its ability to serve unique and varied requirements from a plethora of applications. To give an example, ultralow latency of 5G, as low as 1 millisecond, will allow companies to monetize services that cannot be monetized with a latency of 20 - 30 seconds, which is the norm for 4G technology. Monetization of ultra-low latency services such as Cloud Gaming, which is impossible with 4G technology, will allow cloud gaming companies and telecom companies to optimize their resources, offer their consumers additional value, and drive additional revenue. Investment in Cloud Gaming initiatives will drive revenues for Graphics Processing Unit products, as well as drive additional profits for telecom companies while promoting 5G technology.

From a business perspective, 5G technology will have an impact on the following verticals: Automotive and Transportation, Industrial Automation, Healthcare, Media and Entertainment, and Energy and Utilities. These verticals will tap into 5G's promise of ultra-reliable low-latency communication with latency as low as 1 millisecond, enhanced mobile broadband with a capacity of 10 gigabits per second, and massive machine-type communication with the ability to connect in excess of 1 million devices in a square kilometer. Telecommunications industry sector – Telecom, Mobile, and Wireless Infrastructure – is projected to have a high level of business revenue impact followed closely by Automotive and Transportation.

Fig 2 ; Green 5G: Building A Sustainable World

3. Data Engineering Fundamentals

Data engineering underlies the detailed design of data engineering artifacts for data in data analytics. In the process, the output of data engineering can provide data foundations that are ready for data analytics and updates of data analytics outputs to influence operational decision systems. The life cycle of data engineering for analytics encompasses the ingestion, collection, transport, storage, processing, and organization of data from a variety of sources in varying velocities; the automation and orchestration of data manipulation for analytics; and the management of data quality, availability, trust, and security. The objective of data engineering is to collect raw data from primary sources and transform it in a manner that is optimally useful and economical for analytics as per certain rules, guidelines, and contracts on data quality, availability, integrity, privacy, and security.

Our focus in this chapter is on data design as a core subset of data engineering. Data design is concerned with decisions that govern which data sources will be collected, how data from data sources will be transformed, how data will be stored for data analytics, and what tools will be used for data queries to enable data analytics. Data design is both a precursor to and a product of data analytics, and truly effective data design requires a detailed understanding of the planned analytics and associated queries. Data design is an iterative process where early versions of the data design are refined and made more specific, as specifics of the different analytical queries become clearer. For complex analyses, a simplified data model may be useful in the preliminary stages so that the focus can be on the analyses before the compilation into a final data model. Complications that frequently arise in this process are typical infrastructure considerations around data storage and regularization capabilities required for needs of different types of analyses.

3.1. Data Collection Methods

Data collection methods enable organizations to collect the data needed for analytics. Typically, a combination of these methods is used to collate diverse datasets to support different analytics and data science use cases.

Data collection can be broadly classified into primary data collection and secondary data collection. End-user-generated content is a large source of primary data for an organization. E-commerce companies, for example, collect reviews posted on their sites by their consumers. However, primary data collection mechanisms like surveys, focus groups, interviews, workshops, and crowdsourcing are expensive, time-consuming, and inherently biased. Secondary data collection methods like data provisioned by internal and external systems and sensors that capture user behavior in real-time are easier but limited in terms of coverage and metadata. Their quality is also difficult to ascertain and maintain. Advances in Big Data technologies, as well as improvements in satellite and aerial imagery collection, are changing the data collection landscape, improving coverage, and potentially increasing the quality of data.

APIs provisioned by internal systems, partners, and are used by organizations to collect data consumed during customer interactions. Sensors at point-of-sale terminals, wearables, mobile apps, websites, and smart products record, transmit, and store data regarding customer transactions and interactivity for subsequent analysis. These sensors and devices generate the concept of the Internet of Things – a web of devices interconnected by sensors, data, and APIs. IoT innovations have paralleled and combined with Big Data advancements to improve data

collection. Examples of IoT data collection sources include asset tracking for inventory management, loss prevention, supply chain optimization, and associated customer service analytics; geolocation, near-field communication, and mobile device data for customer journey tracking, customer behavior analytics, and campaign attribution modeling; telemetry and environmental sensors to improve product and supply chain management; and customer location and behavioral insights enabled through app analytics on smart devices.

3.2. Data Storage Solutions

With rising data generation rates and the growing need for user-centered insights across diverse industries such as telecom, media and entertainment, and healthcare, creating and deploying efficient and scalable storage infrastructure has gained even more importance. A data storage solution must be able to store data in batch, near-real time, and real-time data arrival frequencies. Furthermore, depending on the latency requirements or the analytical processes being applied on the data, the storage solution may need to serve data at low latency or high latency. Based on the anticipated latency requirement for read/write operations, data storage solutions may be optimized for high throughput and low latency, or high latency and low throughput. Equally important, different types of data may require optimization of different metrics. For example, storage of image and video data may require optimization of throughput and size, while storage of chat messages may require optimization of throughput and scalability.

Batch processing often writes to low-latency high-throughput storage due to their low cost. Data written to these systems are subsequently read to program data pipelines, at which point data is likely moved to other systems to be optimized for a latent requirement. For example, pipeline outputs are often written to make modeled data available for use by real-time applications such as chat clients, before drafting WriteOps for processing, and subsequently written back to these low-latency systems. In-memory storage systems optimize read/write operations for latency. Data serving systems, meanwhile, work well for low-latency, low-throughput requirements, while analytical data warehouses optimize processing of analytical queries.

3.3. Data Processing Techniques

The amount of generated data requires that Data Processing techniques carried out on the Data already in the Data Operations must become more and more efficient in terms of latency and cost. Data Processing is basically applied Data Science. In the recent big wave of Data Science, which may even be classified as Data Capitalism, Data curatorship, Data Enrichment, Data Governance, and Data Cleansing have gained specialized attention. Data Curation implies that the Data is being kept truly valuable for long-term storage and serving through deletion of unuseful Data and enrichment of the stored Data basically through Data Annotating / Tagging. Data Enrichment is the process of enhancing Data in Data Repositories through processing and integrating agglomerated Data from various original sources and/or doing computation on the Data fields. Data Cleansing is about ensuring that the Data has a high quality of Data Integrity and adheres to the requirements of Data Format and Data Types.

Although the Telecommunications Systems and Business Management environment is still into usage of conventional Data Processing with SQL and NoSQL techniques and theory, as well as the more recent Data Orchestration Approaches to Data Processing through Pre-Processing Data Pipelines, Enhanced Data Preparation and Data Op MLOps, it is worth mentioning that many recent expansions in the Data Processing Modern Approaches Front give support to investing more R&D energy, time, and budget in accelerated planning and implementation of

more innovative Data Processing solutions, through-demand provisioning of Data Warehouse / Lake Faster Growth, Cloud Processing Platform Output, MLOps and AIOps Optimization of Infrastructure Cloud Utilization and Budget Control, Utilitarianism in Current Expenses with Data Engineering without Loss of Prospective Proactive Lifecycle Management of the Telecom Business Digital Asset Data Targeted Performance, among many others.

4. Analytics in Telecom

The development and further adoption of broadband and mobile Internet, mainly established by telecom companies, has brought the predicted digital transformation to several core sectors in economies through the push of the COVID-19 pandemic. The natural response of these companies to digital transformation was the digitalization of their own operations, accompanied by an evolution of the telecom offer, mainly by creating platforms that enable the monetization of the telecom network. In parallel, telecom companies also underwent a consolidation process. The combination of factors finally brought telecom companies closer to or even into the space occupied by digital service providers. Corporate strategy in telecom companies has never been so in focus and so underled, but all the talk on these subjects used to exclude one very important element: analytics or business intelligence. However, analytics in telecom is as old as telecom companies. From day one they had a challenge to aggregate and manage the information that comes from their core mission: delivering voice, video, and data to the customers.

Thanks to the telecommunications, the pioneering applications of analytics in customer behavior analysis, lifecycle management, and loyalty/completion are widely known across industries as well-known use cases. The data flows generated by each call and by real-time mobile GPS systems available also pushed telecom companies into the optimization of the engineering process, through location-based marketing, enabling the execution of commercial actions on very specific target geographies. Analytics are also widely used in telecom companies' operations management, either to drill down financials or cost models from accounting, or to forecast sales, or even to predict operational expenditures in support of forecast P&L. The integration of customer experience – cost to serve – enables analytics to be used for budgetary constraints over P&L, with the inherent base for spending review and cost savings, or even work as a corporate governance tool.

Fig 3 : Telecommunication Network Diagrams

4.1. Customer Behavior Analysis

In telecommunications, mobile operators wish to fully know who their customers are, how they interact with the network and applications, how services and pricing affect their decisions, and what new services might increase both customer loyalty and revenues. Knowing their customers allows operators to price their services correctly according to the type of customer, especially when it is known how to target a declining customer. The customers of operators switch to another operator or cancel their service directly if they feel they are about to get a worse experience than what they paid for. In the media and entertainment business, companies depend on audience behaviors in order to monetize their products from subscriptions, commercials, or pay-per-view. In the healthcare ecosystem, understanding patient behavior is just as important, be it for insurance companies looking to minimize covered treatment costs or caregivers building trust and a longitudinal relationship. The wireless environment has become faster and more complex, with wider bandwidths and a proliferation of devices and services connecting. Volume and veracity are two big qualities affected, where the volume of interactions is far greater than in the past, and the authenticity of data can be put into question. For example, an ever-increasing number of bots are scouring the Internet for automatic message exchange. Visualization of customer behavior in action is paramount, not just through heat maps and demographic exploration where data has been aggregated and shrunk, but through sparse matrix representations and digital lives where every individual action is logged. Companies can then study their customers, looking from this sparse matrix for clusters for big data algorithms and recommendations of the products they have not tried but that other similar customers have enjoyed.

Fig 4 : Flowchart of customer behavior

4.2. Network Performance Optimization

Network dimensioning and planning is the first step to ensure the availability of resources to meet demand. Cognitive Analytics Solutions consider data mining, machine learning, and neural inference as basic analytical methodologies to propose a model of network investment and deployment. In a 4G context with a data demand for 800 GB per hour, over 20 million users spending per month at least 5 GB of mobile data, and a demand for increased data of around 70% per year, in Brazil we estimate an investment in network deployment of ER 100 billion. Mobile Traffic Analytics has been developed by Mobile Network Operators with the goal of providing visibility on Mobile Traffic.

The use of machine learning in real-world automatic maintenance and control systems, including complex systems that encompass real time systems. On this roadmap and platform, our Cellular Network Traffic Anomaly Detection solution promises to predict and detect cellular traffic anomalies and control performance and availability from the mobile operator's point of view. The ever-increasing data traffic that flows through mobile telecommunications networks can only be controlled by Automated Solutions. Over 80% of the networks publicized

as Smart have their operations controlled and organized by Optical Fiber Monitoring and Maintenance Systems that optimize traffic and service Level, detecting up to 91% of the failures and degradations in the Optical Transport Network. Very little attention has been paid to monitoring the performance of active equipment in the Radio Access Network, which is the equipment with the highest incidence of failures and degradations. In this equipment, the data volume increases from 650 TB to over 800 TB per month, and the prediction models currently in use were able to predict only 20% of the failures in equipment and links.

4.3. Predictive Maintenance

Maintaining a reliable service for customers is directly dependent on the activity of hardware components wherever the service runs. In telecom, some hardware components are used to deliver both voice and data services. There are several telecom services and service providers worldwide. Also keeping servers, their reverse proxies, database servers, database clusters, and telecom-specific equipment, such as mobile switching centers completely functional is hard to achieve. Unfortunately, in the near future this will not change as new mobile applications will require additional telecom infrastructure investment. This infrastructure has to be functional all the time. Still, there are plenty of opportunities to improve the current techniques into predictive maintenance based on smart decisions from historical faults records, sensors data fed into various models.

Predictive maintenance is a big step into preventing faults to happen by replacing equipment before the current one fails. Current on-site ledgers mostly do not provide rich enough information to build fault prediction models or find the equipment failure trend for a sole component. This is probably the best solution that can be implemented for telecom service. Some heritage components still have known curves, created in the years by expert engineers, allowing to know roughly when a component needs replacement. This is the technique to use when legacy is the only technique available. Data on failures caused by faulty components can be sourced from fault tracking systems used by all telecom providers. Still, there is a lack of actual data for model creation, especially for telecom-grade equipment that is not so much used for such task.

5. Analytics in Media

Analytics play an important role across the media ecosystem. Broadly speaking, using analytics to derive insights from media data makes it possible to engage audiences at scale. Network traffic and industrial activity are significant data sources for communication service providers in building insights with analytics in the media domain. Data about what appears on the screen provides another key data source. Combined, these data sources can be used to address critical stakeholder concerns involving talent content personalization, guiding creative process and influencer management for content producers; driving audience engagement by providing right content to right audiences at right time for broadcasters; delivering compelling on-screen experiences and post-release success predictions for players; optimizing ad revenue and defining workstream for media services providers and advertising companies; and choosing appropriate media distribution platform for the whole media universe. Communication service providers can gain capabilities to answer key questions relevant to these insights. They can also develop their assets around media analytics and partner with adjacent industries.

These partnerships can involve using advanced capabilities across data engineering and analytics functional layers for derivative activities from immersive customer experience design including user experience testing, to deploying online engaging experiences across connected life devices such as advertising, and experience evaluation through campaign effectiveness

analysis. The media industry is in the middle of an inflection point. The meteoric rise of OTT and the news and sports verticals on OTT has changed the traditional business models across content producers, broadcasters and media services. It has opened new avenues for advertising companies. The impact of data and analytics on the changing business models and relationships within the industry cannot be ignored.

5.1. Content Personalization

Television viewing patterns are being progressively transformed by personalization initiatives. Rather than tuning in to the same show as a part of a bigger audience, viewers now go online to select from a potentially limitless library of video content their favorite shows and as a smaller crowd, or request that content be delivered to their device for later viewing. The advent of video-on-demand systems has generated even more onus on broadcasters and studios to make audience-engagement analytics an important component of their business models. Indeed, any study of content personalization has to contend with the fact that much of the audience data of personalization programmes is not made public. Unlike most website data, which is maintained by third-party specialised data analytics companies and which represent a treasure trove for researchers interested in optimizing webpage content, video audience data are either proprietary or available only from individual services.

Due to this data-centric environment, research about online TV viewing has spurred interest in data sharing and intermediary board and needs supply-side tools to estimate the revenue impact of different recommendations. In particular, given the importance of dynamic personalization and retargeting, this chapter contributes to the audience research literature by assembling the information we can glean from existing datasets. The data for these analyses are based on a number of proprietary datasets from services for major online TV platforms and cable providers. The first question researchers face is how to define the unit of analysis. Recommendations are made to users to optimize the attractiveness of the content during the upcoming viewing period, a process referred to as dynamic personalization.

5.2. Audience Engagement Metrics

Attracting traffic is universally important for social media-based platforms, including the ones that specialize in media content sharing. The metrics that measure traffic capture, however, are distinct for different platforms. Such metrics for photo sharing programs would, for example, consider stickers or idiosyncratic styles developed by users in order to boost virality. Some platforms allow users to have a dedicated homepage that users follow to receive updates about the central account. User engagement metrics for these social channels would mostly involve a strong follower base and mechanisms to measure the virality of content. Such simple heuristics may be metrics that deliver insight about the channel's content-sharing process or its posts characterizing user-friendliness, engagement as actuated by virality – all deduced without any complicated model employed, only based on topological node characteristics.

Fig 5 : Merics Enhancing online Engagement

On the contrary, some platforms consider Subscriber metrics wherein users are prompted to subscribe to a content generator account, thereby increasing the follower metric. Such Subscribers become members of a channel's broader viewing community whenever the channel uploads newer content. While Subscriber metric is, in effect, a medium-level behind-the-scenes pageview metric that instead entices users to permanently follow the publisher channel instead of transiently view, Inactive Subscriber metric tracks channel subscriber accounts that do not engage content for a certain time period and notify content publishers, because audiences that engage content at least once in a stipulated amount of time are integral for its monetizability via ad revenues.

5.3. Ad Targeting Strategies

The effectiveness of advertising is yet another important and special challenge in media analytics. Media is not a science or a system, albeit there have been proponents who argue the contrary. Media and entertainment is partly a data-driven domain and partly where human emotions and behavioral psychology play key roles. Hence, businessman within the media and entertainment industries constantly seek to predict the future reaction of customers to advertisements. A popular idea is to use analytics to segment the customers more effectively. Early advertising and media executives devised the concept of the four Ps of advertising: Right Product for the Right Person at the Right Place at the Right Time. Today, when plethora of data available on the customer journey from the online search to the purchase decision, it is also known that marketing must be and is more targeted than in the past, which is enabled through usage of customer segment data in combination with external customer data. Different ad targeting strategies can be broadly classified depending upon the maturity of historical available visitor level behavioral data on the website or app.

Ad targeting strategies can be broadly classified into two decoupled stages based on maturity of customer data available. At the very low level of data maturity, third-party cookies may be used to implement ad targeting using Affinity Models; Fallback Methods; Interest-based Targeting. With increasing data at the advertiser's domain its advertising gets incrementally better with usage of improving measurement and enrichment methods; Customized Creative Targeting; Improving Look-a-like modelling; Improving Statistical Approaches; Improving Resource Management; Improving Prediction Management.

6. Analytics in Healthcare

Advances in communication technologies and the growing popularity of mobile devices have started to significantly shape modern healthcare. An example of a growing trend in healthcare is the increasing shift of medical consultations to the virtual space. By 2027, 78 million baby boomers will be 65 years old or older. Older adults have the highest demand for primary healthcare. Telehealth services will supplant in-office visits for many healthcare tasks. Patients' real-time post-discharge and in-home activities, symptoms, and concerns should be tracked.

Eqn 1 : Hospital-Acquired Infection Rate (HAI)

$$\text{HAI Rate} = \frac{I}{P} \times 1000$$

- I: Number of hospital-acquired infections
- P: Number of patients admitted
- **HAI Rate**: Infection rate per 1,000 patients — a critical safety indicator.

Highly convenient telehealth consultations give seniors something they've hidden from their families: worries about declining physical or cognitive function. These digital interactions often allow these concerns to come bubbling up. When families are attuned to these changes, they can ensure that the necessary medical works are being done to preserve the senior's well-being. However, practically all telehealth interactions are dependent on the use of data. After all, doctors use these services to deliver the same patient experience that they would provide in-office. And many of these services could be used by large sections of the general public.

These and other patient-consumer services require tremendous amounts of proprietary data to develop useful and effective outputs. Telecom companies should forge collaborations with healthcare service providers. Such collaborations can produce and exploit research-relevant datasets. Telecoms already handle contact and social behavioral data that can help map how telehealth services should be created. But there are significant other telecom-provided data-layers that may have been left unthought of in the past. Telecoms are also behind the scenes in the superior mobile and network security technology, and demographic and contact data—both of which fuel next-generation IM and messaging services—that telehealth services require.

6.1. Patient Experience Improvement

With the recent global pandemic, patients' concerns for visiting hospitals for various ailments due to exposure to the virus increased by manifold, thus mandating an urgent requirement for the rollout of telemedicine services. As the world starts to gradually shift focus towards "normalizing" post times, a hybrid eco-system of face-to-face hospital visits and telehealth consultations would lay the groundwork for the next phase of healthcare delivery. The need of the hour is to enhance the telehealth service experience while improving patient trust and doctor satisfaction to help smoothen the transition for patients over to physical consultations.

Radiating from a theory of well-being, the patient experience is unique to each individual patient as it represents the entire sequence of intra- and extra-personal events affectively loaded involving a patient who sought care for a health issue, and with its overall assessment being comprised of a key decision about the healthcare provider with whom the patient elects to continue care. While the patient experience continuum starts with the pre-care stage where a patient prepares to begin his care journey with a health service provider, it then moves to the preclinical stage of the visit, followed by the clinical stage of care and the post-visit stage where the patient waits for and receives treatment assistance information, the treatment follow-up assessment and reflects back on the quality of shared decision making. To ensure the optimal experience, healthcare providers regularly conduct patient satisfaction surveys. A thorough analysis of the survey results in conjunction with additional data sources allows healthcare organizations to devise ways to improve gaps in service.

Eqn 2 : Patient Satisfaction Score (PSS)

$$\text{PSS} = \frac{\sum_{i=1}^{n} R_i}{n} \times 100$$

- R_i: Satisfaction rating given by the i^{th} patient
- n: Total number of patients surveyed
- **PSS**: Average satisfaction as a percentage

6.2. Telehealth Data Utilization

Telehealth en masse came into healthcare in 2020 as a response to the coronavirus pandemic. While the rise had many complications associated with its rollout, it has proven to be beneficial in practice. Large volumes of utilization data exist for telehealth interactions commencing in 2020. Such data can be valuable to assess and model the effects of telehealth on service quality metrics for the patient population that are especially difficult to engage with in a clinical setting. What factors affected clinicians' assessment of video visit usefulness? How well did these visits meet the care team or patient needs? For what diseases did it help or not help the clinicians determine the plan of care? What patient characteristics played a role? Were short versus long duration video visits differently affected?

Learning from the hard service quality questions that telehealth has posed can inform the future state of service delivery within healthcare ecosystems. A commingling of traditional models from the health service literature with some of the exploratory, descriptive analytics that can be done with the telehealth data can provide insights that are actionable. Future work within a health system is likely to operationalize these models into telemetry that the organization can use as ongoing learning; advancing the state-of-the-art has the potential to impact service quality broadly in the industry.

6.3. Predictive Analytics for Patient Outcomes

The complication and cost of an illness is often a result of its subsequent treatment after initial diagnosis. For instance, diabetes is an important chronic disease considered for analytics use cases since it can be prevalent for long periods of time, with its symptoms of diabetic headache being treated by emergency services. To avoid repeat patients, analysis must utilize data from the triggering event at the hospital. Utilization of predictive analytics on the patient's original complaint is only half the research, however, but the real challenge is on what factors contribute to the time before another headache. Herein also lies the hypothesis testing with possible testing on the discovered cluster, either patients who have had repeat visits to the Emergency Department or to a specific Urban Planning index level area. If known issues arise as a cause for delay for other patients, predictive models could then be made for them or used in design algorithms for that unique group.

Survival analysis allows for proper use of patient health data and algorithm design. Traditionally, SLADMs either ignored the lifetime effect modeling aspect, which is very important as it can make or break the solution, or assumed unrealistic distribution type shapes or survival covariates functions. SLADMs also tended to be forced into little more than a risk factor description, as likelihood estimator fit functions were only approximated. The solution is clear; specialized statistics and survival design researchers are needed to collaborate with other data analytics area researchers to accelerate the increase in true predictive power beyond the current combination of classification and regression analysis techniques, helping researchers show the real prediction piece to the whole predictive model puzzle.

7. Integrating Data Across Sectors

Communications networks and services are at the core of diasporic socio-economic life, enabling always on communication, social entertainment, and commerce behind the scenes. This also means that telecom service providers have access to rich user activity, interest, sentiment, behavioral and thought data. When such data, available with consent, are intelligently integrated with customer experience data from other platforms, a far more holistic, intelligent and useful picture of the customer is available. The converse is also true, where customer experience data from telecom service providers enhance the picture available to other sectors.

Eqn 3 : Data Redundancy Rate

$$\text{Redundancy Rate (RR)} = \frac{D_r}{D_t} \times 100$$

- D_r: Number of duplicate or redundant data records
- D_t: Total number of records
- **RR**: Indicates inefficiencies or integration issues across sectors.

The need for having a 360-degree integrated view of customers has existed for a long time, but with siloed data ecosystems in organizations providing services in disparate sectors that respect different data privacy policies, regulatory compliance is a roadblock to such data integration and collaborative analytics initiatives. With global commerce and entertainment becoming cross-border, the urgency and defendable need for cross-sector collaborative analytics initiatives is heightening. Companies, including telecommunications operators, realize that in order to serve customers effectively, create loyalty, and retain customers, they need to deploy a wider range of products and services in partnership with other players and sectors. Organizations operate with sector-based constraints. Being a data steward is expensive, with privacy compliance investment as well as customer trust hanging in the balance. There needs to be a sensor and analytics ecosystem in place for enabling control, consent, sharing and collaborative analytics between trusted parties while being privacy compliant.

7.1. Cross-Industry Data Sharing

Organizations with mature data governance, management, and analytics capabilities are increasingly developing models for voluntary data sharing across industries. The pioneers in data sharing among telecom executives shared examples including credit scoring, traffic-pattern optimization, and more efficient logistics. Some examples of cross-industry data sharing include local government sharing anonymized vehicle movement data with healthcare providers to understand the spread of COVID-19, a telecom company using third-party location data to measure the effectiveness of a sports organization's marketing outreach, and insurers sharing data about driving behavior in order to validate the efficacy of a locally developed self-driving car engine.

Collaborative predictive analytics, using shared data, enables participants to more accurately estimate the future behavior of customers. The accuracy of their estimates is particularly valuable for reducing risk when, for a given customer, one of the participants has a small amount of on-file data for the customer, but a second participant has a lot of on-file data for the customer in a similar demographic segment. This joint analysis can create predictive performance scores for new mobile or buy-now-pay-later customers from a cluster bank that has limited information for these customers, but for whom a credit bureau can analyze clustered data gathered from its bank customers and representatively similar clusters identified in its bank datasets. Validated scores can then be implemented to improve risk assessment and decision-making.

7.2. Interoperability Challenges

Data interoperability is the connection and integration of data in the right form, at the right time, and for the right purpose, such that the data can be understood and used by different systems. Schemas, taxonomies, and ontologies are crucial to this challenge. Data schema refer to structures for representing information. Taxonomies refer to categorical hierarchies over a

vocabulary. Ontologies provide information about schemas and taxonomies. They rely on the use of formal languages to describe the meaning of words in a vocabulary, and have intellectual foundations in linguistics and philosophy. Moreover, ontologies also require that, for each of the words, a representative instance of the word's meaning is provided, such that these instances can be mapped into related clusters over the space of all possible instances. In addition to helping to share data, ontologies also help machine-to-machine interaction, providing the capacity for computers to effectively automate tasks and decisions that otherwise would require human interaction.

Interoperability can be of two types: syntactic and semantic. Syntactic interoperability is satisfied when two different systems can properly interpret the exchanged data, such that there are no syntax errors. This is a weak requirement because it does not guarantee that the systems will reach an agreement on the meanings associated with the exchanged data. Semantic interoperability is weaker when said agreement is guaranteed. However, syntactic interoperability is a necessary condition for semantic interoperability. In decisions centered on a single sector, the issue of interoperability can be addressed optimally by the organizations and actors involved in that sector. However, when more than one sector is involved, this optimality cannot be guaranteed. Industry solutions may not work across sectors, leading to the demand for public regulatory bodies to create and maintain shared taxonomies and ontologies. The political economy of designing these ontologies, including the definition of their representativeness and the dynamism with which they change, is a crucial area of investigation.

8. Case Studies

Relevant examples of 5G-enabled business innovation have been few, but they are growing and important. Primarily, very few companies actually understand what is possible with 5G, what implications it might have for new services, unique capabilities for partners, or what assets and skills to invest in to capitalize on its unique capabilities. There are, however, ways to speculate and inquire—if perhaps not “understand”—what is possible to do with 5G. In these case studies, we explore how senior leaders in telecom, media, and healthcare are trying to embrace 5G innovation for their companies. 5G is not a bolt-on capability for telecom operations; it requires new transformational minds and ways of looking at what the capability can offer and horticulture to see how companies can change to take advantage of bigger and faster pipes. Telecom operators innovate with 5G to offer business services in highways, the Internet of Things, and emergency service. Bigger, better, faster pipes change the conditions for everything from visibility to point of sale and how goods are moved from point of purchase to factories. Warehouse visibility is increased by 5G vending robots who restock the shelf when the company’s inventory falls below a point, with vending center management done through a partner. The streetlights, traffic signals, utility services, and even home services like heating and plumbing are connected through 5G networks. New solutions come from partnerships with companies who supply solution spaces in high demand for infrastructure as a service.

8.1. Telecom Innovations with 5G

Drawn by persistent pressure to deliver ever better service-level experiences to hyper-connected customers, a new breed of communication service providers (CSPs) is emerging in the 5G era. Poised to drive innovation in telecom while blazing many unique collaborative paths into the future traversing turf owned by traditional players in adjacent industries, these digital-native next-gen CSPs are best positioned to leverage the significant advances in telecom capabilities enabled by 5G and beyond 5G technologies. By not engaging in traditional price wars and instead focusing on superior differentiation and new monetization opportunities, they can potentially transcend the “dumb pipe” status not so long ago assigned to conventional

telcos. In so doing, they will fuel dynamic new waves of customer engagement and experience transformation in telecom, disparate from earlier generations of progress and fueled by exponentially increasing demand for hyper-connectivity anywhere, anytime, along with ever stronger desire from consumers and enterprises for sublimely intriguing service-level experiences enhanced by AR, VR, AI, and ML capabilities. Riding on firm foundations of more ultrareliable low latency communication, broader broadband channel capacity, larger mobile edge compute, and unprecedented support for network slicing and use case diversification, 5G will empower next-gen CSPs to define and deliver radically new and differentiated customer experiences that will successfully compete with adjacent non-telco players leveraging their own business models in adjacent industries. By mastering the 5G era, by proving that they can engage customers to sublime next-gen standards of hyper-personalization, next-gen CSPs will create new models for monetizing next-gen experiences in telecom that are worth emulating.

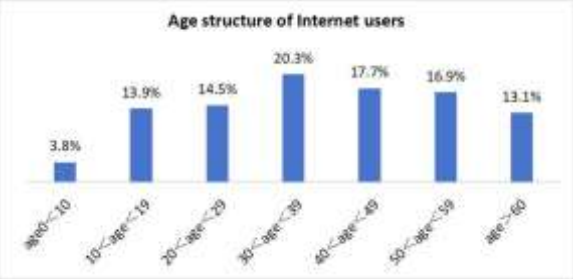

Fig : Age structure of internet users

8.2. Media Success Stories

The media industry boasts an impressive record of building compelling business solutions from advances in digital technology. This record shows how digital technologies improve the customer experience, analytics create new business opportunities, and how advances in networking transform our ability to meet customer needs. In the global markets, the focus of business development for world events from both a business and technical perspective is either Europe or North America. Accordingly, most collection and analysis have an institutional and technical focus on this part of the globe. There are a limited number of large production companies organizing at scale into production hubs, using technology to connect with the audience, and there are a handful of key global events that engage consumers at scale. The television industry has been mastering transmission and signal processing, investing and creating an impressive variety of content consumption models, and building real-time ingestion and post-production solutions for decades. More than any other industry, the television sector has built a wealth of talent. It not only depends on the ingenuity, the systems above all rely on the passion of creatives and technical departments to design, produce, and operate, not only extraordinary events but also daily programming schedules that range from face-to-face media relations to entertainment, passing through news, legitimate information, comedy, educational programs, and many other genres. Resilience is rooted in days of pioneering exploration of new business models, onboarding the broadband transformation and the jump to digital, to smart distribution.

8.3. Healthcare Transformations

Empowered by 5G technologies, collaborative machine learning smart healthcare systems for data from remote surgery robots, multi person remote collaborative diagnosis using Holoportation, telepresence of seniors suffering from dementia using smart glasses, immersive VR experiences of cancer patients with HoloLens+5G, etc. are proposed for next generation

smart health ecosystem equipped with various futuristic smart health devices like digital twin surgery robots, holographic projectors, and content services. Telepresence shows a great potential for future smart healthcare transverse industries which will be led by the 5G futuristic wireless infrastructure. The decision making process and the transforming MAPE-K loop are emphasized for the next generation autonomous telepresence.

5G is expected to bring drastic innovations for smart healthcare systems for the elderly, especially who suffers from chronic diseases or senile dementia. Various pioneering practical applications for the health metaverse enabled by the strengthened secure M2M environment will be inclusive, privacy preserved, and jointly developed by multiple stakeholders. In particular, this text focuses on remote telepresence-related systems, services, Holoportation, robotics, digital twins, AAL, multi person services providing 5G for developing smart hospitals, and teleconsultation or remote surgery robotics. 5G infrastructure and services support the fastest and widest bandwidth, lowest latency, and many devices in small places. It is the perfect, ubiquitous, and intelligent infrastructure for AAL for the elderly or needed, multimodal biometrics, smart telepresence robotics, omnichannel interactive telemedicine for emotional support, remote diagnosis, and remote surgery.

Telepresence services would bring various transforming and attractive applications. Telepresence service is a kind of remote connection-based conversation service with a virtual presence and many essential components like multimedia sensor and actuator for transmitting extremely loud/clear audio, vivid imagery, and effective conveying of facial expression, gesture, and nonverbal cues using super upper body immersive virtual reality. Moreover, telehealth-related services can overcome various important barriers including cost, privacy, and energy consumption. They are attracting wide acceptance by many stakeholders, responsible persons, companies, developers, hospitals, payers, and patients or needed.

9. Challenges in Data Engineering and Analytics

Data engineering and analytics have inherent challenges. The major challenges are data privacy and security, real-time data processing, and scalability issues. The prime requirement for any data-driven business is to capture and store large volumes of data from diverse sources in heterogeneous environments on a unified platform. In the ecosystem, telecom networks generate massive volumes of structured and unstructured data on a daily basis, which are collected and analyzed by different stakeholders in order to create, deploy, and optimize their products and services. Telecom, media, and healthcare companies deploy different analytics solutions on consumer data. For consumer data privacy reasons, it is essential to have a legal agreement between telecom companies and these stakeholders for the usage of telecom data in the analytics solutions.

In a unified data platform, telecom companies store large volumes of telecom customer data related to media usage and healthcare usage, and process it for analysis and decision making within the organization. The set of analytics tools used by telecom companies for decision-making ranges from traditional BI-based reporting tools to AI/ML-based predictive analytics tools. For a telecom industry, using just the telecom data for customer experience analytics in specific industry verticals is not sufficient. Add-on data insights from other data sources, such as media usage data from players and operation/healthcare record data from healthcare players, are essential. In addition to telecom data, their customer databases are also essential for a unified customer experience analytics. Telecom operators store these large databases in their on-prem or in-house cloud analytic platforms. The rental or lease model of commercial telecom platforms is time-consuming, not scalable, and inflexible as per the business requirements of

the analytics solutions deployed in a specific industry vertical. Such constraints on the defined policy guidelines help focus on the new trends in customer experience analytics in the telecom domain.

9.1. Data Privacy and Security

In addition to inconsistent requirements and heterogeneous data sources, an additional challenge of data engineering and analytics is in enabling a privacy-focused, secure framework for either sharing data across domains for collaborative analytics, or establishing a two-way data exchange with customers to enable mutually beneficial enterprise-customer collaborative experiences. We need to be able to utilize 5G-based sensors to gather highly sensitive personal data from customers in domains such as telecom, media, and health, without risking exposure of customer's privacy. More so in these domains than many others, the data engineers and scientists developing collaborative customer experience systems must have a deeply embedded understanding of ethical considerations and stakeholder impacts, even as they are tasked with identifying and engineering data for the discovery of actionable business and clinical insights. At the same time, incentives need to be established for customers to gain from the data exchange at all, in a way that accounts for disparate information sensitivity levels of various customers. Within telecom, media, and healthcare organizations, a careful consideration of what data is shared with analytics practitioners is also critical, so that personnel in those companies do not pose the highest risk for enabling identity theft and fraud. This leads to privacy-preserving data analytics techniques in applied practicality.

In addition to policies and practices that influence or govern ethical data engineering and analytics, privacy-preservation techniques need to be employed in the design of the data pipeline to the end analytics as well. This includes fingerprinting to identify ownership of digital data, Homomorphic encryption, Differential privacy, Secure multiparty computation, and Federated learning.

9.2. Scalability Issues

Scalability is a critical issue for data engineering systems enabling customer experience analytics. Telecom, media, and healthcare industries encounter a deluge of data from user interactions with their services through numerous touchpoints, maintained for years. The data across channels, platforms, and departments comprising the data resource centers is massive and heterogeneous, varying in granularity, structures, and provenance. Operational scalability is expected since there is no reverting back of the collected data from source systems once it gets into the data lakes or data warehouses.

The speed of data growth, however, needs to be proactively addressed by ensuring analytical scalability. For example, the effectiveness of decisioning models can improve when the raw data utilized for training complex predictive models is huge. The raw data pipelines involving the predictive variables that cover the maximum variation allowed by the business rules, model frameworks, and windowing granularity are lengthy and computationally expensive. Such models are usually tuned for each segment of users and can require retraining for immense portions of data from CRM and billing systems, such as geolocation, sentiment, and essential service experience. For such duration, batch retraining can take inordinate time, predominantly when pivoting continuous variables, entering statistical comparisons, and fine-tuning for big data variability. The prediction process also can be time-consuming while modeling the propensity scores and involved when using advertising to replace lost customers.

9.3. Real-time Data Processing

As discussed, telecom, media, and healthcare data is generated continuously and in real-time, and such real-time data can mainly be for two reasons. First, the insights of these data are crucial for any entity, be it a telecom, media, or healthcare company, as it is more personalized and tuned to the user. Also, the data is predominantly location-based and time-sensitive, as it relates to customer experience and quality-of-experience. Hence, actionable insights generated in a near real-time are of utmost importance. Second, due to this time sensitivity, such real-time data also reflects customer intent and context, which means that the subsequent events can also be filtered or removed based on the metadata present on these data. As a result, event data lakes can be created that is based on event marker time which would help further to do longitudinal data analysis.

Data from 5G for telecom, AR/VR for media, and IoMT devices for healthcare organizations are primarily coming in real-time, and hence, they have to filter the pi-cubes that are released in real-time, and thus, they can share only a certain type of cubes in real-time with the pi-coin holders. This helps in incentivizing the pi-coin holders to realize their significance in the company's ecosystem. Event data management from numerous event sources to many clients in a real-time or near real-time manner is still a challenge. The increasing number of social media users and the number of authors/users producing real-time information create the business value of real-time stream delivery. Real-time architecture enables the processing of real-time events from many sources and to many clients in a real-time push manner. But real-time stream processing is subject to several issues such as record loss, offering exactly-once processing guarantees, scaling core infrastructures, using low-latency message queues.

10. Future Trends

The data engineering and analytics landscape is constantly evolving, adapting to changes in technology, telecommunications, medicine, and media. To accurately assess the future landscape, it is essential to consider the major developments within the 5G industry, alongside progressive digital evolution as a whole. Potential bleeding edge technologies are machine learning and cyber-physical systems, with telecommunications networks serving as a conduit to fundamentally reshape, rebuild and redefine multiple industries. Owing to its low latency, high-speed data pipes, recent advances have enabled the Internet of Things to proliferate. Medical devices, through wearables and canned procedures, send and receive terabytes of data daily to healthcare systems and experts hourly or in emergency situations. This avalanche of data, whether considered at the patient or population level, requires the engagement of advanced predictive and prescriptive analytics systems, developed using novel engineering concepts. Telecommunications networks and experts are rapidly finding that their tools of old – databases, big data infrastructure, massive data lakes and robust modeling systems, now must be applied with machine learning and inference capabilities.

The long awaited integration of AI and automation into telecommunication networks, with intent not only to benefit business but to facilitate the growing involvement of 5G in non-business critical operations, is a technological reality. Operating at scale, supporting multiple autonomous services, is the era of Artificial Intelligence for IT Operations. Telecommunication networks are becoming ever so important for the connected experience. In TMT, the critical shift is in augmenting researchers and practitioners with enhancements offered by providers, to drive insights and interventions fast and effectively. As 5G matrices of RF-sensing enhanced devices proliferate, readying artificial and machine intelligence for data and service delivery is paramount.

10.1. Emerging Technologies

We are now entering an era of continuous digital transformation that is driven by the emergence of several new digital, connectivity and industrial technologies. Over the last fifteen years we have seen the emergence of numerous new digital technologies and their application in a variety of industry and functional domains. We are now in the era of Cloud Computing, Data Analytics, Social Media and Networking, eCommerce, Blockchain, Smart Mobile Technologies, Consumer Internet of Things, Digital Content and Services, Cyber Security, Digital Payment Systems, Automation, Digital Identity, Virtual and Augmented Reality, and Voice.

A range of new connectivity technologies has emerged over the last two decades, that allow companies and industries a way to connect, build and sell solutions to customers and consumers directly. The Mobile Connectivity technologies have enabled a plethora of new services including mobile video, content services, mobile gaming, mobile advertising, eCommerce, mobile payment, mobile location-based services and apps, mobile banking, video and audio communications and conferencing. Numerous networks of smart objects have sprung up made possible by the emergence of Wireless Sensor Networks and Smart Mobile Technologies. These Smart Mobile Technologies today leverage such Wireless Connectivity technologies as the various Wireless Sensor Networks, Low Power Wide Area Networks, and Satellite Networks for Direct-To-Device Messaging.

10.2. 5G and AI Integration

Toward this objective, AI-enabled support systems are deployed at an unprecedented scale by integrating 5G networks with dynamic AI capabilities that can model, forecast, and run optimized control of customers' experiences across all platforms, devices, and applications. 5G networks are made smart and dynamic to handle massive amounts of dynamic and real-time performance data with the help of AI for predictive and proactive management and optimization of customer experiences. Inspired by conversational commerce systems that use AI models to maximize customer interaction intelligence and performance across offerings, services, devices, and channels, integrating 5G with systems of systems of IoT, AI, Cloud edge computing, XR, analytical clouds, and business processes are used to synthesize a service-centric view of customers for dynamic and real-time closed-loop experience management. When fused with AI technologies, the anticipated increase in data rates, low latency, high reliability, and increased capacity of 5G networks will facilitate handling larger amounts of different types of real-time performance data that have to be exchanged around the globe in a virtualized and cloud-native manner leveraging the edge and core. We explain how advanced models of machine learning can be employed to use these capabilities of 5G networks for optimizing utilization of these networks for an organization, while also maximizing the modeling accuracy of intelligent systems, such as intelligent virtual assistants and other intelligent applications. To achieve this objective, we explain how knowledge-graph-based fusion technology, powered by advanced machine learning models can be leveraged to interactively assist telecommunications, media, and healthcare organizations in augmenting the dynamism, contextuality, and multimodal aspects of their customer offerings while intelligently optimizing these offerings.

10.3. The Role of IoT

IoT is another key enabler in any target realization. With the new types of use cases and corresponding new industry verticals such as smart transports/services, smart cities, travel, healthcare, and mass deployment of sensor and things enablement; IoT just provides the business case needed for investment. You have vertical business growth and all enablers underneath needed for money-making. The telecom providers can 5G-enable a whole swathe of new business segments, say for example smart cities, and then monetize the deployment and

augmentation of their communication networks. The telecom providers need to act as a neutral player by providing trusted connectivity management solutions for these next-gen IoT platforms and work alongside the existing IoT vendors with its IoT-specific connectivity services hosted as SaaS/PaaS.

Also with upcoming and newer demand from industry conditions like real-time, intelligent, asset instrumentation leveraging AI ML/DL based models, the vertical businesses are looking for partners who can 5G enable their smart city, smart factory and specific to industry enablement and act as trusted technology partners managing the business specific SC capabilities. Model-SC is expected to evolve and mature as the 5G technology stacks, automation, intelligence expand into the specific areas of industry SC usage. Telecom vertical market service provisioning is expected to evolve and mature for task-based models evolving for augmenting SC environments from heterogeneous cloud infrastructures, such as edge or cloud or micro clouds, where the telecom service provider will act as the trusted value builder. This can evolve to provide arch-enabled, low-latency use cases where collab micro-services hosted at the edge can assist and augment SC workflows for rapid delivery.

11. Conclusion

Data engineering and analytics process and systems have been around in Telecom and media for decades, but have always been siloed and rarely see spillovers from one domain to another and from past experiences do not adequately cover emerging new domains like data engineering and analytics in 5G. The use of data engineering and analytics in improving patient experience and outcomes in healthcare is new and are early days. No work exists on semantic integration data model addressing the unique challenges of capturing telecom authentication data in healthcare applications, a domain level model for telecom and telecom driven healthcare use cases and applications, semantic ontology framework, or a comprehensive three tier architecture for telecom healthcare analytics. 5G telecom healthcare analytics and patient experience system is the first to suggest the use of telecom data infrastructure to deliver healthcare services, with the intent of improving the patient experience. The intended audience for the book consists of a diverse group of readers across various fields, including the applied mathematics and statistics area, computer and data science, data and/or software engineering and development, management and business school, operations research, network and systems engineering, and several related fields. This group contains both students and faculty members as well as practitioners. This is to ensure that the reader can benefit both in academic terms as well as in terms of practice. Theoretical concepts, formulas and algorithms are all well stressed and explained, but an equally important part of this book consists of practical aspects, challenges and issues related to the creation, design and implementation of 5G Telecom Patient Service Response. The material in this book should thus appeal to a wide spectrum of people in academia as well as in industry. Students can use this book as a textbook in their applied mathematics, statistics, data science, computer detailing, networks, system, telecom and healthcare related courses since it should provide them an insight on how to apply their knowledge to a real, practical, multidisciplinary setting.

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