Artificial intelligence impact on operational models

AI; Operational model; Autonomous; Data; Analytics; Systematic operating model

White paper

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Introduction

The infusion of artificial intelligence (AI) technologies is a centerpiece in the evolution of processes of organizations in multiple sectors. AI makes it possible to build software systems able to reason and decide better than humans or legacy software systems, and to extract previously undiscovered knowledge dimensions from data. These new software systems leverage the creation of a new generation of work processes: fully automated (obviating human activities in the process workflow), highly adaptable to changes without requiring deep process reengineering, and highly predictive of future happenings.

This new generation of work processes will become the foundation of a new era of operational models, which will be autonomous, intelligent, efficient, self-organized, and predictive. A set of models will make organizations prepared to embrace frequent and rapid changes in their domains, a constant in modern societies, and highly reinforced in the new normal after COVID-19. A new operational model that will pave the way to restructure traditional operations towards unparalleled levels of efficiency.

Concretely for the telecommunications industry, the new operational model must be ready to quickly cope and adapt to a continuum of changing technological context and usage patterns due to the very rapid network technology evolution, societal evolution and extraordinary, and/or unexpected life-changing events. Based on these changes, service providers must prepare to address new challenges that will impact systems' development and deployment methodologies, as well as the established organizational and operational management practices.

In this article, we will elaborate on the necessary changes that will allow business and data science fields to meet, how AI literacy and data culture play a crucial part in this AI infusion process, and, last but not least, how existing organizational and operational management practices must be equated and restructured to achieve an autonomous operational model.

Business and data science

AI literacy

With the advent of digital transformation and the advances in computation power, AI is becoming a more accessible technological area and gathers enormous attention. It is clear to see that, alongside the tremendous industry traction that AI has gained, there is also a proportional, if not larger, amount of hype around it. This extravagant perception of AI is often a product of individual ignorance and exaggerated publicity, one of the key contributors to the failure of AI projects [1] [2]. As natural as it is, this lack of awareness occurs on the dark side of our education, a gap that exists between the intricate details of technology and the business cases tackled by organizations. However, this gap can be covered with an increase in literacy around the subject, providing a level of understanding about AI similar to what we have today regarding computers. Nowadays, most people are comfortable around the idea of owning and interacting with a computer. They understand its impact on their lives and how they fit in everyday life, something that wasn't that common forty years ago. That is the shift that we are currently in need of. It regards the education of our general population, people who don't necessarily develop technological products or services. A group that will be, and a part of it already is, impacted by AI technology. It is paramount that they know what AI is, its benefits, how AI systems generally work, and how to engage with them [3].

Despite the effort needed to educate the general population, AI literacy needs to be pursued even further. The leaders who stand on top of companies need a good understanding of AI in order to start measuring the impact on the markets they currently find themselves in and what internal changes are necessary to cope with this reality. Companies' products, services, and operations need to mutate in order to merge with this future. Their teams must be transported to this new reality, but this change is not enough. Organizations need to clean up their houses and focus on a systematic approach to information architecture. This translates into building a solid data culture that brings down their massive data siloes and harmonizes data access with carefully documented catalogs. Understanding that AI needs a good quality set of data is as important as knowing how it works.

Business-driven AI

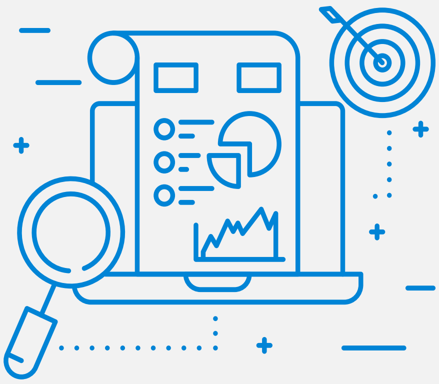
Nowadays, it is strategic for any digital-related organization to achieve business impact with data and AI techniques. Although the AI discipline itself is not new, the rationale for the current wave of disruption is three-fold:

1. More and more **data** from heterogeneous natures and sources is becoming available and ready to use, mostly due to the digital transformation worldwide;
2. From a technical point of view, advanced **data analytics** and **data science** disciplines are getting more and more advanced to turn this ocean of raw data into insights;
3. **Computing power capacity**, which is paramount to store and process the available data, is, on the one hand, significantly increasing in terms of capacity and, on the other hand, decreasing from the investment perspective.

Organizational restructure

Although the AI-discipline enablers are already in place, it is commonly accepted in the industry that AI-based solutions monetization and impact are still a step behind. Moreover, it is also clear that the AI adoption technical enablers – data, analysis and data science techniques, and computational power – are starting to get their space in the organizations. Accommodating and monetizing this new discipline poses new challenges to the organizations' structure and dynamics in order to involve all the business units in the process. This will increase the final impact, as well as the return on investment (ROI).

Following this line of thought, a significant transformation of the organizations' structural parts should be done to start monetizing the AI investment. For the sake of simplicity, we highlight the following two main barriers from our point of view:



Data and business separation

In many organizations, the data science and the business execution units are individual silos that do not intersect and do not communicate as they should. As a result, the produced data science solutions, which are usually very interesting from a technical perspective, do not contribute to evolving the company products, and therefore the associated business is not impacted.

Insight and impact gap

Generating insights is very important and is the first deliverable to be addressed by a data science team. Well-conducted proofs-of-concept (POC) take place and share valuable insights into organizations. Nonetheless, in order to create real impact from the business perspective, it's mandatory to integrate the obtained insights in concrete operational actions, therefore challenging the existing processes and working methodologies, mostly reactive and manually achieved.

To obtain significant business impact, the AI discipline must be a tool serving the organization's business. Therefore, the first thing to do when onboarding AI in the organization is to define a clear vision and business strategy. That will guide the transformation on the organization's other structural areas, as illustrated in **Figure 1**. Following this approach will guarantee that AI is being done "for" and "with" the business.

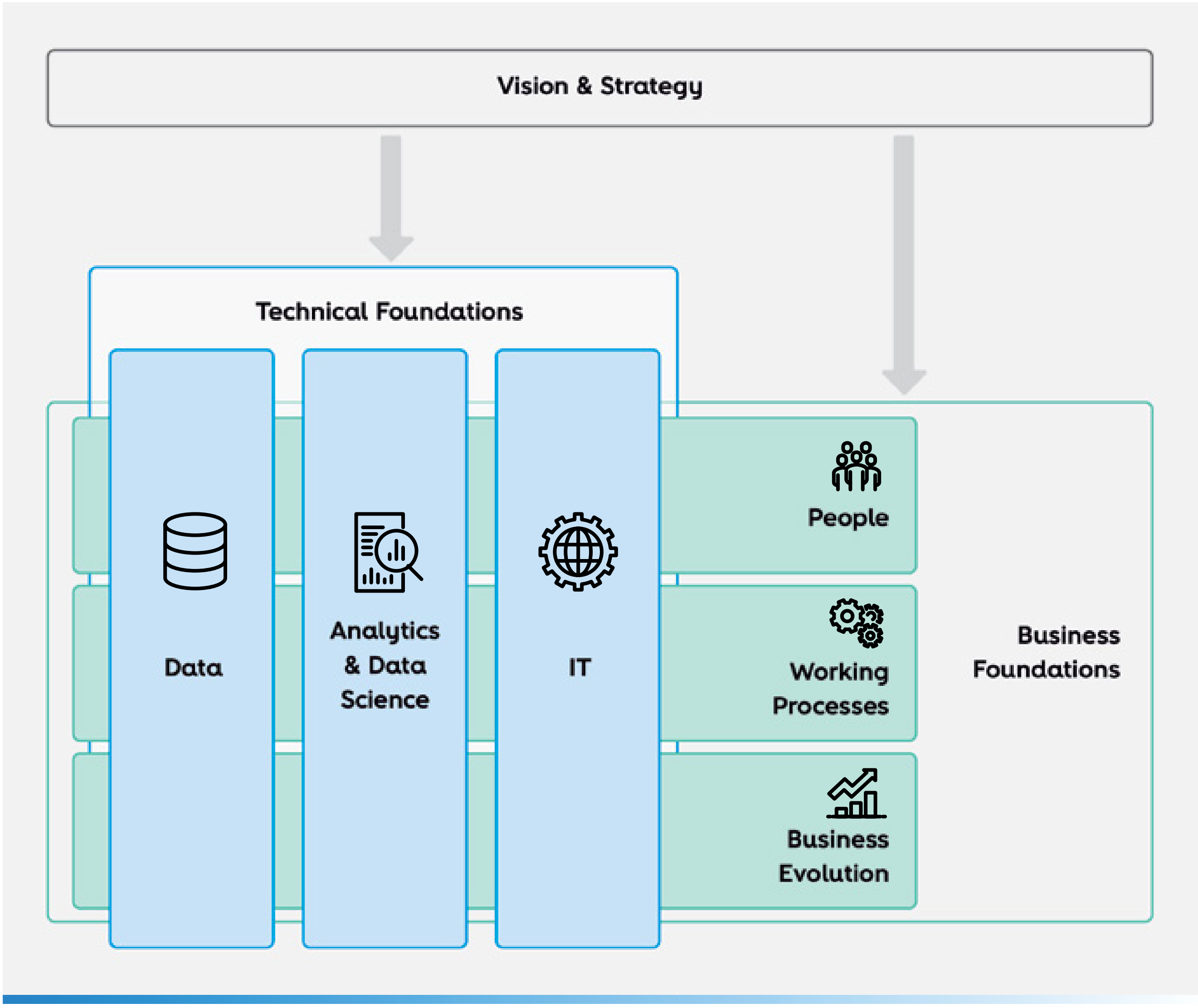


Figure 1 – AI-oriented organization

Thereafter, several technical and business areas should be adapted and transformed. Starting with the structural business-related evolutions, which are transversal to the technical foundations, we highlight the following:

People: since AI is an instrumental tool serving the organization's business, one key topic is the relationship between the data science team and the business units. Herein, the most suitable approach is to create a data science center of excellence in the organization, which is responsible for AI-related activities, as well as for recruitment and ongoing training. Furthermore, AI knowledge cannot live only in this center of excellence. It's fundamental for achieving the desired business impact, that the people from business units involved in the AI value-chain (e.g., sales, enterprise architects, directors, domain experts, etc.) are capable of processing and translating analytics insights into business implications and concrete actions. This is a continuous learning process that will, over time, increase the data science knowledge by people from business units and facilitate the adoption of AI-based solutions. Therefore, data science teams and business units have to work together during the whole AI lifecycle process;

Working processes: working methodologies must also be revised to accommodate this stringent requirement of having the data science center of excellence and the business units working closely. Old processes might need to be adapted and/or automated to guarantee the continuous involvement of the data science team and their mirrors on the business units. A data science systematic approach across the whole organization should be well-defined and clearly presented to the several stakeholders involved in the AI value chain. More details about this are presented next, in the systematic approach process section;

Business evolution: together with the business units, identify which portfolio solutions and/or procedures can be optimized through the infusion of AI capabilities. This raises one of the most critical challenges to the business units' decision-makers – define the impact of AI on their business, which is materialized in concrete products or solutions of the portfolio to be evolved, or in a set of insights-based operational procedures that can be monetized. In any of the abovementioned scenarios, the result will be the definition of the AI use-cases.

Besides the business evolutions, technical adaptations are also required. We briefly highlight the following ones:

Data

The process of data collection, persistence, cleaning, etc., to support the AI use-cases. Security and privacy issues related to the data must also be handled (e.g., the European General Data Protection Regulation).

Analytics & data science

Includes the set of procedures required to transform and obtain insights from the data..

IT

Infrastructural resources (e.g. servers, GPU, etc.) to enable the AI-lifecycle operation

Systematic approach

Besides the organization's structural adaptation described before, it is also key to have a systematic working methodology well-defined and communicated along all the actors to address this discipline. **Figure 2** illustrates a very simple perspective of a business-driven systematic approach to ensure AI results have an organizational impact.

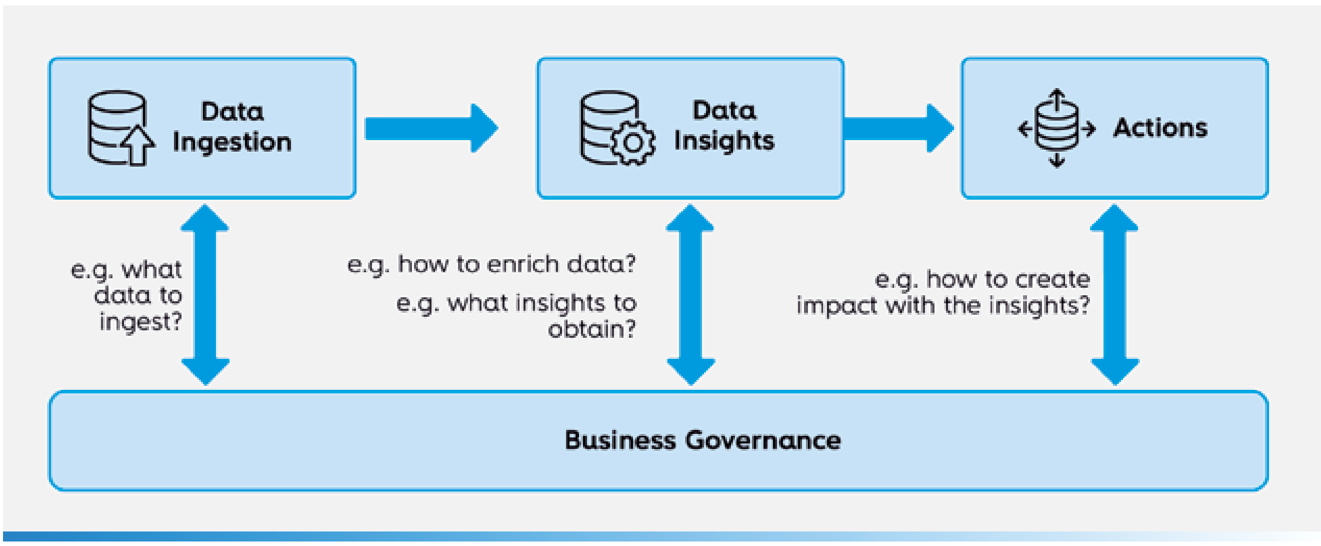


Figure 2 – Systematic operating model

The following three phases are depicted:

Data ingestion: It is a well-known fact that AI without data is impossible. Unprecedented amounts of data are available nowadays to be collected and persisted for obtaining insights. Nevertheless, it's impractical, or at least very expensive, to collect and save all the data generated within an organization. Therefore, one of the first questions to address is what data to collect. The answer to this question is simple: we should collect and store the data that is relevant for the AI use-cases on the organization's strategic roadmap. Having the use-cases to be addressed clear will allow the definition of a strategy to collect and store the required data.

Data insights: After collecting and persisting all the required data, the next step is to generate insights. This is the principal phase in which data science is concerned. One of the key tasks at this stage is, together with the business domain experts, to define the required data transformation and enrichment to represent the reality (features). Since the business domain experts are the ones that know the data and the business itself, it's crucial that they are involved in this stage of the process and help the data science team identifying the most relevant features that should be included in the dataset. After that comes the insights extraction phase. Herein, a large number of AI-technical approaches can be used by data scientists to produce the desired insights.

Actions: Finally, after insights produced by the AI models, specific actions should be defined to translate the technical insights into business value. This is much related to the specifics of the AI use case addressed. For example, when producing insights about a failure of a mobile network operator, it's important to update the operator's processes when such an insight is produced – e.g., automatically re-allocate the field-force team.

Impact on operations

Data-driven culture

In the AI field, everything starts with data. Data is the fundamental centerpiece that will allow your data science endeavors to flourish and bear fruit. It is the basis of all your analysis and models. Without it, there is no value to be extracted. The underlying value that your data holds is, of course, leveraged by the technology and software that you produce, and although it may often feel like a bundle of complicated and hard to understand processes, it is not the biggest obstacle to success. The challenge does not lie on software but on data, teams, and process silos, and that is why companies need a strong data culture.

A data-driven culture is a decision culture [4], where data becomes the core of your business and supports your products, operations, services, internal decisions, and business plans. It is indeed a deeper way of engaging with business, but not only that, it is a way of cultivating a sense of purpose that allows companies to establish their future with clear motives, making your data support your operational decisions and not the other way around.

Implementing such a culture is an arduous task. It involves creating a communication space that often does not exist, a clear channel that allows informed conversations to exist between your C-suite members, top decision-makers, and those who lead AI strategy and initiatives. All this effort to create the habit of making decisions anchored in factual data.

Given that a good foundation for culture has been laid down, the next challenge to tackle regards technology. The mission is to enable a close proximity between the business strategy and the operations, where data is the connecting tissue. This means quickly fixing your data access issues [5]. However, the chances that your company's data is scattered throughout several silos, or data fiefdoms as some refer to them [6], are high, thus creating the monstrous task of assembling all necessary technology and processes to transport all of this data into its new home, the pristine body of water that we call data lake. Unfortunately, this exodus only addresses the underlying data isolation problems. Now you need your teams to interact with each other, hopefully in a transparent and clear way, in order to figure out how to connect data from silo A to silo B, and silo C, and up to silo Z. The final product should be a mint condition data lake with a carefully crafted, and maintained, data catalog that every team in your company can have access to. In this way, data can be used as evidence to back up business hypotheses free of unsubstantiated claims, and to measure the uncertainty that clouds your analytical judgment.

Towards autonomous operations

Typically, the current operations paradigm in communication service providers (CSP), whether they are network, service, or business operations, is mostly reactive. Globally, very few automation procedures are present in current operators. Nevertheless, this mentality is changing, and nowadays, in the digital transformation context, CSP are strongly introducing in their strategy the infusion of AI in their operations - AI in operations (AIOps). AIOps is an approach to use AI technology in order to automate CSP network, service, or business operations. With such an approach, it will be possible to provide fully automated, self-healing, and self-optimizing capabilities to improve customer experience and service enablement. **Figure 3** depicts this evolution.

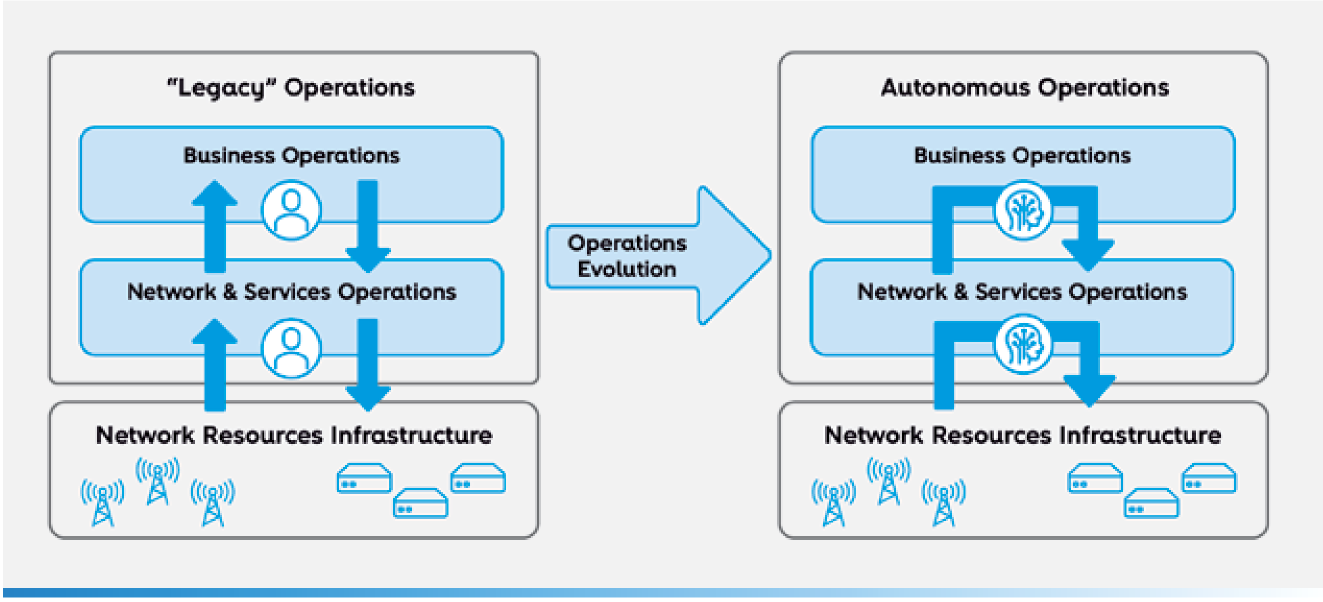


Figure 3 – From "legacy" to autonomous operations

AI impact on operations

According to a report study published by TM Forum [7], CSP already have a clear idea about the key areas that will be optimized by the integration of autonomous operations. As illustrated in **Figure 4**, the top three areas are i) customer experience improvement, ii) capacity optimization, and iii) service performance analysis.

Customer experience is the most impacted area (91%). This is somehow expected since the customer journey process has several subdomains that can be improved through AI. For example, all the chatbots-related use-cases for customer care will improve customer experience by solving customer issues faster and more precisely and, in parallel, reduce operational costs at call centers. Additionally, AI will be very important to analyze and profile the customer behavior, hopefully preventing churn.

Immediately after the customer experience improvement, capacity optimization and service performance analysis are equivalently (77%) identified as important areas to be impacted by AI infusion. Although they have a similar perception of impact, the rationale for each one of them is very different. The capacity optimization case is related to the financing, since this optimization will require less infrastructure investment and, therefore, savings on the CAPEX. As for the service performance analysis case, it is considered a highly impacted area when infusing AI techniques since increasing the service quality implies improving the customer experience. One possible example of a use case in this area is analyzing specific key performance indicators (KPI) about the service performance and proactively detecting and mitigating service degradation.

On the other hand, at the lower end of the identified areas but still with a significant impact (36%), is the network reliability improvement. This is due to the fact that current network deployments, either mobile or fixed, are already very stable.

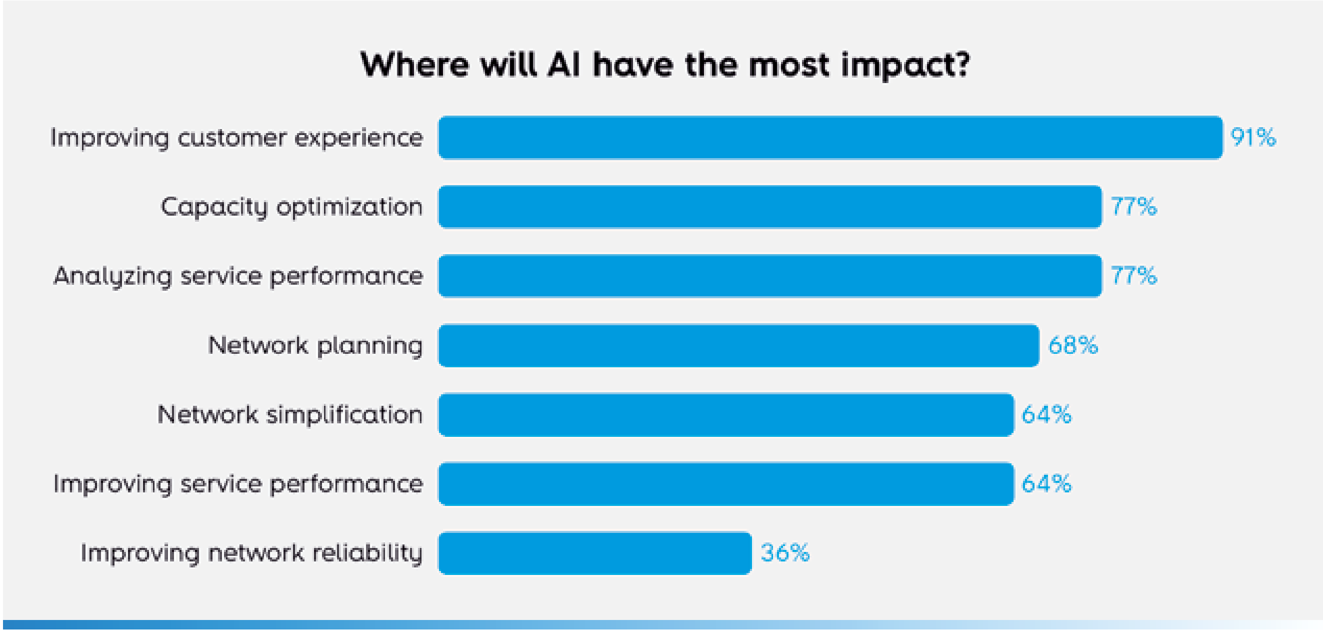


Figure 4 – AI impact on operations [7]

Autonomous operations evolution path

The transformation towards autonomous operations is already ongoing and will be gradually materialized through specific, self-contained POCs before reaching production level maturity. Migrating towards autonomous operations does not mean completely dropping the traditional operations support systems (OSS) and business support systems (BSS). Although the limitations to address automation of such systems become clear, an evolutionary strategy towards autonomous operations should be embraced (instead of a revolutionary one). Therefore, it is expected that CSP will go through several maturity levels before they reach the peak of autonomous procedures. Additionally, this change will not be a uniform evolution within the operator, meaning that specific processes might be evolved prior (e.g., customer experience processes) to other processes (e.g., network reliability processes) due to their AI-enhanced business impact. The decision on which processes to impact first will mostly depend on the business impact and technical feasibility.

As a result, to set a clear evolutionary path towards autonomous operations, six maturity levels, illustrated in **Figure 5**, are defined by TM Forum [8].

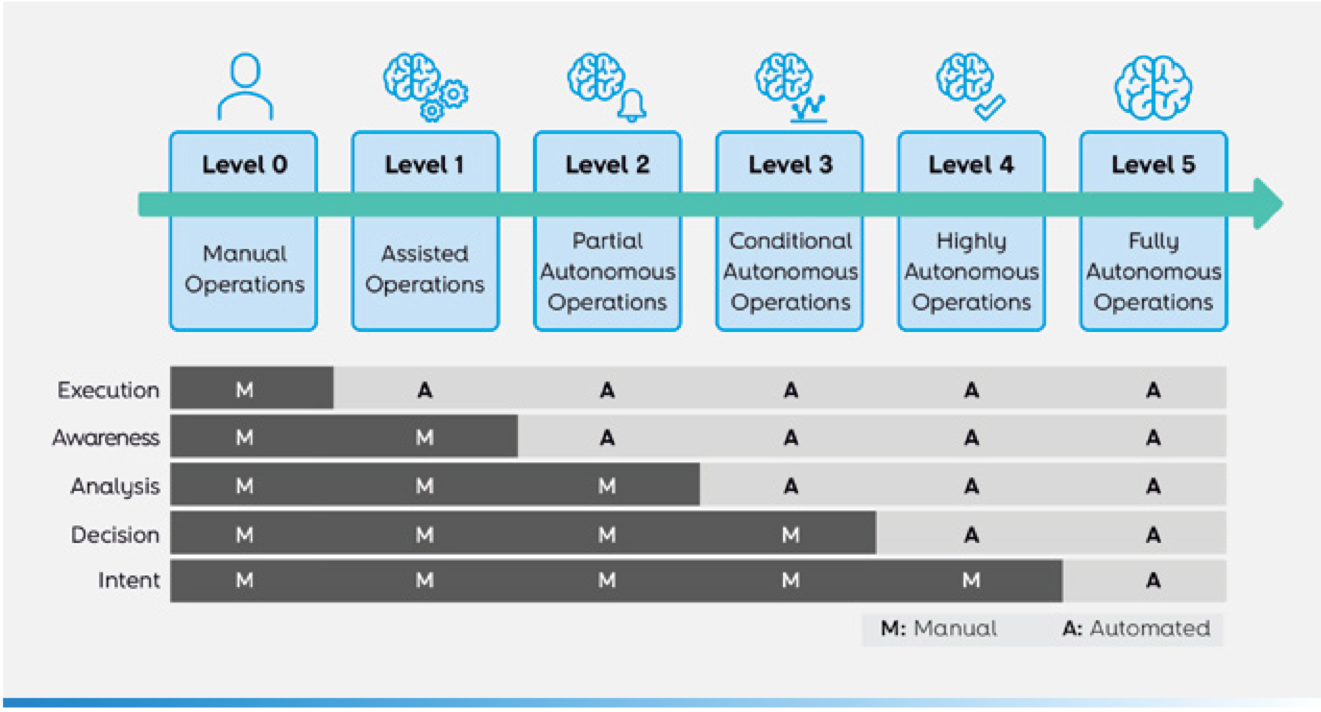


Figure 5 – Autonomous operations evolution path [8]

Hereafter we provide a brief description of each maturity level along with simple examples.

- **Level 0 - manual operations:** The management operations are all assisted by humans, which means there is no automation in the required tasks;
- **Level 1 - assisted operations:** Specific operation rules are pre-configured by a human to execute repetitive and isolated tasks in the system. For example, complex network and service alarm creation based on network events, KPIs based on network events and/or counters, parameters reconfiguration on network equipment, like home devices or mobile network devices;
- **Level 2 - partial autonomous operations:** AI models are introduced to generate insights and raise awareness of the network and service status in specific areas. Based on this information, further analysis, decisions, and mitigation actions can be manually taken by operational teams to close the management loop, for instance, mobile network predictive faults or IPTV set-top boxes (STB) predictive faults;
- **Level 3 - conditional autonomous operations:** advanced AI-based analysis techniques are integrated to enable the identification of the root causes that are compromising the network and service performance parameters. At this phase, decision-making and actuations to close the loop are still manually implemented. For example, mobile network predictive faults and associated root-cause or IPTV STB predictive faults and associated root-cause;

- **Level 4 - highly autonomous operations:** building on previous levels capabilities (awareness and analysis), the system is augmented with AI-based decision-making procedures, incorporating a policy-driven network management architecture in the following cases: call center specific recommendations to fix customer issues, and mobile network equipment's parameters reconfiguration;
- **Level 5 - fully autonomous operations:** this level is the last step of the autonomous operations evolutionary path. The system is able to implement the entire autonomous lifecycle (infer, analyze, decide, and act) across multiple services and domains without requiring any human intervention.

The autonomous lower level 1 and level 2 described can be applied, or in more advanced CSP are already being applied, enabling the gradual integration of these procedures and therefore starting to better understand their impact in real-life operations. Higher levels should be integrated later for specific use-cases and procedures. Overall, this transformation will take several years to reach a significant maturity level, allowing CSP to improve their processes' efficiency over time.

Network automation is a long-term objective with step-by-step processes, from providing an alternative to repetitive execution actions to observing and monitoring the network environment and network device status, making decisions based on multiple factors and policies, and providing effective perception of end-user experience. The system capability also starts from some service scenarios and covers all service scenarios.

This transformation will take several years to fully develop, so we are following an evolutionary process of gradually introducing automation with AI abilities into different domains to bring immediate value.

Conclusions & takeaways

AI is here to stay and may prove essential to organizations' operational models evolution, such as in telco autonomous networks use-cases. However, although this is widely accepted across the industry, it is also clear that achieving impact and monetizing AI-based solutions is still lagging behind. In summary, as described throughout this article, there are two major barriers to achieving business impact with AI solutions. First, data science and business teams separation, leading to the creation of AI-solutions useless from the business exploitation perspective. Second, the difficulty of closing the gap between insight and business impact. That means evolving from AI models that produce interesting insights at a POC level to models in which outcomes are integrated into operational processes that, in the end, can create real impact for the business.

There is no recipe to allow industries to overcome the above-described difficulties. Nonetheless, looking into the community evolution in this domain and from the experience that we have collected so far, with our running AI projects, a few strategic actions can be adopted from our perspective. First, it is crucial to guarantee that AI is being done together with the business, meaning that, before starting any data-related procedure, it is important to identify relevant business use-cases and only after start deciding about the required data and models. Another important action is to prioritize a small set of use-cases that are technically simple and fast to close, guaranteeing the return of investment on the data science team and quickly proving the concept. The use-case selection is critical and should set a gradual and evolutionary path towards AI, depending on the operator's internal AI maturity. For example, from Altice Labs experience, predictive maintenance, field-force optimization, and customer care support improvement were identified as the top-three use-cases towards autonomous operations at this moment. The third strategic action is related to data quality. A significant amount of time should be invested in data exploration and analysis to ensure that its quality is adequate to proceed to the modeling phase and generate valuable insights. Most of the time, bad results on the modeling phase are related to problems regarding data – "garbage-in, garbage-out". On the IT side, a dedicated infrastructure for the data science (DS) team should be prepared, starting with the minimum required assets and progressively growing/ evolving towards a professional and high-performant IT environment, always aligned with the organization's IT department. Finally, and above all, have senior data-scientists to lead and cultivate the data science team and, in parallel, start promoting internal training sessions to recycle software developers. This training process is also important to increase the AI knowledge of the organization's business decision-makers.

AI can also significantly contribute to the COVID-19 pandemic that is currently impacting the whole planet. Due to this "new normal", a massive amount of remote work is underway. This has a tremendous impact on service providers, which must be able to accommodate the huge network usage increase and simultaneously keep the service experience at reasonable levels without increasing monthly fees. Service operations boosted with AI capabilities, also known as autonomous operations, enable a quick and prompt reaction to non-expected traffic patterns due to teleworking. Additionally, potential network and service degradations might be prevented, guaranteeing a positive and effective user experience.

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