WHITEPAPER

TM Forum introductory guide

digital twin for decision intelligence (DT4DI)

IG1307

Maturity Level: Alpha

Release Status: Pre-production

Team Approval Date: 09-Dec-2022

Approval Status: Team Approved

Version: 1.0.0 **IPR Mode:** RAND

Notice

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contents

List of Figures

Executive Summary

'Data are beautiful, but it's decisions that are important.' - Cassie Kozyrkov, Chief Decision Scientist at Google.

To be more competitive, CSPs must move away from traditional Business Intelligence (BI) to a Decision Intelligence (DI) strategy and approach, taking advantage of Digital Twin and AI to effectively become knowledge-driven and results-oriented organizations.

Decision Intelligence (DI) is an emerging discipline (sometimes called Decision Intelligence Engineering or Decision Science) of turning data and information into better actions at any scale, enabled by different practices, techniques, and technologies, including AI and Digital Twin.

Digital Twin (DT) is a broad emerging topic. It is an architectural approach and technique providing virtual representations of real objects, combining multiple technologies. DT applies in many domains to various scenarios and use cases, including Decision Intelligence.

In the **DT4DI** TM Forum collaboration project, after sharing foundational definitions and baselines about DI and DT, we approach the engineering of Decision Intelligence solutions powered by DT and AI, expanding, complementing, and absorbing traditional Business Intelligence (BI) solutions to support the business analysis, business processes, and decision-making processes in the CSPs industry.

This whitepaper is the first deliverable of this new collaboration initiative and introduces the context, background, scope, and project deliverables.

1. Problem Statement

Analytics, data-driven insights, and consequential decision-making are the brain of every business in the digital age.

However, translating insights and analysis results in effective decision-making, executable action plans, and managed outcomes are processes that have much room for improvement.

Despite the considerable investments in the last three decades, data warehouses (DWH), business intelligence (BI), analytics, reporting platforms, data lakes, and related infrastructure, systems, and tools struggle to provide business processes and decision-makers with timely, accurate, deep, context-aware insights, analytics, recommendations, predictions, and pre-processed decisions.

You likely understand this problem if you have participated in executive meetings, steering committees, board meetings, product management meetings, project summits, and any sort of conclave, making more or less relevant business and operational decisions. Overwhelming data but still incomplete information, quantities of reports and dashboards, hundreds of metrics and KPIs from tens of different departments and sources (inconsistent, in most cases), limited time, misinterpreted data, uncertainty, biases, subjective perceptions, etc. Ultimately, decision-makers decide according to their experience, intuition, gut, and bravery. In the worst case, they do not make any decisions and ask for even more data.

Or if you come up from the ranks, you may have lived in situations where you had to decide alone on changing the configuration of technical parameters of a critical system, impacting the entire business with a domino effect that no one could figure out.

These scenarios would become even more exasperated with the growing complexity of the business, the endless data expansion, and the massive deployments of challenging technologies (like AI and DT) that need to be incorporated into the daily business and decision-making processes in a better way than legacy technologies.

In a recent Gartner survey [1], 65% of respondents said the decisions they make are more complex than just two years ago, and 53% said they face more pressure to explain or justify their decisions.

Companies are looking for new ways to make data-driven, focused, causal-effective, and results-oriented decisions and to define coherent and profitable action plans.

They must move away from traditional business reporting, information overwhelming, siloed and partial data analysis to a Decision Intelligence (DI) strategy and approach, taking advantage of DT and AI/ML technologies to effectively become information- and knowledge-driven.

Better decision intelligence means:

- Better performance and financial results. According to [2], research results by Bain show a 95% correlation between decision effectiveness and financial performance.
- More efficiency. According to findings from McKinsey, 72% of executives report that bad decisions are as frequent as good ones, and the average S&P 500 company wastes an average of $250 million per year due to ineffective decision-making [3].
- Higher quality and customer satisfaction. Context-aware, timely, and performance-oriented decisions boost the quality at technical (infrastructure), system (applications), service, and product levels.

Organizations need new descriptive, predictive and prescriptive analytics frameworks and platforms that provide data insights, analysis, predictions, and recommendations to drive real-time decision-making processes and action plans.

The TM Forum DT4DI project aims to define and develop an industry Decision Intelligence framework that integrates DT, AI, and other technologies with business processes to help organizations make analysis, diagnosis, predictions, and decisions faster, more consistently, and more accurately than ever before, unlocking the power of data.

Adopting DT4DI solutions and practices will enable CSPs to predict business results, determine their business strategies' impacts and accurately estimate the return on investment (ROI), reduce business and operational risks, improve customer experience management (CXM/CEM), save costs and increase revenue. In a word, be competitive.

< Back to Contents

2. Decision Intelligence (DI)

Rather than a new discipline, we can see Decision Intelligence (DI) as a disruptive evolution of Business Intelligence (BI) that combines and incorporates evolving and maturing technologies, methods, approaches and skills into their processes.

The essential and innovative contribution of DI is the paradigm and cultural shift from data-centric to decision-centric organizations.

It is common sense that tons of data are available in endless data repositories and lakes (94-97 zettabytes of data generated worldwide at the end of 2022). Still, organizations need help to extract value, organized information, and make effective and context-aware decisions from the data available in their companies. Considering the unbrilliant financial results in the telecom industry in the last decade [4], data have yet to be the new oil in this industry.

In recent years, technologies have been maturing and are now available to support organizations exploring their data.

However, something still needs to be added.

This "something" is the glue combining technologies, processes, methods, people, organizations, governance, and other necessary ingredients to transform data into decisions, actions, and outcomes.

2.1. A BRIEF HISTORY

In this paragraph, we share a brief and inevitably partial view of the history and evolution of the disciplines that enabled and influenced the renaissance of Decision Intelligence (DI).

It is challenging to comprehensively map the evolution of these disciplines for different reasons [5], including needing more standardized categorizations and generally accepted definitions and understanding of BI, DSS, Analytics, and, recently, DI.

Here we provide an approximate view of the history of BI, DI, and related enablers in the telco industry without the pretension of being exhaustive.

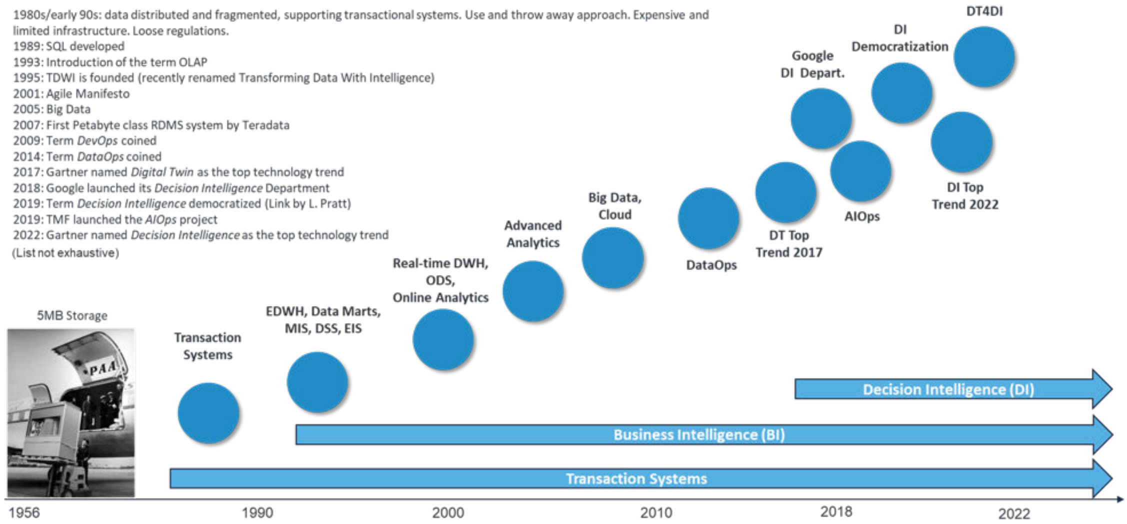

Figure 1. Evolution of BI, analytics, and DI practices, including some of their enablers, in the telco industry.

The map above displays the deployment and evolution of BI and Analytics solutions and technologies in the telco industry.

It does not refer to the genesis or availability of those solutions, which in most cases were available before. For example, the first multidimensional database (Express) was released in 1975 [6]. The first definition of technology-based BI can be traced back to 1958 as "the ability to apprehend the interrelationships of presented facts in such a way as to guide action towards a desired goal" [7] (the concept is still valid today).

In the early 90s, BI solutions slowly gained popularity, reaching a peak in the 2000s, enabled by the accompanying IT innovation (IT infrastructure, platforms, tools) and reduced computing and storage costs.

In the 2010s, the abrupt increase of volume, variety, and velocity (the three Big Data V's) of the data generated in the CSPs and adjacent industries challenged the existing BI architectures, methods, processes, and related organizational structures, raising the need for different approaches.

In March 2018, Google created a new department dedicated to Decision Intelligence and appointed Cassie Kozyrkov as the first-ever Chief Decision Scientist in industrial history.

Other companies followed a similar approach, creating DI groups, labs, or capabilities in their organizations (i.e., Alibaba, Mastercard, Microsoft, Uber, etc.).

It is the Decision Intelligence renaissance or, perhaps, the naissance, i.e., the DI birth.

With her successful book Link - How Decision Intelligence Connects Data, Actions, and Outcomes for a Better World [8] - Lorien Pratt contributed to evangelizing and democratizing this emerging discipline.

In 2022, Gartner named Decision Intelligence one of the top technology trends [9] and estimates that by 2023, more than 33% (one-third) of large organizations will have analysts practicing decision intelligence, including decision modeling [10].

Figure 2. Top strategic technology trends for 2022, according to Gartner

2.2. DEFINITIONS OF DECISION INTELLIGENCE

Although Decision Intelligence is a baby, there are brilliant definitions available that emphasize the scope and goals of this discipline.

Lets' start with the definition stated by one of the pioneers of DI:

Definition 1: Decision Intelligence is the discipline of turning information into better actions at any scale. (Cassie Kozyrkov, [11]).

The essential strategy for turning information into better decisions and actions is to combine scientific and quantitative approaches with social and humanistic/human-centric disciplines such as decision science, social science, and managerial science. Quoting Cassie Kozyrkov again, "Strategies (we add, to address complex challenges) based on pure mathematical rationality without a qualitative understanding of decision-making and human behavior can be pretty naïve and tend to underperform relative to those based on joint mastery of the quantitative and qualitative sides." [11]

Along the same line, Lorien Pratt [8] refers to a new way of thinking and working hand-in-hand with technology "to take actions that go beyond just predicting the future (a task the AI does perfectly) to understanding how to change it." In this sense, DI is not only the evolution of BI but also the next step in the evolution of AI.

Definition 2: DI does not replace existing technologies. Indeed, it supercharges them by unifying them into a single framework (Lorien Pratt, [8])

The challenge is not only to master the enabling technologies, like AI/ML, Big Data, IoT, and in our approach, Digital Twin but also "to develop frameworks and other glue techniques to get these disciplines working together."

In nominating Decision Intelligence in the Top Strategic Technology Trends for 2022, Gartner defines it contextually as follows:

Definition 3: Decision Intelligence is a practical domain framing a wide range of decision-making techniques bringing multiple traditional and advanced disciplines together to design, model, align, execute, monitor and tune decision models and processes. Those disciplines include decision management (including advanced nondeterministic techniques such as agent-based systems) and decision support as well as techniques such as descriptive, diagnostics and predictive analytics. (Gartner [12])

In the wording "practical domain" of the Gartner definition, we read that Decision Intelligence goes beyond traditional analytics and aims to generate practical and concrete decisions and action plans to drive and change business outcomes.

Definition 4: Decision Intelligence is the discipline of using AI and data science to improve business decision-making, and it's enabling organizations to cut through this complexity (IDC - highlighted by Peak AI [13])

The IDC definition emphasizes Decision Intelligence as a necessary discipline to approach and dominate complex business challenges.

In the context of this work, in line with the definitions above, we see Decision Intelligence (DI) as a significant evolution and transformation of CSPs' legacy Business Intelligence (BI) practices leveraging:

- Existing and emerging technologies and techniques such as AI/ML, Digital Twin, Big Data, IoT, edge, fog and cloud computing, hardware accelerators, and graph technology, among others.
- Mature and maturing disciplines, including AI operations (AIOps), data engineering, data science, cognitive science, social science, managerial science, psychology, economics, decision theory, knowledge management, etc.
- New organizational models cohesively combining analysis, diagnosis, decision-making, action plan execution, and outcomes evaluation, and integrating in the loop, on the loop, or out of the loop the appropriate roles and skills (including the fresh decision scientists).

We also consider DI a fundamental discipline in the AI era and, together with AIOps practices ([14]), a necessary precondition for the massive development, deployment, operations, and maintenance of AI-driven systems and solutions.

2.3. DI QUALIFICATION REQUIREMENTS

The foundational requirements that Decision Intelligence (DI) solutions and approaches shall meet to qualify as such are the following:

- DI solutions are analytical (like BI solutions) and decisional, i.e., they shall be capable of making or recommending decisions that lead to actions.
- DI solutions shall predict the future and understand how to change it.
- DI solutions shall connect actions to outcomes, including continually evaluating and optimizing outcomes through a feedback loop.
- DI solutions are not only technical solutions but shall embrace the frameworks combing technologies, processes, methods, people, and outcomes.
- DI solutions shall enable analysts and decision-makers to discover the causal links and relationships in complex problems and systems.
- DI solutions shall enable understanding of the causal chains from actions to outcomes to prevent unintended consequences of decisions.
- DI solutions and processes shall integrate humans and machines at different levels and in multiple ways (according to the context).

This last DI requirement (or guideline) can also be interpreted this way: machines alone can solve only a subset of critical problems.

Machines can perfectly address complicated (from Latin, cum + plica, i.e., with folds) problems, i.e., those problems that we can wholly understand, break down into smaller parts, model them, and implement laborious, precise, and repetitive tasks to "unfold" and solve them (metaphorically, like ironing an unfolded shirt). Examples of complicated problems in the telco industry are the monitoring and configuration of infrastructure components, the setup of the charging & billing systems (and of any system, in principle), and the registration and activation of a new customer (and any repeatable process), to name a few.

Machines struggle to address complex (from Latin, complexus, i.e., wrapped, enclosed) issues and challenges that need a holistic approach to master them (e.g., social systems, economic systems, etc.). Using the same metaphor, if we break down a fabric into smaller parts (the fabric threads), that fabric will not exist anymore. Complex problems need cooperation between humans and machines working hand-in-hand. In our context, examples are customer management strategies, defining operating models, people management, product design, churn reduction, increasing market share in product or customer segments, etc.

"Alexaaa! configure the billing system with products A, B, and C!" This will probably work (hopefully soon!), assuming that products A, B, and C are well-defined (another Pandora's box that DI can help to address).

"Alexaaa! reduce the churn to 2% in the mid and high ARPU customers segments!" This will not work (probably never). Here we enter the realm of Decision Intelligence, where humans, data, and machines are interconnected to design the best options and make the most appropriate decisions in the context.

Another critical expectation about Decision Intelligence is to support or, better, enable effective massive deployments of AI components into vital and strategic business products, services, and processes.

Putting AI at the core of the business requires augmenting the organization's decision-making capability.

Borrowing the term from this HBR article [15], organizations relying on AI shall become "decision factories".

We refer to hundreds or thousands of micro-decisions taken daily at different service and process layers. Most of these decisions are taken autonomously by the AI components. Some of them require highly qualified human involvement and a fast response time. For example, AI feature engineering (i.e., selecting the most appropriate features for a given AI model), defining ML metrics, and selecting suited ML training datasets to train or retrain an AI model are only apparently just technical or operational concerns.

The act of choosing the best features to prevent the risk of customer churn or to make the customers happier opens other Pandora's boxes (again!), which require subject matter expertise, data science, knowledge management, strategic vision, managerial skills, financial view, business context-awareness, and other skills mentioned above in the definitions of Decision Intelligence.

To deploy AI at a massive scale, in addition to adopting AIOps-like frameworks ([14]), it is necessary to set up an embracing and overarching Decision Intelligence framework that allows framing the problems correctly and feeding the insatiable AI components with continuous flows of accurate, reliable, and qualified micro (but not less important) decisions.

Hence, we add to the list above the following DI qualification requirement:

- DI frameworks shall be designed and articulated to enable and support scalable AI development, deployment, and operations.

2.4. DECISION INTELLIGENCE IN ACTION

We mention Google in this paragraph (rather than #4.9) even if CSPs strategists are still resolving if they may consider Google part of the same industry (another Pandora's box, which is outside our scope).

Google is undoubtedly a pioneer and front-runner in Decision Intelligence.

Google has been a front-runner in the massive adoption of AI as well. Google products and services are profoundly and successfully infused with AI technology.

And Google's strategic motivation to invest in DI is precisely the deployment of AI at a massive scale.

"It's (DI) a vital science for the AI era, covering the skills needed to lead AI projects responsibly and design objectives, metrics, and safety-nets for automation at scale", according to Cassie Kozyrkov ([11]).

AI operations need to keep humans in and on the loop to make responsible and business-aware decisions about AI projects and their permanent evolution.

"If you think that AI takes the human out of the equation, think again!"([11]). We couldn't agree more.

Alibaba, one of the world's largest retailers and e-commerce companies serving about 2 billion people worldwide, created a Decision Intelligence Lab, committed to supporting and contributing to the development of "smart decision-making systems". ([16])

Mastercard implemented its AI-driven Decision Intelligence solution to make accurate decisions about whether to decline customers' transactions, impressively reducing false declines and increasing revenues, customer loyalty, and customer satisfaction ([17], [18]).

With the evangelization of Decision Intelligence, different vendors are simultaneously releasing and promoting their Decision Intelligence tools and platforms to get BI and Analytics to the next level: Diwo, Huawei SmartCare®, IBM, Provenir, Salesforce Einstein (name could not be more appropriate..), to mention a few.

Diwo Founder & CEO Krishna Kallkuri summarizes in his company profile ([19]), "Our mission is to bridge the gap between analytical insight and action with Decision Intelligence."

Leo Yin, Director of Huawei SmartCare® solutions, declares: "Decision Intelligence combines the power of human and machine to achieve collaborative intelligence, drives decision-making to be more accurate, scalable and trustworthy." ([20])

They represent a sound and clear vision of the DI software solutions and services market.

3. Digital Twin (DT)

"This book describes an event that will happen someday soon: You will look at a computer screen and see reality. Some part of your world - the town you live in, the company you work for, your school system, the city hospital - will hang there in a sharp color image, abstract but recognizable, moving subtly in a thousand places. This Mirror World you are looking at is fed by a steady rush of new data pouring in through cables. It is infiltrated by your own software creatures, doing your business."

David Galernter formulated this impressive description in the prologue of his visionary book Mirror World published in 1992 [21]. Replacing the words "computer" with "devices" and "cables" with "networks" (wireline and wireless), it perfectly describes today's scenarios and expectations about Digital Twins.

It seems that "someday" is today after a 3-decades incubation when all those enabling "software creatures" have been maturing, evolving, and converging, making the Mirror World/Digital Twin concept a reality.

More precisely, the "creatures" making Digital Twin possible are of different natures:

- Technologies such as AI/ML, modeling tools, simulators, graph technology, Big Data, IoT, edge, fog and cloud computing, hardware accelerators, practically unlimited storage, AR/VR, fast connectivity (fiber, 5G), etc.
- Process and practices, including model-based design methods (MBD), 3D simulation, data engineering, data science, uncertainty quantification (UQ), DevOps and Agile practices, AIOps/MLOps, dataops, design modeling, feature engineering, improved IT & data governance, etc.
- Organizations investing in DT and onboarding people and skills mastering the above disciplines and practices in their organizational positions.

3.1. A BRIEF HISTORY

The development of digital twins goes through three main stages:

- The first stage is the period of technology accumulation. In the last decades of the 20th century, the development of two-dimensional drawing tools and simulation technologies has become a precursor of digital twins.
- The second stage is the concept development period. From 2000 to 2015, the industry proposed a series of fundamental concepts of digital twins adopted mainly by the aviation, aerospace, manufacturing, and military fields.
    - In 2002, The University of Michigan established a PLM (Product Lifecycle Management) Center. Professor Michael Grieves published "Conceptual Ideal for PLM" to industry, proposing a PLM (Product Lifecycle Management) conceptual model for the first time, in which "virtual digital expression equivalent to physical products" was presented, and the description and conflation of real space and virtual space appeared ([22]).
    - In 2010, NASA (National Aeronautics and Space Administration) first introduced the representation of digital twins in its space technology roadmap. In this work, a Digital Twin is specified as "an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin. The digital twin is ultra-realistic ..." ([23]).
    - In 2011, AFRL (U.S. Air Force Research Laboratory) published a public paper disclosing the "Airframe Digital Twin" project, or ADT for short ([24]). The project integrates the static strength data of the fuselage at the time of each aircraft manufacturing, the flight history data of each aircraft, and the daily operations and maintenance data. It uses the simulation method to predict the fatigue cracks of the aircraft fuselage, realize the life management of the aircraft structure, effectively improve the operation and maintenance efficiency of the fuselage, and the service life of the fuselage.

- The third stage is the application explosion period. Digital twin solutions penetrated other industries and fields, covering more and more application scenarios. Internationally, many large manufacturers have proposed product landing solutions based on digital twins.

    - Dassault built a product line based on CAD design software for the aerospace industry and acquisition strategies. In 2012, Dassault presented its 3DEXPERIENCE strategy and launched the 3DEXPERIENCE platform in 2014 ([25]).
    - ANSYS' TwinBuilder is a product package for digital twins that combines the power of a multidomain system modeler with an extensive library of specialized libraries for 3D applications, 3D physics solvers, and reduced-order model (ROM) capabilities ([26]).
    - Digital Twin solutions were extended to energy, smart cities, transportation, agriculture, healthcare, smart homes, and other industries.
    - In 2017, 2018, and 2019 Gartner included Digital Twin in the Top Strategic Technology Trends ([27], [28], [29]).
    - Since 2019, CSPs have started implementing PoC projects deploying DT solutions to address industry use cases ([30]).
    - Meanwhile, the number of published papers on Digital Twin(s) has been growing exponentially ([31]). (One more now!).

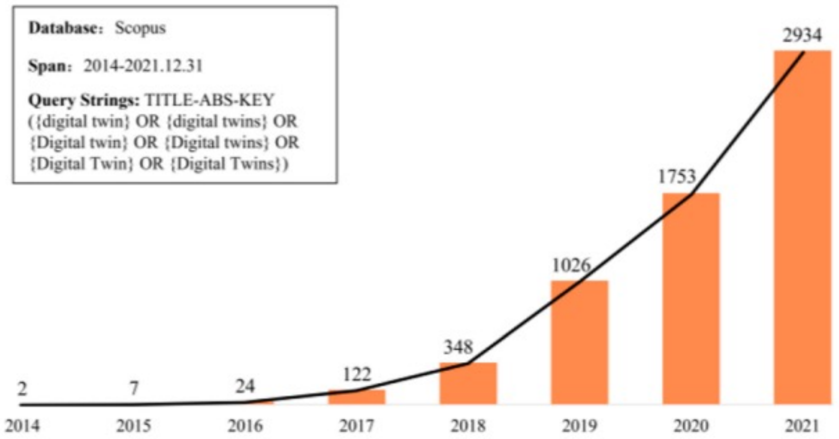

Figure 3. Number of papers published per year during the digital twin growth stage ([31])

3.2. DEFINITIONS OF DIGITAL TWIN

Digital Twin has recently become a hot and trendy topic. However, as shown above, it is not a new concept and has been around for a few decades.

The availability, development, and maturity of enabling technologies and disciplines like AI/ML, IoT, Big Data, cloud infrastructure, hardware accelerators, AR/VR, data engineering, and others have suddenly accelerated the practical adoption of Digital Twins in numerous industries and domains.

As DT is not a new topic, many definitions are available in the industry and literature. We gather here some of them.

The first definition pays homage to the father of Digital Twin, Michael Grieves, who proposed this concept (naming it the Mirror Spaces Model) in 2002 at a SME (Society of Manufacturing Engineers) conference.

Definition 1: the Digital Twin is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. The intent of the Digital Twin is to provide the same or better information that could be obtained by possessing the Physical Twin. (Michael Grieves, [22]).

When Michael Grieves formulated this foundational definition, still valid today, at that time, he had in mind physical objects and assets that you can see and keep in your hands, as typical in manufacturing.

Definition 2: A digital twin is a digital representation of a real-world entity or system. The implementation of a digital twin is an encapsulated software object or model that mirrors a unique physical object, process, organization, person, or other abstraction. Data from multiple digital twins can be aggregated for a composite view across several real-world entities, such as a power plant or a city, and their related processes. (Gartner [32])

The Gartner definition highlights applying the DT approach to immaterial systems and entities like processes, organizations, and, eventually, everything real. Translated in our industry, DT applies to network and infrastructure elements, logistics, and supply chains, but also perfectly to IT capabilities, IT processes (e.g., Capacity Management, Configuration Management, Monitoring & Event Management, etc.), business processes (provisioning, billing, product management, marketing campaigns, service assurance, fraud management), and to Business and Decision Intelligence (DI), which is presently our scope in this work.

Definition 3: A digital twin is a virtual representation of a real-world object or system used to digitally model performance, identify inefficiencies, and design solutions to improve its physical counterpart. Unlike simulations, which operate in entirely virtual environments divorced from the external world, digital twins model specific real-world assets outfitted with sensors that continuously update their virtual counterparts in real time with granular, high-quality information. (Coursera [33])

The Coursera definition puts the accents on the permanent and continuous synchronization between the physical and virtual twins, a crucial qualification requirement differentiating DTs from simulations, DevOps-like Blue-Green environments, and Tests in Production (TIP) practices.

Definition 4: A Digital Twin is a composable digital representation of a system that can span its lifecycle, is continuously updated from design and operational data, and can use simulation, machine learning, and reasoning to augment decision-making and/or control the system. (IBM [34])

IBM here mentions combining other technologies, such as AI/ML, to augment decision-making. DT4DI is not too far from this intent.

DT is an architectural approach that involves designing and combining different building blocks and leveraging various technologies (3D simulation, graph technology, IoT, big data, analytics, edge, fog, & cloud computing, AI/ML, hardware accelerators, etc.).

Definition 5: A digital twin is a virtual representation of real-world entities and processes synchronized at a specified frequency and fidelity.

- Digital twin systems transform business by accelerating holistic understanding, optimal decision-making, and effective action.
- Digital twins use real-time and historical data to represent the past and present and simulate predicted futures.
- Digital twins are motivated by outcomes, tailored to use cases, powered by integration, built on data, guided by domain knowledge, and implemented in IT/OT systems.

(Digital Twin Consortium [35])

Definition 6: Digital twin refers to the processes and methods for describing and modeling the characteristics, behavior, formation process, and performance of physical objects using digital technology, and can also be referred to as digital twin technology. (Zongyan Wang, [36])

According to Zongyan Wang,

- Digital twin is techniques, processes, and methods, and digital twin models are objects and data.
- Digital twin is not only using human theory and knowledge to build virtual models but also can use virtual model simulation technology to explore and predict the unknown world, to find better ways and means, and constantly inspire human innovative thinking.

This last definition (of our whitepaper) pops into our mind a metaphor that we borrow from Thomas W. Malone (Superminds, [37]). Digital Twin (and AI) allows us to see ghosts. We do not refer to imaginary ghosts but to real entities and events around us that are invisible to human eyes and difficult to detect with traditional technologies and tools. These ghosts can be evil, i.e., kablooie to solve (crashes, failures, defects, biases, frauds, revenue leakages, potential complaints, security threats, performance degradation, functional gaps, etc.), or angelic, i.e., business opportunities, efficiency optimizations, and product, process, and service improvements to catch.

We could fill an entire whitepaper with definitions of Digital Twin, though our selection already gives a pretty good understanding of this concept.

3.3. DIGITAL TWIN QUALIFICATION REQUIREMENTS

According to the definitions above and our experience, Digital Twin solutions shall meet the following non-exhaustive list of requirements to qualify as such:

1. Virtual-real mapping: a Digital Twin solution requires a virtual digital representation of the target real-world entity, asset, object, service, product, process, persona, organization, etc.

2. Physical objects in the real world and virtual twin objects in digital space shall achieve two-way mapping, data connection, and state interaction.

3. A Digital Twin system shall emulate the real-world entity as accurately as possible. As stated in the NASA definition, Digital Twin shall be ultra-realistic.

4. Digital twin systems require continuous and recursive process refinement through the exchange of information, including the information flow from sensing systems to AI/ML systems to actuation systems.

5. Real-time synchronization: based on continuous data acquisition and update/alignment, the virtual twin shall accurately emulate and dynamically reflect the state changes of physical objects, including appearance, performance, location, anomalies, etc.

6. Symbiotic evolution: the lifecycle of digital and physical twins evolve simultaneously, hand-in-hand. The mapping and synchronization condition achieved by the digital twin shall cover the entire life cycle from design, deployment, production, and maintenance to retirement.

7. Closed-loop optimization: a Digital Twin solution shall achieve a closed-loop decision-making optimization process for physical entities by describing the internal mechanism of physical entities, analyzing patterns, gaining insights into trends, and forming optimization instructions or strategies to change for the better the physical twin.

8. Digital Twin solutions combine and master multiple technologies, including Big Data, IoT, Analytics, AI/ML, AR/VR, cloud, fog, and edge computing, hardware accelerators, graph technologies, 3D simulation, blockchain, etc.

9. Digital twin systems require continuous and recursive process refinement through the exchange of information, including the information flow from sensing systems to AI/ML systems to actuation systems.

10. Interoperability: a digital twin system may connect to other federated digital twin systems in an industrial metaverse.

This last requirement urges the definition of a standard ontology for digital twin design and operations crossing different domains and industries. ([38]).

We are keen to give our humble contribution in this direction.

3.4. DIGITAL TWIN IN THE TELCO INDUSTRY

At DTW 2022 in Copenhagen ([30]), three catalyst proof-of-concept projects showcased three different DT-based solutions that well represent the range of use cases in the telco industry.

1. The project "Outcome-based Decision Intelligence for Business Growth" (C22.0.384), developed by XL Axiata, HKT, China Unicom, Huawei, SI-Tech, Broadtech, and the universities of Huazhong and Shaanxi, introduces a DT-driven Decision Intelligence (DI) platform and decision-making framework, enabling CSPs to design target marketing and sales campaigns to capture business opportunities and tackle business growth.

2. The project "Digital Twin Network Application in 5G Network Operations" (C22.0.386), implemented by China Mobile, SI-Tech, Ultrapower, and AsiaInfo, demonstrates how a new digital twin network can improve the quality of network operations. The project uses AI models trained to verify the relationship between the number of sessions and traffic and uses network digital twins to verify whether the planning blueprint meets the requirements.

3. The project "Customer avatars unlock Metaverse experience" (C22.0.291), developed by China Mobile, China Telecom, China Unicom, STC, SLT Mobitel, SI-Tech, Boncloud, CAICT, and AsiaInfo, shows how DT-based avatars can differentiate communications with customers in the metaverse.

These three catalyst projects meet typical telco requirements and challenges in the following macro domains:

- Business and Decision Intelligence (BI, Analytics, DI, analytical CRM, product design), including the personification of market segments, target audience analysis, consumer behavioral analysis, customer intent modeling, marketing campaigns, etc.
- Network Planning, Operations & Maintenance, including the service assurance processes.
- Customer Service & Customer Engagement.

In telecom, DT solutions apply to a broad range of business problems in sales and marketing, operations, customer experience, finance, network and IT operations and planning ([39]), such as:

- Gaining cross-functional visibility and insights to understand, design, and optimize customer engagements across the lifecycle.
- Mapping journeys, predicting deviations at future milestones, and providing recommendations for preventive or course correction.
- Customer churn management by detecting real-time service issues, triggering customer unhappiness, and providing an understanding of the event's lead time and cost impact.
- Detecting and preventing telecom frauds, such as subscription frauds, traffic frauds, and subscriber identity module (SIM)-swaps.
- Business simulation use cases, including testing market responses to new product ideas, maximizing customer lifetime value, optimizing steps in the value chain, mergers and acquisitions, risk analysis and mitigation.
- Marketing use cases include identifying challenges and opportunities in new product models, testing a product's or service's impacts on market uptake, risks for cannibalization, customer experience, brand recognition, and NPS.
- Sales use cases embrace the mirroring of the sales channels to detect issues and improve customer sales and post-sales experience.
- Persona - Personification of market segment, target audience analysis, consumer behavioral analysis, customer intent modeling, and interpretation.
- Network Operations use cases include network planning, operational process workflows, capacity expansion, and testing new security protocols.
- IT Operations use cases include Configuration Management, Change Management, Capacity Management, Monitoring & Event Management, among others.
- Finance use cases include identifying the cost to serve, establishing the potential margin in customer opportunities, quantifying the risk/reward of possible strategies, and evaluating new business models.

3.5. DIGITAL TWIN IN OTHER INDUSTRIES

The concept of Digital Twin has been successfully implemented in different industries:

- Aerospace and Aviation to optimize and secure their operations.
- Automobile and heavy electrical engineering to innovate new products and components.
- Manufacturing to improve operational processes or floor jobs.
- Finance and retail to analyze market behavior or prospective fraud tactics.
- IT and digital industry to build accurate digital copies of products, processes, infrastructures, and personas.
- Smart cities to govern the urban management life cycle.

Digital Twins have been beneficially applied in contexts that require the simulation of complex environments.

Let's dive into some examples that can also be a source of inspiration for the telco industry.

3.5.1. DIGITAL TWINS IN AEROSPACE AND AVIATION

In aircraft maintenance, a digital twin of an aircraft can be used to monitor the physical condition of parts within the entire system of the aircraft and make predictions of the life of this part and any failures.

The highly regulated aircraft maintenance requirements require replacing parts preventively based on a maximum number of flight cycles, landings, and time used. Predictive aircraft maintenance with a digital twin can improve the prevention of failures outside these very cautiously set limits and the sustainability of operations by optimizing spare-parts management.

The concept of a digital twin for an aircraft has increased in popularity and market reach, with aircraft maintenance providers and manufacturers offering these services, including setup, data transfer, and analysis.

Additionally, digital twins can simulate complex business environments in aviation.

Digital twins of airline networks can be created using custom or commercially available tools to simulate the complex flight networks of airlines down to each passenger's journey almost in real-time.

Besides the benefit of allowing airlines to better trace any irregularities in their vast networks, twinning the network digitally enables them to simulate how a change in one specific aspect of their operations (e.g., a different aircraft type on a particular route or a different schedule) could affect the overall operational performance in the entire network.

3.5.2. DIGITAL TWIN IN MANUFACTURING

Digital Twin in manufacturing helps monitor assets virtually, avoid unexpected downtime, and improve asset performance.

Digital twins can continuously receive live data from objects with the help of IoT sensors. The physical assets in a factory use these IoT sensors to collect data and transfer it to their digital/virtual counterpart.

For example, an electric motor can have multiple IoT sensors to capture temperature and speed and send them to its Digital Twin in real-time. Based on this data, the Twin can analyze information like the rotation of the shaft and thermal conductivity.

Digital twins can manage assets like machines, plants, and manufacturing machinery. Asset management is simplified by adding analytics, AI, and advanced visualization.

Digital twins enable manufacturers to simulate and test the product behavior before the physical product is built.

Digital twins aid the creation of customized products through several permutations. Incorporating customer feedback into manufacturing processes took a lot of work in the past. But digital twins make it seamless to integrate data and meet customer demands easily and quickly.

Manufacturers also use augmented reality (AR), virtual reality (VR), and mixed reality (MR) applications for training and maintenance. Through AR headsets, technicians can view the most up-to-date models of the machine laid over the one in front of them.

Numerous collaborative research European projects in the manufacturing sector have been funded in the last few years on digital twins. For example, Change2Twin is a European project which supports manufacturing SMEs in their digitalization process by providing Digital Twin solutions ([40]).

3.5.3. DIGITAL TWIN IN SMART CITIES

A digital twin city is a virtualized urban system accurately mapping and matching the physical corresponding town.

The integration of geographic information systems (GIS) and city information models (CIM) with rich urban data (such as census data, socio-economic data, energy consumption data, etc.) and virtual 3D models are the backbones of digital twin cities.

The virtual digital twin and physical cities establish a comprehensive real-time connection to realize the digital recording of the life cycle of urban system elements, real-time perception of urban status, focus interventions, and trend prediction of urban development.

The digital twin city can generate different city views in real-time according to the needs and display spatial and attribute information that the two-dimensional model cannot provide.

Three-dimensional real-time mapping of virtual and real cities increases the city's visual experience, provides more intuitive observation of the urban elements, monitors the urban operation processes and the performance of existing public services, improves city planning, and supports the whole life cycle of urban components and urban construction projects.

Digital twin cities will change the underlying logic of urban planning, construction, and management and inject new vitality into urban governance. From a city management perspective, digital twin cities enable improvements to the urban landscape by simulating how changes affect the urban environment and how assets perform in real time.

For public sector organizations, digital twin cities also serve as an effective engagement tool to facilitate discussions among different segments and industries.

CSPs have a dual opportunity over here.

On the one hand, CSPs can adopt Digital Twin for their business's products, processes, infrastructures, and personas.

On the other hand, CSPs can use anonymized data in their network and systems to assist different industries in creating accurate Digital Twins for other businesses.

4. TM Forum DT4DI Project

Decision Intelligence (DI) solutions leveraging DT and AI take a step forward in the capabilities of traditional business intelligence, analytics, and decision support solutions.

They help businesses make faster and more accurate decisions from potentially holistic and cohesive perspectives, so they can make decisions and act when it matters most, seizing business opportunities to stay ahead of their competitors.

While DI solutions based on the latest cutting-edge technologies are becoming increasingly important, it becomes crucial to industrialize and standardize their engineering and lifecycle management through a comprehensive framework designed to support this emerging application domain.

The CSPs industry has a vacuum of standards guiding and driving the implementation and adoption of effective and reliable Decision Intelligence (DI) solutions.

This emptiness is even more sharpened and silent because of the poorness of standards also in the predecessor BI domain.

The need for standards is even more pressing as DI solutions combine and integrate enabling technologies and techniques, such as AI and Digital Twin, which are challenging and disruptive per se.

We felt then the urgency to kick off a new standardization project in this domain.

This new TM Forum collaboration project aims to set up a foundational ontology, including domain concepts, definitions, and baselines, and to design and engineer knowledge-driven Decision Intelligence solutions powered by DT and AI, supporting vital CSPs' business processes and tactical and strategic decision-making.

4.1 SCOPE

The scope of the TM Forum DT4DI collaboration project is to support CSPs in adopting and deploying DI solutions and practices powered by AI and DT in their organizations.

To thrive in today's more dynamic and uncertain conditions, CSP organizations need to use their data and knowledge better and expand their capacity for analysis, diagnosis, timely decision-making, action plan execution, and outcomes evaluation.

In DI, improving the analytical and diagnostic capabilities and skills of BI through the focus on causation is just a part of the story.

The strategic DI shift is to industrialize the decision-making, the call to action, and the outcome evaluation of those actions, including the feedback loop as a continuous improvement mechanism.

DT- and AI-driven DI solutions create virtual models of customers, products, processes, and resources to drive the faster and deeper investigation, innovation, time-to-market, and accurate decision-making.

With DT4DI, from one side, CSPs can address their consumer markets, becoming more competitive and profitable. On the other side, they can provide to their business, corporate, and public sector markets DT4DI assets and services, helping CSP enterprise customers improve their decision intelligence processes and practices.

From the architectural point of view, BI and DI systems (and DT4DI ones in our case) fall in the domain that TM Forum functional architecture ODA (Open Digital Architecture) generally calls "Intelligence Management," as shown in figure 4 below ([41]).

Despite the vagueness of the name, ODA describes quite precisely the scope of this functional domain as follows :

"Analytical processes use operational data (reference data) and events produced by operational processes or captured from the environment during an interaction with the enterprise .. along with events received from operational processes to produce analyses, correlations, and aggregations that yield a representation of operational reality."

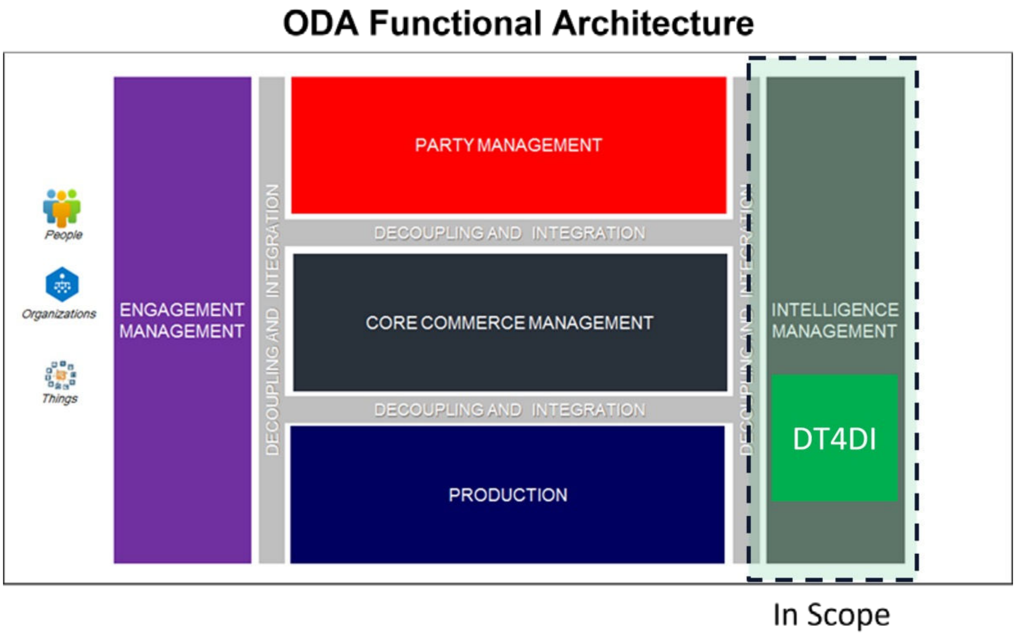

Figure 4. DT4DI solutions are part of the ODA Intelligence Management functional domain.

ODA also describes a list of processes covered by the Intelligence Management domain (and consequently by DT4DI), such as marketing campaign management, market performance management, sales performance management, product performance management, and service quality management, to name a few.

During the DT4DI project activities, TM Forum project members will develop and deliver the following assets that are necessary building blocks to approach the design and implementation of DT4DI solutions systematically:

- **DT4DI Ontology** will describe the definitions of this domain's fundamental concepts and components.
- **DT4DI Reference Architecture** will provide the template solution, including the layers, structures, and integrations of software components, products, data, and capabilities, to build up DT4DI solutions.
- **DT4DI Design Guidance** will recommend guidelines and principles to engineer, deploy, operate and maintain DT4DI solutions.
- **DT4DI Maturity Model** will define and detail the maturity levels of the organization's adoption of DT4DI systems and practices, including the corresponding level's criteria and conditions.
- **DT4DI Use Cases** will show practical implementations of concrete and successful DT4DI solutions in the CSP industry.

4.2. NOT IN SCOPE (OR FUTURE SCOPE?)

By exclusion, all the other ODA application domains are not in the scope of DT4DI, i.e.:

- Party Management, e.g., sales management, customer interaction management, billing account management, party financial management (payment, dunning)
- Core Commerce Management, in charge of Product Offerings and Products Catalogue processes, functions, and repositories, e.g., order handling, from order Capture & Configuration to the orchestration of the customer order delivery, rating/charging, and billing.
- Engagement Management, providing digital and omnichannel interaction capabilities between the enterprise and its ecosystem.
- Production (a bit ambiguous term, as in IT and AIOps, we use it with a different meaning), including Network and IT infrastructure deployment and operations management.

However, it must be noted that Intelligence Management and DT4DI interact and synergy with the other domains through process integration and interfaces.

Indeed, DT4DI solutions not only analyze and govern the business and operational reality as traditional Intelligence Management solutions (e.g., BI & Analytics) but also change it through bidirectional and continuous flows of data, predictions, recommendations, decisions, actions, and outcomes.

This new active role of DI and, in particular, DT4DI, which are more operational and prescriptive than traditional BI that is predominantly analytical, will impact the existing enterprise architectures that need to be refashioned to incorporate the new cross-domain functional role of DT4DI.

Another aspect to consider is the multiplication of DT solutions in all ODA functional domains, creating the need to develop common baselines, guidance, practices, unified data management, and standard digital twin architectural layers (figure 5 below).

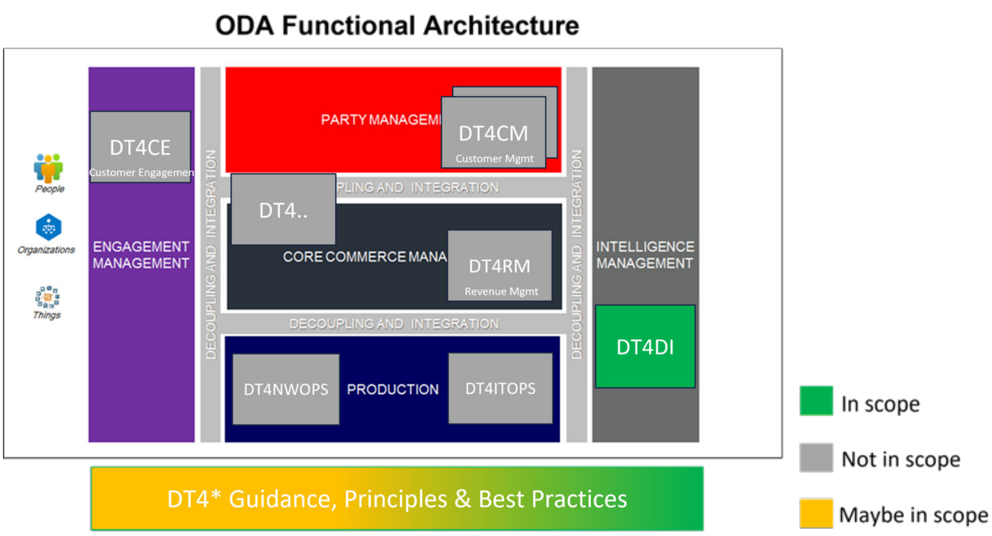

Figure 5. Emerging or potential DT4* projects in ODA functional domains.

The TM Forum DT4DI project can be a helpful reference for this future development and all the other DT4* projects (we hope!).

4.3. THE ROLE OF AI

In the TM Forum AIOps work ([48]), we extensively cover AI's capabilities, opportunities, drawbacks, and challenges so that we will refer to those works.

We want to highlight here the central role that AI plays in DT4DI.

AI is the third brother or a close relative of the Digital Twin family.

We could have called this project AIDT4DI or DTAI4DI, but for conciseness and facilitating the articulation, we preferred DT4DI, considering the AI role as implicit.

AI and Digital Twins boost each other to support Decision Intelligence to elaborate decisions and provide the most optimal scenarios to humans.

- AI enables the exploration of Digital Twin models with powerful discovery, analysis, prediction, correlation, learning, and reasoning capabilities. AI programs are also fundamental to DT systems to represent the operations of the real world for complex systems that can not be modeled using rule-based equations.
- Digital Twins provides structured, comprehensive, and dynamically updated data models simulating the real world (potentially every real entity) that facilitate the development, deployment, and operations of AI solutions. Highly reliable DT virtual models, massive twin data, and real-time two-way dynamic interaction enable diverse and accurate AI models. DT can produce simulated data in virtual environments and go through infinite repetitions and scenarios. The simulated data and virtual environments can be used to effectively and efficiently perform AI model training.

AI and DI also complement each other.

- DI needs AI to produce smart decisions.
- AI needs DI to be smart, i.e., to provide the AI factory with the appropriate micro-decisions that are the necessary inputs for data engineering, feature engineering, algorithms selection, ML training, performance management, and key development and maintenance activities to build compelling and relevant AI components. As mentioned above, this was one of the key reasons Google created a DI department ([49]).

Along this line, DI can solve or mitigate AI drawbacks and challenges such as bias prevention, adversarial attacks, overfitting, performance degradation, iterative maintenance, capacity gaps, continuous data curation, datasets selection and baselining, etc.

AI can also support DT when there is no real-world data available. AI allows a Digital Twin to create its reinforcement learning level data to help make the right decisions (e.g., AlphaZero AI model [55]).

And, just around the corner, DT4DI is the missing link in AIOps (and vice versa).

Interesting (and probably animated) discussions on the horizon!

4.4. GAP ANALYSIS: BI VS. DI/DT4DI

Refraining from Groucho Marx, the American actor and writer, we could pleasantly say that Business Intelligence (BI) is a contradiction in terms.

The only intelligence in traditional BI systems is the intelligence of the people who design, maintain, and use them.

This may sound a bit unfair, as BI & Analytics systems, platforms, and processes have done a great job providing reports, dashboards, insights, analytical methods, and views to support the business in the last three decades.

However, in recent years, with the increase of data sources, data volumes, and problems complexity, BI solutions struggled to address the current business challenges, and they were unable to effectively incorporate new technologies and techniques such as Big Data, IoT, cloud & edge computing, AI/ML, and Digital Twin.

DI represents the next generation of BI & Analytics, natively leveraging and absorbing new and emerging technologies, practices, and skills.

DI fills fundamental gaps in BI solutions that have limited their effectiveness and addresses new challenges that BI was not designed for.

Below, we list our view about the main gaps between BI and DI (more precisely, DT4DI) without the pretension of being exhaustive.

BI	DI/DT4DI
Data-centric	Data- and decision-centric
Analyzing, understanding, and predicting the real world	Analyzing, understanding, predicting, deciding, and changing the real world.
One-way communication (real world to BI).	Two-way communication.
Structurally static and rigid.	Dynamic and flexible by design.
Lengthy, slow, and sometimes faulty processes and interfaces are needed to update the data and analytics and make them available to the end users.	Continuous synchronization with the changes and evolution of data in operations.
Made of forests of tables challenging to map, track and maintain.	Based on Digital Twin models mirroring tangible and intangible assets, processes and resources dynamically.
High customization efforts to adapt the forest of tables to the current business and service status and evolution.	Low customization efforts as designed to sync with the evolving operations automatically.
Focus on data categorizations and correlations.	Focus on causal relationships and causal reasoning.
Linear thinking.	Networked thinking ([42]).
Décalage with the operations.	Real-Time.
Decisions are predominantly human-driven.	Decisions are driven by humans & machines working together.
Incorporating AI/ML models in BI legacy architecture requires laborious engineering and operations tasks.	DT4DI solutions are natively designed to explore and unleash the power of AI.
BI doesn't support the lifecycle of AI components.	DI is necessary to design, develop and maintain AI components at scale (e.g., supporting model design, feature engineering, data engineering, etc.)

One of the key points of DI is the focus on causation, i.e., the relationships between cause and effect.

Analytics and even more AI/ML algorithms are champions in finding correlations.

However, they are not the sharpest sheds in determining causation.

To comprehend causation, a deep understanding of the subject domain must be modeled and infused into the AI/ML models.

That implies that most of the business, functional, and design decisions about AI models need to be taken before the beginning of any AI model's design, development, and ML training phases (this is valid, in general, for any relevant software component).

If you think AI will replace human understanding, intuition, and mastery of disciplines and processes, think again!

In the example below, the author Franz H. Messerli, M.D. correlates Nobel laureates and chocolate consumption, demonstrating brilliantly how correlations and linear thinking can generate not necessarily incorrect (chocolate consumption could hypothetically improve cognitive function) but partial and unhelpful conclusions. This correlation also creates a provocative bias against the outlier Sweden, which has more laureates while consuming less chocolate than others ([43]).

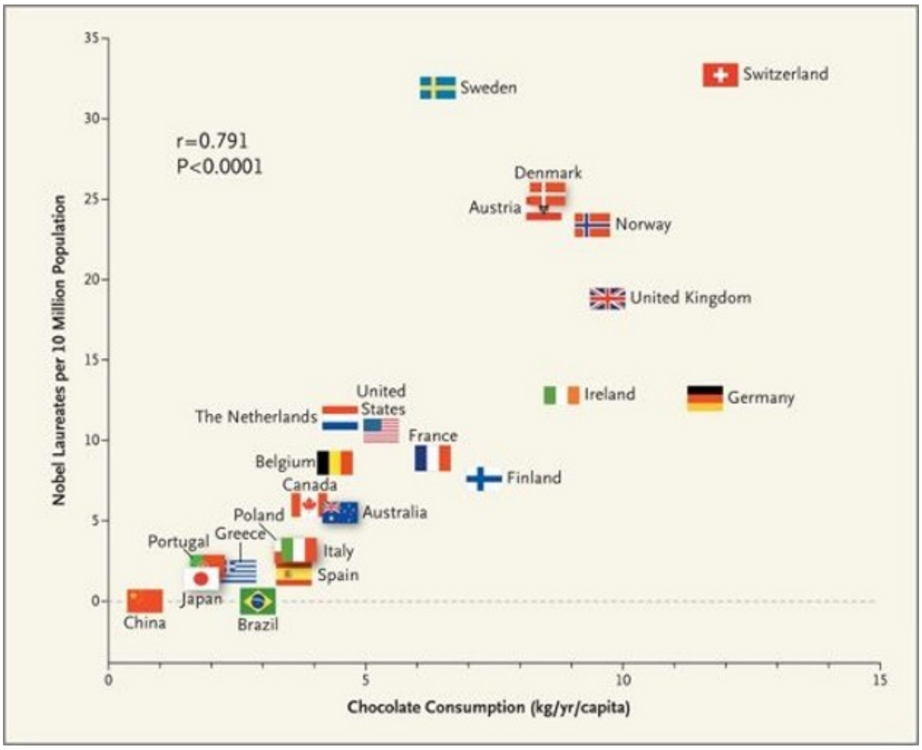

Figure 6. Eureka! We shall eat more chocolate!

In this case, the conclusions are hilarious and innocuous (the bias against Sweden artificially created to justify the outlier is that the Nobel Committee in Stockholm would have some patriotic preference when assessing the candidates for these awards).

In other cases, inappropriate correlations, linear thinking, and lack of causation can generate dangerous decisions, harmful biases, and damaging or devastating actions. The massive deployment of AI may exponentially increase these risks.

4.5. DT4DI ONTOLOGY

The first immediate step of this project will be to define the ontology of the concepts, entities, and components we use or refer to design and manage DI and DT4DI solutions for the CSPs industry.

From the ontological perspective, there is a continuity between BI and DI. However, DI diverges from BI for its purpose, scope, methods, and realization.

Moreover, even BI sometimes needs more standard and universally recognized definitions and categorizations.

Many definitions have been around for years and do not need further clarification.

For others, restating or refreshing the definitions or aligning their meanings in our context may be helpful.

As stated in #3.3, Digital Twin needs shared and consented ontology concepts and models enabling the massive deployment of coherent and interoperable systems.

According to Doug Migliori ([44]), "To realize the true potential of the industrial metaverse (na, a broader concept which includes digital twins as core components), industry consortia must properly align their data models, ontology concepts, and terminology with the goal of defining a top-level ontology."

We hope to contribute to this purpose sideways.

As part of the scope, we will formally define the building blocks and components used in the DT4DI framework and reference architecture.

The DT4DI ontology will also help to understand and state the relationships among the concepts and objects used in this domain.

We will refer to and ensure coherence with the most recognized sources (e.g., ISO/IEC/IEEE) and other industry consortia and fora.

4.6. DT4DI REFERENCE ARCHITECTURE

The second goal of the DT4DI project is to define the reference architecture that guides the design and implementation of DT4DI solutions.

The reference DT4DI architecture shall support and map the typical DT4DI cycle and process, which is bidirectional, cyclic, and continuously iterative, as shown in figure 7 below.

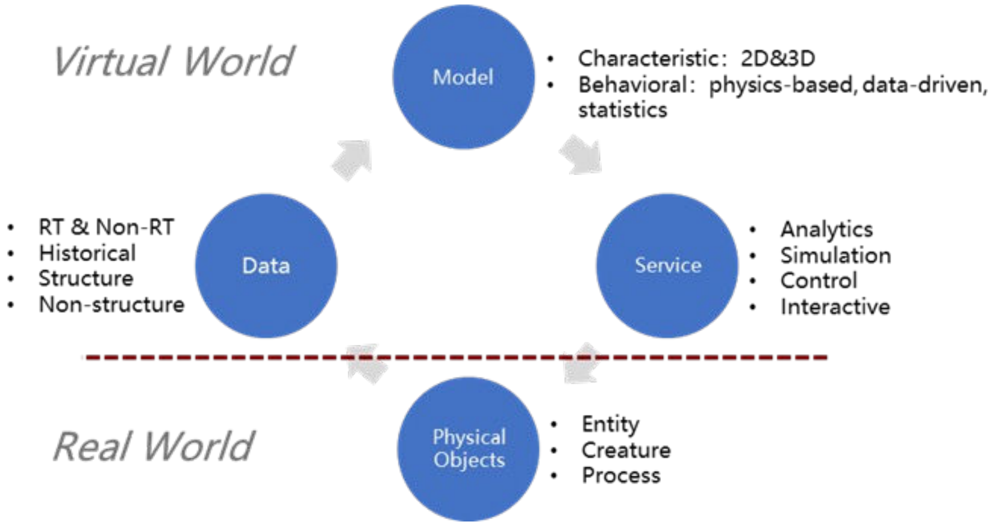

Figure 7. Schematic DT4DI Cycle.

The DT4DI reference architecture that we will define in our work shall provide a template including the critical building blocks, components, relations, and interfaces driving the design of DT4DI solutions.

Figure 8 below shows just a flavor of distinct layers we will encounter and examine in the target DT4DI architecture during the project activities. The names and terms used here are drafts, temporary, and subject to the ontology discussion mentioned above.

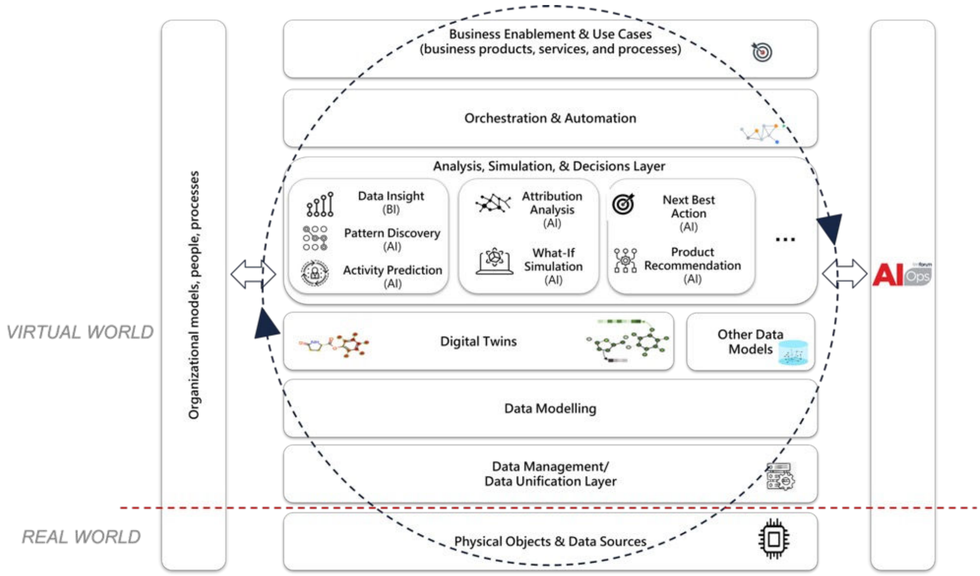

Figure 8. Draft DT4DI High Level Architecture.

The fundamental layers and building blocks of a typical DT4DI architecture are:

- Physical Objects & Data Sources is the layer of the raw data and authentic information of the sources, systems, objects, and sensors needed to model business needs and challenges.
- The Data Management/Unification layer gathers, cleans, formats, and stores data from multiple internal and external sources.
- The Data Modelling layer defines and designs the most appropriate logical data model for the specific business need.
- Digital Twin and other Data Models: we could also call this layer "physical data models" as here is where the target-built data model lives in the architecture. From this architectural perspective, we see Digital Twin as one additional data model which can be particularly effective for specific and complex business challenges. The digital twin and other data models cohabit in the same logical architecture.
- Analysis, Simulation & Decision Layer: this is where data are explored and consumed, digging into the models at the below layer. AI-driven applications and tools are central in this layer to boost diagnostic, discovery, predictive, and prescriptive capabilities.
- Orchestration and automation: this layer coordinates and integrates components, applications, and services, creating an ensemble of multiple tasks to execute articulated workflows.
- Business enablement is the business execution layer where outcomes are consumed and optimized, triggering continual feedback loops.

In the figure above, we show how the architecture needs to be integrated and harmonized with the following:

- Organizational and operating models specifically designed to enable humans to work hand in hand with DT4DI systems.
- AIOps-like frameworks and processes to manage AI components at scale effectively and safely.

In this sense, we shall refer to a TM Forum DT4DI framework, including architecture, processes, and organizational and operating models.

4.7. DT4DI DESIGN & DEPLOYMENT GUIDANCE

"Architectures are beautiful, but it's successful implementations that are important." - The DT4DI Project Team.

The statistics about the success rate of digital transformation projects are scary and troubling (especially for project managers, sponsors, and investors).

According to a McKinsey study, more than 70% of digital transformations fail [45]. Other studies are even more pessimistic [46], reaching estimations beyond 90% (1 successful digital transformation project out of 10. Mayday!).

There are several critical factors in a transformation project's success, and proper architecture design is a necessary but non-sufficient condition.

Project guidance is not the silver bullet but can help (among other key factors).

To support the implementation and deployment of DT4DI solutions (which certainly fall in the category of digital transformation projects), the third goal of this TM Forum initiative is to guide the design and engineering of DT4DI solutions powered by DT, AI, and other enabling technologies.

Due to the differences and gaps between BI and DT4DI solutions and approaches, we need to formulate specific guidelines and principles to design, deploy, manage, and govern DT4DI solutions and operate safely and effectively combined DI and BI applications interacting with other applications domains running together in complex CSPs' operations.

We will also understand what it will take for CSPs to manage the design, deployment, operations, and maintenance of DT4DI solutions in terms of organization, skills, efforts, and cultural changes.

The catalyst project "Outcome-based Decision Intelligence for Business Growth" (C22.0.384) showcased at DTW 2022 settled and explored design and deployment guidelines for DT4DI, called Value Co-realization Pyramid and Execution System ([47]). This catalyst experience will be a helpful input for developing standard DT4DI Guidance.

As AI plays a central role in DI, the TM Forum AIOps framework [48] is one of the essential references for DT4DI projects and solutions.

We will also explore how to combine and synergize AIOps and DT4DI guidance and principles.

4.8. DT4DI MATURITY MODEL

“Ogni scarrafone è bell’ ‘a mamma soja” - Neapolitan proverb.

This ancient proverb tells that moms (and dads) see their kids as beautiful even when they look like a kafkanian cockroach.

While this natural maternal instinct may be good for the self-esteem of the new generations, a similar attitude in corporate environments is inconvenient.

In business, self-reference (we are the best at this! We are the best at that!) is not only unuseful (and somehow a form of narcissism, to stay in the realm of the mirrors) but also toxic as it precludes or limits organizations' continuous improvement, meritocracy, and performance-driven evolution.

For these reasons, standards, frameworks, benchmarks, and a proliferation of maturity models exist in almost every industrial domain, enabling organizations to compare themselves with more objective criteria and universally acknowledged best practices.

For DT4DI, it is not different.

As autonomous components, DT4DI solutions may support business processes and decisions at different pre-defined levels, like the increasing levels of autonomy in self-driving cars.

Thus, one of the deliverables of this collaboration project will be the DT4DI maturity model (yes, another one!).

The DT4DI maturity model differentiates the organizations' capabilities across different agreed levels in data integration, real-time update, modeling refinement, simulation accuracy, dynamic and bidirectional connections, human-machine cognitive abilities, intelligent decision-making, human involvement, outcome evaluation, feedback loops, and other criteria.

The levels' definition and technical conditions will be defined and agreed upon during the project activity.

4.9. DT4DI USE CASES

During the project activities, TM Forum members will share and analyze use cases and best practices related to practical implementations of DT4DI solutions in the telco industry.

We may also share best practices from companies of other industries more well-versed in DI and DT adoption and application.

In this paragraph, we anticipate some DT4DI use cases from TM Forum member companies that we will explore and analyze from the standardization perspective during the project activities.

4.9.1. HUAWEI DT4DI USE CASES

Huawei offers CSPs' organizations a new DI platform using DT and AI that provides data insights and analytics better than traditional BI tools and can drive real-time decision-making and action execution.

Huawei's DT4DI solution (SmartCare®) applies digital twin technology to enhance the efficiency and effectiveness of marketing decision-making processes. By consolidating data sources from OSS, BSS, and social platforms and using knowledge graph technology to model people, places, and products (see figure 9 below), the system automatically creates and updates in real-time:

- digital twins of users group for customer segmentation;
- digital twins of places and products to explore relationships or constraints among them.

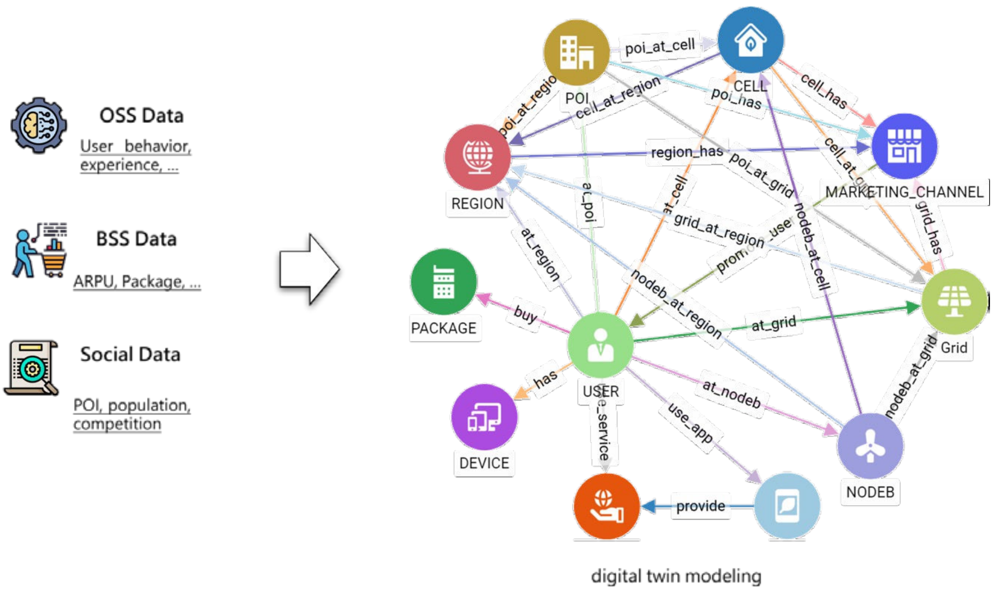

Figure 9. Example of Digital Twin Model

DT4DI Huawei platform enables more in-depth insights, personalized recommendations, and proper channel suggestions on a wide range of use cases (figure 10 below).

It also provides a brand-new perspective for marketing decision-making in terms of discovering issues (What), analyzing and predicting root causes (Why), simulating and supplying Next Best Action (NBA) suggestions (How), and closing the loop with continuous improvement recommendations (outcomes evaluation).

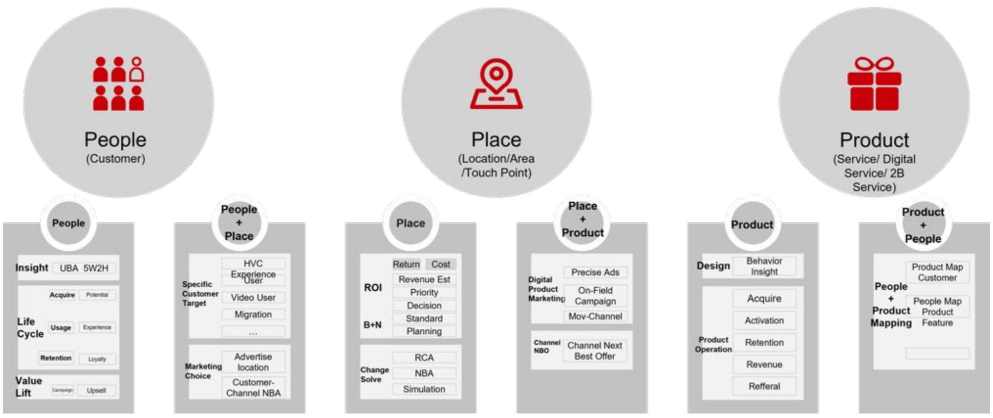

Figure 10. Range of Use Cases

4.9.2. TCS DT4DI USE CASES

Maximize customer's lifecycle value

TCS uses the DT4DI solution approach to predict customers' behavior at various stages, understand their evolving needs, and engage them with the right product-right channel-right time combinations to improve relevance, experience & loyalty, thereby increasing customer value at optimal effort & cost.

Optimize customer journeys

DT4DI can monitor processes to predict deviations proactively, receive actionable insights, and improve operational and business KPIs such as OPEX, TAT, FTR, MTTR, etc.

4.9.3. NOKIA DT4DI USE CASES

Nokia examples of DT4DI Use Cases in Customer Lifecycle Management include:

Customer Profiling and Segmentation Design based on Digital Twin

Customer profiling is creating a customer persona using a set of characteristics such as demographics, behavior patterns, geographic location, and interests.

Customer segmentation involves splitting the existing customer base into subgroups, with each smaller group having specific characteristics.

The DT-based Customer profiling and segmentation solutions exploit the synergy between the current real customers and virtual representations of customer personas driven by continuous data from customer touchpoints, interactions, behaviors, and service usage patterns.

The DT-based customer profiling and segmentation solutions emphasize the real-time analysis of consumer needs and behavior for targeted campaigns, compelling messaging, and service design decisions through the integration of virtual and real-life cycles and the simulation of models.

Businesses utilize data provided by DT-based customer profiling and segmentation capabilities to understand their customers' needs, provide a more personalized customer service experience, and enhance their decision-making process.

Customer Preference and Interaction Design based on Digital Twin

Customer preference refers to individual customers' choice that drives their interaction decisions. Currently, CSPs explicitly determine customer preferences through surveys, interviews, and focus groups or implicitly measure preferences from the customer's ratings of products and services.

The customer preference and interaction design system based on the digital twin model uses intelligent analysis, adaptive design, and decision-making based on a combination of algorithms, reasoning frameworks, and interaction techniques and the use of the virtual and real synchronization among systems to elicit and model the customers' preferences process that results in different alternatives for an optimal choice.

This use case would benefit a company in understanding customers' preferences, increasing personalized interactions, improving service quality, and assessing new service opportunities.

4.9.4. NETCRACKER DT4DI USE CASE

Netcracker DT4DI Use Cases address the Customer Value Management as the following example:

Intelligent Campaign Management

Business Situation: Covid-19 lockdowns accelerated the trend toward remote working and consumption of video and entertainment services at home. This brings many opportunities to CSPs. On the one hand, CSPs can offer Fixed-Wireless Access (FWA) as a backup for wireline connections, providing the same level of quality as the normal fixed broadband. On the other hand, CSPs can sell value added experiences for certain groups of users like gamers. It also allows encouraging entertainment companies to partner with them by offering connectivity with guaranteed SLA and offering special discounts for customers to use CSPs' partner services.

Challenge: For CSPs this posed a major challenge as providing valuable results in a short time with traditional campaign management is near to impossible.

Solution: Digital twin driven campaign helps in reducing the time as it opens up numerous possibilities to experiment and validate the success, while at the same time balance various constraints and conflicts such as revenue vs churn, campaign cost vs returns etc. Additionally, leveraging DT based DI enables a prescriptive decision-making approach giving options for the decision maker to understand the actions required to achieve the expected outcome and effects of decision on the outcome. Figure below illustrates a value chain formed by 4 layers – RT Decision Management, Scenario Analysis and Execution, Digital Twin Ecosystem and traditional CSP business ecosystem.

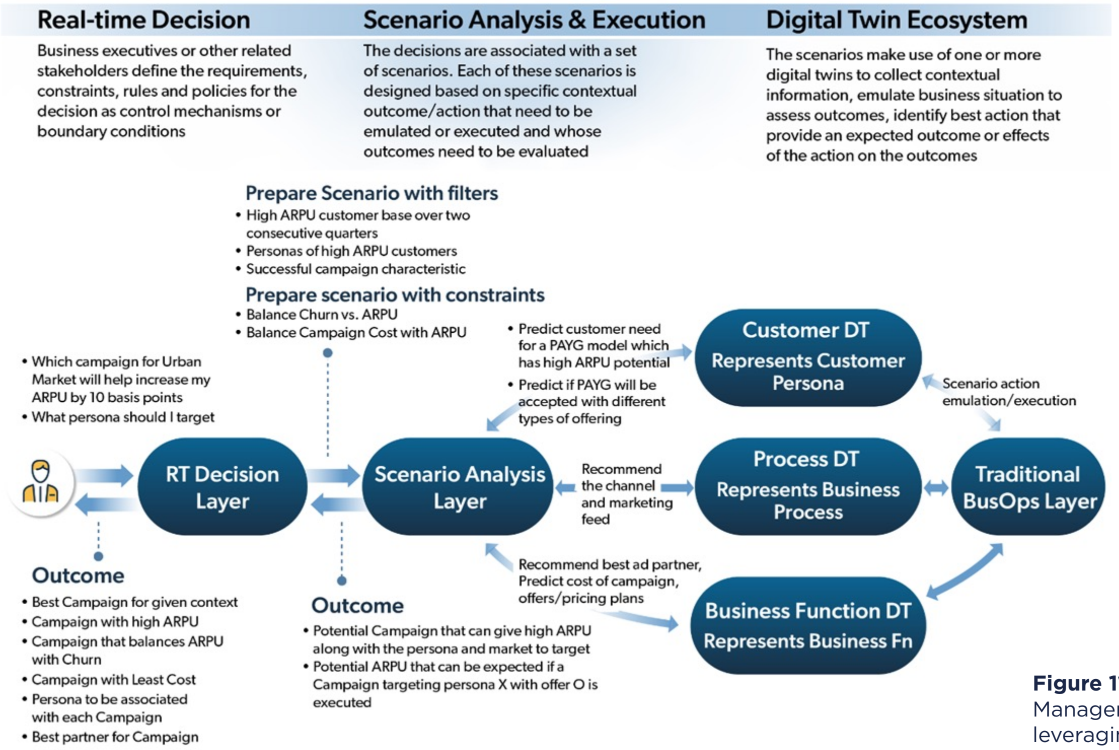

Figure 11. Intelligent Campaign Management Value Chain leveraging DT

In Figure 11 above, business stakeholders use the real-time decision layer to analyze and activate decision context with the help of a set of intents, constraints, rules, and policies. The scenario layer facilitates prescriptive analysis that maps decision context to a set of scenarios that can be evaluated independently and in groups to satisfy constraints. The scenario layer fits an expected scenario to either a realistic or emulated analytics problem, enabling exploration. As part of the decision analysis, any action executed on the RT decision layer is distributed across layers, and outcomes are qualified. Depending on the optimization targets and prescriptive analysis required, the outcomes and feedback of each of these layers are sent back to the previous layer in a closed-loop manner. By using DT, this value chain enables continuous optimization for both decision analysis and decision actions.

5. Conclusions

The growing complexity and faster dynamic of the CSPs ecosystem and the complex business challenges and risks require more competitive analytical and decisional capabilities, processes, systems, and tools.

On the other hand, the massive deployments of critical solutions based on AI and Digital Twin urge to transform organizations into decision factories capable of making in real-time tons of micro-decisions to design, develop, operate, maintain and improve their AI- and DT-driven systems, processes, services, and products.

The TM Forum DT4DI Collaboration Project aims to tackle these challenges by defining, validating, and testing an integrated suite of assets guiding the implementation of DT4DI solutions to enable the telecom business to make better and faster decisions.

"Princess, the people are hungry."

"Give them better decisions!"

7. References

[1] How decision intelligence could democratise analytics - Tamlin Magee - Oct 2021 - https://www.raconteur.net/technology/data-analytics/decision-intelligence-analytics/

[2] The Decision-Driven Organization - HBR - June 2010 - https://hbr.org/2010/06/the-decision-driven-organization

[3] Untangling your organization's decision making - McKinsey - June 2017 - https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/untangling-your-organizations-decision-making

[4] Telecom operators: Surviving and thriving through the next downturn - McKinsey & Company - August 2019

[5] Evolution and Trends of Business Intelligence Systems: A Systematic Mapping Study - Master's Thesis - Pekka Marjamäki - University of Oulu Information Processing Sciences - Apr 2017

[6] OLAP and Business Intelligence History - https://olap.com/learn-bi-olap/olap-business-intelligence-history/

[7] A Business Intelligence System - H. P. Luhn - IBM Journal - October 1958

[8] Link, How Decision Intelligence Connects Data, Actions, and Outcomes for a Better World - Lorien Pratt - 2019 - Emerald Publishing

[9] Gartner Top Strategic Technology Trends for 2022 - https://www.gartner.ca/en/information-technology/insights/top-technology-trends

[10] 12 Data and Analytics Trends to Keep on Your Radar - Gartner - April 2022 - https://www.gartner.com/en/articles/12-data-and-analytics-trends-to-keep-on-your-radar

[11] Introduction to Decision Intelligence - Cassie Kozyrkov - Aug 2019 - https://towardsdatascience.com/introduction-to-decision-intelligence-5d147ddab767

[12] Gartner Glossary - https://www.gartner.com/en/information-technology/glossary/decision-intelligence

[13] Peak AI : What is DI - https://peak.ai/what-is-decision-intelligence/

[14] AI Operations (AIOps) Toolkit - TM Forum - https://www.tmforum.org/toolkits/ai_operationsaiops_toolkit/

[15] Rethinking the Decision Factory - Roger L. Martin - https://hbr.org/2013/10/rethinking-the-decision-factory

[16] Alibaba Damo Academy - Decision Intelligence Lab - https://damo.alibaba.com/labs/decision-intelligence/

[17] Mastercard Rolls Out Artificial Intelligence Across its Global Network - Press Releases - https://newsroom.mastercard.com/press-releases/mastercard-rolls-out-artificial-intelligence-across-its-global-network/

[18] The Amazing Ways How Mastercard Uses Artificial Intelligence To Stop Fraud And Reduce False Declines - Forbes - Nov 2018 - https://www.forbes.com/sites/bernardmarr/2018/11/30/the-amazing-ways-how-mastercard-uses-artificial-intelligence-to-stop-fraud-and-reduce-false-declines/?sh=75edaa7c2165

[19] diwo - https://diwo.ai/company/

[20] Huawei SmartCare® - https://carrier.huawei.com/en/products/service-and-software

[21] mirror worlds - David Gelernter - Oxford University Press - 1992

[22] Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems - Dr. Michael Grieves and John Vickers - (PDF) Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems (researchgate.net)

[23] DRAFT Modeling, Simulation, Information Technology & Processing Roadmap - Technology Area 11 - NASA - 2010

[24] The Airframe Digital Twin: Some Challenges to Realization - Eric J. Tuegel - U. S. Air Force Research Laboratory - https://www.researchgate.net/publication/268478541_The_Airframe_Digital_Twin_Some_Challenges_to_Realization

[25] The 3DEXPERIENCE platform - Dasasult Systemes - https://www.3ds.com/3dexperience

[26] Ansys Digital Twin - https://www.ansys.com/products/digital-twin

[27] Gartner Top 10 Technology Trends 2017 - https://www.gartner.com/smarterwithgartner/gartners-top-10-technology-trends-2017

[28] Gartner Top 10 Technology Trends 2018 https://www.gartner.com/smarterwithgartner/gartner-top-10-strategic-technology-trends-for-2018

[29] Gartner Top 10 Technology Trends 2019 https://www.gartner.com/smarterwithgartner/gartner-top-10-strategic-technology-trends-for-2019

[30] TM Forum Catalyst Projects - TM Forum Labs - https://www.tmforum.org/labs/

[31] Digital twin modeling - Fei Tao, Bin Xiao, Qinglin Qi, Jiangfeng Chen, Ping Ji - Journal of Manufacturing Systems - July 2022

[32] Gartner Glossary - https://www.gartner.com/en/information-technology/glossary/digital-twin

[33] What Is a Digital Twin? Definition, Types, and Uses - coursera - October 2022 - https://www.coursera.org/articles/digital-twin

[34] IBM Digital Twin Point of View - IBM Academy of Technology - December 2022 - https://www.ibm.com/blogs/academy-of-technology/wp-content/uploads/2022/04/AoT-DigitalTwin-PoV.docx.pdf

[35] Digital Twin Consortium - https://www.digitaltwinconsortium.org/initiatives/the-definition-of-a-digital-twin/

[36] Wang, Z. (2020). Digital Twin Technology. Industry 4.0 - Impact on Intelligent Logistics and Manufacturing (pp.95-114). http://dx.doi.org/10.5772/intechopen.80974

[37] Superminds - Thomas W. Malone - Oneworld - 2018

[38] Digital Twin System Interoperability Framework - Digital Twin Consortium - December 2021 - https://go.omgprograms.org/l/658223/2021-11-29/5dv52b

[39] Enhancing Innovation in Telecom with Digital Twins - Harvard Business Review Analytic Services - https://hbr.org/sponsored/2022/03/enhancing-innovation-in-telecom-with-digital-twins

[40] Change2twin - Bringing Digital Twins to Manufacturing SMEs Bringing Digital Twins to Manufacturing SMEs - https://www.change2twin.eu/

[41] GB1022 ODA Functional Architecture Guidebook - TM Forum - https://www.tmforum.org/resources/reference/gb1022-oda-functional-architecture-guidebook-v1-1-0/

[42] Networked thinking: a quiet cognitive revolution - Anne-Laure Le Cunff - https://nesslabs.com/networked-thinking

[43] Chocolate Consumption, Cognitive Function, and Nobel Laureates https://www.nejm.org/doi/full/10.1056/NEJMon1211064

[44] Industrial Metaverse Blueprints, Part 3: System Interoperability Requirements - Doug Migliori - https://www.linkedin.com/pulse/industrial-metaverse-blueprints-part-3-system-doug-migliori/?trackingId=u2gymbcKQb%2B73hD2gMF4KA%3D%3DReimaReimagining_Research_Seamless_customer-journeysgining_Research_Seamless_customer-journeys

[45] 4 Key Factors In Digital Transformation Success - impact. - https://www.impactfirst.co/4-key-factors-in-digital-transformation-success#:~:text=According%20to%20a%20McKinsey%20study,rates%20of%204%2D11%25.

[46] 12 Reasons Your Digital Transformation Will Fail - Mar 2022 - https://www.forbes.com/sites/forbescoachescouncil/2022/03/16/12-reasons-your-digital-transformation-will-fail/?sh=27f4f9441f1e

[47] Catalyst Project C22.0.384 - Outcome-based decision intelligence for business growth - DTW 2022 - https://www.tmforum.org/labs/

[48] AI Operations (AIOps) Toolkit - https://www.tmforum.org/toolkits/ai_operationsaiops_toolkit/

[49] Why Google defined a new discipline to make humans make decisions - Cyara Birne - Jul 2018 - https://www.fastcompany.com/90203073/why-google-defined-a-new-discipline-to-help-humans-make-decisions

[50] Seamless customer journeys - An Enterprise Digital Twin for CSPs - https://www.tcs.com/content/dam/global-tcs/en/pdfs/insights/whitepapers/Digital-Twin-Final.pdf

[51] TCS TwinX™ to Help Organizations Improve Customer Experience- https://www.tcs.com/what-we-do/industries/communications-media-information-services/solution/tcs-twinx-digital-twin-technology

[52] Industrial Metaverse Blueprints, Part 2: The Metaverse Runs on Digital Twins - Embedded Computing Design

[53] Building Industrial Digital Twins - Shiam Varan Nath, Pieter van Schalkwyk - 2021 - Packt Publishing

[54] Groshev, M., Guimaraes, C., Martin-Perez, J. & de la Oliva, A. (2021). Toward Intelligent Cyber-Physical Systems: Digital Twin Meets Artificial Intelligence. IEEE Communications Magazine, 59(8), 14–20. https://e-archivo.uc3m.es/bitstream/handle/10016/33912/Towards_CM_2021_ps.pdf?sequence=1

[55] Silver, D., Schrittwieser, J., Simonyan, K. et al. Mastering the game of Go without human knowledge. Nature 550, 354–359 (2017) https://discovery.ucl.ac.uk/id/eprint/10045895/1/agz_unformatted_nature.pdf

[56] A. Rasheed, O. San and T. Kvamsdal, "Digital Twin: Values, Challenges and Enablers From a Modeling Perspective," in IEEE Access, vol. 8, pp. 21980-22012, 2020, doi: 10.1109/ACCESS.2020.2970143. https://ieeexplore.ieee.org/document/8972429

[57] Decision Making with Descriptive, Predictive & Prescriptive Analytics + Rule-based & Heuristics, by Kai Chew, https://www.linkedin.com/pulse/decision-making-descriptive-predictive-prescriptive-analytics-chew/

[58] Is Decision Intelligence The New AI? - Pascal Bornet - Forbes - May 2022 - https://www.forbes.com/sites/forbestechcouncil/2022/05/25/is-decision-intelligence-the-new-ai/?sh=1131eb574e42

[59] A. Pommeranz, P. Wiggers, and C.M. Jonker. User-Centered Design of Preference Elicitation Interfaces for Decision Support. In G. Leitner, M. Hitz, and A. Holzinger (Eds.). HCI in Work and Learning, Life and Leisure - 6th Symposium of the Workgroup Human-Computer Interaction and Usability Engineering, USAB 2010, LNCS 6389 (pp. 14–33). Springer 2010.

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8. Administrative Appendix

8.1. DOCUMENT HISTORY

8.1.1. VERSION HISTORY

VERSION NUMBER	DATE MODIFIED	MODIFIED BY	DESCRIPTION OF CHANGES
1.0.0	09-Dec-2022	Alan Pope	Final edits prior to publication

8.1.2. VERSION HISTORY

RELEASE STATUS	DATE MODIFIED	MODIFIED BY	DESCRIPTION OF CHANGES
1.0.0	09-Dec-2022	Alan Pope	Initial Release

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